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RESEARCH ARTICLE

Determinants of carbon emissions in Pakistan's transport sector

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Abstract

The transport infrastructure plays an imperative role in a country's progress. At the same time, it causes environmental degradation due to extensive use of fossil fuels. The transport system of Pakistan is largely dependent on nonrenewable energy sources (oil, coal, and gas), which are hazardous to environmental quality. This research uses an autoregressive distributive lag model (ARDL) to examine the impact of oil prices, energy intensity of road transport, economic growth, and population density on carbon dioxide (CO_2) emissions of Pakistan's transport sector during the 1971–2014 period. The ARDL bounding test examines the cointegration and long-run relationships among the variables, and the directions of causal relationships are found through the Granger causality vector error correction model (VECM). The long-run results indicate that increases in oil prices and economic growth help to reduce the transport sector's CO_2 emissions, while rising energy intensity, population concentration, and road infrastructure increase them, with population playing a dominant role. The findings of this study can help authorities in Pakistan to develop suitable energy policies for the transport sector. Among other recommendations, the study recommends investment in renewable energy projects and energy-efficient transport systems (e.g., light train, rapid transport system, and electric busses) and environmental taxes (subsidies) on the vehicles that use fossil fuels (renewable energy).

Keywords Road transport energy intensity · CO_2 emissions from transport · STIRPAT · Pakistan

Introduction

The transport sector is considered an imperative contributor to economic growth of a country. In Pakistan, the transport system largely consists of roads,[1] railways,[2] air transport, and ports and shipping services. China-Pakistan Economic Corridor (CPEC), a project initiated by China, has augmented the importance of transport infrastructure of Pakistan. CPEC is supposed to create a new lucrative trade route between these two countries. Expectedly, more roads will be constructed and

[1] The road network of Pakistan consists of 263,415 km, of which 9324 km (3.53%) belongs to the National Highways and 2280 km the Motorways (0.87%). Expressways cover 262 km and strategic roads cover 100 km, i.e., 0.10%. The remaining road network is under management of provincial highways and local administration.

[2] The rail network comprises 7791 route km managed by the Pakistan Railway. About the railway vehicles, there are 1901 passenger coaches, 515 locomotives, and 17,543 freight wagons. The report is available at http://www.finance.gov.pk/survey/chapters_13/13-Transport%20final.pdf

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old ones will be upgraded for trade accomplishment. Therefore, the transport sector cannot be overemphasized and it can be called a lifeline for the economic development of Pakistan.

This study assesses the impact of oil prices, energy intensity in the transport sector, road infrastructure, economic growth, and population density on the transport sector's CO_2 emissions in Pakistan. The study is important; as the road infrastructure is expanding in Pakistan, more vehicles are adding to road traffic because of increasing population, older vehicles are still part of the road, rail cars are operated using coal consumption, skin diseases are increasing because of air pollution, and overall CO_2 emissions are increasing in Pakistan. In the following paragraphs, we model the main drivers of CO_2 emissions related to transport sector.

Fossil fuels are the main energy sources for Pakistan's transport sector. Increased demand and a limited supply of fossil fuels (oil, coal, and gas) keep the prices increasing. Although fossils fuels are called engines of the economy, there are many downsides to their use, not least among them that they are responsible for climate change and the greenhouse effect and that they raise the pollution level, which is harmful to humans and other life (Chen and Lin 2015). An efficient oil-pricing strategy can improve an economy's energy efficiency and environmental sustainability by discouraging its use (Shahbaz et al. 2015). Besides their negative effects on the environment, fossils fuels require a large amount of foreign reserves if the country imports oil. As oil prices are an important determinant of environmental change, we have included crude oil prices in the CO_2 emissions function.

Road infrastructure and energy intensity are important ingredients of economic growth. Even though they contribute to the economy, these factors are major contributors to the transport sector's carbon footprint, especially in developing nations.

Population density is another main driver of CO_2 emissions of the transport sector. As population increases, the number of vehicles and demand for fuel also increases, accelerating the amount of CO_2 emissions. Population density not only increases human activities but also leads to an increased growth rate of household income (Peterson 2017). A large population needs a huge amount of energy in the form of electricity, coal, and natural gas for uninterrupted work and living. Because of Pakistan's rising economic growth in the last decade and a population increase of more than 190 million, Pakistan has become a high CO_2 emitter among developing countries. Its various modes of transportation and expanding road infrastructure call for an investigation of Pakistan's CO_2 emissions from its transport sector.

The case of Pakistan

Although the transport sector contributes to an economy, it is equally responsible for polluting the environment in developing countries, where fossil fuels are primary energy sources for the sector. The transport sector is the second largest consumer of energy in Pakistan, whose energy mix consists of 97% fossil fuels, about 28% of which go to the transport sector Because of aging vehicles, the lack of emission control policies, the use of low-quality fuel, and poor engine maintenance, the transport sector will soon be the largest emitter of CO_2 in Pakistan, especially in urban areas.

Like other developing countries, Pakistan's lack of environmentally friendly fuels and modes of transportation that use them constantly increases the level of pollutants in the environment. The use coal for the production of electricity is also increasing because of the rising demand for energy. Pakistan's public transport system is underdeveloped, and its middle class is expanding, which has resulted in a recent surge in the number of vehicles, especially private vehicles.

Energy intensity refers to the ratio of total fuel consumption to gross domestic product (GDP). Based on Vision 2025, Pakistan has designed a National Transport Policy, which contains many development projects for the transport sector. The focus of this transport policy is to provide affordable, safe, and fast transportation facilities to netizens. Although the policy contains an environment-friendly provision, the government is not yet able to follow this policy. For example, the rapid transport system, launched in three of Pakistan's megacities of Pakistan, is based on fossil fuels. As a result, public transportation is expected to generate more CO_2 emissions in Pakistan, as will private vehicles. The biggest hurdle in the sustainable transport sector is the electricity crises in Pakistan that need to be settled first. Electric breakdown from 6 to 18 h has failed many industries in Pakistan. Electric vehicles are not successful due to unavailability of constant supply of electricity.

This assessment fills the literature shortage and presents important policy implications for improvement. For example, the CPEC project will see thousands of vehicles involved in trading with China and other One-Belt, One-Road initiative member countries on Pakistani roads and railways. Because these vehicles use fossil fuels, significant emissions will be added to the air of Pakistan. Pakistan needs a comprehensive policy now to avoid further environmental degradation without compromising bilateral trade with other countries and its own economic development. To address this single-country CO_2 emission problem, a study that uses the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model will reveal the environmental factors that determine CO_2 emissions in Pakistan's transport sector. Application of the STIRPAT model can describe the function of CO_2 emissions and its determinants. The autoregressive distributive lag (ARDL) bounding test and the Johansen cointegration test are used to examine the long-run equilibrium relationship among the variables, and the vector error correction model (VECM) method is used to explore short- and long-run causal relationships.

The rest of this paper is organized in a way that section 2 contains the literature review, section 3 describes the data collection and methodology, section 4 presents and discusses the results, and section 5 presents the conclusion and outlines recommendations for practitioners.

Literature review

Sector research helps to identify which sectors need policymakers' attention most urgently (Guo et al. 2018). After the industrial section, the transport sector is contributes the most CO_2 emissions worldwide. Various researchers have investigated the factors that drive CO_2 emissions in this transport sector. Recently, Du et al. (2019) studied the main drivers of CO_2 emissions in China's transport sector, reporting that road transport significantly increases China's CO_2 emissions, while the country's rail infrastructure has been helpful in reducing them. Du et al. (2019) also reported that, in 2012, the road, rail, and air subsectors were the primary CO_2 emissions emitters in 2012.

