Review of Indonesia's Residential and Demographic Carbon Emission Using STIRPAT Model

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Abstract

STIRPAT model is employed to review Indonesia's carbon emission's residential and demographic aspects. Indonesia is on its way to combat carbon emissions. Indonesia is the fourth most populous country in the world, with the current population reaching 275 million in 2020. The country also faced massive economic growth following the growth of population, positioned at 7th in terms of GDP. With the current growth in population and economy, it is needed to identify whether this growth, which also induced by the decision of the population in expanding their family members, could influence the increase of the nation's carbon emission. The effect of some aspects not included in the official government plan, namely population, economy, and residential aspect, is included in the estimation model. Household energy consumption is one of the most significant contributors to Indonesia's Energy-based emissions. Therefore, this paper tries to see whether population size and household could impact Indonesia's carbon emissions. Due to multicollinearity detected on the OLS estimation of the STIRPAT model, the model is regressed the second time using ridge regression. The result shown that Non-Dependent Population (DEP) > Economic Inequality (GINI) > energy consumption (EC) > Total Population (TP) > Urbanization (U) > Household Energy Consumption (HEC) > Gross Domestic Product (GDP) > Household Expenditure (EXP) > Family Size (FAM) > Total Fertility Rate (TFR). It is then found that the economic aspect is the most significant contributor to the carbon emission increase. Therefore, suggestions regarding carbon emission could focus on improving the economy, especially improvement in green industrialization and economic equality for the population. However, mitigation from population aspects could not be overlooked, as the population aspect contributes to driving the increase of carbon emission.

Keywords
STIRPAT, Carbon emission, Anthropogenic, OLS, and Ridge Regression

1. Introduction
Indonesia updated its Nationally Determined Contribution (NDC) in 2021. It was stated on the commitment that Indonesia pledged to reduce 26% of GHG emissions by itself or 41% with international aid in 2030. The energy component will be reduced to 11% unconditionally and 15.5% conditionally from the total business-as-usual (BAU) 2010 GHG emission scenario. In realizing the 1.5°C world, nations should have massive ambition in reducing GHG emissions. Indonesia is one of the nations which not seriously committed to this matter (Dong et al. 2018). This fact is also strengthened by the research made by Climate Action Tracker (2020), which stated that the Indonesians should do more than what they are committed to in the NDC document.

In realizing the emission commitment, perhaps it is crucial to add other aspects with the hope of inducing more reduction to GHG emission. Stern et al. (1992) identified five human-caused (anthropogenic) aspects that are significant in increasing GHG emission; population growth, economic growth, technological change, political-economic institutions, and attitudes and beliefs. Study of the population as a cause of the emission has emerged since years, mainly found out that population, referred by its size, growth, or by a percentage of the urban population, shares a significant portion of carbon emission contribution (Dietz and Rosa 1997; York et al. 2003; Kusumawardani and Dewi 2020).

Household emission also plays a significant role in pushing the increase of carbon emission (Noorpoor and Kudahi 2015; Kurniawan et al. 2018; Soltani et al. 2020; Zhao et al. 2022). It is stated from the Indonesian Ministry of Energy and Mineral Resources (KESDM) that in 2020, household energy consumption contributed around 142,000 tboe (tons of barrel equivalent), which is around 17% of the total consumption. High energy consumption could also contribute to carbon emission (Haseeb et al. 2016; Ibrahim et al. 2017; Kurniawan et al. 2018).

The growth of the population could also induce the rise of the need for energy in the household sector. As the population increases, demand rises (Noorpoor and Kudahi 2015). The Indonesian National Population and Family Planning Board (BKKBN) thrives on meeting the world's benchmark value for the total fertility rate (TFR) of 2.1 in 2024. They have been succeeded in decreasing the value from 5.6 in the 1960s to around 2.3, although stagnated in recent years.

Household energy consumption depends on the number of members in the family (Noorpoor and Kudahi 2015). Bigger households tend to have more considerable demand, and economically affluent families tend to consume more energy. Thus, the decision of families to implement family planning is essential, as it will affect carbon emission through energy demand. Murtaugh and Schlax (2009) claimed that offspring would carry their parents' emission on them; thus, having one more child will affect carbon emission significantly.

