Stochastic Kaya model and its applications

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Abstract

This paper develops a stochastic Kaya model. The elasticity of carbon dioxide emissions with respect 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, we investigate the achievement of each nation to the stabilization of carbon emissions with economic development, using a method of index decomposition analysis. In addition, carbon emissions are projected by 2050 using the model. One of the main findings is that assuming 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 driving forces of the changes in carbon emissions and in future emissions projections.

Key words

Climate change policy; CO2 emissions; emissions scenarios; decomposition analysis

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).

Just by looking at the changes in greenhouse gas (GHG) emissions between two specific time periods (say, between 1990 and 2010) may mislead policy guidance. For instance, GHG emissions reductions of the former Soviet Union countries do not imply that they were approaching the target of sustainable development, since economic downturn during the early 1990s was the driver of the reductions in GHG emissions.

IPAT (Commoner et al., 1971; Ehrlich and Holdren, 1971) and its 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 factor in order to investigate the driving forces of the changes in carbon emissions.

Because of its 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 with empirical data. To this end, 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) develop and apply 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. The current paper is different from the literature in that this paper extends the Kaya identity and uses the panel data from 1960 to 2010.[1] In addition, as applications of the model, this paper investigates the driving forces of CO_2 emissions from 1990 to 2010 with index decomposition analysis (IDA) (Ang, 2005), and future emissions are projected by 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 IPCC Special Report on Emissions Scenarios (SRES scenarios) (Nakicenovic et al., 2000), 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 has its own

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[1] Note that York et al. (2003) use cross-sectional data.

values in that 1) it is much more intuitive; 2) it is easily applicable to other researches according to the topics of interest.

The current paper proceeds as follows. Section 2 presents the model. The anthropogenic drivers of carbon emissions from 1990 to 2010 are investigated using IDA in Section 3 and future carbon emissions are projected in Section 4. Section 5 concludes.

2. The Model and Methods

Carbon emissions are investigated with the model (1) in this paper. The model extends the Kaya model in 1) that the effect of carbon intensity is decomposed into the effect of fossil fuel dependence and emission factor, and 2) that an error term is added for statistical estimation and the elasticity of carbon emissions with respect to each driving force is not one.[2]

$$CO_{2,i,t} = \alpha P_{i,t}^{\beta_P} G_{i,t}^{\beta_A} T_{i,t}^{\beta_T} F_{i,t}^{\beta_F} C_{i,t}^{\beta_C} \varepsilon_{i,t} \tag{1}$$

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

Taking natural logarithm on each side of Equation (1) leads to:

[2] See Waggoner and Ausubel (2002) and Bacon and Bhattacharya (2007) for more discussions on each driving force and its policy implications.

$$ln(CO_{2,i,t}) = \beta_0 + \beta_P ln(P_{i,t}) + \beta_G ln(G_{i,t}) + \beta_T ln(T_{i,t}) + \beta_F ln(F_{i,t}) + u_{i,t} \qquad (2)$$

where $\beta_0 = ln(\alpha)$ and u is the residual. Following the convention of the literature (e.g., York et al., 2003), the residual term captures all remaining factors including the term for emission factor.

Data for population, GDP (PPP, 2005 constant US$), the total primary energy consumption, fossil fuel dependence, and carbon dioxide emissions are collected from the World Development Indicator 2013 dataset of the World Bank. The number of countries where the above-mentioned data are available at least for 5 years during 1960-2010 is 132.

Since this paper uses panel data, ordinary least square (OLS) regression for Equation (2) is subject to problems such as serial correlation and multicollinearity. In order to avoid the problems, the equation for the difference in variables between two points in time (i.e., t_1 and t_2) is used for the OLS estimation instead. Therefore fixed effects or lagged effects, potentially present in panel data, are less severe for Equation (3) than for Equation (2). A disadvantage is that data for the initial year are lost. This method is similar to the first difference method used by Jorgenson and Clark (2010).

$$\begin{aligned} & ln(CO_{2,i,t_2}/CO_{2,i,t_1}) \\ & = \beta_P ln(P_{i,t_2}/P_{i,t_1}) + \beta_G ln(G_{i,t_2}/G_{i,t_1}) + \beta_T ln(T_{i,t_2}/T_{i,t_1}) + \beta_F ln(F_{i,t_2}/F_{i,t_1}) + R_1 \end{aligned} \qquad (3)$$

where $R_1 = R_{1,i,t_1,t_2}$ 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 (results not shown). Table 1 says that 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. These results are generally consistent with the literature (Rosa and Dietz, 2012). For instance, York et al. (2003), with the cross-sectional data for 146 countries in 1996, estimate that the elasticity of CO_2 emissions with respect to population is 1.019.

