

Driving Factors of Energy Consumption and Carbon Emissions and Their Impacts on Sustainable Development in Saudi Arabia

Atef Saad Alshehry

College of Administrative Sciences, Najran University, PO box 1988, Najran 55461, Saudi Arabia

The author is thankful to the Deanship of Scientific Research at Najran University for funding this work through grant research code NU/SHED/15/064 (Sponsoring information).

Abstract

This study identifies the effects of driving factors and measuring their corresponding contribution shares in energy consumption and CO₂ emissions in Saudi Arabia by employing the factor decomposition model and the Stochastic Impacts by Regression on Population, Affluence, and Technology model. The empirical results indicate that the effects of population, GDP per capita and carbon intensity on CO₂ emissions are positive and significant. The results show that technological progress is the main driving factor that leads to increase energy use. Besides, increasing energy efficiency in energy consumption and investment in new technologies and renewable energies should be a good strategy to attain a sustainable development in Saudi Arabia.

Keywords: Energy Consumption, Carbon Emissions, Factor Decomposition Model, STIRPAT Model, Saudi Arabia

1. Introduction

Climate change has been on the agenda since the Rio Earth Summit in 1992. The “Rio Convention” adopted the UN Framework on Climate Change (UNFCCC). It aimed at stabilizing atmospheric concentrations of greenhouse gases (GHGs) to avoid “dangerous anthropogenic interference with the climate system”. Since 1995, there has been an annual conference of parties (COP), which takes place each year in a country. The COP3 adopted the Kyoto Protocol. More recently, COP21 taken place in Paris in December 2015. It will aim to keep global warming below 2°C.

Scientists have reached the consensus that global warming is nowadays a big problem of climate changes. Greenhouse gases are the main driving of increases in global temperature (IPCC, 1995). Hence, all countries, mainly developed ones, have the responsibility to reduce the GHGs in order to mitigate global climate change. Carbon dioxide (CO₂) is the main greenhouse gas that is causing global warming and climate change. In this case, the identification of the factors that have an impact on CO₂ emissions is important for implementing strategies and policies aiming at reducing CO₂ emissions and hence combatting climate changes.

In environmental economics literature, the well-known determinant factors of CO₂ emissions are energy structure, affluence, economic structure, technology level and population constitution. Each of these factors has its role in increasing or decreasing CO₂ emissions. Early studies considered that increases in energy consumption (principally fossil fuels consumption) are the main contributor to increases in CO₂ emissions (Fan et al., 2006). Later, many studies (Engleman, 1994; Cole et al., 1997; Meyerson, 1998) showed that other factors (such as economic activity, population structure, and technology level) could play key roles in explaining CO₂ emission changes. In addition, Shi (2003) found that their impact on CO₂ emissions varies from country to country. Hence, it raises the question of what is the contribution share of each factor and its nature in changes in CO₂ emissions in each country.

In order to answer this question, many studies have been undertaken for many countries and regions by employing the decomposition analysis methods. However, the findings are mixture and there is a consensus that fossil fuels consumption is the main contributor to CO₂ emissions increases. In view of these, firstly, this paper employs the factor decomposition model to determine the driving factors and measuring their corresponding contribution shares in energy use in Saudi Arabia. Secondly, it employs the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to analyze the impact factors of CO₂ emissions in Saudi Arabia over the period 1971-2012. The STIRPAT model has the advantage to let us determine ecological elasticities, which show the sensitivity of carbon emissions impacts to the forces driving them. The results of ecological elasticities can be utile for policy-makers to point out the factors that may be most responsive to policy or measure and implement strategies based on CO₂ abatement.

This paper contributes to the existing empirical literature review by three aspects. Firstly, it addresses an understudied country that has a huge influence in the global energy governance. To our knowledge, this study is the first to use decomposition analysis tools to identify the driving factors of energy consumption in Saudi Arabia, which is one of the world's top 10 CO₂ emitters. Secondly, it is also the only study that investigates the impact of different factors on CO₂ emissions in Saudi Arabia by using the STIRPAT model. Thirdly, the paper seeks to further understanding of the influences of income, energy efficiency, population and urbanization on both indicators of environmental impacts (energy consumption and CO₂ emissions) by employing both IPAT and

stochastic IPAT analyses.

The rest of this paper is organized as follows. In section 2, we present a brief empirical literature review. In section 3, we present the analytical tools and data. The empirical results and their discussions are presented in section 4. Finally, section 5 shows conclusions and policy implications.

2. Literature Review

There is a vast literature review concerning the studies investigating the driving factors of energy consumption and carbon dioxide emissions using different methods of decomposition analysis, input-output matrix or regression. We concentrate our review on some recent studies, which studied the impacts of income, population, energy efficiency and urbanization on energy consumption or carbon emissions employing decomposition analysis or STIRPAT model. Table 1 summarizes these recent studies. Findings from different previous studies varied among the countries studied. Some studies concentrated on single countries whereas others were devoted to a group of countries or regions.

For single countries, the majority of previous studies were devoted to the case of China. All findings showed that economic growth is responsible of increases in energy use or carbon emissions whereas energy intensity or technological progress are the main drivers of decreases in energy use or CO₂ emissions. Recently, Liu (2009) employed the factor decomposition model and found that economic growth and urbanization are leading factors of energy consumption whereas technological progress plays a positive role in decreasing energy use in China over the period 1978-2008. Later, Chen et al. (2013) used the Log Mean Divisia Index (LMDI) method to identify the driving factors of energy-related industrial CO₂ emissions in China over the period 1985-2007. They found that per capita GDP is the main contributor to industrial CO₂ emissions increases, whereas the contribution shares of economic structure, energy structure and population are weak. Zhang and Wang (2013) employed the decoupling index and the LMDI method to identify the factors that influence electricity consumption in China during the period of 1991 to 2009. Their main findings showed that economic growth is the main responsible of electricity consumption increases in China, whereas energy intensity effect is the main driver of electricity consumption decreases. Wen et al. (2015) used the extended STIRPAT model to decompose the driving factors of energy related CO₂ emissions in China over the period 1991-2011. Their results showed that population, industrialization, economic growth, foreign trade and service level are the main driving forces of CO₂ emissions. Zhang and Da (2015) utilized the LMDI method to identify the changes of CO₂ emissions and carbon emissions intensity in China over the period 1996-2010. They found that economic growth is the main driver of carbon emissions increases, while the fall in energy intensity and the cleaning of final energy consumption structure played important roles in reducing carbon emissions. Wang et al. (2015) analyzed the driving forces of energy-related CO₂ emissions in China's Tianjin province using the LMDI method over the period 1995-2012. Their findings showed that per capita GDP and population scale are the main drivers of CO₂ emissions increases, whereas energy intensity is the main contributor to CO₂ emissions decreases. No later, Xiao et al. (2016) identified the main driving forces of CO₂ emissions in China by using structural decomposition analysis. Their findings indicated that urbanization, investment and exports are the main drivers of CO₂ emissions increases, whereas energy intensity is the main driver of CO₂ emissions reduction. Dong et al. (2016) investigated the decoupling effect between energy consumption and economic growth in Chinese Liaoning province by employing the generalized LMDI method over the period 1995-2012. Their results showed that energy intensity played a positive role in the decoupling effect between energy consumption and economic growth. More recently, Wang et al. (2017) investigated the main driving forces of energy related carbon emissions in Xinjiang over a long period of 1952–2012 by employing the STIRPAT model. They divided the period of study into 3 sub-periods: “Before Reform and Opening up” (1952–1978), “After Reform and Opening up” (1978–2000), and “Western Development” (2000–2012). Their findings indicated that the impacts of different factors on energy related carbon emissions are not the same for the three different development stages.