Santos (2017) examined the determinants of vehicle emissions and identified the high cost of renewable energy sources and the absence of legal binding at international levels. Santos endorsed the idea that environmental taxes and subsidies can overcome the high-cost problem and recommended that countries discuss this issue as part of a global agenda. Timilsina and Shrestha (2009) studied the Asian countries to determine the factors that increase CO_2 emissions during the 1980–2005 period and suggested that population growth, economic growth, and transport energy intensity enhance vehicle emissions. Later, Chandran and Tang (2013) checked the influence of foreign direct investment, economic growth, and transport energy consumption on CO_2 emissions in the framework of the environmental Kuznets curve (EKC) hypothesis for the ASEAN-5 countries. Their results indicated that transport energy consumption and economic growth increase emissions, while foreign direct investment has no connection with CO_2 emissions, and that the EKC hypothesis is not valid for Indonesia, Malaysia, and Thailand. Using regional data from China, Zhang and Nian (2013) examined the connection between transport sector–related CO_2 emissions and its determinants over the 1995–2010 period. They used the Pedroni cointegration test to check the long-run equilibrium relationship among the variables across the regional panel and reported that economic growth, population, and oil prices increase the transport sector's emissions, while electricity consumption and freight turnover reduce them. They found similar results for China's east and central regions.

Using the STIRPAT model, Liddle (2013) investigated CO_2 emissions' links with total residential electricity consumption, urbanization, and economic growth by dividing the countries into poor, middle-income, and rich segments. Their cointegration results suggested the presence of a long-run relationship among the variables across the panel countries. The long-run elasticity results showed that economic growth, urbanization, and share of residential energy consumption increase the CO_2 emissions across the panel countries. Using Organization for Economic Co-operation and Development (OECD) countries' data from 1960 to 2008 and a cointegration approach, Saboori et al. (2014) probed the causal and long-run elasticity of transport sector's emissions with the economic growth. Their findings indicated a bidirectional relationship between transport sector energy consumption and CO_2 emissions and between economic growth and CO_2 emissions for all OECD countries.

Shahbaz et al. (2015) checked the causal link between macroeconomic variables and road transport CO_2 emissions using data from Tunisia over the 1980–2012 period. They used the ARDL bounding test to investigate cointegration among the variables. The results of long-run elasticities revealed that road infrastructure increases road emissions, while fuel prices reduce them. Liddle and Liddle (2015) collected data from developed and developing countries to investigate the EKC hypothesis between urban transport–related emissions (CO_2 emissions, volatile hydrocarbon, and nitrogen emissions) and GDP per capita by incorporating urban intensity and fuel prices into the CO_2 emissions function. The panel results indicated support for the EKC hypothesis for all three kinds of emissions, while fuel prices and urban intensity decreased all three kinds of emissions.

Using data from seventy-five countries during the 2000–2014 period and the generalized method of moments (GMM) for long-run estimation, Saidi and Hammami (2017) probed the links between environmental degradation, economic growth, trade openness, energy consumption, and freight transport, finding that environmental degradation increases with increases in economic growth, trade openness, energy consumption, and freight transport. Alshehry and Belloumi (2017) investigated the EKC hypothesis between CO_2 emissions from the transport sector and economic growth for Saudi Arabia from 1971 to 2011 using the ARDL approach. Their estimation results indicated no support for the EKC hypothesis. Kharbach and Chfadi (2017) found support for the EKC hypothesis between CO_2 emissions and economic growth in Morocco by incorporating energy consumption from the transport sector, diesel consumption from the transport sector, and the number of vehicles. Their results supported the EKC hypothesis. More recently, for the case of European countries, Andrés and Padilla (2018) investigated the driving factors of greenhouse gas (GHG) emissions for the transport sector using data from 1980 to 2014 and panel data methodology to calculate the elasticities between the variables. Their results indicated that GHG emissions increase with the rise in population, transport energy intensity, economic growth, and transport volume.

Danish and Baloch (2018) studied the dynamic relationships between energy consumption related to the transport sector, economic growth, and environmental degradation in Pakistan. They measured environmental degradation through sulfur dioxide (SO_2) emissions and reported a positive link between energy use in the transport sector and environmental quality. In another study, Danish et al. (2018a) investigated the effect of transport-related energy consumption and CO_2 emissions in Pakistan, concluding that energy consumption in the transport sector had a significant role in overall CO_2 emissions in Pakistan.

The literature is inconclusive regarding the determinants of transport-related CO_2 emissions in Pakistan, and the roles of energy intensity, oil prices, and population in the presence of economic growth in Pakistan have not been checked in any study. Extant studies have used overall CO_2 emissions to find their determinants, while this study uses CO_2 emissions from the transport sector to determine what drives those emissions in this sector.

Methodology

To evaluate the main driving forces of transport-related CO_2 emissions in Pakistan, this study uses the STIRPAT model to explain the CO_2 function. Then, to check long-run and short-run dynamics, the study uses the econometric technique ARDL. Numerous studies have used the STIRPAT model; for example, Xu and Lin (2015a) generated the STIRPAT model and the prevailing scenario for the transport sector during China's industrialization and urbanization process; Shahbaz et al. (2017) used this model to check the relationship between urbanization and energy demand in Pakistan; Wang et al. (2013) coupled the STIRPAT model with regression to investigate the effect of population, economic development, technological development, urbanization, industrialization, services, energy consumption, and foreign trade on the energy-associated CO_2 emissions in Guangdong Province, China; Wang and Zhao (2015) divided China's thirty provinces into three regions based on their economic growth using a cluster analysis method and designed a STIRPAT model to determine the factors that affected CO_2 emissions; Roberts (2014) used a cross-sectional model of the STIRPAT framework to investigate the role of intergenerational wage transfers on CO_2 emissions at the county level in the USA; and Sheng and Guo (2016) used the STIRPAT model to show the long-run and short-run positive impact of urbanization. Various studies in the field of energy and environment have also used the STIRPAT model (Sheng and Guo 2016; Xu and Lin 2015a, b; Zhang and Lin 2017).

The STIRPAT model stems from the IPAT model, which expresses the impact of human actions on a country's economic development (Ehrlich and Holdren 1971) and is presented as:

$$I = PAT \tag{1}$$

where I is used to represent integration of PAT factors. P is population, A is economic development, and T is technology. The IPAT equation harbors some flaws, as it oversimplifies the problems our environment faces by assuming that the elasticities of each independent variable correspond to 1 (Timma et al. 2016). Therefore, Dietz and Rosa (1997) proposed the STIRPAT for a more precise calculation of environment-influencing factors:

$$I_t = aP^b{}_t A_t{}^c T_t{}^d{}_{e_t} \tag{2}$$

where a is the intercept term, P is population, A is economic development, T is technology, b, c, and d are the coefficients of environmental effects corresponding to P, A, and T, and e_t is the error term. The STIRPAT model has various advantages (York et al. 2003); for example, it is a stochastic model, which is helpful in testing hypotheses; it is equally useful for time series, cross-sectional, and panel data; it can consider the environmental impact of behavioral factors, along with population, affluence, and technology; it explains precisely the environment's sensitivity to CO_2 emissions' drivers; and it can be easily refined to include additional determinants. The model emphasizes that the environmental degradation in a country is a function of the country's population, economic growth, and technology.

