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CO_2 Emissions and The Transport Sector in Malaysia

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Transport is an essential infrastructure for development. With its high share of gross domestic product (GDP), it makes a significant contribution to total CO_2 emissions in Malaysia. It is therefore important to pay greater attention to reducing CO_2 emissions and sustainable development in this sector. Therefore, this study aims at estimating the relationship between transport CO_2 emissions and its key drivers using the Autoregressive Distributed Lag (ARDL) technique. The time period covered by the study extends from 1978 to 2018. It further investigates the response of CO_2 emissions to shocks in the value of other variables by employing the generalized impulse response approach. The results suggest that urbanization is the major contributor to the increase in CO_2 emissions followed by the carbon intensity of energy in the long-run. Carbon intensity of energy, GDP per transport worker and urbanization contribute significantly to increases in transport CO_2 emissions in the short- and long-run. Testing the Environmental Kuznets Curve (EKC) hypothesis recommends that Malaysia continue to be on track to reach the highest level of income and welfare to give pay more attention to the environment. Therefore, the country maintains its CO_2 emissions level in the future because of economic development. Therefore, these findings show that energy and environmental policymakers need to pay more attention to improving energy efficiency and the use of low-carbon technologies and electrification in the transport sector and the use of high-quality public transport, particularly in urban areas, for sustainable urban development.

Keywords: transport CO_2 emissions, energy intensity, urbanization, ARDL, impulse response, Environmental Kuznets Curve

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INTRODUCTION

Transportation, as one of the fundamental infrastructures for economic development, requires energy in a significant manner. It is one of most fast-growing sources of climate change and global warming worldwide (Grazi and van den Bergh, 2008; Stanley et al., 2011). Evidence indicates that the transport sector is one of the major emitters of CO_2 emissions in the world because a high share of transport energy demand comes from fossil fuels. For example, in the world's seven largest CO_2 emitting economies, the transport sector uses over 90% of its energy from fossil fuels (Solaymani, 2019). In 2017, the CO_2 emissions from fuel combustion in this sector were 8,040 million tonnes, the second-largest rank (24.5% of total CO_2 emissions) among other economic sectors and 18% of man-made economy emissions worldwide (Huizenga and Peet, 2017; International Energy Agency-IEA, 2019). Among the transport subsectors, the land transport sector is also one of the leading emitters of CO_2 and one of the most difficult sectors for de-carbonization (Giannakis et al., 2020). Climate change policies in transport, such as electrification and intermodal road-rail operations, without replacing fossil-fuel power plants, increase emissions rather than achieve a low-carbon transition (Pinto et al., 2018; Zhang and Fujimori, 2020). Transport undoubtedly affects the constituents of the environment and through various forms of pollution causes diseases and irreparable damage to the environment. Many researchers have made significant evaluations on ways to reduce environmental pollution in transport (Solaymani et al., 2015a; Soto et al., 2018; Shen and Feng, 2020). In doing so, it is necessary to use renewable energy, electric and hybrid vehicles, and to improve energy efficiency in this sector, in particular in road transport, it can therefore be an important sector for reducing GHG emissions and building low carbon cities in all countries around the world.

Transportation in Malaysia accounted for 8% of real gross domestic product (GDP) and 4% of employment in 2018. It has experienced an average annual growth rate of 3% over the last decade. The transport sector contributes to 36.4% of the total final energy demand (23,555 ktoe) in 2018, which is the largest energy user in Malaysia. Carbon dioxide is responsible for 96% of greenhouse gas (GHG) emissions in this sector. The transport sector is the second biggest driver to CO_2 emissions in Malaysia after electricity and heat production, while the industrial sector is the third-largest contributor (International Energy Agency-IEA, 2019). Emissions levels across all economic sectors have increased over the 2010–2017 period. CO_2 emissions from the transport sector represented 28.8% of total fossil fuel combustion in Malaysia, well above the global average of 24.5% (International Energy Agency-IEA, 2019). Road transport is also the largest CO_2 emitter among all transport subsectors (International Energy Agency-IEA, 2019).

It is clear that the assessment of solutions aimed at reducing the environmental impacts of transportation operations and development can play a key role in reducing the negative effects of transportation and a fundamental step towards social development and the enhancement of the environment. This will not be possible without the assessment of key variables affecting the CO_2 emissions in the transport sector. For this purpose, this study examines the impacts of energy intensity, urbanization, CO_2 (carbon) intensity of energy and share of renewable energy in total final energy consumption on transport CO_2 emissions in Malaysia from 1978 to 2018 by employing the Autoregressive Distributed Lag (ARDL) technique. It also explores the responses of CO_2 emissions to the above-mentioned variables over time using the generalized impulse response method.

Previous studies have focused on environmental emissions in the industrial sector (Peng et al., 2021) and the livestock sector (Elahi et al., 2019). Similarly, optimization of resources and the nexus between input and output has also been determined (Elahi et al., 2020). Some studies emphasized on climate change and behavioral factors for adoption measures (Elahi et al., 2021). Similarly, a link between environmental pollution and human health damages has also been estimated. To date, a few emerging case studies have analyzed CO_2 emissions from transportation in Malaysia; however, they did not examine the impacts of urbanization and energy intensity and carbon intensity on transport CO_2 emissions. Furthermore, they lack an in-depth analysis of impulse responses. Therefore, this study attempts to fill these gaps to make a significant contribution to the literature. The results of this study can help the transport and energy policymakers in explaining the impacts of the important factors of the transport CO_2 emissions in Malaysia.