[Insert Table 1 here]

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

$$\begin{aligned} & ln\left(CO_{2,i,t_2}/CO_{2,i,t_1}\right) \\ & = ln\left(P_{i,t_2}/P_{i,t_1}\right) + ln\left(G_{i,t_2}/G_{i,t_1}\right) + ln\left(T_{i,t_2}/T_{i,t_1}\right) + ln\left(F_{i,t_2}/F_{i,t_1}\right) + ln\left(C_{i,t_2}/C_{i,t_1}\right) \end{aligned} \tag{4}$$

The difference between the two models can be investigated by a simple calculation as follows. Let us assume that per capita GDP growth by a factor of a and energy efficiency increases by a factor of b ($a > 1$ and $b > 1$), other factors remain unchanged for simplicity. For the deterministic model future carbon emissions (CO_{2,i,t_2}) are a/b times higher than the initial carbon emissions (CO_{2,i,t_1}). For the stochastic model, however, the ratio of carbon emissions between the two periods is:

$$\begin{aligned} CO_{2,i,t_2}/CO_{2,i,t_1} &= \left\{\left(aG_{i,t_2}\right)^{\beta_A}/G_{i,t_1}^{\beta_A}\right\}\left\{\left(T_{i,t_2}/b\right)^{\beta_T}/T_{t_1}^{\beta_T}\right\}\left(\varepsilon_{i,t_2}/\varepsilon_{i,t_1}\right) \\ &= a^{\beta_A}b^{-\beta_T}\left(\varepsilon_{i,t_2}/\varepsilon_{i,t_1}\right) \end{aligned} \tag{5}$$

If it is further assumed that the error terms are similar in magnitude, Equation (5) is bigger than a/b since $a^{\beta_A - 1} b^{1-\beta_T} > 1$ for $a > 1$, $b > 1$, $\beta_A > 1$, and $0 < \beta_T < 1$. Note that the conditions for β_A and β_T are consistent with the results in Table 1. In sum, the same amount of change in the driving forces results in lower impacts for the deterministic Kaya model than for the stochastic Kaya model.

3. Driving Forces of the changes in CO_2 Emissions: 1990-2010

3.1. Methods and Data

As an application of the stochastic Kaya model, the driving forces of the changes in carbon emissions (each 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 like Equation (4), this section derives decomposition equations from the stochastic model (Equation 3).

Multiplying $A_{i,t_1,t_2} \equiv (CO_{2,i,t_2} - CO_{2,i,t_1})/ln(CO_{2,i,t_2}/CO_{2,i,t_1})$ to each side of Equation (3), the changes of CO_2 emissions between two periods of interest are decomposed into each driving force as follows.

$$CO_{2,t_2} - CO_{2,t_1} = P_{eff} + G_{eff} + T_{eff} + F_{eff} + R_2 \tag{6}$$

where $P_{eff} = A_{i,t_1,t_2}\beta_P ln(P_{i,t_2}/P_{i,t_1})$, $G_{eff} = A_{i,t_1,t_2}\beta_G ln(G_{i,t_2}/G_{i,t_1})$, $T_{eff} = A_{i,t_1,t_2}\beta_T ln(T_{i,t_2}/T_{i,t_1})$ and $F_{eff} = A_{i,t_1,t_2}\beta_T ln(T_{i,t_2}/T_{i,t_1})$ refer to the population effect, the affluence effect, the energy efficiency effect and the fossil fuel dependence effect, respectively on CO_2 emissions, and $R_2 = A_{i,t_1,t_2}R_1$.

The UNFCCC dataset (in specific, energy related CO_2 emissions) is used for UNFCCC-Annex 1 countries, while the WDI dataset is used for non-Annex 1 countries for analyzing the driving forces. This is because, for the period of interest, the WDI dataset does not provide complete data for CO_2 emissions for some Annex 1 countries (e.g., Germany and the former Soviet Union countries). The UNFCCC dataset, on the other hand, covers complete CO_2 emissions data for Annex 1 countries from 1990. The disadvantage of the UNFCCC dataset is that the data for non-Annex1 countries are rare since it is based on a national inventory report (NIR) of each country. The results of this paper, however, do not change much even if the WDI dataset for all countries is used (results not shown).