The literature has widely discussed the relationship between economic growth and CO_2 emissions through the EKC hypothesis, and the results obtained through the STIRPAT model are identical to those that come from investigations of the EKC hypothesis (Shahbaz et al. 2017). The connection between environmental pollution and technological advancement is comparatively simple and straightforward and suggests that technological progress helps to reduce environmental pollution (Hagemann 2017). Numerous studies are available in the literature which have employed the STIRPAT model to appraise the influence of these driving forces on environmental pollution (e.g., Tan and Wang 2017; Xu and Lin 2015a, b).

Econometric strategy

To examine econometrically the effects of CO_2 determinants from the transport sector, we follow the model suggested by Talbi (2017) and rewrite Eq. (2) as:

$$\mathrm{LogCO}_{2t} = \alpha_0 + \beta_1(\mathrm{LogOP}_t) + \beta_2(\mathrm{LogEI}_t) + \beta_3(\mathrm{LogGDP}_t) \\ \beta_4(\mathrm{LogRI}_t) + \beta_5(\mathrm{LogPD}_t) + \mu_0 \tag{3}$$

where CO_2 is carbon dioxide emissions from the transport sector, OP is crude oil prices, EI is for energy intensity, GDP is economic growth, RI is road infrastructure, PD is population density, μ_0 is the residual, and t is the period. To eliminate the possibility of heteroscedasticity, all variables are managed in log form.

The existing literature depicts several econometric techniques for analyzing time series data, but based on this research's objective, we employ the ARDL bound testing approach proposed by Pesaran et al. (2001) to examine the long-run integration and the relationships among study variables. As Ben and Belloumi (2017) & Belloumi and Alshehry (2015) explained, ARDL has several advantages over other cointegration techniques. For example, it is the most appropriate technique for use with a small dataset, it allows long-run relationships to be tested if regressors are integrated at I(0) at the first level or at mixed integration levels of I(0) and I(1) in cointegration analyses, it produces robust estimates in cases of endogeneity, and it can estimate the long-run and short-run parameters in a single model, without losing any information for the long run. The ARDL is described by the following equation:

$$\begin{aligned}\Delta\mathrm{LogCO}_{2t} = c &+ \sum_{i=1}^{p}\vartheta_{1i}\Delta\mathrm{LogCO}_{2t-i} + \sum_{i=0}^{p}\vartheta_{2i}\Delta\mathrm{LogOP}_{t-i} + \sum_{i=0}^{p}\vartheta_{3i}\Delta\mathrm{LogEI}_{t-i} \\ &+ \sum_{i=0}^{p}\vartheta_{4i}\mathrm{LogGDP}_{t-i} + \sum_{i=0}^{p}\vartheta_{5i}\mathrm{LogRI}_{t-i} + \sum_{i=0}^{p}\vartheta_{6i}\mathrm{LogPD}_{t-i} \\ &+ \phi_1\mathrm{CO}_{2t-1} + \phi_2\mathrm{OP}_{t-1} + \phi_3\mathrm{EI}_{t-1} + \phi_4\mathrm{GDP}_{t-1} + \phi_5\mathrm{RI}_{t-1} \\ &+ \phi_6\mathrm{PD}_{t-1} + \mu_t\end{aligned} \tag{4}$$

where Δ is the first difference operator. The null hypothesis of no cointegration (H_0: $\phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = \phi_6 = 0$) is checked against the alternative hypothesis (H_0: $\phi_1 \neq \phi_2 \neq \phi_3 \neq \phi_4 \neq \phi_5 \neq \phi_6 \neq 0$). We find the F-value to test the cointegration, such that if this F-value is beyond the upper bound, it confirms the cointegration but if it lies below the lower critical bound, it means no cointegration. If cointegration is confirmed, then we further estimate the short-and long-run linkages. To verify the robustness and reliability of the data, we check the autocorrelation, heteroscedasticity, and stability in the model using several diagnostic tests.

Data collection

The crude oil prices are obtained from BP Statistics (2017), while data for the rest of the variables are collected from the World Bank (2017) website for the period from 1970 to 2014. In the present study, CO_2 emissions are used to measure environmental quality and are measured as CO_2 emissions from transport (% of total fuel combustion). The data for CO_2 emissions from the transport sector are limited to 2014 for the case of Pakistan, so we used the maximum data available on WDI. Energy intensity is calculated as road transport energy consumption divided by GDP. Per capita GDP is used as a proxy for economic growth based on constant 2010 US \$. The total length of roads is used to measure road infrastructure. Population density is measured as people per square kilometer of land area. Figure 1 depicts the time series trends in data of underlying variables.

Results and discussion

Unit root test

It is the first condition of the ARDL approach that all the data series should be stationary at level or first difference, and second difference is not allowed. This implies us to check the unit root in the data series. The objective of the time series constituent unit root test is to check the stationary properties of the data. If time series data contains a unit root, we cannot proceed further towards bound testing or ARDL estimations. Table 1 shows the results of the Ng-Perron test, and Table 2 presents the unit root results estimated through the augmented Dicky-Fuller test. Both tests confirm that all variables are stationary either at level I(0) or at 1st difference I(1).

Cointegration results

After confirming stationarity, we move on to find the cointegration by calculating the F-value using the bound test statistic. The results of the bound test statistic, shown in Table 3, indicate that the value of the F-statistic exceeds the upper bound value, so we reject the null hypothesis of no cointegration at the 1% level of significance and conclude that the study's core variables are cointegrated. The lag length 1 is selected through the Schwarz information criterion under the vector autoregressive (VAR) system. We also use diagnostic tests to check the validity and reliability of the bound testing result. For example, we use the Breusch-Godfrey test to check the serial correlation and the ARCH test to find heteroscedasticity. The results of both tests show that the residual is white noise. We also use the Ramsey RESET test to check regressors' specification errors in the model, and the results indicate good model specification. We use the Johansen cointegration method to test the robustness of the cointegration results obtained through bound testing and divide the results (Table 4) into two groups of statistics: trace statistics and eigenvalue statistics. The Johansen cointegration