LITERATURE REVIEW

High consumption of fossil fuels in the transportation sector results in CO_2 emissions even in the long-run for most countries (Saboori et al., 2014). Evidence shows that the optimization of energy consumption and the structure of the transport sector can reduce the level of CO_2 emissions in this sector (Zhu and Gao, 2019). Carbon emissions could be reduced by further optimizing energy structures and controlling the private vehicle population (Solaymani, 2019). Many studies suggest the use of electric vehicles in the fleet to reduce energy consumption and consequently carbon dioxide emissions in the transport sector (Teixeira and Sodré, 2018), others introduced carbon and energy tax policies (Solaymani et al., 2015a). Santos (2017) believes that environmental taxes, R&D subsidies and investments in clean infrastructure, as well as international agreements, can reduce transport-related CO_2 emissions. But data from Europe suggest that the new car CO_2 regulations have reduced road emissions by only about 10% since 1998 (Todts, 2018). In some cases, democracy may reduce real and potential CO_2 emissions in the transport sector (Adom et al., 2018). Higher oil prices reduce actual and potential emissions of CO_2 from the transportation sector (Solaymani et al., 2015; Scheelhaase et al., 2021). Energy efficiency improvement is also an effective policy in reducing energy consumption and CO_2 emissions in energy-intensive sectors such as the transport sector (Li Y and Solaymani, 2021). Other research revealed that the removal of energy subsidies is effective in reducing energy consumption and consequently carbon dioxide emissions in the transport sector at low levels (Solaymani and Kari, 2013; Solaymani and Kari, 2014; Solaymani, 2021a). Wang et al. (2017) also emphasized the importance of urban planning for land use and spatial optimization of the urban population in achieving CO_2 emission reductions.

In terms of modeling carbon dioxide emissions in the transport sector, Lin and Benjamin (2017) used GDP, energy intensity, carbon intensity and urbanization. They found that urbanization compared to other variables has the lowest impact on the increase in CO_2 emissions from Chinese transport. Andrés and Padilla (2018) showed that population and energy intensity of transport, in comparison with GDP of transport, is more important to explain the CO_2 emissions of transport. However, Cai et al. (2012) demonstrated that transport-related CO_2 emissions in China are strongly linked to GDP. Achour and Belloumi (2016) also employed transportation intensity, population scale, transportation structure and energy intensity in their model. They suggested that the majority of variables, with the exception of energy intensity, have a positive and significant effect on CO_2 emissions. Vehicle ownership is another variable that is used in some studies, which is the major source of CO_2 emissions in the road transport sector (Kharbach and Tarik, 2017). Luo et al. (2017) used the mode share, average trip times and travel distance as key factors in CO_2 emissions. They also demonstrated that load effect and energy efficiency are the major contributors to the mitigation of CO_2 emissions in urban transport in China. Andrés and Padilla (2018) also examined the sources of carbon dioxide emissions in the EU transport sector by considering key macro variables, such as real per capita GDP and population, and transport variables, such as transport energy efficiency, transport volume and modal share in their study.

The above literature shows that the major sources of transport-related CO_2 emissions are energy consumption, energy efficiency, GDP, population and energy intensity. However, limited studies and a gap exist with respect to the use of other important variables such as urbanization, and the carbon intensity of energy, which the current study attempts to address this gap using these variables in its suggested model.

MODEL AND METHODOLOGY

The Model

The production of a good depends on the factors that make it up. Based on the studies discussed in the literature, CO_2 emissions from the transport sector are attributed to production in this sector, GDP, capital formation and urbanization. In addition, other variables may affect the level of CO_2 emissions, such as energy intensity, trade, renewable energy consumption and carbon intensity. Accordingly, this study considers the following model as the primary model:

$$CO_2 = f(PGDP, EI, URB, CIN, SRE) \tag{1}$$

Where CO_2 denotes the level of carbon dioxide emissions in the transport sector (million tonne); *PGDP* indicates the GDP per capita of the transport sector (the ratio of value-added to labor employment in the transport sector) (RM million constant 2015); *EI* is the energy intensity million tonnes of oil equivalent/GDP (RM million constant 2015); *URB* denotes urbanization (percentage of the population live in urban areas) (thousand); *CIN* indicates the carbon intensity of energy [ratio of CO_2 emissions (million tonne) from the transport sector to total energy consumption in this sector (ktoe)]; and finally, *SRE* represents the share of renewable energy in total final energy consumption. Therefore, according to the explanations provided, the natural logarithmic shape of the model is as follows:

$$LCO2_t = \lambda_0 + \lambda_1 LPGDP_t + \lambda_2 LEI_t + \lambda_3 LURB_t + \lambda_4 LCIN_t + \lambda_5 LSRE_t + \varepsilon_t \tag{2}$$

The study period is 1978–2018 and the energy data have been collected from the department of statistics of Malaysia's and other data have been extracted from the World Bank database (world development indicator). The coefficients of the variables (i.e., λ_1, λ_2, λ_3, λ_4 and λ_5) indicate the elasticities of the dependent variable (i.e., transport's CO_2 emissions) in response to changes in independent variables (i.e., per capita GDP, energy intensity, urbanization, carbon intensity of energy and share of renewable energies). λ_0 is the constant term and ε_t denotes the random disturbance term. This study uses the time series data by employing the autoregressive distributed lag (ARDL) to estimate the coefficients of considered variables in Model 2. It also uses the impulse response function to examine the effect of a shock to the explanatory variables in the model on CO_2 emissions.