This study tries to observe the impacts of two aspects in the residential sector, namely population and household emission, on Indonesia's carbon emissions. Hopefully, this study could illustrate which aspect could be the focus for carbon emission mitigation. Moreover, this study could also recommend steps to reduce carbon emission through the most critical driver illustrated.

1.1 Objectives

This research wants to illustrate how the identified driving factors in the residential sector could affect the increase of Indonesia's GHG emission, which is calculated through its most significant component, carbon dioxide (CO2). Hopefully, this research will strengthen the recommendation to reduce carbon emission from population and household energy aspects. The study also seeks another way to reduce carbon emission besides what has been stated in research employing STIRPAT model.

2. Literature Review

Climate change, according to UNFCCC (1992), refers to a change in climate that is affected directly or indirectly by human activities that alter the composition of the atmosphere and add to the variability of the natural climate over a comparable period. In contrast, IPCC (2019) defined climate change as changes in climate condition that can be identified and persists for a long time. Hanley and Owen (2004) explained that greenhouse gases, consisting of carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF6), could be the cause of the world's temperature increase and inducing climate change.

The study on environmental impact mainly focused on GHG and carbon emission has employed many models. One of the most notable models is the IPAT model was proposed by Ehrlich and Holdren (1971). Dietz and Rosa (1997) then improved the model to be stochastic to facilitate hypothesis testing. Since then, the model has become a hot take for environmental impact research (Fan et al. 2006; Shahbaz et al. 2017; Zuo et al. 2020).

Since the beginning, the STIPRAT model has been used to determine the effect of driving factors like population and economy on increasing CO2 emission (Dietz and Rosa 1997; York et al. 2003; Shi 2003). The research which conducted on several countries at once to show the difference between effects on each country. The findings from the studies showed that population, mainly represented as urbanization, economic affluence, represented as the gross domestic product (GDP), and energy use did affect the increase of emissions.

STIRPAT model usage on assessing carbon emission driving forces has taken place in many world regions. Liu (2018) assessed the effects of driving factors on carbon emission in 30 provinces of China, which are divided into three regions. When estimated collectively, it was found that energy intensity was shown to be the most influential in carbon emission increase. The results differ on three regions, which shown an increase of economy influenced carbon emission increased the most in Western and Eastern Regions and energy intensity became the most influential on Central Regions. Perhaps due to the importance of researching the effects of driving forces on emission, a study using the STIRPAT model mainly focused on the China region (Vélez-Henao et al. 2019). There are also other regions studied using this model, namely Turkey (Chekouri and Benbouziane 2020), Iran (Noopoor and Kudahi 2015), and Colombia (Vélez-Henao 2020). Also, this model can be used to study many countries at once, for example, OECD countries (Liddle 2011) or APEC countries (Usman and Hammar 2021).

Not much research employs the STIRPAT model on Indonesia's environmental impact. For example, Kusuwardani (2020) assessed whether combatting economic inequality could reduce Indonesia's carbon emissions. It was found that economic equality could affect the reduction of carbon emissions. Immayawahyu (2019) employed the STIRPAT model to assess the impacts of population, economic affluence, and technology in Indonesia on two different presidential regimes. Though so, research considering Indonesia is mainly included while estimating many regions collectively. Fan et al. (2006) studied the influences of carbon emission driving factors like economic age and age proportion. It was found that age proportion positively influenced carbon emission in middle and lower economy countries like Indonesia.

STIRPAT model has been extended to the point where its estimation is combined with other methods. STIRPAT model is mostly estimated in its logarithmic form. As STIRPAT uses time-series data, sometimes more than one way of regression is needed to estimate the values. Partial Least Square (Jia et al. 2009; Noorpoor and Kudahi 2015; Chekouri and Benbouziane 2020) or Ridge Regression (Lin et al. 2009; Jin et al. 2016) to remove the harmful effects of multicollinearity on time-series data. Other regression methods, for example, Fully Modified OLS; FMOLS (Liddle 2011), were also implied on the look of perfect estimation of the driving factors. Other estimating and forecasting methods are also combined with this model to further assess the driving force effects into the development plan to recommend reducing environmental impact. Zuo et al. (2020) combine STIRPAT with Long Short-Term Memory (LSTM) model to forecast an increase in future carbon emission, while others like Chai et al. (2018), Wu et al. (2018) used custom scenario analysis to see the future of environmental impact further.

