A Stochastic Kaya Model and Its Implications for Climate Policy*

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Abstract: This paper develops a stochastic Kaya model. The elasticity of carbon dioxide emissions in relation to population, per capita GDP, energy efficiency, and fossil fuel dependence is estimated using the panel data of 132 countries from 1960 to 2010. As an application of the stochastic Kaya model, the achievements of each nation in the stabilization of carbon emissions with economic development are investigated, using a method of index decomposition analysis. In addition, using the model carbon emissions are projected to 2050. One of the main findings is that the unit elasticity for each driving force underestimates the scale effect (population change and economic growth) and overestimates the counteracting technology effect. This results in significant differences in quantifying the driving forces for changes in carbon emissions and future emissions projections.

Key Words: Climate Change, Climate Policy, Kaya Identity, Carbon Dioxide Emissions, Decomposition Analysis

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1. Introduction

This paper investigates how we are approaching the goal of greenhouse gas emissions reduction stated as “the stabilization of greenhouse gas concentrations in the atmosphere” in a manner to “enable economic development” (UNFCCC, 1992: Article 2: Objective). Broadly speaking, this objective can be rephrased as the notions of “sustainable development” or “ecological modernization” (Hajer, 1995; Langhelle, 2000; Mol and Sonnenfeld, 2000; Jänicke, 2008).

If we look at the changes in greenhouse gas (GHG) emissions between two specific time periods (e.g., 1990 and 2010), this approach may mislead policy guidance. For example, GHG emissions reductions by the former Soviet Union do not imply that they were approaching the target of sustainable development since the economic downturn during the early 1990s was the driver of the reductions in GHG emissions.

The Impact Population Affluence Technology (IPAT) model (Commoner et al., 1971; Ehrlich and Holdren, 1971) and IPAT variants including Kaya (Kaya, 1990), IPBAT (Schulze, 2002), and ImPACT (Waggoner and Ausubel, 2002) have been widely used for analyzing the drivers of environmental impacts since the early 1970s (Chertow, 2001; Rosa and Dietz, 2012). IPAT assumes that human impacts (I) are equivalent to the product of population (P), affluence (A), and technology (T). Kaya (1990) extends IPAT by splitting technology into energy efficiency and emission factors in order to investigate the driving forces of changes in carbon emissions.

Because of simplicity, the Kaya identity has been widely used in the literature (e.g., Dietz and Rosa, 1997; Hoffert et al., 1998; Greening et al., 1998; Shi, 2003; Bacon and Bhattacharya, 2007; Agnolucci et al., 2009; Jorgenson and Clark, 2010; Jotzo et al., 2012; Mahony et al., 2012; Brizga et al., 2013; Rafaj et al., 2013). However, Kaya assumes
that a unit increase in a driving force induces a unit increase in carbon emissions, which is not supported by empirical data. This paper empirically tests a stochastic Kaya model. Therefore, panel data from the World Development Indicators 2013 (World Bank, 2013) are used. The dataset includes country level data from 1960 to 2010.

Dietz and Rosa (1994) and York et al. (2013) developed and applied a stochastic IPAT model, namely the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT). The STIRPAT model includes an error term and non-unit elasticity of an environmental impact with respect to each driving force. This paper extends the Kaya identity and uses panel data from 1960 to 2010.\(^1\) In addition, as an application of the model, this paper investigates the driving forces of CO\(_2\) emissions from 1990 to 2010 with index decomposition analysis (IDA) (Ang, 2005). Future emissions are also projected for 2050. The applications show that the stochastic model results in different implications for climate policy from the usual applications of the deterministic Kaya model. More specifically, the scale effects (population change and economic growth) are underestimated, whereas the counteracting technology effects (energy efficiency improvement and decreasing fossil fuel dependence) are overestimated by the deterministic Kaya model.

