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Effects of Fossil Fuel Usage in Electricity Production on CO_2 Emissions: A STIRPAT Model Application on 20 Selected Countries

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ABSTRACT

This article examines the causes of air pollution while paying particular attention to the effects of fossil fuel use in electricity generation. Dietz and Roza's (1994) STIRPAT model, which is a reformulated version of the IPAT model, was used. The data includes the 20 countries with the highest CO_2 emission levels and covers the years 1991-2015. According to the empirical results of this article, increases in population and GDP per capita are followed by a proportional increase in CO_2 emissions. Moreover, the results show that the share of coal in electricity generation has a negative impact on CO_2 emissions in selected countries. On the other hand, the results show that the share of gas in electricity generation does not have a significant impact on CO_2 emissions in selected countries and selected period.

Keywords: CO_2 Emission, Energy, Environment, STIRPAT Model
JEL Classifications: Q4, Q5, Q42, Q43

1. INTRODUCTION

Any formation or effect that disrupts the ecological system can be defined as environmental pollution. These pollutions damage the nature and directly or indirectly cause negative effects on all living things living in nature. As a result of the increasing environmental pollution and the deterioration of the ecosystem balance, the geography of the world is changing, and as a result of global warming, climate changes occur. Moreover, food and water resources are depleted, energy and food scarcity occur, and biodiversity decreases as a result of the extinction of living things. With the emergence of such strong effects, studies on environmental pollution are gaining importance day by day.

Environmental problems that have evolved from local to global have also accelerated the search for policies to reveal and eliminate the causes and effects of these problems, both in the academic, social and political arenas. Many economic, social, political, technological and cultural factors are decisive in the emergence of environmental problems. Determining how important these factors are and separating their effects is essential in tackling emerging and future problems and policy making. In this context, it would not be misleading to say that there has been a significant increase in the number of studies on environmental problems in the economic literature in recent years. In the literature, it is seen that many environmental indicators such as carbon dioxide, sulfur dioxide, methane, and deforestation are used in the investigation of environmental damage. These listed environmental indicators are a specific and partial indicators of environmental impact. On the other hand, ecological footprint (EF), which is accepted as a more comprehensive representative of environmental problems (Saboori et al., 2016), is a more general environmental indicator that has been used recently in the environment and economics literature.

Electricity production has an important share in CO_2 emissions. Cutting our electricity consumption is a way to decrease our carbon footprints, but there is a limit to that. Alternatively, there are different ways to produce electricity. Different in their costs, their efficiency and also their CO_2 emissions. So, how we produce electricity matters a lot. There are clean ways to produce electricity, for example, by using nuclear, solar or wind energy. And there are dirtier ways, using coal or gas. some countries are lucky to have rivers that they can build dams on; one of the cleanest ways to produce electricity. Some aren't that lucky. This study's aim in this papers is to examine the driving forces of air pollution, as well as examining the effects of different methods in producing electricity on CO_2 emissions. Thus, the literature will be further expanded, especially in the context of selected countries.

In the first part, selected studies from the relevant literature will be included. In the second part, it briefly gives a comparison of the IPAT and STIRPAT models, methodology and some information about the data used. The last section gives the empirical results and conclusion.

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2. LITERATURE REVIEW

York et al. (2003a) investigated the determinants of carbon dioxide emissions and energy footprints around the world within the framework of the STIRPAT model. In the study, which includes the year 1996 and 148 countries for CO_2, the year 1999 and 138 countries were selected for the energy footprint. According to the results of the regression analysis, the square of the population aged 15-65 and the urbanization rate were found to be statistically insignificant. On the other hand, other variables affect statistically significant and environmental variables positively. In addition, the population has been determined as an important determinant on both CO_2 and energy ecological footprint. Theoretical findings regarding the validity of the Environmental Kuznets Curve (EKC) hypothesis for CO_2 were obtained in the model in which the square of the per capita income was used. However, it was stated that the validity of the hypothesis would not be possible in practice, since the turning point involved a very high-income level.

York et al. (2003b) investigated the determinants of global warming potential of CO_2, CH4 and both pollutants together for 1991 in 137 countries representing approximately 95% of the world's population and income, using the Least Squares Method. Findings from the study show that other variables, except the working-age population, positively affect CO_2 emissions. However, the total population and industrialization are the most important determinants of CO_2 emissions. Only population and urbanization have a statistically significant and positive effect on the other pollutant CH_4. In the model in which the global warming potential is used, results similar to CO_2 were obtained. Accordingly, increases in variables also increase the potential for global warming. There was no evidence that the EKC hypothesis and modernization theory are valid for all pollutants used in the study.