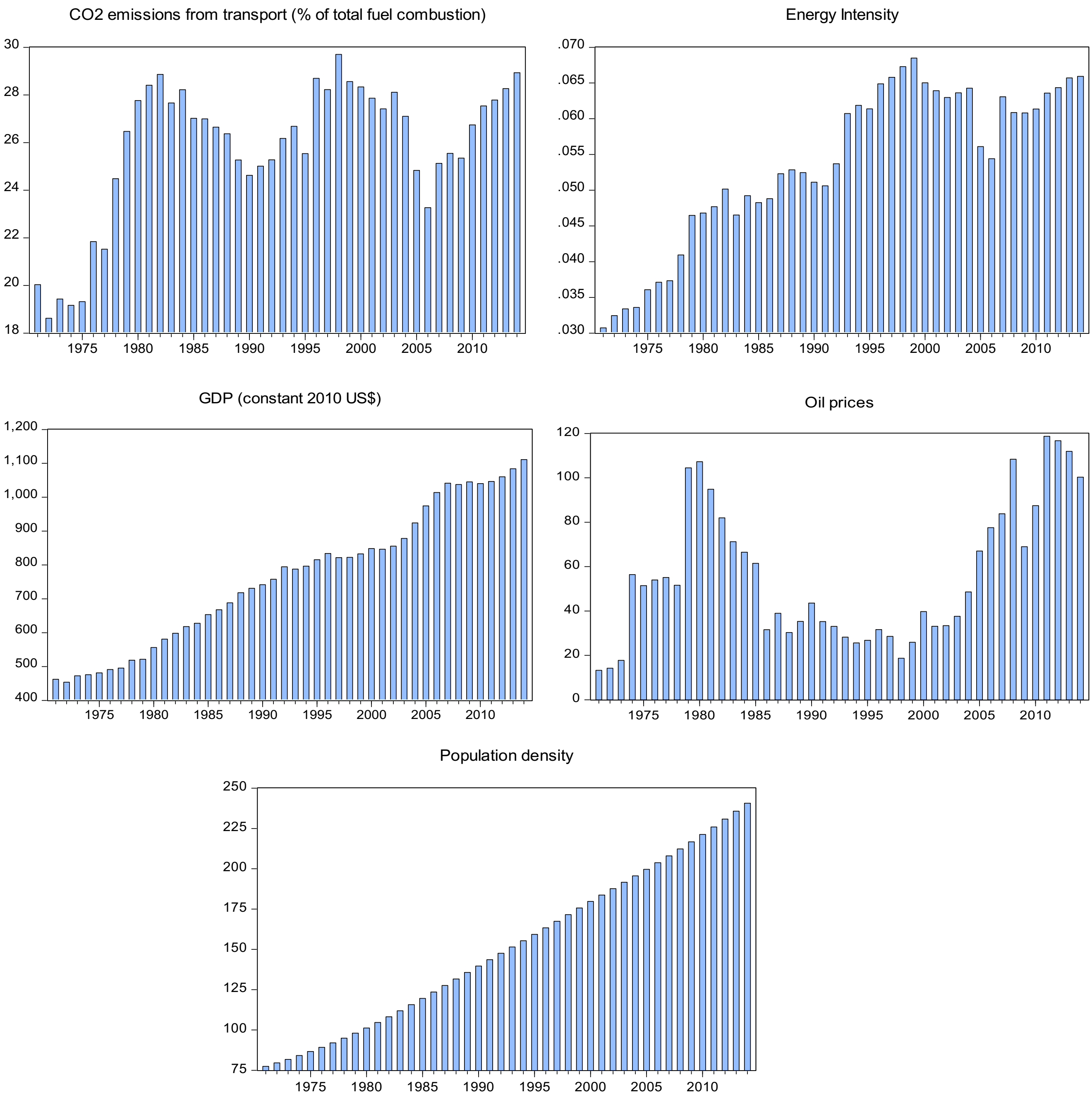

Fig. 1 Trends in CO_2 emissions, energy intensity, GDP, oil prices, and population density from 1970 to 2014

test confirms cointegration between the variables of interest, so results from the bounding test are reliable.

Long-run and short-run relationships

After confirming the long-run cointegration between the variables, we employ the ARDL to explore the long-run and short-run dynamics among the study variables. In the long run, the negative coefficient (− 0.122116) shows that crude oil prices have a strong negative relationship with CO_2 emissions in Pakistan, so when oil prices increase, CO_2 emissions decrease as people reduce the use of their personal vehicles. These results are consistent with those of Shahbaz et al. (2015) for Tunisia.

The effect of energy intensity (0.837775) on CO_2 emissions is positive and significant in the long run. The results reveal that a 1% increase in energy intensity brings a 0.837% increase in CO_2 emissions, and vice versa. The positive coefficient of energy intensity implies that environmental standards and energy technologies are not up to the mark and

Table 1 Results of Ng-Perron test statistics

Variables	MZ^a	MZ^t	MS^B	MP^T	MZ^a	MZ^t	MS^B	MP^T
$LogCO_2$	0.86744	0.78691	0.90717	56.9328	− 20.1495	− 3.17377	0.15751	4.52429
LogOP	− 2.11556	− 0.80299	0.37956	9.73027	− 20.9882	− 3.23496	0.15413	4.36902
LogEI	0.34129	0.28955	0.84839	45.4701	− 20.7359	− 3.20891	0.15475	1.22018
LogGDP	1.00238	0.84542	0.84341	51.4522	− 14.8813	− 2.69785	0.18129	1.75957
LogRI	− 2.13666	− 1.02188	0.47826	11.3622	− 13.6165	− 2.60714	0.19147	1.80749
LogPD	0.63614	0.42754	0.67208	32.9048	− 10.8697	− 2.33115	0.21446	8.38401
Asymptotic critical values								
1%	− 13.8000	− 2.58000	0.17400	1.78000				
5%	− 8.10000	− 1.98000	0.23300	3.17000				
10%	− 5.70000	− 1.62000	0.27500	4.45000				

a, b, and C are an indication of the level of significance at 1%, 5%, and 10%, respectively. MZ^a , MZ^t , MS^B , and MP^T are the four statistics used by the Ng-Perron test which are modified statistics of Phillips and Perron unit root. The values of these four statistics are compared with critical values. If calculated values are smaller than critical values, we reject the H_0

not helpful in mitigating the CO_2 emissions (Du et al. 2012; Lin and Xu 2017). Our findings are consistent with those of Zhang and Nian (2013) for China.

These results have several policy implications. Modern, energy-efficient technology is needed in the transport sector to protect the environment, but more research and development investment is required (Filipescu et al. 2013). In the absence of a significant investment in R&D personnel, it is complicated to develop superior environmental safety and energy-efficient technologies, and more investment is required in the renewable energy infrastructure to reduce dependence on fossil fuels. In addition, there should be a comprehensive transport policy with respect to aging vehicles, as checks should be required to ensure proper engine maintenance. Some filling stations also sell degraded (cheap) fuels, a practice that must be stopped to ensure environmental sustainability. In metropolitan areas, alternate days can be assigned to use personal vehicles in order to avoid smoke pollution.

As for the nexus of GDP and CO_2 emissions, our findings suggest that GDP per capita has a significant negative effect on the transport sector's CO_2 emissions. As reported in Table 5, a 1% increase in GDP per capita accounts for a 0.828% reduction in the transport sector's CO_2 emissions in the long run. This incremental effect could be due to the growth in GDP's reinforcing people's living standards, so they can buy more energy-efficient vehicles that use less energy and reduce air pollution. With respect to the relation between GDP and transport sector's CO_2 emissions, our findings are similar to those of Achour and Belloumi (2016), but our results contrast those of Wang and Li (2015), who claimed that an increase in economic growth leads to an increase in CO_2 emissions. The difference between the results may be due to the difference in the regions investigated and the nature of data used. In Pakistan, there is a large gap in the income levels of different classes; wealth distribution is not equal. When the GDP rises, rich people become richer and poor people get poorer. Some of the poor reduce their use of transportation, while some rich people switch to energy-efficient vehicles. The net results may be a reduction in the transport sector's CO_2 emissions.