Estimation Method

One of the dynamic models suitable for the long-run relation is the Autoregressive Distributed Lag bounds testing approach, which provides relatively biased estimates of long-run coefficients. Unlike other common techniques in the cointegration analysis method, such as the Engle-Granger method, there is no need to know the degree of stationary of the underlying variables (Pesaran and Pesaran, 1997). This method is also able to simultaneously estimate the short- and long-run coefficients of the model and determine the causal direction between the model variables. In addition, the ARDL approach is suitable for smaller samples, while larger samples are required to trust the results of the Johansson approach (VAR and VECM models) (Solaymani, 2021b). In the ARDL approach, it is possible to consider different optimal lags for each variable at different estimation stages, while in the Johansson approach, this is not possible (Li Z and Solaymani, 2021).

The estimation of the ARDL model consists of two steps for estimating long-run coefficients. In the first stage, the presence of a long-run relation forecasted by economic theory is examined between the considered variables, and if a long-run relationship is confirmed, both the long-run and short-run coefficients will be estimated at the second stage. The overall form of the ARDL model of **Eq. 2** is as follows:

$$\begin{aligned}\Delta LCO2_t = {} & \rho_0 + \rho_1 LCO2_{t-1} + \rho_2 LPGDP_{t-1} + \rho_3 LEI_{t-1} + \rho_4 LURB_{t-1} \\ & + \rho_5 LCIN_{t-1} + \rho_6 LSRE_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta LCO2_{t-j} \\ & + \sum_{j=1}^{q} \beta_j \Delta LPGDP_{t-j} + \sum_{j=1}^{q} \gamma_j \Delta LEI_{t-j} + \sum_{j=1}^{q} \gamma_k \Delta LURB_{t-j} \\ & + \sum_{j=1}^{q} \delta_j \Delta LCIN_{t-j} + \sum_{j=1}^{q} \theta_j \Delta LSRE_{t-j} + \varepsilon_t\end{aligned} \tag{3}$$

In **Eq. 3**, long-run relationships are represented by ρ_i (i = 1,. . .,5) and the error correction for the short-run relationships is represented by other summations. To explain the first step, without having any basic information on the structure of relationships between the variables *LCO_2*, *LPGDP*, *LURB*, *LCIN*, and *LSRE*, five F-statistics are estimated. In each of them, one of the seven variables is selected as a dependent variable (see **Table 4**).

The joint F test or Wald test is applied to examine the long-run relation between the variables under consideration. The null hypothesis for no long-run relation (no cointegration) exists is H_0: $\rho_1 = \rho_2 = \rho_3 = \rho_4 = \rho_5 = 0$ and the alternative hypothesis is H_1: $\rho_1 = \rho_2 = \rho_3 \neq \rho_4 \neq \rho_5 \neq 0$. The values of the calculated F-statistics for each dependent variable are compared with the critical values (lower and upper limits) of Pesaran et al. (2001) criteria. The null hypothesis will be accepted, regardless of the level of stationary I (0) and I (1), if the estimated F-statistics are larger than the critical value and if they will be upper than the upper limit of the critical value from Pesaran et al. (2001) the null hypothesis will be rejected and will confirm that a long-run relationship exists. If the value of the estimated F-statistic is between the lower and upper

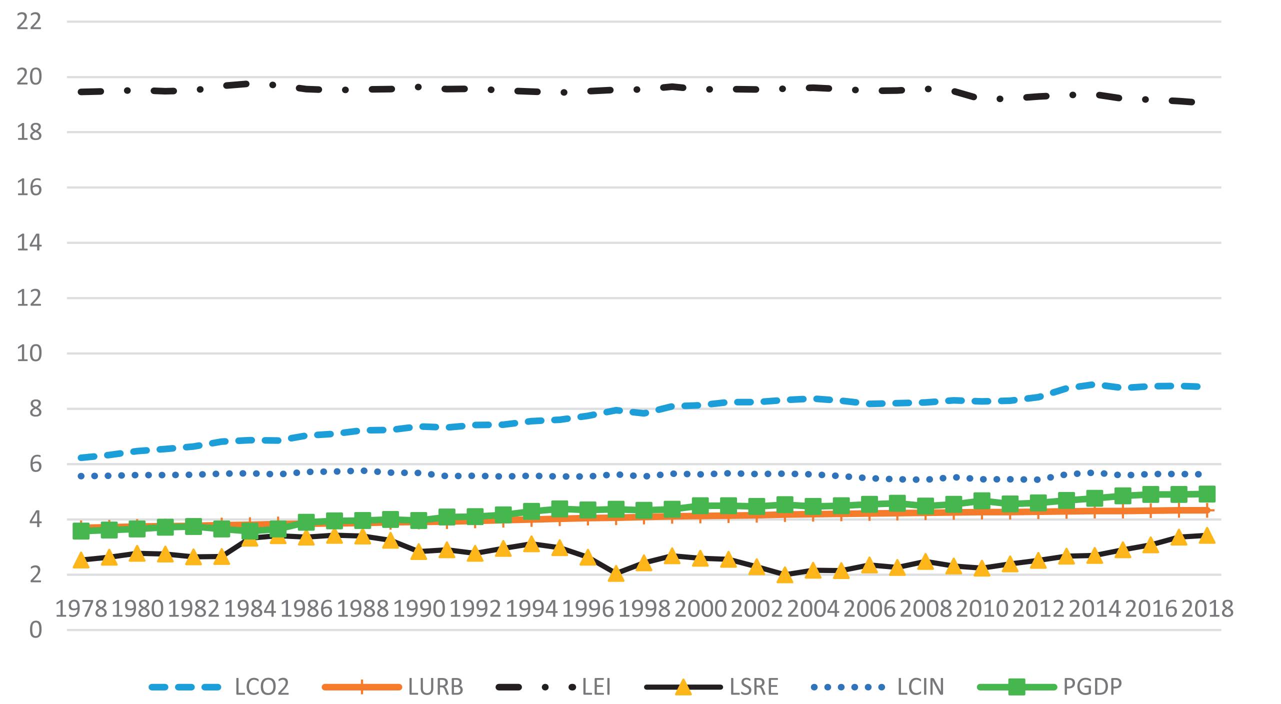

FIGURE 1 | Trends of the natural logarithms of all variables.