By considering a developed country, Kwon (2005) determined the main factors in the change in CO₂ emissions from car travel in Great Britain over the period 1970-2000 by using various index decomposition methods starting from the IPAT identity equation. He found that the affluence factor, represented by car driving distance per person, was the main dominant force for the growth of CO₂ emissions from car travel over the period studied in Great Britain whereas the contribution of technology factors (fuel efficiency and fuel substitution to diesel fuel partly) was relatively small. For a newly industrialized country, Tunc et al. (2009) tried to identify the driving factors of changes in CO₂ emissions in Turkey over the period 1970–2006 by employing the LMDI method. They found that economic activity is the main contributor to changes in CO₂ emissions in Turkey. De Freitas and Kaneko (2011a) investigated the determinants of CO₂ emissions change from energy use in another newly industrialized country (Brazil) over the period 1970–2009 by employing the LMDI method. They found that economic activity and demographic pressure are the main driving factors of CO₂ emissions increases. They concluded, “Brazilian efforts to reduce emissions are concentrated on energy mix diversification and carbon intensity control while technology intensive alternatives like energy intensity has not demonstrated

relevant progress". In the same line, De Freitas and Kaneko (2011b) used the log-mean Divisia index method to identify the determinants of CO₂ emissions change from energy consumption for Brazil over the period 2004-2009. Their results showed that the carbon intensity and energy mix are the main factors that lead to CO₂ emissions reduction in Brazil. No later, Borba et al. (2012) showed that the potential to reduce future energy-related GHG emissions is around 27% in 2030. However, this Brazilian mitigation potential effect is not sufficient to reduce the energy-related GHG emissions in 2030 below their current level. For the case of Italy, the findings of Andreoni and Galmarini (2012) are in the same line of previous studies. By employing a more developed index decomposition analysis, Andreoni and Galmarini (2012) found that energy intensity and economic growth are the main drivers of CO₂ emissions in Italy during the period of 1998 to 2006.

For the case of a developing country, Achour and Belloumi (2016) determined the driving forces of energy consumption in the transport sector in Tunisia by employing the LMDI method and annual data during the period of 1985 to 2014. They found that the factors of economic growth, transport intensity, transport structure and population affect positively transport energy consumption, whereas the energy intensity factor affects negatively transport energy consumption. For the case of Saudi Arabia, Belloumi and Alshehry (2016) analyzed the dynamic causal relationship between economic growth, urbanization and energy intensity by employing the ARDL bounds testing to cointegration approach. Their findings indicated that urbanization leads to increase economic output, which leads to increase energy intensity in the long run.

The studies investigating a group of countries are multiple. By employing the STIRPAT model for a group of 146 countries for the CO₂ emissions analysis and 138 countries for the energy footprint analysis, York et al. (2003) found that affluence affects positively both CO₂ emissions and the energy footprint whereas the impact of population on CO₂ emissions and the energy footprint is proportional. Later, Fan et al. (2006) used the STIRPAT model to analyze the effects of affluence, population and technology on CO₂ emissions for countries with different income levels over the period 1975–2000. They found that the influences of the three factors vary with the level of development of countries. Diakoulaki and Mandaraka (2007) analyzed the changes in industrial CO₂ emissions caused by the factors of output, energy intensity, structure, fuel mix and utility mix in 14 EU countries using a decomposition analysis based on the Laspeyres model over the period 1990–2003. They divided the studied period in two sub-periods: pre-Kyoto protocol period (1990-1997) and post-Kyoto protocol period (1997-2003). Their findings showed that the decoupling effort of EU countries is important but insufficient. They indicated that there is no significant reduction of CO₂ emissions in the post-Kyoto protocol period. Lu et al. (2007) investigated the impacts of different factors such as vehicle fuel intensity, emission coefficient, vehicle ownership, population intensity and economic growth on carbon dioxide emissions from highway vehicles in Germany, Japan, South Korea and Taiwan over the period 1990-2002 by using the Divisia index framework. Their results indicated that economic growth and vehicle ownership were the main driving factors of CO₂ emissions increases, whereas population intensity is the main contributor of CO₂ emission decreases. The authors concluded that energy conservation and CO₂ emissions mitigation are dependent on environmental pressure and economic growth for all the countries studied.

By employing the STIRPAT model, York (2007) found that population, economic development, age structure and urbanization affect positively energy use for a group of 14 advanced European countries over the period 1960-2000. Papagiannaki and Diakoulaki (2009) analyzed the changes in carbon dioxide emissions from passenger cars in Denmark and Greece using a decomposition analysis based on the LMDI method during the period of 1990 to 2005. Their findings showed that the factors related to vehicles ownership, fuel mix, annual mileage, engine capacity and technology of cars affect the trend of CO₂ emissions in both countries. Poumanyong and Kaneko (2010) estimated a STIRPAT model to study the impact of urbanization on energy consumption and CO₂ emissions for a sample of 99 countries over the period 1975-2005. They found that the impact of urbanization on energy use is positive in the middle and high-income countries, while its effect is negative in the low-income group. However, urbanization affects CO₂ emissions positively for all income groups. Mundaca et al. (2013) provided a decomposition analysis of CO₂ emissions from fuel combustion for eight regions during the period of 1971 to 2010. Their results showed that the performance of majority of regions is worse. They concluded that reductions of CO₂ emissions are necessary to maintain global warming below the 2 °C. Using the STIRPAT model, Bargaoui et al. (2014) studied the impact of urbanization, economic growth, energy intensity, population growth and Kyoto protocol obligations on carbon dioxide emissions for 214 countries over the period 1980 to 2010. They found that the variables of urbanization, economic growth, population growth and Kyoto protocol obligations have significant effects on CO₂ emissions and these effects are dependent on the income level.