Rosa et al. (2004) investigated the determinants of 6 different ecological footprints for 142 countries in 1998 by using a cross-section analysis. According to the results of the study, it has been determined that the most important determinant of the ecological footprint is the population size. In the study, no conclusion was reached regarding the validity of the EKC hypothesis.

Fan et al. (2006) investigated the determinants of CO_2 emissions in countries with different income levels in the 1975-2000 period using the PLS method. According to the results obtained in the study, the effects of population, economic growth and technology on CO_2 differ according to the income levels of the countries. Accordingly, economic growth and population are the most important determinants of CO_2 in all country groups. Energy intensity and working-age population are the most important causes of CO_2 emissions in the low-middle-income country group. In addition, the working-age population negatively affects CO_2 emissions in high-income countries. On the other hand, the most important determinants of emissions in these countries are economic growth, population and urbanization. Findings on a global scale reveal that the biggest contribution to CO_2 emissions is made by economic growth and energy intensity. However, in the study, it was determined that the contribution of energy intensity to CO_2 emissions decreased with economic growth. Based on this determination, the authors stated that one of the biggest obstacles to economic growth is access to energy and efficient use of energy.

Jia et al. (2009) investigated the determinants of ecological footprint for the 1983-2006 period in Henan, China, using the PLS method. According to the findings, while urbanization affects the ecological footprint negatively, economic growth affects the shares of sectors other than the total population and services sector in GDP positively. On the other hand, the authors found that the major determinant of ecological footprint is total population size.

Tang et al. (2011) investigated the determinants of ecological footprint with the LCC method for the period 1995-2008 in Sichuan, China. According to OLS estimation results, the main determinants of ecological footprint were determined as population and urbanization. On the other hand, economic growth and the size of the industrial sector reduce the ecological footprint. However, variables other than the size of the industry sector have a statistically insignificant effect.

Shahbaz et al. (2016) investigated the determinants of CO_2 emissions for Malaysia in the period 1970Q1-2011Q4. In the study, in which ARDL methods, which take into account Bayer-Hanck cointegration and structural break, were used, all variables were divided by population and expressed per capita, and the effect of the population on CO_2 was considered constant. According to the findings obtained from the study, economic growth is the most important determinant of CO_2 emissions. Similarly, energy intensity also increases CO_2 emissions. In addition, foreign trade has a positive effect on CO_2 emissions by creating an income effect. On the other hand, there is an inverted U-shaped relationship between urbanization and CO_2 emissions. Accordingly, as urbanization increases, CO_2 emissions increase initially and decrease in later stages.

Bello et al. (2018) investigated the determinants of ecological footprint, carbon footprint and water footprint in addition to CO_2 for Malaysia in the period 1971-2016 using ARDL bounds test approach. According to the findings obtained from the study, economic growth affects all environmental variables positively. Accordingly, the most important determinant of environmental quality is income level. On the other hand, the authors concluded that the EKC hypothesis was valid in the period under review. In addition, hydroelectric consumption and urbanization affect all footprint variables negatively and CO_2 emissions positively.

Dai et al. (2018) investigated the determinants of CO_2 emissions in China and its different regions during the period 1970-2008 with panel data analysis. According to the findings obtained from the study, the explanatory variables used, total population, per capita income, urbanization and the share of the manufacturing industry in GDP are statistically significant and have a positive effect on CO_2. In addition, population and urbanization have been identified as the most important determinants of CO_2 emissions in cities located in the interior and east coast parts of China. Another result obtained from the study is that the EKC is valid in the east coast parts, but invalid in the whole of China and inland.

Wu et al. (2018) investigated the determinants of carbon intensity by panel data analysis for 30 regions of China. According to the findings obtained in the study, in which the data for the period 1995-20014 were used, the carbon intensity of economic growth, openness and foreign direct investment is negative. Coal consumption, urbanization and industrialization have a positive effect. On the other hand, urbanization was determined as the most important determinant of carbon intensity in regions with low and medium carbon intensity, and coal consumption in regions with high carbon intensity.

Usman et al. (2022) investigated the effects of nuclear energy and human capital on the ecological footprint of 12 developed economies during the 1980-2015 period. They applied the (CS-ARDL) estimation technique, which can solve the Cross-sectional Dependency (CSD) problem and also handle the mixture of I(0) and I(1) variables. The results show that nuclear power could prove to be a panacea for problems of energy security and environmental degradation. Therefore, they concluded that increasing nuclear energy production should be a part of the energy and environmental policies of all countries in the world.

