



Gasoline Consumption, CO₂ Emissions and Transportation Infrastructure Investment: Transportation Kuznets Curve in Selected Developing Countries

Mehmet Aldonat BEYZATLAR*, İstemi BERK**

ABSTRACT

This study examines the links between gasoline consumption, CO₂ emissions and transportation infrastructure investment using an autoregressive distributed lag model based on the pooled mean group estimation (ARDL-PMG) for a panel consisting of selected upper middle-income countries for the period between 1994 and 2014. The long-run PMG estimates show that transportation infrastructure investment increases both gasoline consumption and CO₂ emissions, while its quadratic form (squared of transportation infrastructure investment) has negative effect. Hence, these results overall imply the existence of transportation Kuznets curve for upper middle-income countries.

Keywords: Transportation Infrastructure Investment, Gasoline Consumption, CO₂ Emissions, Transportation Kuznets Curve, Panel ARDL

JEL Classification: C23, Q41, Q51

Benzin Tüketimi, CO₂ Emisyonu ve Ulaşım Altyapı Yatırımları: Seçilmiş Gelişmekte olan Ülkelerde Ulaşım Kuznets Eğrisi

ÖZ

Bu çalışma, 1994 ve 2014 döneminde aralarında seçilmiş üst orta-gelir seviyesindeki ülkelerden oluşan panel için toplulaştırılmış ortalama grup tahminlemesine dayalı gecikmesi dağıtılmış otoregresif modeli (ARDL-PMG) kullanılarak benzin tüketimi, CO₂ emisyonu ve ulaşım altyapı yatırımları arasındaki bağlantıyı incelemektedir. Uzun dönemli PMG tahminleri, ulaşım altyapısı yatırımının hem benzin tüketimini hem de CO₂ emisyonunu artırdığını (pozitif), ikinci dereceden formunun ise (ulaşım altyapısı yatırımının karesi) azaltıcı (negatif) etki yaptığını göstermektedir. Bu nedenle, sonuçlar genel olarak üst orta-gelirli ülkeler için ulaşım Kuznets eğrisinin varlığını göstermektedir.

Anahtar Kelimeler: Ulaşım Altyapı Yatırımları, Benzin Tüketimi, CO₂ Emisyonu, Ulaşım Kuznets Eğrisi, Panel ARDL

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* Dr. Öğr. Üyesi, Dokuz Eylül Üniversitesi, İşletme Fakültesi, İngilizce İktisat Bölümü, mehmet.beyzatlar@deu.edu.tr, ORCID: 0000-0002-8434-8447.

** Dr. Öğr. Üyesi, Dokuz Eylül Üniversitesi, İşletme Fakültesi, İngilizce İktisat Bölümü, istemi.berk@deu.edu.tr, ORCID: 0000-0003-3507-2293.

1. INTRODUCTION

The development of key infrastructures, such as transportation, water, electricity and communication systems, are vital for countries' economic development and the society's prosperity (World Bank, 1994). In fact, United Nations identified one of the seventeen global sustainability goals as "building resilient infrastructure, promote sustainable industrialization and foster innovation" (UN, 2015). Yet, the infrastructure development must not contradict with other sustainable development goals, such as decreasing greenhouse gas (GHG) emissions or increasing energy efficiency. For instance, many researchers have found positive relationship between development of transportation infrastructure and economic growth (e.g., Fedderke and Bogetic, 2006; Pradhan and Bagchi, 2013; Badalyan et al., 2014; Arvin et al., 2015; Maparu and Mazumder, 2017). Moreover, there is also a consensus in the literature that economic growth fosters energy consumption and CO₂ emissions (e.g., Holtz-Eakin and Selden, 1995; Acaravci and Ozturk, 2010; Pao and Tsai, 2010; Arouri et al., 2012, Farhani and Ozturk, 2015).¹ Hence, it is reasonable to expect that the transportation infrastructure development would increase energy (mostly fuel) consumption and GHG emissions while promoting economic growth.