Admittedly, the model of this paper for emissions scenarios is much simpler than the models currently used for policy recommendations such as the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) (Nakicenovic et al., 2000), International Energy Agency (IEA) Energy Technology Prospective (ETP) scenarios (IEA, 2010), and the Representative Concentration Pathways (RCP) scenarios (van Vuuren et al., 2011). However, the approach of this paper is much more intuitive and is easily applicable to other

\(^{1}\) Note that York et al. (2003) use cross-sectional data.
types of research according to the topic of interest.

The paper proceeds as follows. The model is presented in Section 2. The anthropogenic drivers of carbon emissions from 1990 to 2010 using IDA are investigated in Section 3 and future carbon emissions are projected in Section 4. The discussion and conclusions are presented in Sections 5 and 6.

II. The Model and Methods

Carbon emissions are investigated by the model (1) in this paper, which extends the Kaya model. The effect of carbon intensity is decomposed into the effect of fossil fuel dependence and emission factor, and an error term is added for the statistical estimation and the elasticity of carbon emissions with respect to each driving force is not 1.

\[
CO_{2,i,t} = \alpha P_{i,t}^{\beta_P} G_{i,t}^{\beta_G} F_{i,t}^{\beta_F} C_{i,t}^{\beta_C} e_{i,t}
\]

where and denote a country and an annual time period, P, G, T, F and C are the driving forces of carbon dioxide emissions, denoting population, per capita gross domestic product (GDP), energy intensity (the reciprocal of energy efficiency), fossil fuel dependence, and emission factor, respectively. is a constant, is the elasticity of carbon emissions with respect to each driving force, and is the error term.

A natural logarithm is given on each side of Equation (1):

\[
\ln(CO_{2,i,t}) = \beta_0 + \beta_P \ln(P_{i,t}) + \beta_G \ln(G_{i,t}) + \beta_F \ln(T_{i,t}) + \beta_C \ln(F_{i,t}) + v_{i,t}
\]

2) See Waggoner and Ausubel (2002) and Bacon and Bhattacharya (2007) for more discussion on each driving force and its policy implications.
where $\beta_0 = \ln(\alpha)$ and $\nu$ is the residual. Following the literature (e.g., York et al., 2003), the residual term captures all remaining factors including the term for the emission factor, $\beta_c \ln(C_{t,i})$.

The population data, GDP (PPP, 2005 constant US$), total primary energy consumption, fossil fuel dependence, and carbon dioxide emissions are collected from the World Development Indicator 2013 dataset of the World Bank.

Ordinary least square (OLS) regression for Equation (2) is subject to limitations such as serial correlation and multicollinearity since this paper uses panel data. The equation for the difference in variables between the two points in time (i.e., $t_1$ and $t_2$) is used instead in order to avoid these limitations. A disadvantage is that the data for the initial year are lost. This method is similar to the first difference method used by Jorgenson and Clark (2010).

$$\ln(CO_{2,i,t_2}/CO_{2,i,t_1}) = \beta_P \ln(P_{i,t_2}/P_{i,t_1}) + \beta_G \ln(G_{i,t_2}/G_{i,t_1}) + \beta_T \ln(T_{i,t_2}/T_{i,t_1}) + \beta_F \ln(F_{i,t_2}/F_{i,t_1}) + R_i$$

where $R_i = R_{i,t_1,t_2}$ is the residual.

Table 1 shows the results. The model does not suffer from serial correlation (Durbin-Watson: 2.346) or multicollinearity (VIF), and all coefficients are statistically significant (p-value). Heteroskedasticity is not a significant problem for the model. A 1% increase in population, per capita GDP, energy intensity, and fossil fuel dependence lead to 1.03%, 1.05%, 0.67% and 0.58% increase in CO$_2$ emissions, respectively. In general, these results are consistent with the literature (Rosa and Dietz, 2012). For example, York et al. (2003) analyzed cross-sectional data for 146 countries in 1996 and estimated that the elasticity of CO$_2$ emissions was 1.019 with respect to population.