As there is plenty of research that employs STIRPAT to estimate impacts from the population, only a few, like Noorpoor and Kudahi (2015), Soltani et al. (2020), and Zhao et al. (2022), use the STIRPAT model to estimate household energy usage impact on carbon emission. However, the study towards is not uncommon, in a way where some research like Kurniawan et al. (2018) had already employed other methods to estimate carbon emission increase due to household energy consumption effects.

This research contributes to implementing the STIRPAT model to estimate new types of driving forces of GHG emissions. NDC document is not a new reason to conduct a study regarding the quantitative effects of driving forces on environmental impacts. Fang et al. (2019) tried to forecast China's carbon emissions to ensure their NDC was well fulfilled. Wu et al. (2018) and Chekouri and Benbouziane (2020) also start their research concerning China's and Algeria's NDC fulfillment consecutively. Studies regarding the effects of population and household energy emission are also research that has been researched, which can be explored deeper. Therefore, this study can be considered the first research to employ the STIRPAT model to check the implication of one or more children in a family on Indonesia's carbon emission mitigation. This research also employs new variables, namely TFR and family rate, to add to the STIRPAT model.

3. Methods

The STIRPAT model was started as the IPAT model, which first came up as an idea of Ehrlich and Holdren (1971). IPAT tries to investigate the relationship between environmental impact, noted by I, to three anthropogenic driving factors, population (noted by P), economic growth (noted by A for affluence), and technology (noted by T). The IPAT model took form as accounting equation $I = P \times A \times T$. IPAT model was unable to differ the proportions of the contribution of each factor (Zuo et al. 2020). How the influence of all variables is seen as a constant fraction can be considered one of the most considerable constraints on this model (Usman and Hammar 2021). Waggoner and Ausubel (2002) redesigned the IPAT model into the ImPACT model. The model aims to identify factors that can be adjusted to mitigate environmental impacts while also investigating factors that influence each other (York et al. 2003).

Dietz and Rosa (1997) tried to tackle the limitations of IPAT. They then proposed the term Stochastic Impacts by Regression on Population, Affluence, and Technology, simplified as STIRPAT. STIRPAT enables statistical tests, also allowing non-proportionality on each impact of variable included (Jin et al. 2016). STIRPAT, which also allows hypothesis testing, taking a model of (eq. 1):

$$I = aP^b A^c T^d e \quad (1)$$

With *I* as environmental impact, *P* as population, *A* as affluence, and *T* as technology. a is the intercept, while *b*, *c*, *d* are the exponents of *P*, A, and *T*, while e is the error term. York et al. (2003) also proposed the model to take logarithmic form for tests, which is (eq. 2):

$$lnI = a + b(lnP) + c(lnA) + d(lnT) + lne \quad (2)$$

OLS

We then proceeded to estimate the STIRPAT model using OLS. The estimation results are both the coefficient itself and Variance Inflation Factor (VIF). VIF is estimated to check whether there is multicollinearity, which could cause inaccuracy of estimation due to the correlation of independent variables on each other. Multicollinearity also increases the variance of the coefficients while producing a high R-squared value. A negative coefficient also can be caused by multicollinearity (Chekouri and Benbouziane 2020).

Ridge Regression

Ridge regression is used to mitigate multicollinearity. By modifying ordinary least squares (OLS), the regression method allows bias to estimate regression coefficients. Though a biased estimation, the minimum biased k-value added to the coefficient can significantly improve the estimation and reduce the overall mean squared error. The increasing k-value also drives the coefficient towards zero. The *k*-value of zero (*k* = 0) also allows the estimation back to the OLS.