critical values, it will be inconclusive. The optimal lag length is determined based on one of the criteria of Akaik, Schwartz-Bayesian and Hanan-Quinn criteria. The number of regressions $(p + 1)$ k will also be estimated by applying the ARDL bounds testing technique, in which p is the lag and k is the number of the model's variables. After checking the existence of long-run relationships using the bounds testing approach, the long-run results of the model can be obtained by estimating **Eq. 4**.

$$\Delta LCO2_t = \rho_0 + \sum_{j=1}^{q} \beta_j \Delta LPGDP_{t-j} + \sum_{j=1}^{q} \gamma_j \Delta LEI_{t-j} + \sum_{j=1}^{q} \gamma_k \Delta LURB_{t-j} + \sum_{j=1}^{q} \delta_j \Delta LCIN_{t-j} + \sum_{j=1}^{q} \theta_j \Delta LSRE_{t-j} + \varepsilon_t \quad (4)$$

Finally, the ordinary least squares (OLS) technique is used to estimate the selected model. After choosing the lag, if a long-run relation exists, the error correction model (*ECM*) estimates as given by **Eq. 5**.

$$\Delta LCO2_t = \rho_0 + \sum_{j=1}^{q} \beta_j \Delta LPGDP_{t-j} + \sum_{j=1}^{q} \gamma_j \Delta LEI_{t-j} + \sum_{j=1}^{q} \gamma_k \Delta LURB_{t-j} + \sum_{j=1}^{q} \delta_j \Delta LCIN_{t-j} + \sum_{j=1}^{q} \theta_j \Delta LSRE_{t-j} + \phi \mathrm{ECM} \quad (5)$$

This study also uses the *CUSUM* and *CUSUMSQ* tests introduced by Brown et al. (1975) to determine the stability and structural stability of the model. In this test, the null hypothesis estimates the stability of parameters at the 5% level of significance. If the test statistics are within the critical bounds, the null hypothesis of stability of the coefficients cannot be rejected.

Although the results of the ARDL bound testing technique examine the long- and short-run coefficients of the considered variables in the model, it does not explain how each variable reacts to shocks from other variables and how long these reactions will take in the future. In this study, to estimate such responses to shocks the generalized impulse response method, introduced by Koop et al. (1996) and Pesaran and Shin (1998), is applied.

Figure 1 illustrates the trends for the six variables reported in the natural logarithms over the study period, indicating a common trend for the variables under consideration. **Table 1** provides the descriptive statistics for each variable under consideration in the model.

RESULTS AND DISCUSSION

The ARDL Model

Prior to assessing the short- and long-run coefficients of the model it is important to test the stationary of variables. To carry out this test on the time series data, we use three tests, namely Phillips-Perron (PP), Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). The time series variables are stationary at a significant level of 5% is the null hypothesis in these tests.

Table 2 presents the findings of the unit root test. According to the ADF test, the null hypothesis for all variables cannot be rejected with the 5% error, whereas, according to the PP test, all variables, except *LURB*, cannot be rejected at the 5% error. But, the null hypothesis at the first difference for all variables, except for *LURB*, can be rejected with the 5% error. Hence, based on both the ADF and PP tests, it can be specified that all variables, which are time series, are integrated of the order one, (1). The exception here is for *LURB* which is integrated of the order zero, I (0).

TABLE 1 | Descriptive statistics of variables.

Statistics/Unit	LCO_2	LPGDP	LURB	LCIN	LEI	LSRE
	Million tonne	RM Million/worker	Thousand	Million tonne/ktoe	ktoe/RM Million	%
Mean	7.755208	9.973177	4.054389	5.600082	−13.8779	2.73069
Median	7.945991	10.08428	4.085909	5.614852	−13.8497	2.66648
Maximum	8.885709	10.55848	4.331207	5.762943	−13.6923	3.42906
Minimum	6.228105	9.330439	3.695632	5.434598	−14.2169	2.00143
Std. Dev	0.767738	0.355635	0.202032	0.081394	0.134688	0.41250

TABLE 2 | Estimated results for the Unit root test at the level of the variable.

Variable	KPSS†		Phillips–Perron		Augmented dickey fuller	
	Level	First difference	Level	First difference	Level	First difference
LCO_2	0.780*	0.261	−1.304	−5.621*	−0.360	−5.903*
LPGDP	0.758*	0.096	−0.160	−6.610*	−0.360	−5.903*
LEI	0.218	0.492**	−2.290	−5.380*	−0.612	−5.382*
LURB	0.786*	0.523**	−2.917***	−0.865	−1.404	−0.785
LCIN	0.226	0.070	−2.392	−7.092*	−2.392	−7.112*
LSER	0.206	0.375**	−1.656	−5.270*	−1.455	−5.335*

†Kwiatkowski-Phillips-Schmidt-Shin.

Since the stationarity tests revealed a mixed stationary of I (0) and I (1), and the sample size is 41, which is relatively small, the ARDL approach is the most suitable to perform the cointegration test. However, before estimating the long- and short-run connections, the optimal lag length must be determined (Solaymani, 2021a; Li Y and Solaymani, 2021). The Schwarz information criterion (SIC) results show that the optimal lag length is 1 (**Table 3**).