3.2. CO_2 Emissions

Table 2 shows CO_2 emissions of major countries and groups. The shaded cells highlight countries or groups where their CO_2 emissions were reduced during the past two decades. The Kyoto target of each country is also presented for comparison. Although the Kyoto target is about the aggregate GHG emissions during the first commitment period (2008 – 2012), it can serve as a measure of each country's achievement during the past two decades. CO_2 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 emitted less CO_2 in 2010 than in 1990. The other countries and groups presented in Table 2 increased CO_2 emissions. Especially CO_2 emissions of South Korea and emerging markets including China, Brazil, and India doubled or more during the past two decades. Global CO_2 emissions were increased more than 50% from 1990 to 2010.

[Insert Table 2 here]

3.3. Driving Forces of CO_2 Emissions

The IDA method gives quantitative information about the effect of each driving force on the changes in CO_2 emissions. The driving forces of CO_2 emissions between 1990 and 2010 are presented in Table A.1 in Appendix A. As The main drivers of CO_2 emissions for almost all countries were the affluence effect and the population effect, whereas the energy efficiency effect and the fossil fuel dependence effect played a role in (partially) offsetting CO_2 emissions. The relative magnitude of each driving force was different from country to country.

The results in Table 2 and Table A1 are sensitive to the choice of the time period. Thus this paper applies a chained decomposition analysis (Ang et al., 2010), 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 sum of the energy efficiency effect, the fossil fuel dependence effect, and the others) are investigated below, instead of dealing with each effect in details.

Figure 1 shows the results. The number of countries analyzed is 111 (some countries with incomplete data for the time period of 1990-2010 are dropped). It 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 (negative, respectively) scale effect means that the economy has grown economically in terms of GDP (undergone economic recession, resp.) and thus the scale effect played a role in increasing (reducing, resp.) carbon emissions. The negative (positive, respectively) technology effect implies that abatement-related technologies have improved (deteriorated, resp.) and thus the technology effect played a role in reducing (increasing, resp.) carbon emissions. The point below (above, respectively) the diagonal in the second quadrant denotes that the economy has fully (partly, resp.) offset carbon emissions from the scale effect. Therefore, if a country achieved the objective of UNFCCC as illustrated in Section 1, the country would be located below the diagonal in the second quadrant.

[Insert Figure 1 here]

As Figure 1 shows, however, most countries did not achieve the goal of the stabilization of CO_2 emissions with economic development during the past two decades. In fact, many countries have deteriorated abatement-related technologies including energy efficiency and renewable energy. Meanwhile, some countries have undergone economic recessions especially during 1990s. This pulled down the points of the countries below the diagonal but this is never what is hoped for.

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 CO_2 emissions with economic development relative to the other countries. The recent global economic recession has led the path of each nation to the direction toward the third quadrant of the figure, 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 CO_2 emissions from the scale effect but they have not been enough for achieving the goal, although the magnitude of changes is different from country to country. The scale effect has been great in South Korea but the technology effect has increased (not offset) CO_2 emissions, unlike the other nations.

The bottom left panel shows the results for Russia, some emerging markets, and least developed countries (LDC) as a group, following the United Nations classification. Russia has suffered from economic downturn in early 1990s and the emissions reduction during the period constitutes almost all reduction that Russia has achieved for the past two decades. Since then CO_2 emissions have increased steadily again in Russia. Brazil and LDC deteriorated abatement-related technologies and the technology effect has increased CO_2 emissions like South Korea. Although there has been a progress in abatement-related technologies in China and India, their technology effects have not been enough for fully offsetting their huge scale effects. Even worse is the recent trend of China: the offsetting ratios have decreased since 2000. Considering its amount of CO_2 emissions, the Chinese path is one of the main contributors for the global trend in CO_2 emissions.

Finally, the bottom right panel shows the results for the world total, EU, UNFCCC Annex 1 (EIT and non-EIT), and OECD. As a group EU has followed a path of almost offsetting CO_2 emissions from the scale effect by the technology effect. Annex 1 has undergone a similar path with EU, but this was almost due to EIT countries. Non-EIT has steadily increased CO_2 emissions except for the period of current economic recession. The path of OECD was similar to non-EIT. The global situation became worse similar to the Chinese case since 2000: the counteracting effect has reduced since the early 2000s.