Ridge regression increases the stability of the model. It also produces mean square error and standard error lower than OLS. The estimation results will be closer to the actual value (Hoerl and Kennard 2000). The standard formula of ridge regression is as follow; we first take a standard model for multilinear regression:

$$Y = X\beta + \varepsilon \quad (3)$$

Assuming that X is $(n \times p)$ and of rank *p*, while *β* is $(p \times 1)$ and being unknown. Thus,

$$\hat{\beta} = (X'X + kI)^{-1}X'Y \quad (4)$$

Independent variables seem to be multiple while linear, but OLS estimators, in contrast, is seemingly in a worse condition, while the value of $|X'X| \approx 0$. We assume that *X'X* could be added to a normal number matrix *kI* (*k* > 0). This implies to where the proximity of $X'X + kI$ to a singular degree shrinks. Therefore, the ridge regression estimator can be obtained by:

$$\hat{\beta} = (X'X + kI)^{-1}X'Y \quad (5)$$

k is ridge parameter when k > 0. When k = 0, the ridge regression can be converted back to the OLS (Hoerl and Kennard 2000).

Multicollinearity can be measured by Variance Inflation Factor (VIF). The bigger the value, the more likely there are multicollinearity exists. VIF is bounded to the value of 10 for the cut-off. Ridge regression also pushes the VIF value to a minimum. One of the most critical aspects of ridge regression is choosing *k*-value. The method was done using both analytical tools, which produce an exact value of *k*. The other way is through observation on the ridge trace. This method is done by picking the *k*-value, which shows stabilized regression coefficient.

Data

This study tries to observe the selected driving factors of carbon emission's effect on the carbon emission of Indonesia within the 2000-2016 period. Most of the data we gather through the World Bank Database can be accessed through internet service. Like average family size, some other data is from the Indonesian Central Statistic Body (BPS), and the household energy consumption is from the Indonesian Ministry of Energy and Mineral Resources (KESDM).

STRIPAT model is employed to estimate the effect of the driving forces on Indonesia's carbon emission. We include several recurring variables like population size, urbanization, and non-dependent population, a population at the age of 15-64 (Liddle 2011), to measure the population-based impact on carbon emission. We also included new variables like TFR and average family size to see whether family choices to add more members to the family through birth could affect the carbon emission. GDP per capita is also a recurring variable for estimation using STIRPAT. Since we try to identify the household energy usage effects on carbon emission, we also need to employ household expenditure to see whether household well-being could be the main reason for peaking energy usage. Gini Index is also included as there is a chance that household income could drive the increase of carbon emission. Lastly, we use a direct variable of household energy consumption to measure how it affects Indonesia's carbon emissions.

Through employing STIRPAT model and including all the variables related, the model can be specified as follow:

$$lnCE = a + \beta_1(lnTP) + \beta_2(lnU) + \beta_3(lnTFR) + \beta_4(lnFAM) + \beta_5(lnDEP) + \beta_6(lnGDP) + \beta_7(lnEXP) + \beta_8(\ln GINI) + \beta_9(\ln EC) + \beta_{10}(\ln HEC) \quad (6)$$

With *CE* as carbon emission, *TP* as total population, *U* represents urbanization, *FAM* as average family size, *DEP* as non-dependent aged population, *GDP* represent Indonesian GDP per capita, *EXP* as household expenditure, *GINI* as Gini coefficient, *EC* as total energy consumption and *HEC* represents household energy consumption. The variables are defined on Table 1.

Table 1. Variable definition

Symbol	Variable	Definition	Unit	Source
CE	CO2 emission	Carbon dioxide emissions stem from the burning of fossil fuels and the manufacture of cement	Kilotons (kt)	World Bank
TP	Total population	All residents regardless of legal status or citizenship	Number	World Bank
U	Urbanization	Urban population refers to people living in urban areas as defined by national statistical offices, counted in %	%	World Bank
TFR	Total fertility rate	Number of births per woman	Number	World Bank
FAM	Average family size	Count of family member in a household	Number	BPS
DEP	Non-dependent population	Population ages 15-64, counted in %	%	World Bank
GDP	GDP per capita	Gross domestic product divided by midyear population	Current US $	World Bank
EXP	Household expenditure	The market value of all goods and services, including durable products	Current US $	World Bank
GINI	Gini index	The equality of income distribution among populations	Number	World Bank
EC	Total energy consumption	Measure of total consumption of energy, excluding biomass	Tboe	KESDM
HEC	Household energy consumption	Measure of total consumption of energy in household only, excluding biomass	Tboe	KESDM

4. Data Collection

Before collecting the data from the related database, we decide what variables to include in our model. We list the variables related to carbon emission caused by population growth and household energy consumption. Then, we search the relevant database which provides the data needed, for example, World Bank Database (https://data.worldbank.org) and the government database.