To determine the cointegration relationships (or long-run relationships) between the dependent variable and explanatory variables, the bounds testing with a joint F-statistic is used. The null hypothesis of no conintegration is $H_0 = \rho_1 = \rho_2 = \rho_3 = \rho_4 = \rho_5 = 0$ and the opposite hypothesis is $H_1 = \rho_1 \neq \rho_2 \neq \rho_3 \neq \rho_4 \neq \rho_5 \neq 0$. To carry out this test, each variable of the model is selected as a response variable and the other variables take as independent variables. The value of the F-statistic for each model is compared with the Pesaran et al. (2001) criteria. Since the absolute values of the estimated F-statistic in **Table 4** for the CO_2 and PGDP equations are higher than the upper bounds of the critical value, we cannot accept the null hypothesis and thus the long-run relationships between their corresponding variables are confirmed. Therefore, a long-run relation for **Eq. 4** is obtained for the 1978–2018 period at least at a significant level of 5%.

Table 5 reports the long- and short-run estimates based on **Eqs 4** and **5**. The findings of the long-run estimates demonstrate that the majority of the variables under consideration have the expected signs and are statistically significant. The coefficient of *LEI* is positive and insignificant, suggesting that technological improvement does not promote the efficiency of energy demand. Urbanization is the most important variable in increasing carbon dioxide emissions in the transport sector. The positive coefficient of *LCIN* is statistically significant and indicates that carbon intensity contributes significantly to CO_2 emissions from transport. The coefficient of the share of renewable energy in total energy consumption (*SER*) shows that it has a negative, but statistically insignificant impact on carbon emissions from transportation.

The short-run results show that all variables considered in the model, except SRE, are statistically significant and have the projected signs. Similar to the long-run coefficient, the coefficient of transport GDP per worker is positive and statistically significant, but with a smaller magnitude compared to the long-run coefficient. Despite the long-run coefficient, the short-run coefficient of energy intensity is positive and statistically significant. Carbon intensity of energy followed by urbanization are the main contributors to the rise in CO_2 emissions in the short-run. The urbanization coefficient is also positive and is statistically significant. Similar to the long-run results, the coefficient of the share of renewable energy in total energy consumption (*SER*) is negative, but statistically insignificant impact on carbon emissions from transportation. The coefficient of the error correction term is negative and statistically significant.

Table 6 provides the diagnostic tests of the ARDL model. The coefficients of determination (adjusted R-squared in **Table 5**) are significantly high, indicating that a high proportion of the variation in CO_2 emissions is strongly explained by the explanatory variables. The Durbin-Watson statistic is also high and shows a low level of autocorrelation in the residuals of the model. Other statistics also indicate that there is no serial correlation, functional form, normality and heteroscedasticity problems in the model.

The results of CUSUM and CUSUMSQ tests, which examine the stability of the model, are presented in **Figure 2**. As observed, since the estimated parameters fall between the two lines, the estimated parameters are statistically significant at the 5% level of significance.

Impulse Response Results

This section explains the results of the impulse response technique. This methodology is related to the estimated VAR model with one lag. It is used to look at the impact of a change in

TABLE 3 | Selecting optimal lag according to VAR lag order.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	183.4549	NA	2.75E-12	−9.59216	−9.33093	−9.50006
1	448.565	429.9083	1.18E-17	−21.9765	−20.14788*	−21.3318
2	498.5775	64.88108*	6.51e-18*	−22.7339	−19.3379	−21.5367
3	541.0488	41.32343	7.27E-18	−23.0837	−18.1204	−21.3339
4	593.3658	33.93534	9.01E-18	−23.96572*	−17.435	−21.66332*

TABLE 4 | The estimated result for the ARDL bounds test (1,0,0,0,0).

Dependent variables	SIC Lag	*F*-statistic (*k* = 4)		Outcome
LCO$_2$ = *f* (*LPGDP, LEI, LURB, LCIN, LSER*)	1	14.981*		Cointegration
LPGDP = *f* (*LCO*$_2$*, LEI, LURB, LCIN, LSER*)	1	3.733**		Cointegration
LEI = *f* (*LPGDP, LCO*$_2$*, LURB, LCIN, LSER*)	1	2.113		Non-cointegration
LURB = *f* (*LEI, LPGDP LCO*$_2$*, LCIN, LSER*)	1	2.868		Non-cointegration
LSER =*f* (*LCIN, LURB, LEI, LPGDP, LCO*$_2$)	1	1.189		Non-cointegration
Critical value, Pesaran et al. (2001)		I (0)	I (1)	
1% significance level		2.73	3.90	
5% significance level		2.17	3.21	
10% significance level		1.92	2.89	

, Denote statistical significance level at 1 and 5%, respectively.*

TABLE 5 | The long- and short run estimated results of the ARDL (1,1,2,2,1,0) model.