We observe that the positive effect of an increase in road infrastructure on CO_2 emission is stronger. This means that expansion in road infrastructure generates a substantial amount of CO_2 emission with the passage of time in Pakistan. It directs towards the linear relationship between road infrastructure and transport energy consumption. This means that an increase in the number of vehicles on the road pollutes the environment. This may occur due to the reason that road transport is the backbone of the transport sector in Pakistan, but it makes a significant contribution to the emissions of CO_2. Therefore, this road transport is a huge financial burden on the economy of the country such as half of the imported oil consumed by road transportation (UNDP 2015). This result is backed by Solís and Sheinbaum (2013) who calculated that a number of vehicles contribute to the emission of carbon dioxide in the case of Mexico. Further, the private car (gasoline), light-duty fright,

Table 2 Augmented Dickey-Fuller test

Variables	Level	Prob.*	First-Difference	Prob.*
$LogCO_2$	− 1.852547	0.6614	− 6.537202	0.0000
LogOP	− 2.168943	0.4941	− 6.382842	0.0000
LogPD	− 1.025672	0.9285	− 6.529976	0.0000
LogEI	− 1.998570	0.5855	− 6.491309	0.0000
LogGDP	− 1.596604	0.7775	− 5.889063	0.0001
LogRI	0.881080	0.9997	− 4.022475	0.0160

*shows the significance of value for decision. If probability value is less than 0.1, it means data is stationary otherwise non-stationary. All the variables are stationary at first difference level

Table 3 ARDL bound testing & diagnostic test results

	Bound testing approach			Diagnostic test		
Equation	*F*-value	Lag order	Conclusion	Ramsey	LM	ARCH
CO_2 = f(OP, EI, GDP, RI, PD)	5.26533[a]	(2, 2, 1, 0, 3, 0)	Conclusive	0.86029 (0.3972)	1.23197 (0.3082)	0.911944 (0.5359)
Critical value bounds						
Significance	I0 bound	I1 bound				
10%	2.08	3				
5%	2.39	3.38				
2.5%	2.7	3.73				
1%	3.06	4.15				

"a" represents the level of significance. Parenthesis in diagnostic tests represents *P* values

busses (which burn diesel), and heavy-duty vehicles contribute 32.6%, 25%, 11.3%, and 12%, respectively to CO_2 emissions. For instance, Shahbaz et al. (2015) affirm that road infrastructure is the primary producer of pollutants in the transport sector in the case of Tunisia.

We find a positive and significant link between population and CO_2 emissions, as a 1% increase in population density increases CO_2 emissions by 0.555%. These results are important because the population in Pakistan is increasing rapidly, leading to an increase in the number of vehicles on the roads. Pakistan's government should develop rural areas by providing education, health, employment, and other basic needs to empower the agriculture sector and should control the rising urbanization. Saidi and Hammami (2017) reported similar results for seventy-five countries.

We found several short-run links between our variables: oil prices are positively linked with CO_2 emissions in the short run, but this link is insignificant; population density has the same short-run positive and significant impact on CO_2 emissions as it does in the long run; the impact of energy intensity on CO_2 emissions in the short run is positive but insignificant; GDP has a negative but insignificant link with CO_2 emissions; and road infrastructure positively and significantly impacts CO_2 emissions in the short run. Herein, it is worth mentioning that the environmental pollution, particularly the accumulation of greenhouse gases at a large scale in the environment, poses a grave danger to the life and health of people. These life-threatening high levels of emissions of greenhouse gases are the impetus for the stakeholders of the transportation sector to expedite its shift on new, less-polluting energy sources and also find out sustainable substitutes of the energy obtained from fossil fuels. Thus, in this way, environmental pollution can reign to an acceptable level (Song et al. 2014).

In order to check the robustness of analysis, we have used diagnostic tests. For example, $\chi 2$-RESET, $\chi 2$-LM, and $\chi 2$-ARCH tests are used to find heteroscedasticity and

Table 4 Johansen cointegration

Unrestricted cointegration rank test (trace)				
Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Prob.**
None*	0.892296	191.0447	95.75366	0.0000
At most 1*	0.691113	104.1382	69.81889	0.0000
At most 2*	0.491747	58.32183	47.85613	0.0039
At most 3*	0.383159	31.92755	29.79707	0.0280
At most 4	0.271367	13.08494	15.49471	0.1117
At most 5	0.018749	0.738135	3.841466	0.3903
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized no. of CE(s)	Eigenvalue	Max-Eigen statistic	0.05 critical value	Prob.**
None*	0.892296	86.90648	40.07757	0.0011
At most 1*	0.691113	45.81636	33.87687	0.0012
At most 2*	0.491747	26.39428	27.58434	0.0704
At most 3	0.383159	18.84261	21.13162	0.1015
At most 4	0.271367	12.34680	14.26460	0.0983
At most 5	0.018749	0.738135	3.841466	0.3903

Max-eigenvalue analysis specifies 3 cointegrating equation(s) at the 5% significance level

*Explains the rejection point at the 5% significance level

**Shows *P* values estimated through MacKinnon-Haug-Michelis (1999) autocorrelation as depicted in Table 5. The result of $\chi 2$-RESET, $\chi 2$-LM, and $\chi 2$-ARCH confirm that energy intensity, oil prices, economic growth, and population density elucidate deviation in CO_2 emissions in the presence of autocorrelation and heteroscedasticity. Moreover, to check the endogeneity and steadiness of the model, we have used CUSUM of residual and CUSUMsq of residual as shown in Figs. 2 and 3, respectively. The blue line in between the upper and lower red lines states that the model is robust at the 5% significance level.

VECM results

The results of ARDL confirm the one-way relationships among the variables. To find the directions of two-way relationships, we used the vector error correction model (VECM) approach. According to Toda and Phillips (1993), when the long-run relationship is confirmed, VECM is a good option for checking causality. VECM differentiates the Granger causality results in terms of long run and short run. We measured the causality through the Wald statistic which determines the coefficients of all the variables for difference and lag difference. Table 6 presents the results of the Granger causality test.

We estimate long-run causality using the error correction term (ECT) and short-run causality with the help of the Wald test (F-statistics). If ECT_{t-1} is significant and negative, it shows that long-run causality exists (Danish et al. 2018b). The econometric equation for VECM is written as:

$$\begin{bmatrix} \Delta \log CO_{2t} \\ \Delta \log OP_t \\ \Delta \log PD_t \\ \Delta \log EI_t \\ \Delta \log GDP_t \\ \Delta \log RI_t \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{bmatrix} + \sum_{p-1}^{q} \begin{bmatrix} \theta_{11p} & \theta_{12p} & \theta_{13p} & \theta_{14p} & \theta_{16p} & \theta_{17p} \\ \theta_{21p} & \theta_{22p} & \theta_{23p} & \theta_{24p} & \theta_{25p} & \theta_{26p} \\ \theta_{31p} & \theta_{32p} & \theta_{33p} & \theta_{34p} & \theta_{35p} & \theta_{36p} \\ \theta_{41p} & \theta_{42p} & \theta_{43p} & \theta_{44p} & \theta_{45p} & \theta_{46p} \\ \theta_{51p} & \theta_{52p} & \theta_{53p} & \theta_{54p} & \theta_{55p} & \theta_{56p} \\ \theta_{61p} & \theta_{62p} & \theta_{63p} & \theta_{64p} & \theta_{65p} & \theta_{66p} \end{bmatrix} \tag{5}$$

$$\times \begin{bmatrix} \Delta \log gCO_{2,t-p} \\ \Delta \log Oil_{t-p} \\ \Delta \log PD_{t-p} \\ \Delta \log EI_{t-p} \\ \Delta \log GDP_{t-p} \\ \Delta \log RI_{t-p} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \end{bmatrix} ECT_{t-1} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \\ \mu_{4t} \\ \mu_{5t} \\ \mu_{6t} \end{bmatrix}$$

The VECM results indicate a bidirectional relationship between the transport sector's CO_2 emissions and oil prices. Shahbaz et al. (2015) reported similar results for Tunisia. A unidirectional relationship runs from population density to transport sector's emissions. Similarly, population (Granger) causes economic growth in one direction. The association between population density and road infrastructure is unidirectional, running from population density to road infrastructure. Energy intensity (Granger) causes the transport sector's carbon emissions. Our results suggest that economic growth (Granger) causes CO_2 emissions, but in return the transport sector's CO_2 emissions do not (Granger) cause economic growth. However, Alshehry and Belloumi (2017) found no causal relationship between the transport sector's CO_2 emissions and economic growth. Road infrastructure (Granger) causes oil prices, but this result is not consistent with Shahbaz et al. (2015) for Tunisia.