3. Methodology and Data

3.1 Factor Decomposition Model

In order to identify the influences of driving factors and measuring their corresponding contribution shares in energy consumption in Saudi Arabia, we use the factor decomposition model (FDM) (Ang and Zhang, 2000;

Ang, 2004; Chung et al., 2013). Ang (2004) presents an overview of the application and methodology development of decomposition analysis. When considering energy demand, decomposition analysis methods try to quantify the relative contributions of the impacts of structural change and energy intensity change (Ang, 2004).¹

By following Ang (2005), if we consider that C_t , G_t , I_t , and P_t denote, respectively, energy consumption, gross domestic product, energy intensity and population at time t , we can decompose energy consumption as follows:²

$$C_t = \frac{C_t}{G_t} * \frac{G_t}{P_t} * P_t \quad (1)$$

Eq. (1) shows that we decompose energy consumption in three factors: energy intensity ($I_t = C_t/G_t$), GDP per capita ($M_t = G_t/P_t$) and population. Then the variation of energy use between two successive periods ($\Delta C_t = C_t - C_{t-1} = I_t M_t P_t - I_{t-1} M_{t-1} P_{t-1}$) can be decomposed as follows:

$$\begin{aligned} \Delta C_t &= (I_t M_t P_t - I_{t-1} M_t P_t) + (I_{t-1} M_t P_t - I_{t-1} M_{t-1} P_t) \\ &+ (I_{t-1} M_{t-1} P_t - I_{t-1} M_{t-1} P_{t-1}) \end{aligned} \quad (2)$$

Therefore, the variation of energy use between the two periods t and $t-1$ is decomposed in three parts: technological progress or energy efficiency ($I_t M_t P_t - I_{t-1} M_t P_t$), economic growth ($I_{t-1} M_t P_t - I_{t-1} M_{t-1} P_t$), and population scale ($I_{t-1} M_{t-1} P_t - I_{t-1} M_{t-1} P_{t-1}$).

Following previous studies such that of Liu (2009), we add the variable urbanization (U) in Eq. (1) by decomposing P in total population and urban population because it can affect energy consumption. Hence, we obtain the following equation:

$$C_t = I_t * M_t * P_t * U_t \quad (3)$$

Using Eq. (3), we decompose the variation of energy consumption in four factors as follows:

$$\begin{aligned} \Delta C_t &= I_t M_t P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1} = (I_t M_t P_t U_t - I_{t-1} M_t P_t U_t) + (I_{t-1} M_t P_t U_t - I_{t-1} M_{t-1} P_t U_t) \\ &+ (I_{t-1} M_{t-1} P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_t) + (I_{t-1} M_{t-1} P_{t-1} U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}) \end{aligned} \quad (4)$$

Where ($I_t M_t P_t U_t - I_{t-1} M_t P_t U_t$) stands for the changes in energy use caused by technological progress, ($I_{t-1} M_t P_t U_t - I_{t-1} M_{t-1} P_t U_t$) represents the variation in energy consumption caused by economic growth, ($I_{t-1} M_{t-1} P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_t$) stands for the variation in energy consumption caused by the variation in population, and ($I_{t-1} M_{t-1} P_{t-1} U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}$) represents the changes in energy consumption caused by the urbanization process. Using Eq. (4), we derive the contribution share of each factor as follows:

$$\omega_{TEC} = \frac{I_t M_t P_t U_t - I_{t-1} M_t P_t U_t}{I_t M_t P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}} \quad (5)$$

$$\omega_{EG} = \frac{I_{t-1} M_t P_t U_t - I_{t-1} M_{t-1} P_t U_t}{I_t M_t P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}} \quad (6)$$

$$\omega_P = \frac{I_{t-1} M_{t-1} P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_t}{I_t M_t P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}} \quad (7)$$

$$\omega_U = \frac{I_{t-1} M_{t-1} P_{t-1} U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}}{I_t M_t P_t U_t - I_{t-1} M_{t-1} P_{t-1} U_{t-1}} \quad (8)$$

Where ω_{TEC} , ω_{EG} , ω_P , and ω_U represent, respectively, the contribution share of technological progress (or energy efficiency), the contribution share of economic growth, the contribution share of population scale, and the contribution share of urbanization to energy consumption. These shares correspond to the driving forces of

¹ Since 1990, many studies have used decomposition analysis methods to identify the driving factors of energy related carbon dioxide emissions (Ang, 2004).

² Ang (2005) gives a practical guide to the logarithmic mean divisia index method. Chung et al. (2013) use the LMDI method to decompose the components of energy consumption in transport sector in China over the period 2003-2009.

energy consumption changes in time. Each factor can be positive or negative. When it is positive, the factor contributes in increasing energy consumption whereas when it is negative it contributes in decreasing energy consumption.

3.2 STIRPAT Model

In order to investigate the impact of population, affluence and technology level on CO₂ emissions in Saudi Arabia, we use the STIRPAT model developed by York et al. (2003). This model takes its origin from the equation $I = PAT$, where I is environmental change, P is population, A is affluence and T is technology. By introducing a stochastic term (ε) in the IPAT identity, we have the following specification of the STIRPAT model (Fan et al., 2006):

$$I = aP^b A^c T^d \varepsilon \quad (9)$$

By applying the natural logarithm to eq. (9), we obtain the following linear model:

$$\ln I_t = b_0 + b_1 \ln P_t + b_2 \ln A_t + b_3 \ln T_t + \varepsilon_t \quad (10)$$

Where the operator ln is the natural logarithm and the subscript t represents time (year).

In our study, the variables I, P, A and T are, respectively, represented by CO₂ emissions, population, GDP per capita, and carbon intensity (CO₂ emissions per unit of GDP)³. Following Dietz and Rosa (1994) and Fan et al. (2006), we decompose P in total population and urban population. Hence, our empirical STIRPAT model is written as follows:

$$\ln I_t = b_0 + b_1 \ln P_t + b_2 \ln A_t + b_3 \ln T_t + b_4 \ln U_t + \varepsilon_t \quad (11)$$

Where U is the urbanization rate. Since we have a logarithmic form, all the coefficients b_1 , b_2 , b_3 , and b_4 are elasticities. They are interpreted as changes in percentage terms. York et al. (2003) called them ecological elasticities (EE). Each EE represents the responsiveness or sensitivity of CO₂ emissions to a change in any of the independent variables.

3.3 Variables Description and Data Used

The data used in this paper concern Saudi Arabia and cover the period 1971-2012. The variables of interest are energy intensity, energy use, economic output, urbanization, carbon intensity, CO₂ emissions and population. The variable energy consumption is the total energy consumed by economic activities (expressed in kt of oil equivalent). The variable energy intensity is determined by energy consumption in kg of oil equivalent per \$1000 GDP (expressed in constant US\$2005). Economic output is determined by real per capita GDP (expressed in constant US\$2005). The variable urbanization reflects the percentage of people living in urban areas. Carbon intensity is measured by CO₂ emissions per unit of GDP (expressed in kg per US\$2005). CO₂ emissions are measured in kt. Finally, population represents the number of residents living in the country. All data are obtained from the World Development Indicators online database of the World Bank (WDI, 2015). The descriptive statistics of the different series are presented in Table 2.