3. METHODS AND MATERIALS

The STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model is a modified version of the IPAT model, which was first proposed by Ehrlich and Holdren (1971) and formulated and tested by Commoner et al. (1971), in accordance with regression analysis. IPAT is a simple mathematical equation, represented by equation (1):

$$I = P \, x \, A \, x \, T \tag{1}$$

In this equation, I, P, A and T represent the environmental variable, population, welfare level and technology variable, respectively. This mathematical equation is a useful model for showing the effect of a change in its components on the environmental variable. However, it establishes a constant and linear relationship between the components and the environmental variable; does not allow linear or non-proportional relationships (York et al., 2003a). In order to compensate for this inadequacy of the IPAT model, the model was reformulated by Dietz and Rosa (1994) and arranged in a stochastic form suitable for hypothesis testing as shown in equation (2):

$$I = a \, P_i^b A_i^c T_i^d e_i \tag{2}$$

The IPAT model accepts a=b=c=d=ei=1 as a constant proportionality assumption in equation (2). Therefore, the IPAT model is not suitable for hypothesis testing as it assumes that each variable has the same effect proportionally. However, the STIRPAT model considers a, b, c, d, and ei as parameters and coefficients to be calculated (York et al., 2003a). On the other hand, it is not possible to say that a variable in the IPAT model affects the environmental indicator independently from other variables. Since, IPAT is a multiplicative specification.

Therefore, the change in one of the variables is multiplied by the other variables. Within the framework of this problem, the STIRPAT model creates a framework in which the net effect of each variable can be analyzed separately and used in other social, political and economic variables as well as environmental factors. In this context, equation (3) is obtained when equation (2) is rewritten in logarithmic form.

$$lnl_i = \alpha + \beta \, lnP + \theta \, lnA + \gamma \, lnT + \varepsilon \tag{3}$$

In equation (3), α, constant term β, θ and γ represent the coefficients or elasticities obtained from the estimation of the model, and ε the residuals. Therefore, the STIRPAT model can be a guide in policy making by revealing the factors affecting the environment and the relative importance of these factors (Hummel et al., 2009).

The STIRPAT model, like the IPAT model, accepts that environmental change or environmental pollution is determined by population, wealth or income level, and technology. However, the STIRPAT model can be extended with many variables. Because technology is not considered as a specific variable in the model. Economic, social, cultural and other factors other than population and income level can be considered as T (Dietz and Rosa, 1997:175). On the other hand, with the same logic, the technology variable can also be evaluated in error terms (Rosa et al., 2004). In this context, it is noteworthy that many variables are used to represent technology in the literature. Some of these variables are urbanization (Dai et al., 2018; Bello et al., 2018), size of the industry sector (Wu et al., 2018; York et al., 2003b; Tang et al., 2011), fossil fuel-based electricity generation (Thombs, 2018), energy density (Fan et al., 2006) may be listed as.

In this article's datas consist of 20 countries[1] which are among the highest polluters in the world in terms of CO_2 emissions. The data covers the period between 1991 and 2015. The dependent variable is

1 Australia, Brazil, China, Egypt, France, Germany, India, Indonesia, Iran, Italy, Japan, South Korea, Mexico, Poland, Russia, South Africa, Saudi Arabia, Spain, UK and USA.

"CO_2 emissions (kt)" and the independent variables are "Population (total)", "GDP per Capita, PPP (constant 2015 International $)", "Industry, Value Added (% of GDP)", "Energy use (kg of oil equivalent) per $1,000 GDP (constant 2015 PPP)". Additionally, it has been used two more variables, namely, Electricity production from coal sources (% of total) and Electricity production from natural gas sources (% of total). All of the data is taken from the World Bank.

Our activities produce many pollutants that are harmful for the environment, but since there are not sufficient amount of data for most of these pollutants that covers large number of countries and time, the studies usually take CO_2 emissions as proxy to environmental "Impact". As a proxy for "Technology", "share of industry in GDP" along with energy intensity which is measured as energy use per unit of GDP are generally used. Although, some studies use "share of manufacturing in GDP" instead of "share of industry in GDP," but this is not a big difference.