[Insert Figure 2 here]

4. CO_2 Emissions Projection

4.1. Scenarios

For another application of the stochastic Kaya model, global CO_2 emissions (2011-2050) are projected in this section.[3] To this end, the population prospect of the United Nations Population Division (UNPD) is used for world population by 2050. More specifically, following the no-change scenario global population is projected to be about 10.2 billion by 2050.

For the economic growth prospect, the growth rate of per capita GDP is simply assumed to be 2%/yr.

For the technology prospects the trend of each indicator in Equation (4) from 1960 to 2010 is investigated (see Figure A.1 in Appendix A). There is a tendency to decrease in energy intensity and fossil fuel dependence during the past 5 decades (except for China: increasing fossil-fuel dependence). The trend of emission factor is not as transparent as the other two indicators, except for the recent (slightly) increasing emission factor.[4] It is also found that the globally averaged technology indicators have not reached (although it becomes close to) the level of EU in 1970 for the past 40 years. A simple thought says that the global technology indicators in 2050 (another 40 years ahead from now) would not be better than the current EU level (in 2010). Simply put, this observation can be rephrased as a statement that there is a technology gap of about 40 years or more between EU and the world average. This constitutes a reference scenario for the technology prospects in this paper. Beside the reference scenario, more scenarios are formulated according to the speed of technological improvements. For instance, the 'EU2010×0.5' scenario in Figure 3 below refers to the case

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[3] For emissions projections, the residual in Equation (3) is further decomposed into the emission factor effect and remaining errors using the following model: $u_{i,t} = \beta_{0,r} + \beta_C ln(C_{i,t}) + \upsilon_{i,t}$, where $\beta_{0,r}$ is a constant and υ is the remaining error. The elasticity of CO_2 emissions with respect to emission factor is estimated to 0.875. There is no statistical problem for the OLS regression.

[4] One of the reasons is the changes in fuel-mix from oil to coal on account of high prices of oil.

where each global technology indicator in 2050 decreases to 50% of the current EU level. Note that decreasing indicator means there is a technological improvement (see Equation 1).[5] 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.

4.2. Results

Figure 3 shows the results. Although the model of this paper is much more simpler, the results are well in the range of scenarios of more demanding models (e.g., Nakicenovic et al., 2000; IEA, 2010). Following the 'EU2010' scenario, which denotes the case where all global technology indicators decrease at the historical rate of improvement (see Section 4.1), global CO_2 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 CO_2 emissions from the scale effect. If 50% reduction of CO_2 emissions is aimed for by 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 the technological improvements this paper means not the level of technological frontiers such as Germany or Japan, but the world-averaged level.

[Insert Figure 3 here]

The projected CO_2 emissions are sensitive to the scale effect. For instance if the growth rate of per capita GDP is assumed to be 1%/yr (3%/yr, respectively), other things being equal, CO_2 emissions are projected to increase by a factor of two or less (a factor of 4, resp.)

[5] These constructions of scenarios, especially high technological improvements scenarios, may not be realistic, because there is a limit to improvement for each technology indicator. For instance, there is a limit for substituting coal for natural gas. The deployment of renewables may be restricted from natural capacity.

compared to the level in 1990 (see the top panel in Figure A.2).

The cumulative emissions are sensitive to the speed of technological improvements, even if targets for emissions reduction are same. For instance, a 10 year faster improvements in technology than the reference scenario, which means the technology target is reached by 2040 and remains constant thereafter, result in 6.9% reduction in cumulative emissions (see the bottom panel in Figure A.2). For the 'EU2010*0.5' scenario, other things being equal, a 10 year faster improvements in technology results in 15.4% reduction in cumulative emissions.

5. Discussion

To see the impacts of using the deterministic model instead of the stochastic model, Equation (4) is applied for IDA and CO_2 emissions projections as in Sections 3 and 4. Figure 4 shows the results for IDA. 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, as shown in Section 2, applying the unit elasticity of carbon emissions with respect to population or per capita GDP, which is actually higher than 1, results in the reduced scale effect. By the symmetry, the technology effect is calculated higher for the deterministic model than for the stochastic model.