4. Results and Discussions

4.1 Results of Factors Decomposition Model

We determine the contribution share of each factor on energy use over the period 1971-2012 by using the factors decomposition model. Using the Eqs. (5)-(8), the values of ω_{TEC} , ω_{EG} , ω_P , and ω_U are shown in Table 3 over the whole period for Saudi Arabia. Their trends are shown in Fig. 1. It is shown that the factors of economic growth, technological progress, population scale and urbanization process are playing vital roles in affecting the increases of energy consumption in Saudi Arabia. Overall, technological progress is the main driving force of energy consumption followed by economic growth and population growth.

The contribution share of urbanization to changes in energy use is positive but it is the smallest comparatively to the other factors. From Figure 1, it is seen that it is relatively stable and the smallest changes are seen in the 2000s whereas the largest variations are observed in the 1980s. The contribution share of urbanization declines from 0.193 in 1973 to 0.013 in 2012. This can be explained by the rapid growth of urbanization process following the 1970s oil crisis and its slowdown during the last years. The annual urban population growth rate is about 8% in the 1980s in Saudi Arabia, whereas it is only about 3% in the 2000s (World Development Indicators, 2015). Overall, the positive contribution share of urbanization may be attributed to the increase in urbanization due to the rapid population growth in Saudi Arabia during the whole period of study. This result is conform to that found by Liu (2009) when using the factor decomposition model to investigate the impact of urbanization on energy use for the case of China. In addition, the positive contribution of urbanization to energy use in Saudi Arabia is in line with that of Poumanyong and Kaneko (2010) who found

³ CO₂ emissions = Population x (GDP/Population) x (CO₂ emissions/GDP).

that urbanization has a positive effect on energy consumption for the high-income countries.

The per capita GDP does not only represent economic growth but also the standard living for the population. Decomposition results from Table 3 and Fig. 1 display a positive contribution of economic growth in 22 years during all the period 1972-2012. This implies that economic growth leads to increases in some years and decreases in other years of energy consumption in Saudi Arabia. The years of 1985, 1989 and 2011 are characterized by large negative contributions of economic growth to energy consumption. During these years, economic growth led to reduce energy use in Saudi Arabia. The positive contributions of economic growth to energy use are mainly observed during the periods following the oil shocks of 1973, 1979 and 2008. The increases of oil prices and their high level of volatility characterize these periods. Therefore, the increases of oil prices are beneficial for the economic growth in OPEC countries such as Saudi Arabia but not for the environment as they are followed by increases in energy consumption and CO₂ emissions. This finding can be explained by the absence of energy policies aimed to attain sustainability. Our result is conform to many previous findings such that of González et al. (2014) for the case of the most developed European countries where economic growth is the main driver of energy consumption.

In respect to the decomposition analysis results, the contribution of population is positive in the majority of years. Hence, our results reveal that the role of population in the increasing of energy consumption in Saudi Arabia is important. We expect to find this result because increases in population induce increases of mobility demand and thus more energy consumption (Zhang and Lin, 2012). As shown in Fig. 1, the largest contribution shares of population to the increases of energy use are observed in the second half of the 1980s. It can be explained by the rapid growth of Saudi's population, particularly ten years after the 1973 and 1979 oil shocks. The annual population growth rate varies from 5% to 6% in the 1980s in Saudi Arabia (World Development Indicators, 2015). The majority of previous studies found that population growth causes increases in energy consumption, and hence increases in carbon emissions (e.g. Achour and Belloumi, 2016).

As energy intensity is a measure of energy consumption divided by gross domestic product, it reflects the efficiency of energy use. As shown in Table 3 and Fig. 1, the contribution of energy efficiency is positive in majority of years except in 1986 and 2005, implying that there is a large inefficiency of energy use in Saudi Arabia. The positive contribution of energy efficiency is unexpected as technological progress may lead to the reduction of energy consumption in general due to energy efficiency and energy savings. Our finding may be attributed to the overuse of energy caused by the lower prices of oil, natural gas and electricity in Saudi Arabia. The low levels of energy prices in Saudi Arabia are the result of their high subsidization (Alshehry and Belloumi, 2015). Between 2000 and 2012, Saudi Arabia's oil consumption was multiplied by two (Alshehry and Belloumi, 2014). In addition, Saudi's energy consumption relies completely on fossil fuels, which are less efficient than renewable resources. The result of energy intensity is in line with those found by Achour and Belloumi (2016) for the case of Tunisia and Supasa et al. (2016) for the case of Thailand. However, it is not in line with some more recent studies that found energy intensity plays a positive role in reducing energy consumption and CO₂ emissions, mainly for the case of China (Liu, 2009; Wang et al., 2014; Wang et al., 2015; Dong et al., 2016, Zhang et al., 2016).

4.2 Results of Factors Decomposition Model

The estimation of STIRPAT model, given by Eq. (11), using the OLS (Ordinary Least Squares) method gives biased results because we found that the error terms are correlated and heteroskedastic. Therefore, we use the Robust Least Squares method to avoid the problems of autocorrelation and heteroscedasticity. The results of robust estimators are shown in Table 4. It is shown that all the coefficients are statistically significant at 1% level. Except the ecological elasticity of urbanization, all other elasticities are positive. In addition, the absolute values of all elasticities are superior to 0.55, so all the factors play important roles in explaining the growth of CO₂ emissions in Saudi Arabia.

The result of ecological elasticity of population is conform to Malthusian theory that involves a larger population could result in more energy consumption, and hence more CO₂ emissions induced by fossil fuels consumption. When population increases by 1%, the CO₂ emissions rise by 1.09%. This implies that the variation in CO₂ emissions is proportional to that of population. This result confirms our finding of decomposition analysis that shows population plays an important role in energy use increases, and hence in CO₂ emissions increases. In addition, our result is conform to those obtained by Dietz and Rosa (1997) and York et al. (2003) who found that the ecological elasticity of CO₂ emissions with respect to population is nearly one.

The ecological elasticity of income is equal to 0.925, implying that an increase of 10% in real GDP per capita leads to an increase of 9.25% in CO₂ emissions. As Saudi Arabia is one of the high-income level countries, its higher GDP per capita can lead to more energy use and hence more CO₂ emissions. This result is evident because Saudi Arabia is still in the first phase of development where there is a monotonically increasing relationship between its real per capita GDP and its CO₂ emissions. The Environmental Kuznets curve hypothesis does not hold for the case of Saudi Arabia (Alshehry and Belloumi, 2017). The higher GDP per

capita is mainly devoted to the oil rents and not economic activities. Many previous studies found the same results (e.g., Tunc et al., 2009; Andreoni and Galmarini, 2012; Wen et al., 2015; Zhang and Da, 2015; Wang et al., 2015).