To see the effects of different sources in electricity production on the CO_2 emissions, we have chosen "coal" (Coal) and "natural gas" (Gas). There are other sources to produce electricity (e.g. nuclear, wind and solar energies and oil). The reason why we didn't include them in our analysis is that; nuclear, wind and solar sources produce very little CO_2 to have a significant effect on CO_2 emissions. Also their usage is very low. And the "oil" nearly has the same CO_2 emission levels as "coal," so adding this variable would be like adding the same variable to the equation. Another reason is the usage of oil in electricity production has been dramatically decreased over the years. It is now mostly used in generators. Since this study aims to show the effects of widely used fossil fuels in electricity production on the CO_2 emissions, ain't thought of it was necessary to add this variable. One can argue that decreases in the usage of oil in electricity production cause the demand for oil to decrease and thus the price of it, therefore encouraging its usage in other areas (e.g. transportation) and will result in higher CO_2 emissions. But since the demand for oil is not so price-elastic, it has been assumed this will not have a significant effect, therefore preferred to exclude this variable from the model.

4. EMPIRICAL RESULTS

The estimation results for CO_2 emissions are shown in Table 1. Before doing any estimation, it has been checked if the variables have unit root, since non-stationary variables cause coefficients and standard errors to be biased. According to two first generation unit root tests, namely, Levin et al. (2002) and Pesaran et al. (2007), all of the variables are non-stationary.[2]

The first and second equations are as follows:

$$MODEL\,I: lnCO_2 = \alpha + \delta_{1j} lnGDP_{pc} + \delta_{2j} lnpop + \delta_{3j} lndshare + \delta_{4j}\, lnEnint + \varepsilon_{ij}$$

2 According to LLC and IPS 'population' is stationary and, its first difference looks nonstationary. But other first generation unit root tests (e.g. Phillips and Perron (1998) and ADF) suggest population is non-stationary. To be sure, we took first difference and checked with two of the second generation unit root tests, namely, Moon and Perron (2004) and Pesaran (2007). Results show that first-difference of population is stationary. These results are not reported. Available on request.

Table 1: Regression results for CO_2 emissions

Variable (*ln*)	Case	
	Model I	Model II
Population	0.986 (2.98)® (0.0576)***	0.890 (2.86)® (0.0576)***
GDP per capita	1.065 (4.95)® (0.019)**	1.059* (5.22)® (0.019)**
Enint	0.796 (3.23)® (0.003)*	0.812 (3.18)® (0.003)*
dshare	0.095 (1.05)® (1.00)	0.131 (0.96)® (0.953)
Coal	N	0.09 (1.25)® (0.0325)**
Gas	N	0.016 (0.21)® (0.605)
Adj. R_2	0.26	0.28
Observations	560	560
No. of countries	20	20

All variables are held in natural log form and estimated in first differences. ®denotes heteroskedasticity consistent z-values. *, ** and *** denote significance at 1%, 5% and 10% levels, respectively. The first difference causes R^2 values to become lower.

and,

$$MODEL\,II: lnCO_2 = \alpha + \delta_{1j} lnGDP_{pc} + \delta_{2j} lnpop + \delta_{3j} lndshare + \delta_{4j}\, lnEnint + \delta_{5j} lnCoal + \delta_{6j} lngas + \varepsilon_{ij}$$

We have estimated two models with random effects. The result of Hausman Test is as follows:

$$X^2\left(4\right) = 1.65 \text{ and } Prob > X^2 = 0.926$$

In the first model, column 1 of the Table 1, we have estimated the effects of "Population" (lnPop), "GDP per capita" (lnGDPpc), "Energy Intensity" (lnEnint) and the "Share of Industry in GDP" (lndshare) on CO_2 emissions. The results support the findings reported by Dietz and Roza (1997), York et al. (2003a) and Neumayer (2004). Logged form of variables allows the coefficients to be interpreted as elasticities. The population has a positive and significant effect on the CO_2 emissions. Its elasticity is nearly equal to unitary (0.986). Therefore we can say that, 1% increase in total population increases CO_2 emissions by nearly the same amount. GDP per capita also has a positive and significant effect on the CO_2 emissions. Its elasticity is just below unitary (1.065). 1% increase in GDP per capita increases CO_2 emissions by nearly the same amount, but a little bit less. Energy Intensity has a positive and significant, but lesser effect than the first two variables. Its elasticity is 0.796. 1% increase in energy intensity increases CO_2 emissions by 79.6%. Like in the literature, the share of industry in GDP doesn't have a significant effect on CO_2 emissions.