There is a long-run feedback relationship between the transport sector's CO_2 emissions and oil prices, while the relationship between oil prices and energy intensity is bidirectional. However, a unidirectional causality runs from population density to CO_2 emissions, oil prices, and energy intensity. Similarly, economic growth causes the carbon emissions of the transport sector, oil prices, and energy intensity in the long run.

Impulse response functions

Figure 4 shows fluctuations occurred in CO_2 emissions of the transport sector with the changes occurring in other determinants in the short run and long run. As the figure shows, rising oil prices first increase the transport-related CO_2 emissions before decreasing them later. Increasing population density gradually increases CO_2 emissions, but increasing energy intensity decreases CO_2 emissions in the long run. At the beginning of the period, economic growth decreases the transport sector's CO_2 emissions, but it increases them in the middle of the period. Expanding

Table 5 Analysis of long-run and short-run dynamics

Variables	Coefficient	Std. Error	t-statistics	Prob.
Long-run analysis				
LogOP	− 0.122116	0.01602	− 7.622622	0.000
LogPD	0.555413	0.242161	− 2.29357	0.0309
LogEI	0.837775	0.076463	10.95667	0.000
LogGDP	− 0.82835	0.205015	− 4.04044	0.0005
LogRI	0.176145	0.092406	1.906216	0.0687
C	− 1.848	0.278568	− 6.63392	0.000
Short-run analysis				
D (LNOP)	0.04881	0.030115	1.620816	0.1181
D (LNPD)	11.752001	3.470146	3.386602	0.0019
LOG_EI	0.034282	0.078082	0.43906	0.6645
D (LOG_GDP)	− 0.447123	0.393676	− 1.135764	0.9250
LOGRI	0.268010	0.105211	− 2.547364	0.0160
CointEq(− 1)	− 0.84874	0.202084	− 4.19995	0.0003
R-square	0.992519			
ARCH	0.759730	0.3890		
Ramsey	2.083383	0.1593		
LM	1.898914	0.1784		

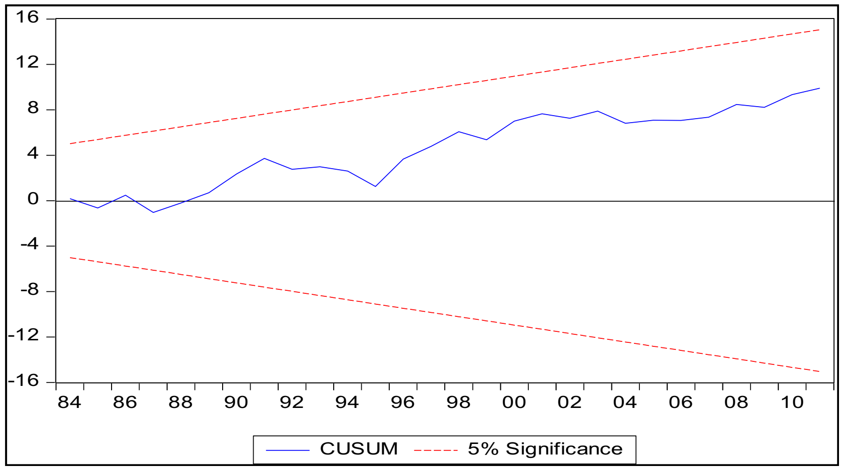

Fig. 2 Results of CUSUM of residual

road infrastructure does not significantly influence the emissions in both the short run and long run. At first, the sector's increasing CO_2 emissions do not affect oil prices, but then they increase them before slowly decreasing them. Increasing population density increases oil prices with the passage of time. The influences of rising energy intensity, economic growth, and road infrastructure on oil prices are not significant in the impulse response function. Increasing CO_2 emissions from the transport sector and increasing energy intensity and economic growth do not affect the population in the short or long run. At the start of the period, increasing oil prices increase population density but decrease it in the long term. Expanding road infrastructure gradually increases population density. These results indicate the shocks between the transport sector's CO_2 emissions and energy intensity in the short run, while later the transport-related CO_2 emissions diminish the energy intensity. Rising oil prices first increase economic growth but later decrease it. Widening road infrastructure raises economic growth in the selected period, while rising oil prices reduce road infrastructure in the long term. Population density has a stable relationship with road infrastructure in the first half of the period, after which increasing population density starts to decrease road infrastructure.

Variance decomposition

We use the variance decomposition approach to assess contribution of different variables in transport CO_2 emissions. The forecast error variance is helpful in investigating the relative proportion of each driving force. In order to explain short- and long-run variations, we selected a 10-year period for variance decomposition. The results are shown in Table 7.

The oil prices explain 0.049% of the transport sector's CO_2 emissions in the first 2 years and 5.71% of those emissions in the last 2 years. Economic growth explains 4.12% of the transport sector's short-run carbon emissions and 6.133% in the long run. Energy intensity shocks have greater effects than oil prices or economic growth, explaining 5.035% of the transport sector's short-run carbon emissions and 8.04% in the long run.

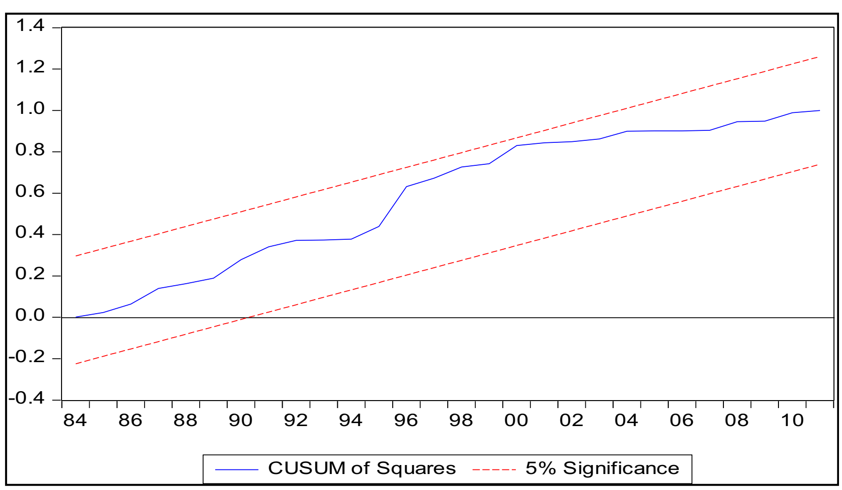

Fig. 3 Results of CUSUMsq of residual

Table 6 VECM results

	Short run						Long run
	ΔLogCO_2	ΔLogOP	ΔLogPD	ΔLogEI	ΔLogGDP	ΔLogRI	ECT-1
ΔLogCO2		5.4593^{a} (0.0036)	3.7719^{b} (0.0194)	5.3538^{a} (0.0040)	2.6804^{c} (0.0623)	0.9516 (0.4278)	− 0.6765^{a} [− 5.6680]
ΔLogOP	2.5283^{c} (0.0737)		1.1211 (0.3542)	1.1834 (0.3305)	1.9940 (0.1334)	5.7158^{a} (0.0031)	− 0.6233^{a} [− 3.9448]
ΔLogPD	0.9667 (0.4197)	2.0617 (0.1237)		1.8168 (0.1627)	0.7358 (0.5380)	1.6981 (0.1878)	− 0.0077 [− 0.2459]
ΔLogEI	1.0855 (0.3684)	0.3523 (0.7877)	0.3091 (0.8186)		0.3576 (0.7840)	0.6829 (0.5692)	− 0.8308^{a} [− 5.1263]
ΔLogGDP	1.9863 (0.1345)	0.4915 (0.6905)	4.0789^{b} (0.0141)	0.4239 (0.7370)		0.2008 (0.8950)	− 0.1554 [− 1.3568]
ΔLogRI	1.4919 (0.2360)	1.0651 (0.3781)	2.4977^{c} (0.0780)	0.4582 (0.7134)	0.0999 (0.9594)		− 0.2867 [− 0.4198]