CO2 Emission

The calculation of CO2 emission includes CO2, which came from fossil fuel burning, manufacture of cement, consumption of fuels in solid, liquid, and gas states, and gas flaring. Figure 1 shows Indonesia's increase of CO2 emission (CE) against its population from 2000 to 2016 (Figure 1). The average annual growth rate is calculated to be 3.73%. It is shown that the emission increased through time while having a 6.66% decrease in 2013 while coming back 7.86% in 2014 and going up ever since.

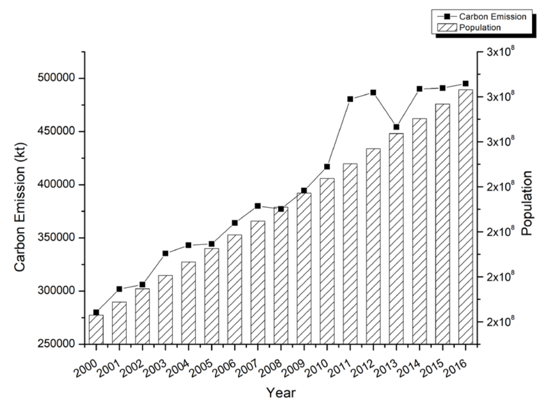

Figure 1. Carbon emission vs. population variation

Population

Indonesia is the fourth most populous country in the world. Though having thousands of islands, the population distribution is mainly centered in Java, Jakarta's capital city resides. Urbanization is increasing every year, reaching 50% in 2011. The number has been increasing ever since, leaving the Indonesian rural population to decrease every time. Indonesia's population is calculated through the number of current populations, without dividing legal status or citizenship. The population of Indonesia increased relatively constantly from 2000 to 2016. The average annual growth rate is calculated to be 1.34%, and the population is not having any decrease. Meanwhile, the Indonesian total fertility rate and average family size are decreasing gradually, although they stagnate. Indonesia's productive age is also increased every year, although insignificant.

Economy

Indonesia's economy is rising annually. Indonesia's GDP per capita increased 10.56% on average. GDP increase also shows that the Indonesian population is exposed to increased wealth over time. The ability of Indonesian consumption on all goods services, including durable products, is significantly increasing over time. The average annual growth rate is 11.54%. Though so, the Indonesian Gini index is still rising, which means that there is still inequality in Indonesia's economy. The Gini index of zero represents perfect equality of income distribution, while the Gini index of 100 shows otherwise. Despite the plan to reduce poverty, Indonesia's Gini index still ranges from 30 to 40, with an average annual growth rate of 1.78%.

Energy

Indonesia's total energy consumption raised around 2.48% on average. This is measured from energy consumption in industrial, household, commercial, transportation, and others while ignoring biomass energy usage. Most Indonesian total energy consumption comes from the industrial sector, with around 34% of total consumption. Household consumptions share the second-biggest share of total consumption with 16.8%. The consumption also increased every year, with a 1.77% increase.

5. Results and Discussion

5.1 OLS Results

We can see through Table 2 the descriptive statistics of the included variable. It is known that standard deviations of the variables are ranging from 0.019748 to 0.600979 (Table 2).

Table 2. Descriptive statistic of the model

Variable	Observation	Minimum	Maximum	Mean	Std. Dev.
lnCE	17	12.54315	13.11227	12.87373	0.189953
lnTP	17	19.1698	19.38216	19.27703	0.06725
lnU	17	3.737717	3.98878	3.872153	0.079844
lnTFR	17	0.859509	0.922273	0.906391	0.019748
lnFAM	17	1.280934	1.386294	1.312496	0.035412
lnDEP	17	6.617747	8.214562	7.567606	0.594576
lnGDP	17	4.168345	4.208313	4.188536	0.012966
lnEXP	17	25.34157	27.01275	26.34566	0.600979
lnGINI	17	3.353407	3.688879	3.559269	0.110063
lnEC	17	20.04773	20.52294	20.29578	0.147104
lnHEC	17	18.20789	18.56061	18.33004	0.104015

Table 3 provides information about the correlation between variables. A pairwise correlation investigation indicates that TFR and average family size are negatively correlated to carbon emission. Meanwhile, other variables seem to be correlated otherwise.