The effects of transportation infrastructure development on fuel consumption and GHG emissions are particularly important for developing countries, as these countries have tendency to prioritize transportation infrastructure investments to meet their increasing mobility needs and to promote economic development (Khasnabis et al., 2010). Moreover, increasing factor mobility would also foster economic and social effects of transportation infrastructure through better access to education, health care, finance and faster dispersion of information and technology in developing economies (Banerjee et al., 2012). To this end, the paper at hand, is trying to assess the effects of transportation infrastructure development on energy consumption and CO₂ emissions in transportation sector of developing countries. We use panel data set covering eight selected upper middle-income countries, including Turkey, over the period from 1994 to 2014 and employ panel Autoregressive Distributive Lag (ARDL, hereafter) approach following Pesaran et al. (1999), in order to estimate the short- and long-run linear and quadratic relationships between variables under consideration.²

Although there is an extensive literature on the determinants of transport energy demand³, there are only a limited number of studies focusing directly on the effects of transportation infrastructure development on energy consumption and CO₂ emissions. Pradhan (2010), for instance, using a data set covering the period from 1970 to 2007 analyzed the nexus between transport infrastructure, energy consumption and economic growth in India and found a significant causality from transport infrastructure to energy consumption. Abdallah et al. (2013), moreover, investigates the causal relations between transport value added, road transport energy consumption, fuel prices and transportation sector CO₂ emissions in Tunisia during the period 1980–2010. The authors suggest that there exists a long-run mutual causality between road infrastructure, CO₂ emissions from transportation sector and road transport-related energy consumption. Achour and Belloumi (2016) later extended the work of Abdallah et al. (2013) by including the rail transportation infrastructure in Tunisia and found evidence towards a unidirectional causality from railway infrastructure to rail transport related energy consumption

¹ The economic growth and energy consumption nexus has been extensively studied since seminal paper of Kraft and Kraft (1978). Please see Ozturk (2010) for a comprehensive literature review.

² The theoretical framework used in this study is following Pesaran et al. (1999) which suggests a dynamic panel data methodology for those panels with large time dimension and smaller cross-sectional dimension. After testing for possible unit-root or cross-sectional dependence problems we first used Westerlund's cointegration test and then pooled mean group estimator of Pesaran et al. (1999). Please see section 2 for the details on the methodology.

³ See for instance, Samimi (1995), Wohlgemuth (1997), Bauer et al. (2003), Haldenbilen and Ceylan (2005), Murat and Ceylan (2006), Poudenx (2008), Liddle (2009), Anable et al. (2012) Pietzcker et al. (2014), among others.

after employing structural VAR methodology on the data set covering the period from 1971 to 2012. Within a more micro-analysis, Meng and Han (2018) explored the causality between road infrastructure, GDP growth and CO₂ consumption in Shanghai province of China and found that while the road infrastructure development did not contribute to GDP growth in the region it caused an increase in road transportation related CO₂ emissions. More recently, Saidi et al. (2018) analyzed the effects of transport energy consumption and transportation infrastructures on economic growth using a panel data set on selected MENA (Middle East and North Africa) countries for the period between 2000 and 2016. The authors stressed the importance of investing into transportation infrastructure that considers for energy-efficiency, for sustaining an economic growth with minimum amount of negative externalities.

This paper contributes to the literature in two-fold. Firstly, to the authors' best knowledge, there are only a limited number of studies examining the topic and only one of them, i.e., Saidi et al. (2018), is based on cross-country analyses. Hence, our paper would shed more light on the dynamics of the causal relations between the infrastructure, energy consumption and CO₂ emissions in the transportation sector using a panel data set. Secondly, inclusion of quadratic terms would allow us to test whether there exists a non-linear relationship between variables within the same fashion as Environmental Kuznets curve (EKC). Environmental Kuznets curve hypothesis suggests that there is a quadratic relation between per capita income and environmental degradation, controlled mainly by greenhouse gas emissions particularly CO₂ (Grossman and Krueger, 1991). Hence, our analyses would test the existence of transportation Kuznets curve for selected upper middle income countries.

The results of the cointegration test and the error correction model reveal the existence of a long-term association among variables under consideration. Moreover, the estimation results suggest that transportation infrastructure investment has significant effects on both transportation energy consumption and CO₂ emissions from transportation. We also found that while linear form of the infrastructure investment is positively affecting the dependent variables, its quadratic form has negative effect. These relations indicate that there is an inverted U-shape relation between transportation infrastructure and transportation energy consumption and CO₂ emissions from transportation. Consequently, the results overall indicate the existence of transportation Kuznets curve in these selected upper middle-income countries.