[Insert Figure 4 here]

The difference between the two models is even more significant for emissions projections. As shown in Figure 5, the application of the deterministic model greatly lowers the projected level of carbon emissions compared to the one from the stochastic model. For instance, for the reference scenario, the level of carbon emissions in 2050 is projected to be 30% less for the deterministic model compared to the level projected from the stochastic model. The difference becomes greater for the other stringent policy scenarios. If a society aims for halving 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 for achieving the target if the deterministic Kaya model is used.

[Insert Figure 5 here]

6. Conclusion

The stochastic Kaya model is developed in this paper. From the panel data from 1960 to 2010 it is found that a 1% increase in population, per capita GDP, energy intensity, and fossil-fuel dependence result in 1.03%, 1.05%, 0.67% and 0.58% increase in CO_2 emissions, respectively. This is far (and statistically) different from the unit elasticity as assumed in the deterministic Kaya model. This difference induces a problem for quantifying driving forces of the changes in carbon emissions and for carbon emissions projections: the 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, this is not supported by the stochastic Kaya model.

The Kaya identity has been widely used for policy recommendations about climate policy. However, the deterministic nature of the Kaya model is not supported by empirical data. The stochastic modification of the Kaya model is worthwhile in the following reasons: 1) it retains simplicity; 2) it corrects potential bias in estimating the driving forces of the changes in CO_2 emissions and future emissions projections. Simplicity has value in that currently used models on emissions projections are so complex and demanding that they are not easily accessible and understandable to the general public. In addition, the stochastic Kaya model is easily applicable to other researches according to research purposes. One of the main policy implications we can derive from the applications of the stochastic model is that more efforts than the levels calculated from the deterministic Kaya model are required for our society to achieve the target for emissions reduction (say, 50% reductions by 2050) with economic growth.

Supplementary Results

[Insert Table A.1 here]

[Insert Figure A.1 here]

[Insert Figure A.2 here]

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Table 1 The OLS results

	β	Standard error	VIF
Population	1.030***	.017	1.372
per capita GDP	1.049***	.020	2.274
Energy intensity	.670***	.020	1.507
Fossil-fuel dependence	.575***	.024	1.438

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

Table 2 CO_2 emissions

Country/ Group	CO_2 emission (1990)		CO_2 emission (2010)		Change of emissions (1990-2010)		Kyoto target
	$MtCO_2$	% World emissions	$MtCO_2$	% World emissions	$MtCO_2$	% 1990 emissions	% 1990 emissions
France	371	1.7	370	1.1	-1	-0.4	0.0
Germany	979	4.4	772	2.3	-207	-21.2	-21.0
Italy	404	1.8	404	1.2	-1	-0.1	-6.5
Spain	206	0.9	261	0.8	56	27.0	15.0
UK	573	2.6	493	1.5	-80	-14.0	-12.5
EU	4,109	18.5	3,655	10.9	-454	-11.1	-8.0
Australia	260	1.2	385	1.1	125	48.3	8.0
Canada	425	1.9	511	1.5	85	20.0	-6.0
Japan	1,068	4.8	1,137	3.4	69	6.4	-6.0
US	4,912	22.1	5,586	16.6	674	13.7	n.a.
Annex1	14,054	63.2	13,440	40.0	-614	-4.4	-5.2
Annex1-EIT	3,999	18.0	2,431	7.2	-1,567	-39.2	n.a.
Annex1-nonEIT	10,055	45.2	11,009	32.7	953	9.5	n.a.
Mexico	314	1.4	444	1.3	129	41.1	n.a.
South Korea	247	1.1	568	1.7	321	129.8	n.a.
OECD	11,282	50.8	12,592	37.5	1,309	11.6	n.a.
Brazil	209	0.9	420	1.2	211	100.9	n.a.
China	2,461	11.1	8,287	24.7	5,826	236.8	n.a.
India	691	3.1	2,009	6.0	1,318	190.9	n.a.
World	22,223	100.0	33,615	100.0	11,393	51.3	n.a.

Note: n.a.: not applicable.