3) Broadly speaking, this is to ensure the validity of the estimation procedure.
<table>
<thead>
<tr>
<th>(Table 1) Statistical results</th>
<th>( \beta )</th>
<th>Standard error</th>
<th>VIF</th>
</tr>
</thead>
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<tr>
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</tr>
<tr>
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<tr>
<td>Energy intensity</td>
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<tr>
<td>Fossil-fuel dependence</td>
<td>.575***</td>
<td>.024</td>
<td>1.438</td>
</tr>
</tbody>
</table>

Note: ** p-value < .05, *** p-value < .001, Number of observations: 4,416, adjusted \( R^2 \) is 0.617

Since the elasticity of each driving force is different from 1, there may be a significant difference in the results for the stochastic model Equation (3) and for the deterministic model (4).

\[
\ln \left( \frac{CO_{2,t+1}}{CO_{2,t}} \right) = \ln \left( \frac{P_{t+1}}{P_{t}} \right) + \ln \left( \frac{G_{t+1}}{G_{t}} \right) + \ln \left( \frac{T_{t+1}/T_{t}} \right) + \ln \left( \frac{F_{t+1}/F_{t}} \right) + \ln \left( \frac{C_{t+1}/C_{t}} \right)
\]

The difference between the two models can be investigated by a simple calculation. Let us assume that per capita GDP growth is determined by a factor of \( a \) and energy efficiency increases by a factor of \( b \) (\( a > 1 \) and \( b > 1 \)), and other factors remain unchanged for simplicity. The deterministic model for future carbon emissions (\( CO_{2,t+1} \)) are times higher than the initial carbon emissions (\( CO_{2,t} \)). However, the ratio of carbon emissions between the two time periods for the stochastic model is:

\[
\frac{CO_{2,t+1}}{CO_{2,t}} = \left\{ \left( \frac{aG_{t+1}}{G_{t}} \right)^{\beta_G} \left( \frac{T_{t+1}}{T_{t}} \right)^{\beta_T} \left( \frac{F_{t+1}}{F_{t}} \right)^{\beta_F} \left( \frac{C_{t+1}}{C_{t}} \right)^{\beta_C} \right\} \left( \frac{e_{t+1}}{e_{t}} \right)
\]

If we further assume that the error terms are similar in magnitude, Equation (5) is greater than \( a/b \) since \( a^{\beta_G} b^{1-\beta_T} > 1 \) for \( a > 1 \), \( b > 1 \), \( \beta_T < 1 \). Note that the conditions for \( \beta_G \) and \( \beta_T \) are consistent with the results in Table 1. In summary, the same amount of change in the driving forces results in lower impacts for the deterministic Kaya model than for the stochastic Kaya model.
III. Driving Forces of the Changes in CO₂ Emissions: 1990–2010

1. Methods and Data

As an application of the stochastic Kaya model, the driving forces for the changes in carbon emissions (i.e., country level) from 1990 to 2010 are investigated in this section. More specifically, the logarithmic mean Divisia index (LMDI) decomposition method (Ang, 2005) is applied. Whereas usual LMDI derives equations for decomposition from a deterministic model such as Equation (4), this section derives decomposition equations from the stochastic model such as Equation (3).

If we multiply \( \frac{A_{t+h}-A_{t}}{A_{t+h}} = \log \left( \frac{CO_{2_{t+h}}}{CO_{2_{t}}/CO_{2_{t+h}}} \right) \) to each side of Equation (3), the changes of CO₂ emissions between the two time periods of interest are decomposed into each driving force:

\[
CO_{2_{t+h}} - CO_{2_{t}} = P_{eff} + G_{eff} + T_{eff} + F_{eff} + R_{2}
\]

where \( P_{eff} = A_{t+1} \beta \log (P_{t+1}/P_{t}) \), \( G_{eff} = A_{t+1} \beta \log (G_{t+1}/G_{t}) \), \( T_{eff} = A_{t+1} \beta \log (T_{t+1}/T_{t}) \) and \( F_{eff} = A_{t+1} \beta \log (F_{t+1}/F_{t}) \) refer to the population effect, affluence effect, energy efficiency effect and fossil fuel dependence effect, respectively, on CO₂ emissions and \( R_{2} = A_{t+1} R_{2} \).