The results of the impacts of population and income on CO₂ emissions are conform to those obtained by previous studies using the STIRPAT model. In fact, both population and income are significant drivers of carbon emissions where their elasticities are not very far from unity. Furthermore, we find that population has a greater impact than income as found by the majority of previous studies (Martinez-Zarzoso et al., 2007).

The effect of carbon intensity on CO₂ emissions is positive and it is near one. A 10% increase in carbon intensity should lead to 10% increase in CO₂ emissions. This result confirms our previous finding for energy efficiency, which contributes positively to energy consumption increases. This result is explained by the high subsidization of oil prices in all sectors of Saudi Arabia's economy, which leads to energy inefficiency. These results imply that Saudi Arabia has not invested on new technologies based on reducing energy consumption and CO₂ emissions. This is why Saudi Arabia is considered as one of the main polluters in the world. Our results are conform to those obtained by Fan et al. (2006) for high-income countries and by Andreoni and Galmarini (2012) for Italy but different from that of De Freitas and Kaneko (2011a) for the case of Brazil.

The ecological elasticity of urbanization is about -0.55, implying that a 10% increase in urbanization rate may lead to a fall of CO₂ emissions by 5.5%. This result is different from that of population. In this case, urbanization may lead to energy-saving behaviors. This finding supports the urban compact hypothesis implying that urban cities may benefit from economies of scale for public services and infrastructure. In fact, urbanization may be a driving factor of reducing energy consumption mainly in transport sector due to more dense concentrations of population. This finding is conform to that of Fan et al. (2006), who found a negative impact of urbanization on carbon dioxide emissions for a group of high income countries. Saudi Arabia is considered as a high-income country according to the Gross National Income per capita indicator that is developed by the World Bank. However, this result is somewhat different from those obtained by Poumanyong and Kaneko (2010) and Belloumi and Alshehry (2016).

Overall, our findings from STIRPAT model indicate that economic activity (GDP per capita), carbon intensity and population are the main factors that positively affect CO₂ emissions in Saudi Arabia. Economic growth and population size are well known in the literature of environmental economics that are the main drivers of pollution. However, carbon intensity is found to have a negative impact on CO₂ emissions in the majority of studies concerning, principally, developed countries (González et al., 2014). Saudi policies should be based on more investments in new technologies and development of clear strategies that lead to the abatement of CO₂ emissions. Such strategies could be based on the application of regulation policies (administrative measures, economic instruments such as tax, subsidies, etc.). In addition, the policies based on subsidization of oil prices in Saudi Arabia should be revised because they lead to energy inefficiency. Therefore, the reduction of carbon emissions is still a long-term process in Saudi Arabia.

5. Conclusions and Policy Implications

An exploration study of main driving factors of energy consumption and carbon dioxide emissions has not been conducted in Saudi Arabia. All previous studies on Saudi Arabia investigated the causal relationship between economic activity, energy use and carbon dioxide emissions. Different from previous studies, this paper investigates the driving forces of CO₂ emissions using the STIRPAT model and identifies the contribution shares of energy efficiency, urbanization, economic growth and population on the total energy consumption over the period 1971-2012 in Saudi Arabia. The investigation and identification of driving forces of energy use and carbon emissions may help to implement energy saving strategies in Saudi Arabia.

Firstly, a factor decomposition model is used to measure the contribution impact of each driving factor on energy consumption. The results of factors decomposition model indicate that the urbanization process pulls much smaller contribution share on Saudi Arabia's energy use, and therefore, the urbanization process is putting less pressure on the energy demand. The urbanization management needs the integration of energy component and the policy measures should be participatory and multidimensional. Overall, economic growth and population scale have positive contributions to energy use indicating that Saudi Arabia is still in the phase of development. Moreover, technological progress contribution on Saudi Arabia's energy consumption is positive indicating that there is a large inefficiency in energy use in the majority of years over the period of study.

Secondly, this study develops a STIRPAT model that relates CO₂ emissions to income, population, urbanization and carbon intensity to determine the ecological elasticities. The results show that all elasticities are positive, except for urbanization, and they are significant even at 1% level. The value of ecological elasticity of urbanization implies that a 1% increase in urbanization causes a decline of 0.55% in carbon dioxide emissions. This result supports the urban compaction hypothesis. Economic activities, population and carbon intensity continue to rise in Saudi Arabia, and hence they may lead to more carbon emissions. In addition, our findings show that economic growth, population scale and energy intensity have positive and significant impacts on CO₂

emissions whereas urbanization has a negative impact on CO₂ emissions in Saudi Arabia. These findings serve as a useful and straightforward addition to a field that is often marked by convoluted debate. Investment in energy saving technologies and renewable energies is necessary to reduce energy consumption without restraining economic activities, and hence CO₂ emissions in Saudi Arabia to fulfill its obligations aimed at keeping global warming below the level of 2°C in respecting environment.

Finally, it is suggested to study in the near future the driving factors of energy consumption and CO₂ emissions in the different sectors of Saudi Arabia, and to determine which sectors have the highest potential of reducing energy consumption and CO₂ emissions. Such kind of study can lead to sectoral policy implications. In addition, some further future studies should focus on energy rebound effect that leads to obtain the true value of energy conservation caused by technological change in Saudi Arabia (Zhang et al., 2017; Zhang and Peng, 2017).