It has been solved this problem by taking the first-difference of the variables. The results are shown in Table 2:

In the second model, we added two more variables. "Coal" (Coal) represents the share of coal in producing electricity and "Gas" (Gas) represents the share of gas in producing electricity. This modification didn't change the coefficients or significance of the variables in

Table 2: Panel unit root tests (the first generation)

Variables (ln)	Case	Common unit root (LLC)		Individual unit root (IPS)	
		Level	First dif.	Level	First dif.
CO_2	Constant	–1.865**	–13.990*	1.115	–13.646*
		(0.038)	(0.000)	(0.132)	(0.000)
	Constant and Trend	0.032	–13.102*	–1.118***	–11.651*
		(0.489)	(0.000)	(0.098)	(0.000)
GDP_{pc}	Constant	0.102	–10.065*	3.902	–10.213*
		(0.745)	(0.000)	(1.000)	(0.000)
	Constant and Trend	1.998	–10.996*	2.012	–8.661*
		(0.992)	(0.000)	(0.99)	(0.000)
Pop	Constant	–6.995*	–2.117***	–1.865***	–3.955**
		(0.006)	(0.078)	(0.055)	(0.048)
	Constant and Trend	–1.860**	8.378	–3.030*	0.267
		(0.015)	(0.98)	(0.001)	(0.695)
dshare	Constant	–1.675*	–9.685*	–1.019	–12.005*
		(0.003)	(0.000)	(0.196)	(0.000)
	Constant and Trend	–1.285*	–11.962**	–3.237**	–10.742*
		(0.000)	(0.035)	(0.012)	(0.000)
Enint	Constant	1.238	–14.059*	0.991	–8.655*
		(0.438)	(0.000)	(1.000)	(0.000)
	Constant and Trend	–0.453*	–10.565*	–2.510***	–7.325**
		(0.000)	(0.000)	(0.064)	(0.042)
Coal	Constant	0.876	–10.998*	2.724	–10.174*
		(0.215)	(0.000)	(0.882)	(0.000)
	Constant and Trend	0.939	–12.585*	0.956	–13.864*
		(0.775)	(0.000)	(0.556)	(0.007)
Gas	Constant	–8.102*	–11.890*	–1.985*	–7.207*
		(0.000)	(0.000)	(0.000)	(0.000)
	Constant and Trend	–5.553*	–7.556*	–1.362*	–6.993*
		(0.000)	(0.000)	(0.000)	(0.000)

The null hypothesis for both tests are unit root. All variables are held in natural log form. The numbers in parentheses are P-values. *, ** and *** denote significance at 1%, 5% and 10% levels, respectively.

the Model I. The results show that “coal” is significant, but “gas” is are not significant. As expected, “coal” and “gas” variables have a positive relationship with CO_2 econometrically. We were expecting, because approximately 20% of CO_2 emissions comes from electricity production and not all of it comes from “coal.” This positive relationship means that CO_2 emissions increase as the percentage of “coal” use in electricity generation increases. However, only the “coal” coefficient is significant, “gas” is not.

Coal has a positive and significant effect on the CO_2 emissions. Its elasticity is just below unitary (0.09). 1% increase in coal, CO_2 emissions increases 9%.

Average shares of coal and gas in electricity production in our data are 40.1% and 26.4% respectively. Countries like South Africa, Poland, Australia and China produce most of their electricity by coal sources (average 82.8%), while countries like Brazil, Egypt, France, Iran and Saudi Arabia nearly don’t use coal in electricity production at all (average 1.2%).

This result is very important because coal has a very high CO_2 emission compared to other sources when producing electricity.[3]

3 CO_2 emissions of coal and gas are, 888 and 499 tonnes per GWh of electricity; while nuclear and hydroelectric sources have 29 and 26 tonnes of CO_2 emissions per GWh of electricity, respectively. Source: World Nuclear Association Report (2011). (The World Nuclear Association, 2011)

5. CONCLUSION

Air pollution caused by industrial development in the world is becoming a more important problem day by day. In this study, in order to draw more attention to this problem, with the help of STIRPAT model, GDP per capita, electricity production from natural gas sources (% of total), electricity production from natural coal sources (% of total), population, Industry Value Added (%) of GDP)”, energy use (kg of oil equivalent) were analyzed by econometric methods.

The results give us an idea of why we should turn to renewable energy. In this study, analysis was made only on coal and gas used in electricity production. Although “gas” is meaningless in our research, the negative effect of gas use in electricity production on CO_2 emissions is an undeniable fact. Considering that these two sources are also used in other sectors, this rate will be even higher with our results. The increase in CO_2 emissions of Coal and Gas has reached life-threatening levels according to many studies.

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