The United Nations Framework Convention on Climate Change (UNFCCC) dataset on specific energy related CO₂ emissions is used for UNFCCC-Annex 1 countries, while the World development Indicators (WDI) dataset is used for non-Annex 1 countries for analyzing the driving forces. The WDI dataset does not provide complete data for CO₂ emissions for some Annex 1 countries (e.g., Germany and the former Soviet Union). On the other hand, the UNFCCC dataset covers complete CO₂ emissions data for Annex 1 countries since 1990. The disadvantage of the UNFCCC dataset is that the data for non-Annex
1 countries are rare since the dataset is based on a national inventory report (NIR) of each country. However, the results of this paper do not change much even if the WDI dataset for all countries is used.

2. CO₂ Emissions

Table 2 shows CO₂ emissions of major countries and groups. The shaded cells highlight countries or groups where their CO₂ emissions were reduced during the past two decades. The Kyoto Protocol target of each country is also presented for comparison. Although the Kyoto target refers to the aggregate GHG emissions during the first commitment period (2008–2012), the target can serve as a measure of each country’s achievement during the past two decades. The CO₂ emissions of Germany, the United Kingdom (UK), France and Italy in 2010 were less than their levels in 1990. In addition, their amounts of reductions already exceeded the Kyoto targets, except for Italy. As a group, the European Union (EU) and UNFCCC Annex 1 countries emitted less CO₂ in 2010 than in 1990. The other countries and groups presented in Table 2 increased CO₂ emissions. Especially, the CO₂ emissions of South Korea (hereafter, Korea) and other emerging markets including China, Brazil, and India more than doubled during the past two decades. Global CO₂ emissions increased more than 50% from 1990 to 2010.

〈Table 2〉 CO₂ emissions

<table>
<thead>
<tr>
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<td></td>
<td>MtCO₂</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>371</td>
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<td>370</td>
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<td>772</td>
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<td>Italy</td>
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<td>404</td>
<td>1.2</td>
<td>-1</td>
<td>-0.1</td>
</tr>
<tr>
<td>Spain</td>
<td>206</td>
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<td>261</td>
<td>0.8</td>
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<td>27.0</td>
</tr>
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</tr>
</tbody>
</table>
3. Driving Forces of CO₂ Emissions

The IDA method provides quantitative information about the effect of each driving force on CO₂ emissions changes. The driving forces of CO₂ emissions between 1990 and 2010 are presented in Table A.1 (Appendix A). The main drivers of CO₂ emissions were the affluence effect and population effect for almost all countries. However, energy efficiency effect and the fossil fuel dependence effect played a partial role in offsetting CO₂ emissions. The relative magnitude of each driving force was different by country.

The results in Table 2 and Table A.1 are sensitive to the choice of the time period. Thus, this paper applies a chained decomposition analysis (Ang et al., 2010), which is a series of decomposition analyses applying time-series data. For the purpose of this paper, the aggregate effects such as the scale effect (the sum of the population effect and the affluence effect) and the counteracting technology effect (the
The sum of the energy efficiency effect, the fossil fuel dependence effect, and other effects) are investigated below instead of dealing with each effect in detail.

Figure 1 shows the results. Countries with incomplete data for 1990-2010 are disqualified. Remaining 111 countries are analyzed. The figure shows how the scale effect and the technology effect evolve over time for the past two decades. Each effect is divided by the total changes in carbon emissions between the two points in time. The positive scale effect means that the economy has grown economically in terms of GDP, and thus the scale effect played a role in increasing carbon emissions. The reverse is true for the negative scale effect. The negative technology effect implies that abatement-related technologies have improved, and thus the technology effect played a role in reducing carbon emissions. The reverse is true for the positive technology effect. The point below the diagonal in the second quadrant denotes that the economy has fully offset carbon emissions from the scale effect. The reverse is true for the point below the diagonal in the second quadrant. Therefore, if a country achieved the UNFCCC objectives as illustrated in Section 1, the country would be located below the diagonal in the second quadrant.