Long-run estimation				Short-run estimation (ECM)			
Dependent variable: LCO_2	**Coefficient**	**Standard error**	***T*-statistic (Prob)**	**Dependent variable: LCO_2**	**Coefficient**	**Standard error**	***T*-statistic (Prob)**
C	−15.810*	3.649	−4.333 (0.000)	C	—	—	—
LPGDP	0.625*	0.240	2.603 (0.014)	D (LPGDP)	0.569*	0.121	4.692 (0.000)
LEI	0.196	0.167	1.172 (0.251)	D (LEI)	0.575*	0.116	4.936 (0.000)
LURB	2.665*	0.515	5.175 (0.000)	D (LURB)	0.957***	0.484	1.975 (0.057)
LCIN	1.161*	0.271	4.284 (0.000)	D (LCIN)	1.060*	0.120	8.829 (0.000)
LSER	−0.047	0.054	−0.865 (0.394)	D (LSER)	−0.017	0.018	−0.950 (0.349)
−	−	−	−	CointEq (−1)*	−0.359*	0.136	−2.640 (0.013)
Adjusted R	0.997			Adjusted R	0.889		

, Denotes statistical significance level at 1 and 5%, respectively.*

the independent variables. This technique describes the dynamic responses of a variable to the shock to other variables in the model and plays a substantial role in the recognition of shocks in model variables and in estimating the effects of such shocks.

Figure 3 represents the reactions of the transport-related CO_2 emissions to the changes in its influencing factors in the short- and long-run. A change of one standard deviation to GDP per worker increases carbon dioxide emissions from this sector over the short and long term. In fact, economic growth increases CO_2 emissions over time and it does not achieve an equilibrium during this time period to reduce CO_2 emissions. Therefore, the response of transport CO_2 emissions to economic growth does not show the existence of the EKC hypothesis.

CO_2 emissions in the transport sector show a negative reaction to energy intensity fluctuation in the short-run as a result of improved energy efficiency. However, in the long run, it increases with a diminishing rate of its intensity over time, perhaps due to the lack of energy efficiency improvements and the increase in passenger turnover leading to a temporary increase in CO_2 emissions.

The short run response of the transport sector's CO_2 emissions to urbanization is positive. CO_2 emissions from the transport sector indicate a positive response to the fluctuation in the share of renewable energy consumption in total final energy consumption in the short-run because of the low use of renewable energies in transportation. But the results show that it negatively responses to renewables' share of total energy consumption. This may occur because of the increased use of biodiesel in the transport sector. However, the response of transport CO_2 emissions to the carbon intensity of energy is negative in the short and long run. This is because of the use of low carbon emission fuels in the transport sector, such as CNG and LPG, in recent years in Malaysia.

TABLE 6 | Diagnostic tests for the ARDL model.

Diagnostic tests	Tests	Statistics	Test-statistic	Prob
Autocorrelation	Durbin-Watson stat		1.876	
Serial correlation	Breusch-Godfrey LM Test	CHSQ (1)	0.256	0.613
Functional form	Ramsey Reset Test	CHSQ (1)	0.471	0.492
Normality	Jarque-Bera	CHSQ (2)	0.597	0.742
Heteroscedasticity	ARCH LM	CHSQ (1)	0.339	0.560