Structure of the paper is as follows. Section 2 will introduce the data used and the methodology applied in this study. Empirical results will be introduced in Section 3. Finally, Section 4 will conclude with policy implications.

2. DATA AND METHODOLOGY

This study uses a panel data set including eight upper middle-income countries covering a period from 1994 until 2014.⁴ The variables of interest include per capita motor gasoline consumption in barrels/year (MGC, hereafter) as a proxy for transport energy consumption and the share of CO₂ emissions from road in total CO₂ emissions (CER, hereafter) as dependent variables, road infrastructure investment per one thousand units of GDP in current USD (RII, hereafter) and the squared of RII (RIIS, hereafter) as independent variables. MGC has been calculated by using motor gasoline consumption 1000 bbl/day and population raw data, which have been taken from the International Energy Agency and World Wealth and Income statistics

⁴ Selected countries include Albania, Armenia, Azerbaijan, Bulgaria, Mexico, Romania, Russia, and Turkey. These upper middle-income countries are defined as those with a GNI per capita, calculated using World Bank Atlas method, between \$3,896 and \$12,055. According to the World Bank classification, there are 56 countries within the upper middle-income economies yet due to data availability only mentioned eight countries could have been chosen.

databases, respectively. CER has been calculated by using share of CO₂ emissions from road in total CO₂ emissions from transport and share of CO₂ emissions from transport in total CO₂ emissions raw data, which have been taken from OECD Stat Extracts statistics database. RII has directly been obtained from OECD Stat Extracts statistics database. Table 1 provides the descriptive statistics for all variables.⁵

Table 1: Descriptive Statistics of Variables over 1994-2014

Variables	Mean	Median	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
CER	0,211	0,162	0,136	0,052	0,643	1.347	4.408
MGC	1,007	0,679	0,682	0,162	2,489	0.771	2.309
RII	10,952	7,090	10,465	0,170	56,800	1.961	7.499
RIIS	228,663	50,268	480,592	0,003	3226,240	4.169	23.939

The methodology of this study comprises ARDL approach (Pesaran et al., 1999) in order to examine the short and long-run relationship between dependent and independent variables. In addition to this two-step procedure, error-correction based panel cointegration (Westerlund, 2007) is performed. Persyn and Westerlund (2008) describes the data generating process assumed by this error-correction test as follows:

$$\Delta y_{i,t} = \delta'_i d_t + \alpha_i y_{i,t-1} + \lambda'_i x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{i,j} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{i,j} \Delta x_{i,t-j} + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is dependent variable, which in our case is either MGC or CER and $x_{i,t}$ is the independent variable, which is RII for our case, for country $i = 1, \dots, T$ in year $t = 1, \dots, N$. Westerlund (2007) is based on the null hypothesis of $H_0: \alpha_i = 0$ using four different tests, namely the group mean tests G_τ and G_α , whose alternative hypothesis is $H_A: \alpha_i < 0$ for at least one i and the panel tests P_τ and P_α , whose alternative hypothesis is $H_A: \alpha_i < 0$ for all i . If the cointegration relationship is established, the long-run equation can be estimated. Moreover, as suggested by Pesaran et al. (1997), Westerlund panel cointegration procedure is more advantageous than that of previous ones, such as that of Pedroni (1999) as it avoids the problem of common factor restriction.

According to Pesaran et al. (1999), ARDL procedure is convenient for testing the short-run and long-run relationship when dependent and independent variables are I(1), and panel data is formed as time dimension greater than the cross-sectional dimension ($T > N$). Panel ARDL approach is based on deriving Pooled mean group (PMG, hereafter) estimators, which are asymptotically and normally distributed. PMG estimation removes the problems arising from endogeneity by including lag length for both endogenous and exogenous variables. This estimator is based on maximum likelihood method that provide considerable evaluation of the long-run nexus by considering cross-sectional characteristics. In reference to Pesaran et al. (1999), the ARDL (p, q, q) model, including the long-run relationship is structured as follows:

⁵ All variables have tested for stationarity by common (Levin-Lin-Chu and Breitung) and individual (Im-Pesaran-Shin, Fisher-ADF and Fisher-PP) panel unit root tests. Please also note that all variables are used in natural logarithms.