Δ denotes the first difference operator. ^{c}, ^{b}, and ^{a} show the significance levels of 10%, 5%, and 1%, respectively. Brackets contain the *t*-values. Parentheses reveal the *P* values

A for the variables' effects on oil prices, the transport-related CO_2 emissions explain 6.96% of oil prices in the short term and 2.82% in the long term, so shocks in the CO_2 emissions have a decreasing influence on oil prices. Population density explains 1.42% of oil prices in the second period and 7.91% in the last period. Energy intensity does not significantly explain oil prices during the period, but economic growth explains 8.67% of oil prices in the short term and 20.45% in the long term, while road infrastructure explains 2.40% of oil prices in the second period and 35.13% in the last period of the term.

Regarding the effect of different factors on population density, oil prices explain 0.504% of population density in the second period of the short term and 17.79% in the long term. Road infrastructure contributes a miniscule 0.001% to population density in the short run and 17.43% in the long run. In the short run, economic growth explains a small 0.35% of population density, but in the long run, it explains 1.57% of population density.

As for economic growth, the transport sector's CO_2 emissions explain 13.99% of economic growth in the second period of the short run and 19.67% in the last period of the long

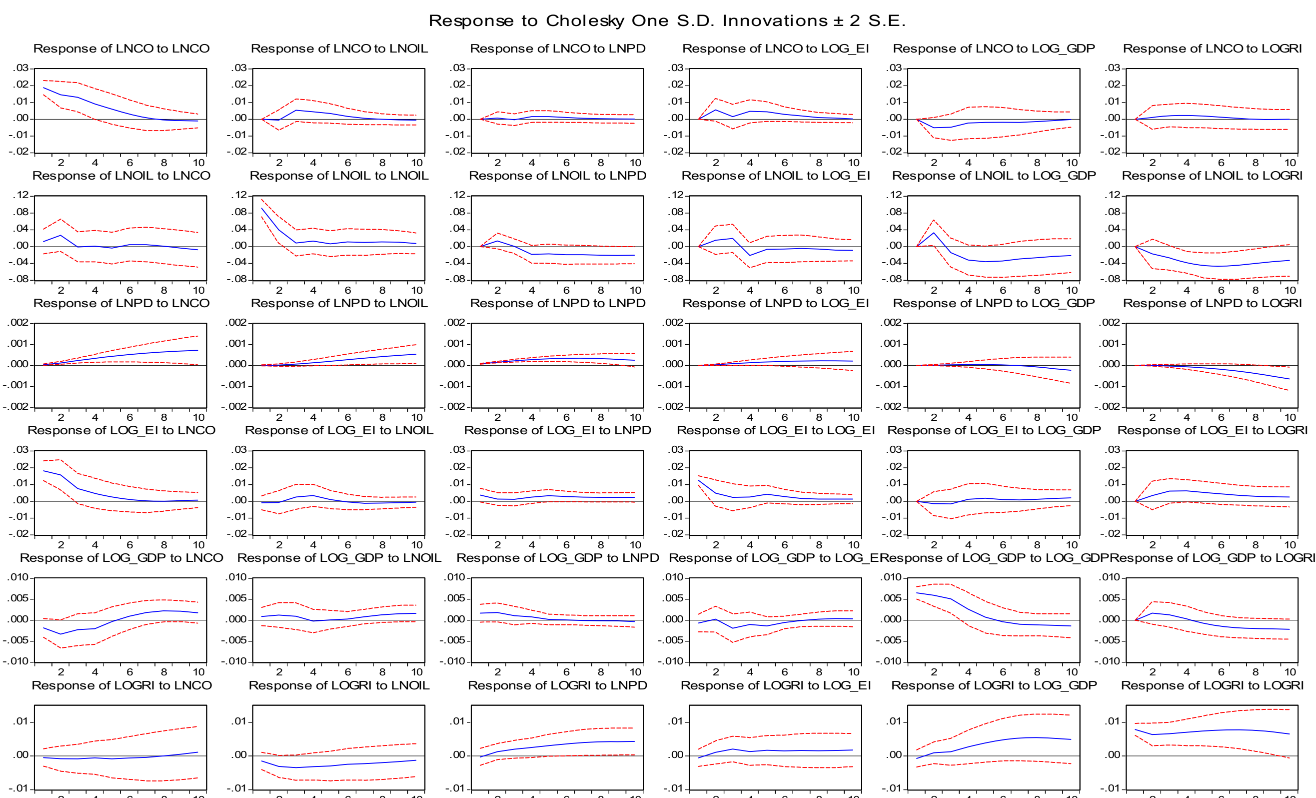

Fig. 4 Impulse response function 1

Table 7 Variance decomposition of $LNCO_2$

Period	S.E.	LNCO	LNOP	LNPD	LOG_EI	LOG_GDP	LOGRI
1	0.018834	100	0.000	0.000	0.0000	0.00000	0.0000
2	0.024987	90.56114	0.049205	0.071918	5.035149	4.120994	0.161593
3	0.029191	86.26133	3.311213	0.060943	3.958767	5.719594	0.688154
4	0.031423	82.66651	4.86257	0.300948	5.613909	5.461937	1.094124
5	0.032634	80.04226	5.586452	0.521686	7.090588	5.432464	1.326551
6	0.033046	78.94023	5.716226	0.618731	7.698895	5.614602	1.411318
7	0.033178	78.36452	5.696464	0.647838	7.961322	5.907685	1.422171
8	0.033228	78.13721	5.679752	0.652553	8.027253	6.085309	1.41792
9	0.03326	78.05183	5.690849	0.653147	8.049388	6.137295	1.417494
10	0.033284	78.04118	5.713621	0.652272	8.043002	6.133955	1.415965
Variance of LNOP:							
1	0.092232	1.73192	98.26808	0.0000	0.0000	0.00000	0.0000
2	0.112379	6.969988	78.70587	1.428438	1.819548	8.673212	2.402943
3	0.118409	6.282704	71.41722	1.288462	4.349606	9.269411	7.392594
4	0.131946	5.066447	58.5182	2.995001	5.973416	13.328	14.11893
5	0.145277	4.243774	48.48654	3.902122	5.129742	17.047	21.19082
6	0.158146	3.668338	41.40261	4.783989	4.476125	19.06454	26.6044
7	0.168395	3.315343	36.87574	5.535414	4.015066	19.84663	30.41182
8	0.176734	3.012106	33.86869	6.347043	3.767512	20.27397	32.73068
9	0.183558	2.828262	31.71521	7.158037	3.704494	20.39595	34.19805
10	0.189348	2.820345	29.96915	7.913751	3.704759	20.45593	35.13607
Variance decomposition of LNPD:							
1	8.88E-05	20.44214	0.037553	79.52031	0.0000	0.00000	0.0000
2	0.000218	33.79206	0.504632	63.37268	1.9699	0.35933	0.001395
3	0.000401	41.75568	2.324336	49.67305	5.235305	0.613472	0.398152
4	0.000628	46.53831	4.971359	40.00648	6.619123	0.738613	1.126111
5	0.000878	48.68651	7.791313	33.50971	7.161673	0.658102	2.192687
6	0.001142	49.44122	10.5957	28.54463	7.166598	0.45652	3.795327
7	0.001416	49.24628	13.08898	24.33137	6.901173	0.30095	6.131236
8	0.001701	48.26154	15.14044	20.50266	6.451023	0.372483	9.271854
9	0.002002	46.54585	16.70449	16.97133	5.867688	0.792806	13.11784
10	0.00232	44.19276	17.79327	13.79068	5.212211	1.579507	17.43157
Variance LOG_EI:							
1	0.022366	66.31346	0.174514	2.65065	30.86138	0.0000	0.0000
2	0.028052	73.54127	0.161952	1.917053	22.61883	0.249834	1.511064
3	0.029969	70.84038	0.906623	1.821906	20.43161	0.506759	5.492723
4	0.031378	66.83293	2.069348	2.25516	19.32807	0.594924	8.919566
5	0.032443	63.1458	2.030861	3.172461	19.75174	0.884881	11.01425
6	0.033015	61.1155	1.982168	3.776696	19.76847	0.969224	12.38794
7	0.033367	59.8369	2.057171	4.204855	19.6048	1.012816	13.28346
8	0.033648	58.84138	2.125792	4.599734	19.44515	1.112011	13.87593
9	0.033921	57.91335	2.152119	5.002777	19.28853	1.351364	14.29187
10	0.034195	57.02934	2.141075	5.389688	19.11679	1.7092	14.61391
Variance LOG_GDP:							
1	0.00705	6.837057	1.488867	5.621056	0.944756	85.10826	0.0000
2	0.010182	13.99328	2.14728	5.949199	0.502574	74.65707	2.750597
3	0.011915	13.86805	2.168361	5.184954	2.986708	72.6567	3.135225
4	0.012447	15.3925	2.019487	5.155283	3.437987	71.05771	2.937034
5	0.012567	15.17764	1.986565	5.074289	4.537793	70.02569	3.198022

Table 7 (continued)

Period	S.E.	LNCO	LNOP	LNPD	LOG_EI	LOG_GDP	LOGRI
6	0.012702	15.35832	1.984888	4.968557	4.636156	68.6175	4.434578
7	0.013025	16.60748	2.29826	4.726998	4.411887	65.78831	6.167063
8	0.01347	18.23579	3.055654	4.426593	4.15252	62.2078	7.921648
9	0.013935	19.31288	4.070776	4.152629	3.953198	58.91108	9.599435
10	0.014379	19.67485	5.06495	3.946465	3.76353	56.21361	11.33659
Variance LOGRI:							
1	0.008084	0.341531	3.367099	0.124641	0.481625	0.846345	94.83876
2	0.010942	0.716609	10.03588	1.381365	1.160692	1.185535	85.51992
3	0.013629	0.877756	12.97967	2.990114	3.034655	1.580336	78.53747
4	0.016101	0.736978	13.14632	4.40652	2.827996	3.87605	75.00613
5	0.018762	0.749578	12.23735	6.039479	2.914992	7.028563	71.03004