Table 3. Correlation between variables

Variable	lnCE	lnTP	lnU	lnTFR	lnFAM	lnDEP	lnGDP	lnEXP	lnGINI	lnEC	lnHEC
lnCE	1.000										
lnTP	0.978	1.000									
lnU	0.981	0.998	1.000								
lnTFR	-0.819	-0.878	-0.848	1.000							
lnFAM	-0.876	-0.851	-0.860	0.664	1.000						
lnDEP	0.974	0.964	0.974	-0.746	-0.892	1.000					
lnGDP	0.975	0.998	0.996	-0.878	-0.856	0.963	1.000				
lnEXP	0.980	0.972	0.982	-0.759	-0.892	0.998	0.971	1.000			
lnGINI	0.975	0.954	0.963	-0.738	-0.868	0.974	0.952	0.982	1.000		
lnEC	0.976	0.948	0.957	-0.736	-0.865	0.969	0.947	0.970	0.965	1.000	
lnHEC	0.559	0.627	0.581	-0.881	-0.382	0.427	0.623	0.457	0.479	0.463	1.000

We perform OLS estimation using the software Eviews 11. From Table 4, we can see that the multicollinearity between variables exists; some are incredibly high. However, the variable average family size did not show any multicollinearity, as their VIF value was not higher than 10. Multicollinearity could alter the value of the coefficient, which then results in no reflection of the actual relationship between independent variables (Chekouri and Benbouziane 2020).

Table 4. OLS estimation result

Variable	Coefficient	Standard Error	t-Statistic	Probability	VIF
lnTP	-22.72927	21.59294	-1.052625	0.333	39760.72
lnU	19.41623	16.47543	1.178496	0.2832	32629.05
lnTFR	-11.03006	7.264817	-1.518284	0.1797	388.1061
lnFAM	-0.37576	0.517614	-0.725947	0.4952	6.335084

lnDEP	0.386162	0.427347	0.903626	0.401	1217.384
lnGDP	-16.56002	11.18029	-1.48118	0.1891	396.2705
lnEXP	-0.456481	0.532559	-0.857145	0.4243	1931.544
lnGINI	1.22445	0.666758	1.836425	0.116	101.5475
lnEC	0.584822	0.249025	2.348443	0.0572	25.30376
C	0.21852	0.459784	0.475266	0.6514	
R-squared	0.991181				
Adjusted R-squared	0.976483				
F-statistic	67.43668				
Prob(F-statistic)	0.00023				
Durbin-Watson stat	2.924087				

We encountered a massive value of multicollinearity, defined by VIF on the OLS estimation. Re-estimation is needed to reduce the influences of the variables on each other. Ridge regression is employed in this study to shake off the multicollinearity problem using NCSS 2021 software. k coefficient is the core in ridge regression. The value of k is calculated within 0 to 1 interval. NCSS provides an analytical result of k, but we can also observe a ridge trace graph (Figure 2) to pick the minimum k on which the curve began to stabilize.

5.2 Graphical Results

NCSS 2021 recommended k = 0.050392, which we then used as our regression coefficient value. Table 5 shows the ridge regression coefficients. We reduced VIF to the point far below 10, ranging from 0.7498 to 4.1349.

Table 5. Ridge regression result

k = 0.050392				
Variable	Ridge Coeff.	Standardized Ridge Coeff.	Standard Error	VIF
C	2.327283			
lnTP	0.2287157	0.150385	0.081	0.7498
lnU	0.1882154	0.1605835	0.0791	1.2051
lnTFR	-0.7280177	0.9936266	-0.0757	2.8226
lnFAM	-0.2902362	0.5604382	-0.0541	2.8874
lnDEP	0.5286972	1.050507	0.0361	1.3602
lnGDP	0.03680008	0.02565482	0.1152	1.7057
lnEXP	0.03560176	0.01847729	0.1126	0.904
lnGINI	0.3372028	0.1978657	0.1954	3.4768
lnEC	0.3164747	0.1614481	0.2451	4.1349
R-squared	0.9773	F-statistic	25.8514	
RMSE	0.04671771	Prob(F-statistic)	0.000381	