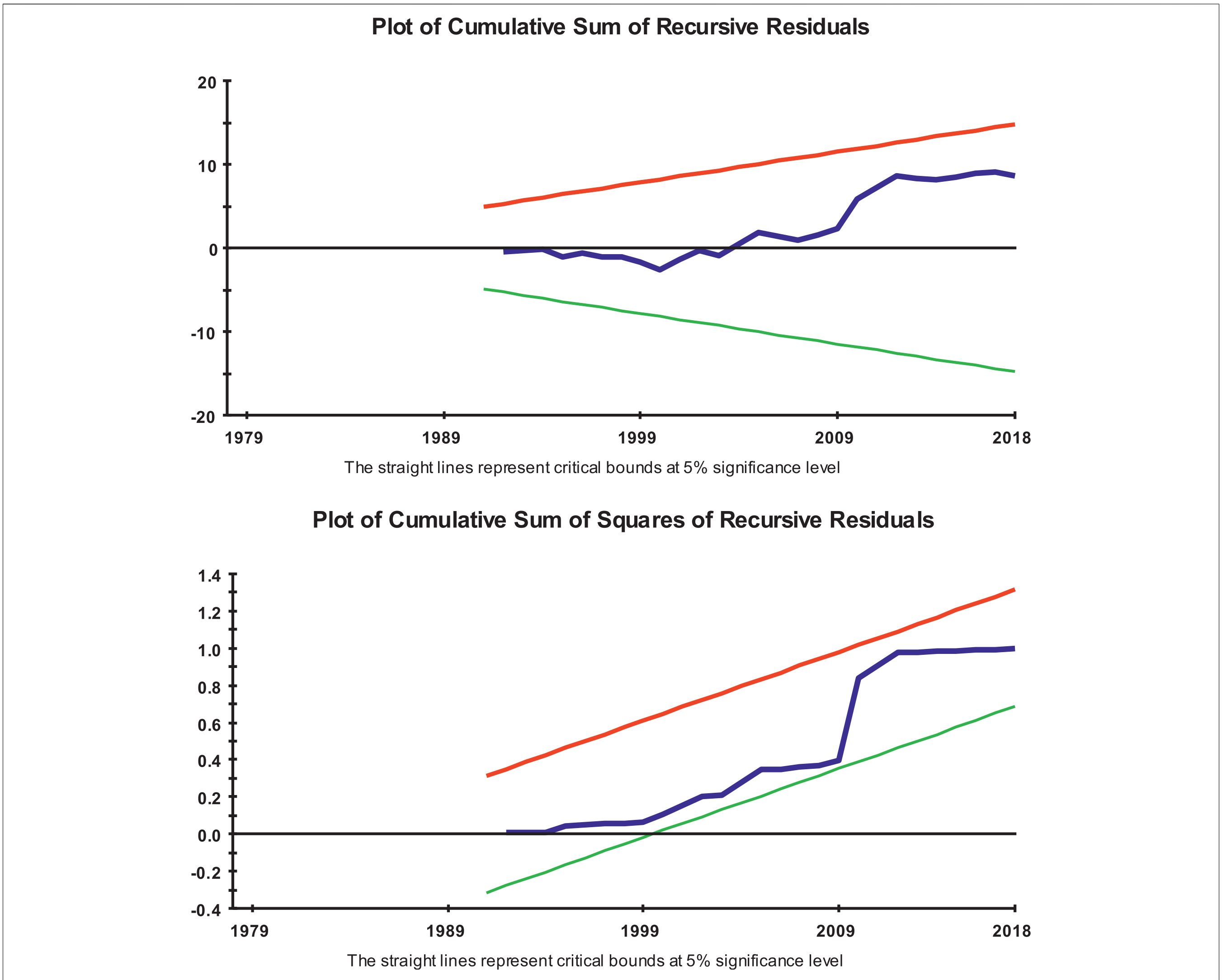

FIGURE 2 | CUSUM and CUSUMSQ.

DISCUSSION

The transport sector is one of the major energy users in most countries and uses a high percentage of fossil fuels for daily activities. Therefore, this sector is one of the major driving sources of GHGs emissions and negatively affects the air quality of large cities worldwide has led to global warming and climate change. Some factors may affect the transport CO_2 emissions, such as transport GDP, urbanization, energy efficiency and renewable energy consumption which are considered in this study.

The results of this study show that there is a positive and statistically significant relationship between transport CO_2 emissions and transport GDP per worker. This shows that a 1% increase in GDP per worker raises carbon emissions in this sector by 0.63%. This is consistent with research findings from Sousa et al. (2015). The urbanization coefficient suggests that

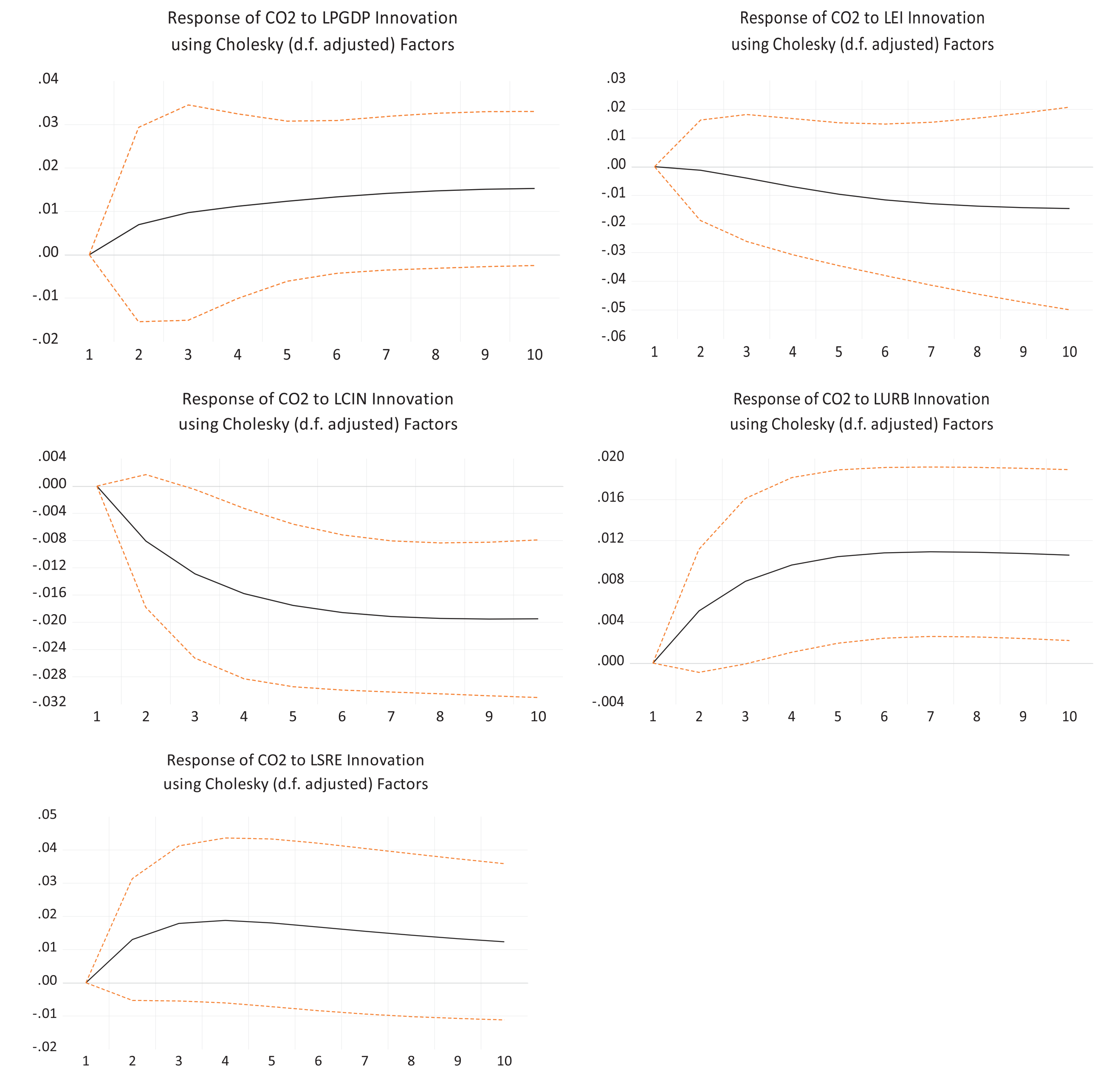

FIGURE 3 | Impact of one standard deviation shock to all variables on CO_2 emission.

urbanization is the major source of transport CO_2 emissions and that a 1% increase in urbanization increases CO_2 emissions by 2.67%. These findings are supported by the outcomes of Lv et al. (2019) for China and of Bekhet and Othman (2017) for the entire economy of Malaysia. Sodri and Garniwa (2016) also found that urbanization is the main contributing factor to energy use and CO_2 emissions in transport. They pointed out that there is a one-way relationship from urbanization to CO_2 emissions in the short-run. The coefficient of the renewables shares in total energy consumption (*SER*) is not significant and shows that the share of renewable energy in total final energy demand is not significant to be able to reduce a significant magnitude of CO_2 emissions from the transport sector.