6	0.021372	0.660314	10.79999	7.458398	2.738635	10.43342	67.90924
7	0.023871	0.558241	9.594094	8.765062	2.650796	13.35339	65.07842
8	0.026085	0.467515	8.625873	9.905719	2.591828	15.47137	62.9377
9	0.027981	0.441499	7.853625	10.94083	2.587176	16.95716	61.2197
10	0.029571	0.534988	7.218622	11.89896	2.65752	17.93991	59.75

run. About 2.14% variance in economic growth is due to the shock in oil prices in the second period of the short run, while in the long run, oil prices contribute 5.06% of the variance in economic growth. The contribution of population density and energy intensity to economic growth is almost the same in both periods. While road infrastructure explains 11.33% of economic growth in the long term, it explains only 2.75% in the short term.

The carbon emissions of the transport sector possess an immaterial effect on road infrastructure in the short run, as only 1.38% of the variance in road infrastructure is explained by the transport sector's CO_2 emissions in the short run. However, in the long term, the transport sector's CO_2 emissions explain 11.89% of the variance in road infrastructure. Oil prices explain 10.03% and 7.21% of the variation in road infrastructure in the second term of the short run and the last period of the long run, respectively. Economic growth accounts for around 1.18% in the short run and 17.93% in the long run for the increase in road infrastructure of Pakistan.

Conclusion

This study investigates the factors of CO_2 emissions generated from the transport sector of Pakistan. The study found that oil prices, economic growth, population density, and energy intensity changes in transportation are main drivers of transport-related emissions in Pakistan. Among the other reasons, one is the shifting of energy utilization from industrial sector to transport sector. Ten years back, contribution of industrial manufacturing to CO_2 emissions was 36% and of the transport sector was 16% respectively. But in 2014, the contribution of these two sectors has reached to 28%. There are two reasons behind these facts. First, there are immense energy crises in Pakistan which have caused closing of many industries. Thus, CO_2 emission contribution of the industrial sector has decreased. Secondly, there is a massive increase in road vehicles due to population and urbanization since the previous decade which has raised energy demand in the transport sector. In Pakistan, more than 90% of energy production depends on fossil fuels and the energy efficiency is also very weak. Therefore, the contribution of the transport sector to CO_2 emissions has increased. The rising trend of CO_2 emissions from the transport sector has motivated us to investigate the driving factors.

The results of the ARDL bounding approach confirm a strong long-run connection of the transport-related CO_2 emissions with oil prices, energy intensity, economic growth, population density, and road infrastructure. In particular, the empirical data shows that oil prices and economic growth play a vital role in reducing the sector's CO_2 emissions, while population density, energy intensity, and road infrastructure increase them. The VECM test results suggest a feedback relationship among the transport-related CO_2 emissions, oil prices, and energy intensity, while unidirectional causality runs from population density, economic growth, and road infrastructure to the transport-related CO_2 emissions, oil prices, and energy intensity.

Pakistan's government has undertaken a few initiatives to overcome the problem of energy consumption and CO_2 emissions, most of which are caused by the transport sector. Fluctuations have been seen in fuel rates, which are not set according to supply and demand or for future needs, which may increase external threats regarding the availability of energy.

This is the right time for policymakers to design a Clean Transport Policy for Pakistan that will reduce environmental pollution and manage the rising pressure on roads. The government should first address the country's electrical energy crises so people can use electric and hybrid vehicles. Investors introduced hybrid cars and electric bicycles in Pakistan, but those investments failed because of severe shortages in electrical energy. For the time being, subsidies should be offered to people who use environmentally friendly vehicles.

Another important policy change is to strengthen the public transport system. Energy-efficient public busses that use separate tracks to save time should be available at inexpensive rates. The time-saving and cost-saving features of the public transport system will motivate people to prefer public transport over using their private vehicles.

This study's primary limitation has to do with its data coverage, as data from Pakistan is not available before 1971 or after 2014, so changes that occurred in the last 5 years are not incorporated in this study. However, since the policies suggested in this study are not yet in effect in Pakistan, the most popular mode of transport in Pakistan is the road. Future studies may include disaggregated data related to intra-modal shifts in road transport and those shifts' effect on CO_2 emissions from the transport sector.

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