References

- Achour, H. & Belloumi, M. (2016), "Decomposing the influencing factors of energy consumption in Tunisian transportation sector using the LMDI method", *Transport Policy* **52**, 64-71.
- Alshehry, A.S. & Belloumi, M. (2014), "Investigating the Causal Relationship between Fossil Fuels Consumption and Economic Growth at Aggregate and Disaggregate Levels in Saudi Arabia", *International Journal of Energy Economics and Policy* **4**(4), 531-545.
- Alshehry, A.S. & Belloumi, M. (2015), "Energy consumption, carbon dioxide emissions and economic growth: The case of Saudi Arabia", *Renewable and Sustainable Energy Reviews* **41**, 237-247.
- Alshehry, A.S. & Belloumi, M. (2017), "Study of the environmental Kuznets curve for transport carbon dioxide emissions in Saudi Arabia", *Renewable and Sustainable Energy Reviews* **75**, 1339-1347.
- Andreoni, V. & Galmarini, S. (2012), "Decoupling economic growth from carbon dioxide emissions: A decomposition analysis of Italian energy consumption", *Energy* **44**, 682-691.
- Ang, B.W. (2004), "Decomposition analysis for policymaking in energy: which is the preferred method", *Energy Policy* **32**, 1131-1139.
- Ang, B.W. (2005), "The LMDI approach to decomposition analysis: a practical guide", *Energy Policy* **33**, 867-871.
- Ang, B.W. & Zhang, F.Q. (2000), "A survey of index decomposition analysis in energy and environmental studies", *Energy* **25**, 1149-1176.
- Bargaoui, S.A., Liouane, N. & Nouri, F.Z. (2014), "Environmental impact determinants: An empirical analysis based on the STIRPAT model", *Procedia – Social and Behavioral Sciences* **109**, 449-458.
- Belloumi, M. & Alshehry, A.S. (2016), "The Impact of Urbanization on Energy Intensity in Saudi Arabia", *Sustainability* **8**, 375-391.
- Borba, B.S.M.C., Lucena, A.F.P., Rathmann, R., Costa, I.V.L., Nogueira, L.P.P., Rochedo, P.R.R., Branco, D.A.C., Júnior, M.F.H., Szklo, A. & Schaeffer, R. (2012), "Energy-related climate change mitigation in Brazil: Potential, abatement costs and associated policies", *Energy Policy* **49**, 430-44.
- Chen, L., Yang, Z. & Chen, B. (2013), "Decomposition analysis of energy-related industrial CO₂ emissions in China", *Energies* **6**, 2319-2337.
- Chung, W., Zhou, G. & Yeung, I.M.H. (2013), "A study of energy efficiency of transport sector in China from 2003 to 2009", *Applied Energy* **112**, 1066-1077.
- Cole, M.A., Rayner, A.J. & Bates, J.M. (1997), "The environmental Kuznets curve: an empirical analysis", *Environmental Development Economics* **2**(4), 401-416.
- De Freitas, L.C. & Kaneko, S. (2011 a), "Decomposition of CO₂ emissions change from energy consumption in Brazil: Challenges and policy implications", *Energy Policy* **39**(3), 1495-1504.
- De Freitas, L.C. & Kaneko, S. (2011 b), "Decomposing the decoupling of CO₂ emissions and economic growth in Brazil", *Ecological Economics* **70**(8), 1459-1466.
- Diakoulaki, D. & Mandaraka, M. (2007), "Decomposition analysis for assessing the progress in decoupling industrial growth from CO₂ emissions in the EU manufacturing sector", *Energy Economics* **29**(4), 636-664.
- Dietz, T. & Rosa, E.A. (1994), "Rethinking the environmental impacts of population, affluence and technology", *Human Ecological Review* **1**, 277-300.
- Dietz, T. & Rosa, E.A. (1997), "Effects of Population and Affluence on CO₂ Emissions", *Proceedings of the National Academy of Sciences, USA*, **94**, 175-179.
- Dong, B., Zhang, M., Mu, H. & Su, H. (2016), "Study on decoupling analysis between energy consumption and economic growth in Liaoning Province", *Energy Policy* **97**, 414-420.
- Engleman, R. (1994), "Stabilizing the atmosphere: population, consumption and greenhouse gases", <http://www.cnie.org/pop/CO2/intro.html>.
- Fan, Y., Liu, L.-C., Wu, G. & Wei, Y.-M. (2006), "Analyzing impact factors of CO₂ emissions using the STIRPAT model", *Environmental Impact Assessment Review* **26**, 377-395.
- González, P.F., Landajo, M. & Presno, M.J. (2014), "Multilevel LMDI decomposition of changes in aggregate

- energy consumption. A cross-country analysis in the EU-27”, *Energy Policy* **68**, 576–584.
- Intergovernmental Panel on Climate Change (IPCC) (1995), IPCC working group I summary for policymakers. Cambridge: Cambridge University Press.
- Kwon, T.H. (2005), “Decomposition of factors determining the trend of CO₂ emissions from car travel in Great Britain (1970–2000)”, *Ecological Economics* **53**(2), 261–275.
- Liu, Y. (2009), “Exploring the relationship between urbanization and energy consumption in China using ARDL (autoregressive distributed lag) and FDM (factor decomposition model)”, *Energy* **34**, 1846–1854.
- Lu, I.J., Sue J. Lin, S.J. & Lewis, C. (2007), “Decomposition and decoupling effects of carbon dioxide emission from highway transportation in Taiwan, Germany, Japan and South Korea”, *Energy Policy* **35**(6), 3226–3235.
- Martinez-Zarzosos, I., Benochea-Morancho, A. & Morales-Lage, R. (2007), “The impact of population on CO₂ emissions: evidence from European countries”, *Environmental and Resource Economics* **38**, 497–512.
- Meyerson, F.A.B. (1998), “Population, carbon emissions and global warming: the forgotten relation at Kyoto”, *Population Development Review* **24**(1), 115–130.
- Mundaca, L.T., Markandya, A. & Norgaard, J. (2013), “Walking away from a low-carbon economy? Recent and historical trends using a regional decomposition analysis”, *Energy Policy* **61**, 1471–1480.
- Papagiannaki, K. & Diakoulaki, D. (2009), “Decomposition analysis of CO₂ emissions from passenger cars: The cases of Greece and Denmark”, *Energy Policy* **37**(8), 3259–3267.
- Poumanyong, P. & Kaneko, S. (2010), “Does urbanization lead to less energy use and lower CO₂ emissions? A cross-country analysis”, *Ecological Economics* **70**, 434–444.
- Shi, A. (2003), “The impact of population pressure on global carbon dioxide emissions, 1975–1996: evidence from pooled cross-country data”, *Ecological Economics* **44**(1), 29 – 42.
- Supasa, T., Hsiau, S-S., Lin, S-M., Wongsapai, W. & Wu, J-C. (2016), “Has energy conservation been an effective policy for Thailand? An input–output structural decomposition analysis from 1995 to 2010”, *Energy Policy* **98**, 210–220.
- Tunc, G.I., Turut-Asik, S. & Akbostanci, E. (2009), “A decomposition analysis of CO₂ emissions from energy use: Turkey case”, *Energy Policy* **37**(11), 4689–4699.
- Wang, W., Liu, X., Zhang, M. & Song, X. (2014), “Using a new generalized LMDI (logarithmic mean Divisia index) method to analyze China's energy consumption”, *Energy* **67**, 617–622.
- Wang, Z., Zhao, L., Mao, G. & Wu, B. (2015), Factor decomposition analysis of energy-related CO₂ emission in Tianjin, China”, *Sustainability* **7**, 9973–9988.
- Wang, C., Wang, F., Zhang, X., Yang, Y., Su, Y., Ye, Y. & Zhang, H. (2017), “Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang”, *Renewable and Sustainable Energy Reviews* **67**, 51–61.
- Wen, L., Cao, Y. & Weng, J. (2015), Factor decomposition analysis of China's energy-related CO₂ emissions using extended STIRPAT model”, *Political Journal of Environmental Studies* **24**(5), 2261–2267.
- World Development Indicators (2015), World Bank, Washington, US. Accessed at <http://www.worldbank.org/data/online-databases/online-databases.html>.
- Xiao, B., Niu, D. & Guo, X. (2016), “The Driving Forces of Changes in CO₂ Emissions in China: A Structural Decomposition Analysis”, *Energies* **9**(4), 259–275.
- York, R. (2007), “Demographic trends and energy consumption in European Union Nations, 1960–2025”, *Social Science Research* **36**, 855–872.
- York, R., Rosa, E.A. & Dietz, T. (2003), “STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts”, *Ecological Economics* **46**(3), 351– 365.
- Zhang, Y-J. & Da, Y-B. (2015), “The decomposition of energy-related carbon mission and its decoupling with economic growth in China”, *Renewable and Sustainable Energy Reviews* **41**, 1255–1266.
- Zhang, Y-J., Peng, H-R. & Su, B. (2017), “Energy rebound effect in China's Industry: An aggregate and disaggregate analysis”, *Energy Economics* **61**, 199–208.
- Zhang, Y-J. & Peng, H-R. (2017), “Exploring the direct rebound effect of residential electricity consumption: An empirical study in China”, *Applied Energy* **196**, 132–141.
- Zhang, W., Li, K., Zhou, D., Zhang, W. & Gao, H. (2016), “Decomposition of intensity of energy-related CO₂ emission in Chinese provinces using the LMDI method”, *Energy Policy* **92**, 369–381.
- Zhang, C. & Lin, Y. (2012), “Panel estimation for urbanization, energy consumption and CO₂ emissions: A regional analysis in China”, *Energy Policy* **49**, 488–498.
- Zhang, M. & Wang, W. (2013), “Decoupling analysis of electricity consumption from economic growth in China”, *Journal of Energy in Southern Africa* **24**(2), 57–66.