However, most countries did not achieve the goal for the stabilization of CO₂ emissions with economic development during the past two decades (Figure 1). In fact, many countries have deteriorated abatement-related technologies, which include energy efficiency and renewable energy. Meanwhile, some countries have experienced economic recession, especially during the 1990s. This reduced the points of the countries below the diagonal in the second quadrant, which is a condition that is not desired by a country.

The results for some major economies and groups are presented in Figure 2. The top left panel shows the results for some non-EIT (Economies in Transition) EU countries. Germany and the UK have
followed good paths in terms of the stabilization of CO₂ emissions with economic development relative to other countries. The recent global economic recession has led the path of each nation in the direction toward the third quadrant, which means that emissions have been reduced. This is one of the main reasons why Italy and France have reduced their emissions in 2010, below their levels in 1990.

The top right panel shows the results for some non-EU OECD member states. For the United States, Japan, Australia and Canada, technological improvements have partially offset CO₂ emissions from the scale effect. However, technological improvements have not been enough for achieving the goal to offset CO₂ emissions even though
Figure 2) Chained IDA results for selected countries: 1990–2010 (Top left panel): non-EIT European countries. (Top right panel): non-EU OECD members. (Bottom left panel): Emerging economies, Russia and LDC (least developed countries: UN classification). (Bottom right panel): Group

The magnitude of changes is different from country to country. Unlike other countries, the scale effect has been great in Korea, but the technology effect has increased CO$_2$ emissions.

The bottom left panel shows the results for Russia, some emerging markets, and least developed countries (LDC) as a group, which follow the United Nations classification. Russia suffered from economic downturn in the early 1990s. The emissions reduction during this period constitutes almost all of the reduction that Russia achieved for the past two decades. Since then, CO$_2$ emissions have increased steadily in Russia. Brazil and the LDCs deteriorated abatement-related technologies and the technology effect has increased CO$_2$ emissions such as in Korea. Although there have been abatement-related technologies progress in China and India, their technology
effects have not been enough to fully offset their huge scale effects. Even worse is the recent trend for China. The offsetting ratios for China have decreased since 2000. China’s path is one of the main contributors for the global trend in CO₂ emissions when we consider the amount of CO₂ emissions.

Finally, the bottom right panel shows the results for the world total, EU, UNFCCC Annex 1 (EIT and non-EIT), and the Organisation for Economic Co-operation and Development (OECD). As a group, EU followed a path of almost offsetting CO₂ emissions from the scale effect and the technology effect. Annex 1 countries experienced a similar path as the EU, but this was due to the EIT countries. Non-EIT countries have steadily increased CO₂ emissions, except for the current economic recession period. The path of OECD was similar to the non-EIT countries. The global situation was similar to China’s experience and became worse since 2000. The counteracting effect has reduced since the early 2000s.

### IV. CO₂ Emissions Projection

1. Scenarios

Global CO₂ emissions for 2011 to 2050 are projected in this section as another application of the stochastic Kaya model. The population prospect of the United Nations Population Division (UNPD) is used for the world population by 2050 (specifically, the no-change scenario).

4) For emissions projections, the residual in Equation (3) is further decomposed into the emission factor effect and remaining errors using the following model: $u_{i,t} = \beta_{i,t} + \beta_{i,n} (C_{i,t}) + v_{i,t}$, where $\beta_{i,t}$ is a constant and $v$ is the remaining error. The elasticity of CO₂ emissions with respect to emission factor is estimated to 0.875. There is no statistical problem for the OLS regression.
Global population is projected to be approximately 10.2 billion by 2050.