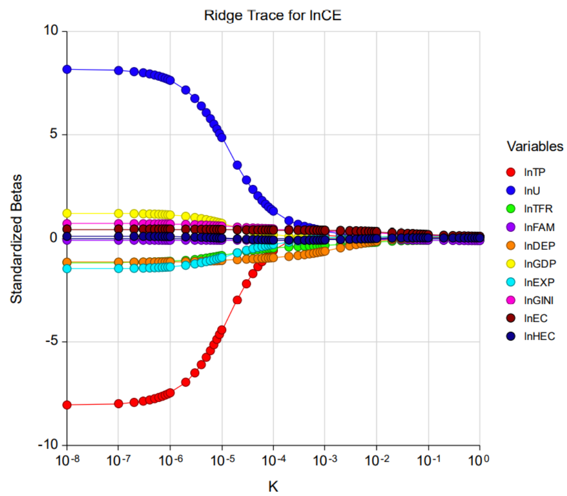

Figure 2. Ridge trace

R-squared shows a great value of 0.9773, meaning the independent variables included in the model can explain the dependent variable by 97.73%. We are then able to alter the STIRPAT model to as follow:

$$\begin{aligned} lnCE = -3.699111 + \ & 0.2287157(lnTP) + 0.1882154(lnU) - 0.7280177(lnTFR) \\ & - 0.2902362(lnFAM) + 0.5286972(lnDEP) + 0.03680008(lnGDP) \\ & + 0.03560176(lnEXP) + 0.3372028(lnGINI) + 0.3164747(lnEC) \\ & + 0.07756005(lnHEC) \end{aligned} \quad (7)$$

The ridge regression result shows that all variables positively affect carbon emission, but TFR and average family size show otherwise. TFR and average family size negatively affect carbon emission. Indonesia's non-dependent population, which is the population age ranged from 15-64 years old, affects carbon emission the greatest, with a coefficient of 0.5286972. This is followed by inequality of income distribution, represented by Gini Index, then others. Meanwhile, average family size and TFR are current decreasing trends helping reduce carbon emission. Log-log regression model interprets 1% increase of independent variables resulting independent variable to increase in a percentage of the independent variables' coefficient (Lin et al. 2009; Jia et al. 2009; Noorpoor and Kudahi 2015). Therefore, with the increase of 1% in the population, the carbon emission will increase by around 0.23%. A negative result, otherwise, turns out indicates that there will be a decrease in carbon emission as the independent variable increases.

Table 6. Effect and contribution to change of carbon emission

Variable	Ann. Growth Rate	Regression Coeff.	Effect on Change	Contribution Degree
lnCE	3.74%			
lnTP	1.34%	0.2287157	0.31%	8%
lnU	1.58%	0.1882154	0.30%	8%
lnTFR	-0.38%	-0.7280177	0.28%	7%
lnFAM	-0.46%	-0.2902362	0.13%	4%
lnDEP	0.25%	0.5286972	0.13%	4%
lnGDP	10.56%	0.03680008	0.39%	10%
lnEXP	11.54%	0.03560176	0.41%	11%
lnGINI	1.94%	0.3372028	0.66%	18%
lnEC	2.48%	0.3164747	0.79%	21%
lnHEC	1.77%	0.07756005	0.14%	4%
Other Factors (C)		-3.699111	0.22%	6%

1% increase of total population will increase carbon emission by 0.23%. We calculated that through 2000-2016 population increased 1.34%. Therefore, multiplying the coefficient and annual growth rate gives us the value of the effect of population on change of environmental impact (Lin et al. 2009), which is 0.31%. Other variables like TFR, GDP per capita, and household expenditure also moderate carbon emission change with around 0.30%-0.40% of the effect. However, it experienced a higher annual increase than the others; GDP per capita and household expenditure seems not to affect carbon emission change as significantly as expected. Nevertheless, it was the Gini index, and total energy consumption shares the most significant effect on carbon emission change —dividing effect on change by dependent variable's average annual growth results in contribution degree of independent variables in affecting the dependent variable. Contribution to the change could determine the importance of the influence on environmental change (Lin et al. 2009, Lin et al. 2017). Gini index and total energy consumption contribute the most to changes in carbon emission with 18% and 21% of contribution degree respectively.