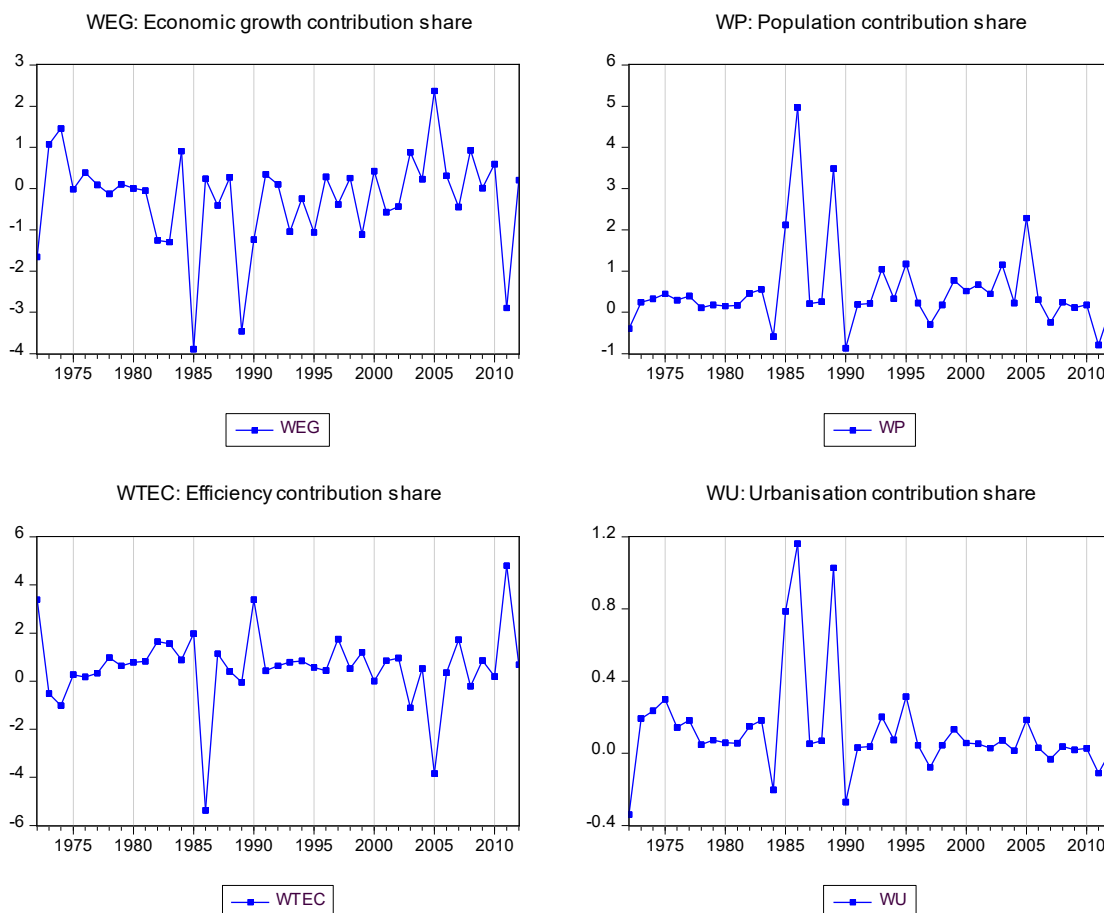


Figure 1. Trends of Contribution Shares of Driving Forces of Energy Consumption in Saudi Arabia over 1971-2012

Table 1. Some IPAT and Stochastic IPAT Studies on Driving Factors of Energy Consumption/Carbon Emissions

Authors	Method	Period	Countries	Main results
Liu (2009)	Factor decomposition analysis	1978-2008	China	Economic growth and urbanization lead to increases in energy use; technological progress leads to decreases in energy use
Chen et al. (2013)	log-mean Divisia index method	1985-2007	China	Per capita GDP is the main contributor to industrial CO ₂ emissions increases
Zhang and Wang (2013)	Decoupling index combined with log-mean Divisia index method	1991-2009	China	Economic growth is the main responsible of electricity consumption increases; energy intensity effect is the main driver of electricity consumption decreases
Wen et al. (2015)	STIRPAT model	1991-2011	China	Population, industrialization, economic growth, foreign trade and service level are the main driving forces of CO ₂ emissions
Zhang and Da (2015)	log-mean Divisia index method	1996-2010	China	Economic growth is the main driver of carbon emissions increases; fall in energy intensity leads to carbon emissions reductions
Wang et al. (2015)	log-mean Divisia index method	1995-2012	China's Tianjin province	Per capita GDP and population scale are the main drivers of CO ₂ emissions increases; energy intensity is the main contributor to CO ₂ emissions decreases
Xiao et al. (2016)	Structural decomposition analysis	1997-2010	China	Urbanisation, investment and exports are the main drivers of CO ₂ emissions increases; energy intensity is the main driver of CO ₂ emissions reduction
Dong et al. (2016)	LMDI method	1995-2012	Chinese Liaoning province	Energy intensity played a positive role in the decoupling effect between energy consumption and economic growth
Wang et al. (2017)	STIRPAT model	1952-2012	Xinjiang	The impacts of driving factors on energy related carbon emissions are dependent on the development stage.
Kwon (2005)	Index decomposition	1970-2000	Great Britain	The car driving distance per person was the main