The per capita GDP growth rate is simply assumed to be 2%/yr for the economic growth prospect. The trend of each indicator in Equation (4) from 1960 to 2010 is investigated for the technology prospects (see Figure A.1, Appendix A). There is a tendency to decrease energy intensity and fossil fuel dependence during the past five decades. However, China increased fossil-fuel dependence. The trend of the emission factor is not as transparent as the other two indicators, except for the slightly recent increased emission factor.5) We also found that the global averaged technology indicators have not reached, although became close to, the level of the EU in 1970 for the past forty years. For simplification, the global technology indicators in 2050 would not be better than the current EU level in 2010. This observation can be rephrased as a technology gap of about forty years or more between the EU and the global average. This constitutes a reference scenario for the technology prospects in this paper and more scenarios are formulated according to the speed of technological improvements. For example, the ‘EU2010×0.5’ scenario in Figure 3 refers to the case where each global technology indicator in 2050 decreases to 50% of the current EU level. Note that the decreasing indicator means that there is a technological improvement (see Equation 1).6) Finally, each scenario has a target for technological improvements by 2050 and a linear trend for the technological improvements between 2010 and 2050 is assumed for simplicity.

5) One of the reasons is the changes in fuel-mix from oil to coal on account of high prices of oil.

6) These constructions of scenarios, especially high technological improvements scenarios, may not be realistic because there is a limit of improvement for each technology indicator. For example, there is a limit for substituting coal for natural gas. The deployment of renewables may be restricted from natural capacity.
2. Results

Figure 3 shows the results for the model of this paper, which is much simpler than the range of scenarios for more demanding models (e.g., Nakicenovic et al., 2000; IEA, 2010). The 'EU2010' scenario denotes the case where all global technology indicators decrease at the historical rate of improvement (see Section 4.1). However, global CO₂ emissions are projected to increase more than 250% by 2050, relative to the level in 1990. This implies that the current rate of technological improvements is too slow to offset CO₂ emissions from the scale effect. If a 50% reduction of CO₂ emissions is the aim for 2050, each technology indicator should be improved by a factor of two or more relative to the current EU level (see ‘EU2010*0.5’). Note that by technological improvements, this paper means the global average and not the level of technological frontiers such as Germany or Japan.

The projected CO₂ emissions are sensitive to the scale effect. For example, if the growth rate of per capita GDP is assumed to be 1%/yr and 3%/yr with other factors remaining constant, then CO₂
emissions are projected to increase by a factor of two or less and a factor of 4, respectively, compared to the level in 1990 (see top panel in Figure A.2).

The cumulative emissions are sensitive to the speed of technological improvements, even if the targets for emissions reduction are the same. For example, a faster ten year improvement in technology compared to the reference scenario means that the technology target is reached by 2040. This remains constant thereafter, resulting in a 6.9% reduction in cumulative emissions (see bottom panel in Figure A.2). For the 'EU2010*0.5' scenario with other conditions remaining unchanged, a faster ten year improvement in technology results in a 15.4% reduction in cumulative emissions.

V. Discussion

The impacts of using the deterministic model instead of the stochastic model are illustrated in Equation (4), which applies IDA and CO₂ emissions projections as in Sections 3 and 4 of this paper. Figure 4 shows the results for IDA. 7) The scale effect is calculated lower for the deterministic model than for the stochastic model. Reversely, the technology effect is calculated higher for the deterministic model than for the stochastic model. This is because the unit elasticity of carbon emissions with respect to population or per capita GDP results in the reduced scale effect (Section 2). By this symmetry, the technology effect is calculated higher for the deterministic model than for the stochastic model.

The difference between the two models is even more significant for emissions projections. The application of the deterministic model greatly lowers the projected level of carbon emissions compared to

7) The numerical results in detail are available upon request by the author.
(Figure 4) Comparison of IDA results. Stochastic refers to the case where the stochastic Kaya model is applied, whereas the others refer to the case where the deterministic model is applied.
the level of carbon emissions from the stochastic model (Figure 5). For example, the level of carbon emissions in 2050 is projected to be 30% less for the deterministic model compared to the stochastic model in the reference scenario. The difference is greater for the other stringent policy scenarios. If a society aims to halve carbon emissions by 2050 relative to the 1990 level, only 30~40% (as opposed to 50~60% for the stochastic model) improvement in each indicator is enough to achieve the target if the deterministic Kaya model is used.