Table A.1 Driving forces of CO_2 emissions: 1990-2010

Country/ Group	Driving forces of CO_2 emissions (% 1990 emissions)					Scale (% 1990 emissions)	Technology (% 1990 emissions)	Offsetting ratio (%)*
	Population	GDP per capita	Energy intensity	Renewables	Emission factor			
France	11.0	20.8	-10.2	-8.8	-13.2	31.8	-32.2	101.2
Germany	2.7	24.3	-21.0	-5.3	-21.8	26.9	-48.1	178.6
Italy	6.6	13.8	-3.1	-4.4	-13.1	20.4	-20.5	100.6
Spain	19.8	36.5	-9.8	-1.1	-18.4	56.3	-29.3	52.0
UK	8.0	35.4	-29.1	-1.4	-27.0	43.4	-57.5	132.3
EU	5.7	29.3	-19.5	-5.0	-21.6	35.0	-46.1	131.5
Australia	32.4	47.8	-22.8	0.9	-10.1	80.3	-32.0	39.9
Canada	23.2	30.8	-21.2	-0.2	-12.6	54.1	-34.0	62.9
Japan	3.3	17.0	-4.2	-2.6	-7.1	20.3	-13.9	68.3
US	23.6	30.8	-24.6	-1.6	-14.4	54.4	-40.7	74.8
Annex1	9.2	30.4	-22.2	-2.9	-18.8	39.6	-43.9	111.0
Annex1-EIT	-4.4	25.0	-28.4	-2.7	-28.8	20.6	-59.8	290.1
Annex1-nonEIT	15.2	28.0	-17.2	-2.4	-14.1	43.2	-33.7	78.1
Mexico	38.7	25.3	-11.0	1.7	-13.6	64.0	-22.9	35.8
S. Korea	22.8	140.0	-1.0	-1.0	-31.0	162.8	-33.0	20.3
OECD	16.4	29.0	-16.6	-2.3	-15.0	45.5	-33.9	74.5
Brazil	39.6	51.6	3.3	3.6	2.9	91.2	9.8	-10.7
China	33.0	373.1	-121.1	16.5	-64.7	406.0	-169.3	41.7
India	60.3	176.7	-53.1	27.7	-20.7	237.0	-46.1	19.5
World	33.9	33.5	-12.1	0.1	-4.2	67.4	-16.2	24.0

Note: * The ratio of the technology effect to the scale effect is defined as the offsetting ratio, following Bacon and Bhattacharya (2007). Therefore the offsetting ratio above 100% means that CO_2 emissions from the scale effect were fully offset by the technology effect. The shaded cells highlight the countries or groups in which CO_2 emissions are reduced compared to the 1990 levels. The negative offsetting ratios for some countries were originated from technological deterioration.