$$\Delta y_{it} = \omega_{1i} + \beta_{1i}y_{it-1} + \beta_{2i}x_{1,it-1} + \beta_{3i}x_{2,it-1} + \sum_{j=1}^p \varphi_{1i}\Delta y_{it-j} + \sum_{i=0}^q \varphi_{2i}\Delta x_{1,it-j} + \sum_{i=0}^q \varphi_{3i}\Delta x_{2,it-j} + \varepsilon_{1it} \quad (2)$$

In this regression, y_{it} is dependent variable, which in our case is either MGC or CER (in natural log), $x_{1,it}$ and $x_{2,it}$ are the independent variables, which are RII and RIIS (also in natural log) for our case, respectively. The choice of a lagged variable is based on the AIC (Akaike Information Criterion). The short-run dynamic relationship by estimating an ARDL (p, q, q) model is defined as follows:

$$\Delta y_{it} = \omega_{1i} + \sum_{j=1}^{p-1} \vartheta_{1ij}\Delta y_{it-j} + \sum_{i=0}^{q-1} \vartheta_{2ij}\Delta x_{1,it-j} + \sum_{i=0}^{q-1} \vartheta_{3ij}\Delta x_{2,it-j} + \mu_{1i}ECT_{1,it-1} + \varepsilon_{1it} \quad (3)$$

where y_{it} , $x_{1,it}$ and $x_{2,it}$ are same variables as stated previously in the long-run model. ε_{1it} denotes residuals, which are independent and normally distributed with zero mean and constant variance. $ECT_{1,it-1}$ is the error-correction term deduced from the long-run relationship and its coefficient μ_{1i} refers the speed of adjustment to the equilibrium level.

3. EMPIRICAL RESULTS

To determine the testing procedure our panel data set covering large T and small N dimensions, cross-section dependence is firstly tested. According to test results, there is no cross-section dependence as also can be shown in Table 2.

Table 2: Panel Cross-Section Dependence Test Results

	CER is Dependent Variable	MGC is Dependent Variable
Breusch-Pagan LM	37.091	28.678
Pesaran Scaled LM	1.215	0.091
Bias-Corrected Scaled LM	1.004	-0.132

Note: ***, ** and * represents significance at 1%, 5% and 10% levels, respectively. The null hypothesis of Breusch-Pagan LM, Pesaran scaled LM, and Bias-corrected scaled LM panel cross-section dependence tests is that the series contains no cross-section dependence.

Therefore, authors do not need to perform second-generation panel unit root tests and can continue with first-generation panel unit root tests. To test the stationarity of the variables, a variety of common and panel unit root tests, such as common Levin, Lin and Chu (2002) and Breitung (2000) and individual Im, Pesaran and Shin (2003), Fisher-type test using ADF test (Maddala and Wu, 1999) and Fisher-type test using PP test (Choi, 2001) tests have been used. As represented by Table 3, all variables are integrated of order one, I(1).

Table 3: Panel Unit Root Test Results

	CER	CER (Δ)	MGC	MGC (Δ)	RII	RII (Δ)
Panel A. Common Unit Root Tests						
Levin-Lin-Chu	0.663	-8.139***	0.271	-8.879***	0.699	-5.499***
Breitung	-0.151	-5.500***	0.206	-3.078***	-0.703	-4.820***
Panel B. Individual Unit Root Tests						
Im-Pesaran-Shin	2.154	-8.801***	-1.435	-7.634***	0.122	-3.043***
ADF- Fisher	9.856	95.708***	22.421	114.126***	12.816	39.256***
PP-Fisher	6.726	116.277***	20.365	145.358***	16.039	117.580***

Note: ***, ** and * represents significance at 1%, 5% and 10% levels, respectively. The null hypothesis of Levin-Lin-Chu, Breitung, Im-Pesaran-Shin, ADF-Fisher, and PP-Fisher panel unit root tests is that the series contains a unit root.