(Figure 5) Comparison of emissions-projections. Stochastic refers to the case where the stochastic Kaya model is applied, whereas the others refer to the case for the deterministic model

VI. Conclusions

The stochastic Kaya model is developed in this paper. We found in the 1960 to 2010 panel data that a 1% increase in population, per capita GDP, energy intensity, and fossil-fuel dependence resulted in 1.03%, 1.05%, 0.67% and 0.58% increase in CO₂ emissions, respectively.
This is statistically different from the unit elasticity assumed in the deterministic Kaya model. This difference induces a problem for quantifying the driving forces of changes in carbon emissions and carbon emissions projections. Thus, application of the deterministic Kaya model underestimates the scale effect and overestimates the technology effect. If the deterministic Kaya model is used for policy guidance, less stringent efforts to improve emissions abatement technologies would be recommended. However, these findings are not supported by the stochastic Kaya model.

The Kaya model has been widely used for climate policy recommendations. However, the deterministic nature of the Kaya model is not supported by empirical data. The stochastic modification of the Kaya model is worthwhile because the model retains simplicity and corrects potential bias in estimating the driving forces in CO₂ emissions changes and future emissions projections. Simplicity has value in that the currently used emissions projection models are too complex and demanding, and are not easily accessible and understandable to the general public. In addition, the stochastic Kaya model is easily applicable to other types of research. One of the main policy implications we can derive from the stochastic model application is that more effort is required for our society to achieve emissions reduction targets with economic growth (e.g., 50% reductions by 2050) than the emissions levels calculated from the deterministic Kaya model.

Reference


# Appendix A. Supplementary Results

## Table A.1 Driving forces of CO₂ emissions: 1990–2010

<table>
<thead>
<tr>
<th>Country/Group</th>
<th>Driving forces of CO₂ emissions (% 1990 emissions)</th>
<th>Scale (% 1990 emissions)</th>
<th>Technology (% 1990 emissions)</th>
<th>Offsetting ratio(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Population</td>
<td>GDP per capita</td>
<td>Energy intensity</td>
<td>Renewables</td>
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<td>11.0</td>
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Note: The ratio of the technology effect to scale effect is defined as the offsetting ratio, following Bacon and Bhattacharya (2007). Therefore the offsetting ratio above 100% means that CO₂ emissions from the scale effect were fully offset by the technology effect. The shaded cells highlight the countries or groups in which CO₂ emissions are reduced compared to the 1990 levels. The negative offsetting ratios for some countries were originated from technological deterioration.
Figure A.1: Trend of technology indicators for some selected countries: 1960–2010 (Top panel): Energy intensity. The right axis is for China. (Middle panel): Fossil-fuel dependence. (Bottom panel): Emission factor. For data source see Section 2.
〈Figure A.2〉 Global CO₂ cumulative emissions trajectory: 1990–2050
(sensitivity analysis) (Top panel): Sensitivity to the growth rate of per capita GDP (3%/yr, 2%/yr, 1%/yr). (Bottom panel): Sensitivity to the rate of technological improvements. The growth rate of per capita GDP is assumed to be 2%/yr

황인창: 네덜란드 암스테르담 자유대학(Vrije Universiteit Amsterdam)에서 경제학 박사학위를 취득하고 현재 한국환경정책·평가연구원(KEI)에 재직 중이다. “Climate policy under fat-tailed risk: An application of DICE”, “Fat-tailed risk about climate change and climate policy”, “MAED 모형을 이용한 서울시 에너지 수요 전망”, “기후변화 대응전략에 따른 이산화탄소 배출량 변화요인 분석: 생태적 근대화 전략을 중심으로” 등의 논문을 발표한 바 있다(ichwang@kei.re.kr).

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