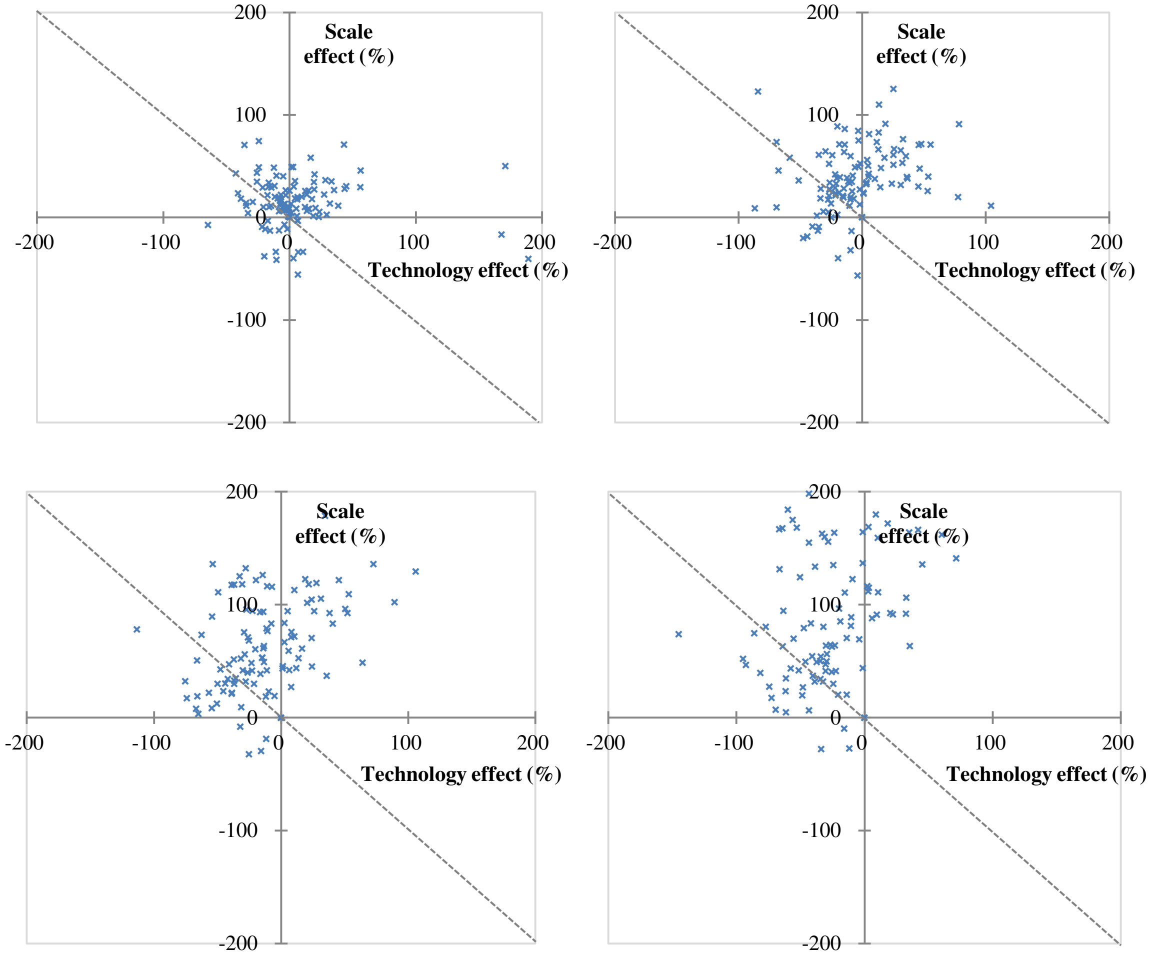


Figure 1 IDA Results (Top left panel): 1990-1995. **(Top right panel):** 1990-2000. **(Bottom left panel):** 1990-2005. **(Bottom right panel):** 1990-2010.