Based on the results of the panel unit-root and cross-section dependence tests, Westerlund panel cointegration test has been applied to test whether there exists a long-run relationship between variables. To proceed, optimal lag and lead lengths of the variables have been chosen via Akaike Information Criteria (AIC). Moreover, following Persyn and Westerlund (2008) the Kernel width has been set as $4(T/100)^{(2/9)}$, where T is the number of observations in time series dimension. After estimating Eq. (1), following the procedure described in the previous section, the results of the cointegration tests has been presented on Table 4. All test statistics, except for G_{τ} test on MGC vs. RII, lead us to reject the null hypothesis of no cointegration between CER and RII as well as between MGC and RII, at 1% significance level. Hence, these results overall confirm the existence of a long-run relationship among the variables under consideration.

Table 4: Westerlund Panel Cointegration Test Results

Relationship Tested	G_{τ}	G_{α}	P_{τ}	P_{α}
MGC vs. RII	-2,773*	-19,333***	-10,529***	-21,904***
CER vs. RII	-6,575***	-29,291***	-16,320***	-42,195***

Notes: Optimal lag and lead lengths selected via AIC are both 1 and optimal Barlett Kernel window width is set to be 3. All variables are in natural logarithms. ***, ** and * represents significance at 1%, 5% and 10% levels, respectively.

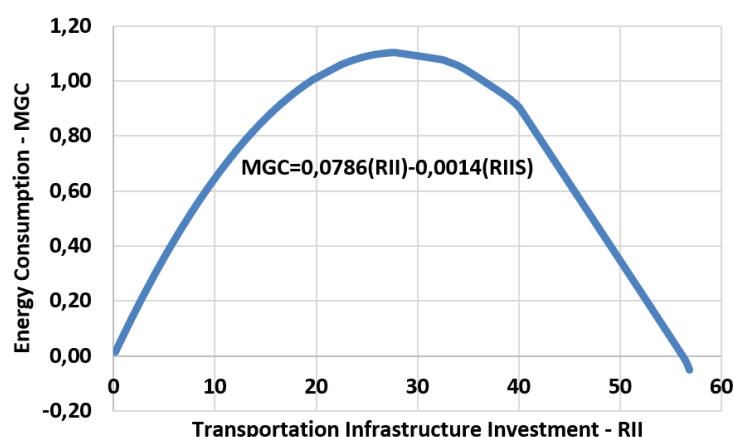
Table 5 shows the results of short- and long-run elasticities of MGC (columns 1 and 2) and CER (columns 3 and 4) with respect to RII and RIIS. According to the short-run estimates, the effects of RII and RIIS on both dependent variables are insignificant except for those that are represented on column 2. Although short-run estimates do not suggest any consistent relationship between the variables, long-run estimates consistently reveal positive and negative effects of RII and RIIS, respectively.

Table 5: Long-run and Short-run ARDL-PMG Estimations

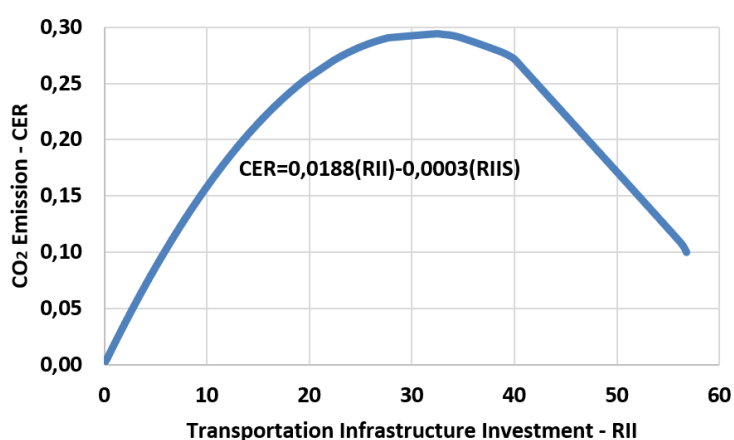
	Dependent Variable: MGC		Dependent Variable: CER	
	ARDL(1,1)	ARDL(2,1,1)	ARDL(1,2)	ARDL(1,2,2)
Long-Run Equation				
RII	0.0186***	0.0786***	0.0036***	0.0188***
RIIS		-0.0014**		-0.0003***
Short-Run Equation				
ECT (-1)	-0.1233*	-0.1206**	-0.2037***	-0.1554*
ΔRII	0.0174	-0.0626**	-0.0001	-0.0041
ΔRII (-1)			0.0006	-0.0081*
ΔRIIS		0.0045*		0.0002
ΔRIIS (-1)				0.0005
C	0.0877*	0.0321	0.0455***	0.0297**

Notes: All variables are in natural logarithms. ***, ** and * represents significance at 1%, 5% and 10% levels, respectively.