	analysis			dominant force for the growth of CO ₂ emissions from car travel; the contribution of technology factors was relatively small.
Tunc et al. (2009)	Log Mean Divisia Index method	1970–2006	Turkey	Economic activity is the main contributor to changes in CO ₂ emissions
De Freitas and Kaneko (2011a)	log-mean Divisia index method	1970–2009	Brazil	Economic activity and demographic pressure are the main driving factors of CO ₂ emissions increases.
De Freitas and Kaneko (2011b)	log-mean Divisia index method	2004-2009	Brazil	Carbon intensity and energy mix lead to CO ₂ emissions reduction
Andreoni and Galmarini (2012)	Index decomposition analysis	1998-2006	Italy	Energy intensity and economic growth are the main drivers of CO ₂ emissions
Achour and Belloumi (2016)	log-mean Divisia index method	1985-2014	Tunisia	Economic growth, transport intensity, transport structure and population affect positively transport energy consumption; energy intensity affects negatively transport energy consumption
York et al. (2003)	STIRPAT model	1995, 1996, 1999	Group of 146 and a group of 138	Affluence influences positively CO ₂ emissions and the energy footprint; the effect of population on CO ₂ emissions and the energy footprint is proportional.
Fan et al. (2006)	STIRPAT model	1975–2000	55 high-income countries, 40 upper-middle income countries, 54 lower-middle income countries, 59 low-income countries	The effects of affluence, population and technology on CO ₂ emissions vary with the level of development of countries
Diakoulaki and Mandaraka (2007)	Laspeyres decomposition analysis model	1990–2003	14 EU countries	The decoupling effort of EU countries is important but insufficient.
Lu et al. (2007)	Divisia index approach	1990-2002	Germany, Japan, South Korea and Taiwan	Economic growth and vehicle ownership have a positive effects on CO ₂ emissions; population intensity has a negative effect on CO ₂ emission
York (2007)	STIRPAT model	1960–2000	14 foundational European Union countries	Population, economic development, age structure and urbanization affect positively energy use
Papagiannaki and Diakoulaki (2009)	Log Mean Divisia Index method	1990-2005	Denmark and Greece	Vehicles ownership, fuel mix, annual mileage, engine capacity and technology of cars affect the trend of CO ₂ emissions
Poumanyvong and Kaneko (2010)	STIRPAT model	1975-2005	99 countries	The impact of urbanization on energy use is positive in the middle and high-income countries; the impact of urbanization on energy use is negative in the low-income group; urbanization affects CO ₂ emissions positively for all income groups
Mundaca et al. (2013)	Index decomposition analysis	1971-2010	Africa, Asia, Latin America and the Caribbean, the Middle East, non-OECD Europe and countries from the former Soviet Union, Oceania, OECD Europe, and OECD North America	Driving factors do not lead to significant reductions of CO ₂ emissions in majority of regions
Bargaoui et al. (2014)	STIRPAT model	1980-2010	214 countries	Urbanization, economic growth, population growth and Kyoto protocol obligations have significant effects on CO ₂ emissions; effects are dependent on the income level

Table 2. Summary of Descriptive Statistics

	Carbon emissions	Energy intensity	Energy use	Real GDP per capita	Carbon intensity	Urbanization	Population
Mean	247295.0	298.55	80856.3	15011.85	1.002	73.16	16653726
Median	217093.7	347.73	74413.6	13191.14	1.084	77.20	17001754
Maximum	515000.0	469.26	222200	22109.70	1.389	82.49	28287855
Minimum	59808.77	56.40	6250.7	11605.39	0.546	50.60	6059524
Std. Dev.	123135.1	136.97	57704.8	3422.44	0.233	9.28	6845414
Obs.	42	42	42	42	42	42	42

Table 3. Decomposed Results of Total Energy Use

Years	ω_{EG}	ω_P	ω_{TEC}	ω_U
1972	-1.656	-0.395	3.391	-0.339
1973	1.074	0.246	-0.514	0.193
1974	1.456	0.326	-1.017	0.235
1975	-0.016	0.449	0.267	0.299
1976	0.385	0.295	0.175	0.143
1977	0.090	0.395	0.331	0.183
1978	-0.130	0.109	0.973	0.047
1979	0.109	0.177	0.640	0.073
1980	0.004	0.151	0.784	0.059
1981	-0.047	0.167	0.823	0.056
1982	-1.257	0.458	1.649	0.150
1983	-1.294	0.554	1.556	0.183
1984	0.910	-0.588	0.880	-0.203
1985	-3.890	2.121	1.981	0.787
1986	0.242	4.964	-5.369	1.161
1987	-0.406	0.210	1.141	0.053
1988	0.272	0.254	0.402	0.070
1989	-3.458	3.481	-0.050	1.027
1990	-1.238	-0.868	3.376	-0.270
1991	0.341	0.192	0.432	0.032
1992	0.104	0.216	0.640	0.038
1993	-1.041	1.044	0.793	0.202
1994	-0.244	0.332	0.837	0.074
1995	-1.063	1.174	0.575	0.314
1996	0.282	0.228	0.443	0.045
1997	-0.380	-0.292	1.751	-0.078
1998	0.255	0.177	0.521	0.045
1999	-1.114	0.778	1.201	0.134
2000	0.425	0.516	-0.001	0.058
2001	-0.570	0.666	0.850	0.052
2002	-0.436	0.448	0.958	0.029
2003	0.880	1.153	-1.106	0.072
2004	0.230	0.230	0.523	0.015
2005	2.369	2.287	-3.843	0.185
2006	0.313	0.306	0.348	0.031
2007	-0.445	-0.247	1.724	-0.032
2008	0.930	0.241	-0.210	0.038
2009	0.013	0.113	0.853	0.019
2010	0.597	0.179	0.194	0.028
2011	-2.898	-0.794	4.802	-0.109
2012	0.205	0.099	0.681	0.013

Table 4. Robust OLS estimators of STIRPAT model

Variables	Coefficient	Std. Error	Prob.
GDP per capita	0.925	0.009	0.00
Population	1.095	0.012	0.00
Urbanization	-0.552	0.041	0.00
Carbon intensity	1.00	0.013	0.00
Constant	-12.306	0.116	0.00
R-squared	0.79		