5.3 Proposed Improvements

Indonesia has missions to reduce its greenhouse gas emission and increase the welfare of its population. Recent data shows that the Gini index is still increasing over time, meaning that the inequality of Indonesians' income distribution is not yet to be mitigated. Kusumawardani and Dewi (2020) also confirm that Indonesian income inequality could increase carbon emission, thus need to be reduced. This problem then can be addressed as to how a wealthier portion of the population could degrade the environment while sharing the impacts with the poor (McGee and Greiner 2018). Research employing the STIRPAT model also confirmed that the economy could affect carbon emission. The increase of economy induces the ability of the population to consume products, for example, energy, food, or transportation, thus causing the increase of carbon emission (Liddle 2011; Ratanavaraha et al. 2015; Shahbaz et al. 2017). We illustrate how household financial ability increase could drive carbon emission, which also contributes much to the emission changes.

Energy consumption could be influenced by many things, including urbanization (Lin et al. 2009; Haseeb et al. 2016) and economy (Lin et al. 2009). It is said that the rising economy affluence between populations will increase energy consumption through industrialization processes, commercial and everyday uses (Ratanavaraha et al. 2015, Yang et al. 2021). The rise of energy consumption led to carbon emission through its production, then its usage (Liddle 2011, Yang et al. 2021). Indonesia's carbon emission caused by energy consumption comes from coal, fossil fuel, and natural gas IEA (2020). Therefore, perhaps mitigation by employing renewable energy sources could answer energy-based carbon emissions. Haseeb et al. (2016), Usman and Hammar (2021), Zuo et al. (2020) also confirmed that renewable energy could help in decreasing carbon emission through statistical calculation.

Much research has investigated the effect of the population on the increase of carbon emissions. Like Lin (2017) and Usman and Hammar (2021), other studies involving the population also found that population is a crucial influence in the increase of environmental impact. At the same time, Ratanavahara et al. (2015) found out that population indirectly influences carbon emission by transportation as its authentic influencer. Indonesia has been on its way to mitigating population bursts by employing several programs, including planned family. While not as strict as China's One-Child Policy, this program only suggests families limit their children only up to 2. Indonesia's Central Statistical Agency (BPS) predicts that Indonesia's population will increase until 2045, despite the total fertility rate (TFR) reaching 2.1. We can see through this measure that eventually, the population will influence the increase of carbon emissions. The result shows that the decreasing TFR and average family size help in giving negative impact to Indonesia's carbon emission increase, indicating the decision of having fewer children will reduce carbon emission. We also illustrated that the productive age population (people aged 15-64) could drive carbon emission increase from their activities. This has been confirmed through some research (Liddle 2011), and mitigation could come from energy usage limitations (Yang et al. 2021), employment of renewable energy to industries, and transportation (Ratanavahara et al. 2015), or the decision to limit the number of children in a family.

6. Conclusion

Indonesian carbon emission drivers could be illustrated through STIRPAT analysis. The non-dependent population affects carbon emission increase the most. Though so, the economic aspect (GDP per capita, household expenditure, and Gini index) play the contribute the most to the increase of Indonesia’s carbon emission, followed by the energy aspect (total energy consumption, household energy consumption), and lastly the population (total population, urbanization, TFR, and average family size). Non-dependent population, which is the productive population plays a big role in pushing the country’s economy forward. Improvement in the economy could then improve technology, thus increasing industrial production and energy usage (Yang et al. 2021). As much research suggests, mitigating carbon emission through the economy could employ green economy regulation (Yang et al. 2021), develop eco-friendly technologies (Usman and Hammar 2021), and tackle economic inequality (McGee and Greiner 2018; Kusumawardani and Dewi 2020). The Indonesian government could also implement green energy to provide energy usage for households, reducing emissions from this sector, as some research suggests (Zhao et al. 2022). The encouragement of family planning could also be considered in mitigating carbon emissions.

This research has illustrated how population, economic, and residential energy consumption. However, some flaws and limitations to this research could be reviewed and improved. Future research regarding carbon emission in Indonesia can implement panel research consisting of 34 provinces in Indonesia to reduce bias on emission each province produces.

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