The results of long-run estimates in which only linear independent variable is included (columns 1 and 3), imply that a 1% increase in RII increases MGC and CER by 0.0186% and 0.0036%, respectively. Furthermore, according to the results of ARDL (2, 1, 1) model with linear and quadratic forms of independent variable (column 2), while an increase of 1% in RII increases MGC by 0.0786% and an increase of 1% in RIIS decreases MGC by 0.0014%. Likewise, in ARDL (1, 2, 2) model in column 4, an increase of 1% in RII increases CER by 0.0188% and an increase of 1% in RIIS decreases CER by 0.0003%. Hence there exist significant quadratic relationships between infrastructure investment and dependent variables. Finally, the error-correction term (ECT (-1)) is negative and statistically significant for all estimations, suggesting that any deviation from the long-run equilibrium is corrected thus the long-run relationship between variables stays consistent.



Panel (a) quadratic relationship between MGC and RII



Panel (b) quadratic relationship between CER and RII

Note: MGC, CER and RII values are in natural log form in both graphs above.

Figure 1: Transportation Kuznets Curve: an illustration

Estimated quadratic relationships between road infrastructure investment and motor gasoline consumption and CO₂ emissions in the transportation sector imply the existence of transportation Kuznets curve in upper-middle income countries. We illustrate these using parameters estimated by the long-term models in Figure 1. While panel (a) of the figure shows the Kuznets relation between transportation infrastructure investment and motor gasoline consumption, panel (b) shows that of between infrastructure investment and transportation sectors' CO₂ emissions. As can be seen from the figures MGC and CER increase until RII reaches to 27.76 and 32.38, respectively and then they both decrease. Hence, for the selected eight upper middle-income countries transportation infrastructure investment positively contributes to sustainable development after it reaches a certain level.

4. CONCLUDING REMARKS

This paper aims at analyzing the effects of transportation infrastructure investment (such as building up new highways, maintenance of existing roads) on per capita motor gasoline consumption, and the share of transportation sector in total CO₂ emissions in the country. To this end, data from eight upper middle-income countries over the period between 1994 and 2014 is used to conduct panel ARDL approach. Long-term estimates reveal the fact that transportation infrastructure investment positively affects both gasoline consumption and CO₂ emissions.

Yet, when squared infrastructure investment term is included in the estimations, we found quadratic relationship between variables. Such that, while road infrastructure investment has positive effect on motor gasoline consumption and CO₂ emissions, its quadratic form has negative effect. Hence, motor gasoline consumption and transportation CO₂ emissions in upper middle-income countries first increase as the up to some certain level of transportation infrastructure and then start to decrease as the infrastructure investment further continues. The results therefore suggest the existence of Transportation Kuznets Curve in the selected developing economies.

Although it is accepted that the developing economies are prioritizing transportation infrastructure investments in order to meet increasing factor mobility needs that would promote economic growth, policy-makers should be aware of the fact that early phases of development of transportation infrastructure would increase fuel consumption and environmental degradation. First of all, if the country under consideration is an energy import dependent economy, such as Turkey, although higher factor mobility fosters economic growth, increasing fuel demand would create a burden in current account deficit. Secondly, positive economic effects of transportation infrastructure investments should not be offset by negative environmental externalities, particularly GHG emissions.

This study is distinguishing itself from the related literature, which is quite scarce to the author's best knowledge. There is only one study, namely Saidi et al. (2018), which analyses the topic for selected Middle East and North Africa (MENA) countries. Most of those MENA countries are exporters of different primary energy sources, such as oil and gas. Hence the results and corresponding policy implications achieved in the study at hand would shed more light on the topic of sustainable transportation infrastructure for energy import dependent developing countries. The analyses in this study may be extended using a data set, which comprises more developing economies, as long as data availability issue is dealt with. Moreover, it would also be valuable for policy makers to analyze the effect of transportation infrastructure on gasoline consumption and CO₂ emissions over different regions or cities in a specific developing country. Yet, this analysis is also possible provided that necessary data is available.

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