However, the short run results show that a 1% increase in GDP per worker in the transport sector increases CO_2 emissions from this sector by 0.57%. The coefficient of energy intensity shows that energy efficiency improvements in this sector have not been able to reduce energy consumption, which leads to a temporary rise in CO_2 emissions in the short-run (Xu and Lin, 2015). Similarly, the coefficient of urbanization shows that a 1% increase in urbanization leads to a 0.96% increase in CO_2 emissions in the short-run. The negative and statistically significant coefficient of error correction term suggests that

35% of the disequilibrium modifies toward equilibrium in the long-run. It is worthy to note that the magnitude of all significant variables in the short-run is lower than that of the long-run values.

The impulse response results show that the response of transport CO_2 emissions to economic growth does not show the existence of *EKC* hypothesis. This is based on the study by Talbi (2017) which argued that the form of impulse response can confirms the existence or non-existence of the Environmental Kuznets Curve (*EKC*) hypothesis. This means that per capita GDP growth in the transport sector does not pursue an inverted "U-shaped" pattern in respect to CO_2 emissions. This finding is consistent with the results of the study conducted by Alshehry and Belloumi (2017) arguing that the EKC hypothesis is not validated for the relationship between transport CO_2 emissions and GDP growth in Saudi Arabia. The response of transport CO_2 emissions to urbanization is positive in the short run. This is because, in the short run, a significant number of rural households migrated to urban areas, which led to an increase in the urban population. The increase in energy and emission lifestyles of urban households as a result of the increase in their incomes leads to an increase in carbon dioxide emissions. However, in the long-run, after reaching a certain level, urbanization reduces the transport CO_2 emissions. This is consistent with the results of the study conducted by Ahmed et al. (2019).

The above findings reveal that the transport sector, particularly road transport, has attempted to reduce energy consumption through the use of low carbon fuels, such as CNG and LPG, resulting in a decline in CO_2 emissions. However, the government needs to play an important role in reducing GHG emissions. It is necessary for the government to implement new and more practical environmental policies and increase R&D investments in energy-saving technologies that reduce CO_2 emissions from the sector.

CONCLUSION

This study estimated the long and short-run relations between the main drivers of CO_2 emissions in Malaysia's transport sector. It employs the Autoregressive distributed lag (ARDL) method on the dataset from 1978 to 2018. The short and long-run results of the estimated model show that the coefficient of GDP per worker is positive and statistically significant. It emphasizes the positive relationship between transport, economic growth and transport CO_2 emissions. It is noteworthy that a positive relationship between GDP growth and environmental pollution in the country's transport sector is predictable. Since vehicle technology has low environmental standards so that environmental degradation is a key input in creating and increasing production. The long-run coefficient of urbanization is positive and significant and shows that this variable is the main source of CO_2 emissions in the transport sector. It is also the second-largest contributor to CO_2 emissions in the short-run. In other words, as the percentage of the urban population increases, environmental pollution in the transport sector also increases. Therefore, the current situations of economic growth and urbanization in the country are not yet in a situation where economic growth and increased urban population reduce emissions of environmental pollutants, especially carbon dioxide as achieved in developed countries (See Adams et al., 2020; Hashmi et al., 2021).

The short-run coefficient of energy intensity is positive and statistically significant, but in the long-run it is positive and insignificant. This shows that energy efficiency improvements in the transport sector cannot reduce CO_2 emissions, particularly in the short-run. The negative but statistically insignificant coefficient of the share of renewable energy in total final energy consumption implies low use of renewable energy commodities in this sector, which shows that renewable energy consumption in this sector is not able to decrease CO_2 emissions. This means that these agents, i.e., economic activities and modes of transport, do not use energy-efficient and low carbon technologies. The positive and statistically significant coefficient of the carbon intensity of energy in the short and long-run shows that the transport sector uses high-polluting fuels for its regular operations.

In addition, the impulse response results show that the Kuznets environmental hypothesis has not existed for the country's transport sector. The response of transport CO_2 emissions to urbanization is positive in the short-run, but, in the long-run, after capturing a certain level, urbanization reduces CO_2 emissions.

From the above results, it is suggested that due to the positive relationship between carbon dioxide emissions and the variables considered (i.e., GDP per worker, energy intensity and carbon intensity of energy) to decrease the level of carbon dioxide emissions in the transport sector, it is necessary to shift away from highly polluting fuels towards low-carbon fuels, such as natural gas, and other renewable energy sources like biodiesel and solar in this sector. Furthermore, the positive relationship between CO_2 emissions and urbanization puts more emphasis on the use of energy-efficient and low-carbon fuels and the development of public transportation in the big cities of the country. With the introduction of electric vehicles in private transport and particularly in public transport, significant reductions in annual emissions will be obtained.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

SS: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Visualization, Investigation, Supervision, Software, Validation, Writing- Reviewing and Editing.

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