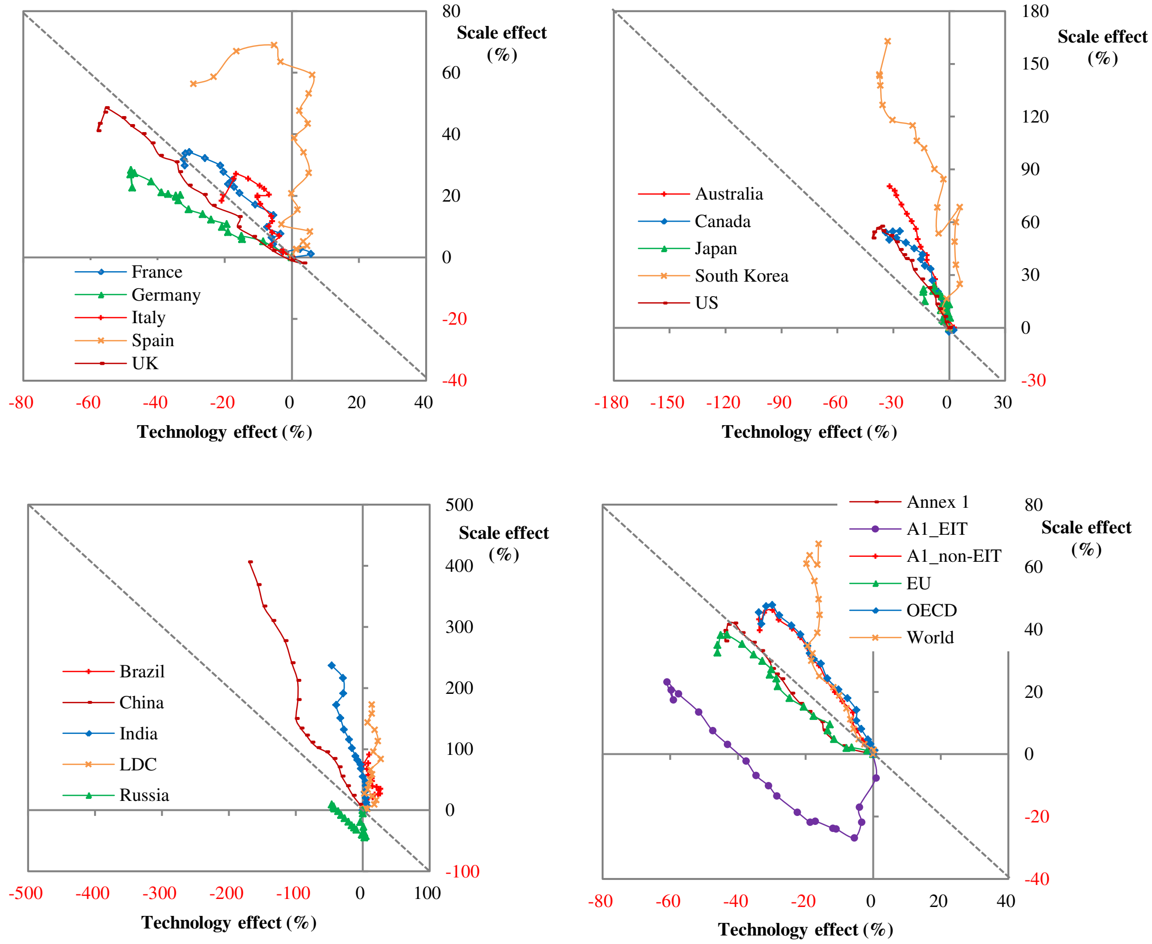


Figure 2 Chained IDA results for selected countries: 1990-2010 (Top left panel): non-EIT European countries. **(Top right panel):** non-EU OECD members. **(Bottom left panel):** Emerging economies, Russia and LDC (least developed countries: UN classification). **(Bottom right panel):** Group.

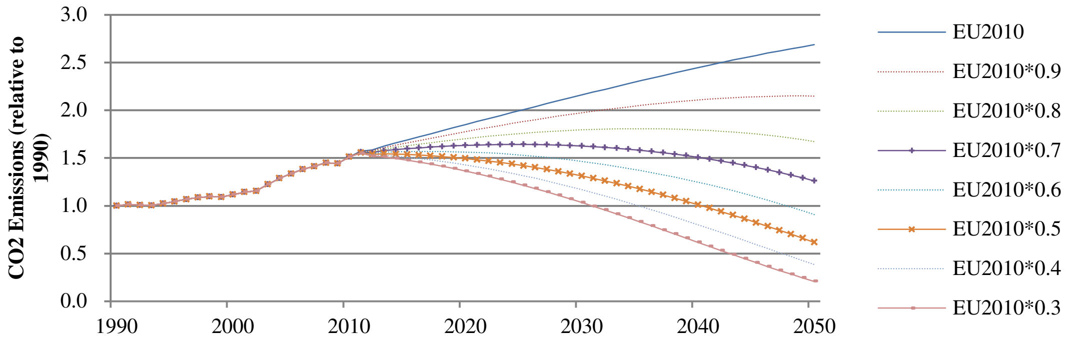


Figure 3 Global CO_2 emissions projections (2011-2050)

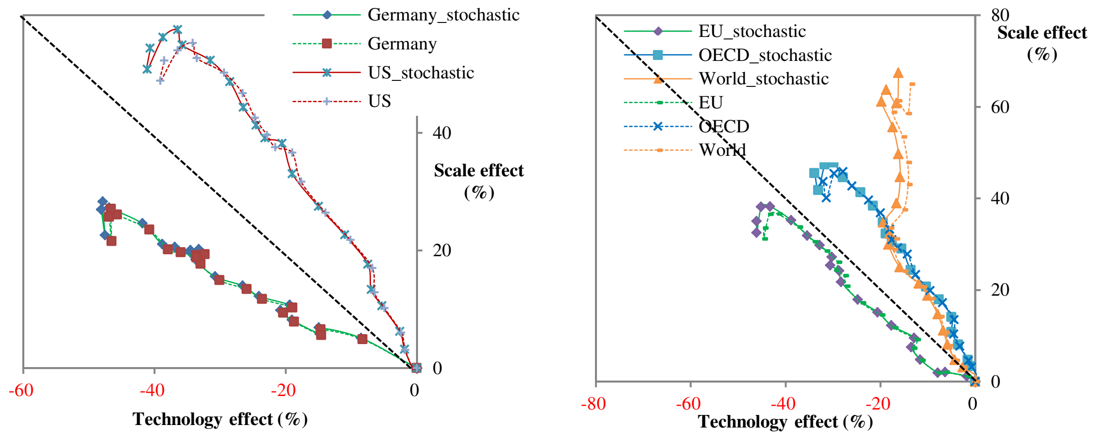


Figure 4 Comparison of IDA results Stochastic refers to the case where the stochastic Kaya model is applied, whereas the others refer to the case where the deterministic model is applied.

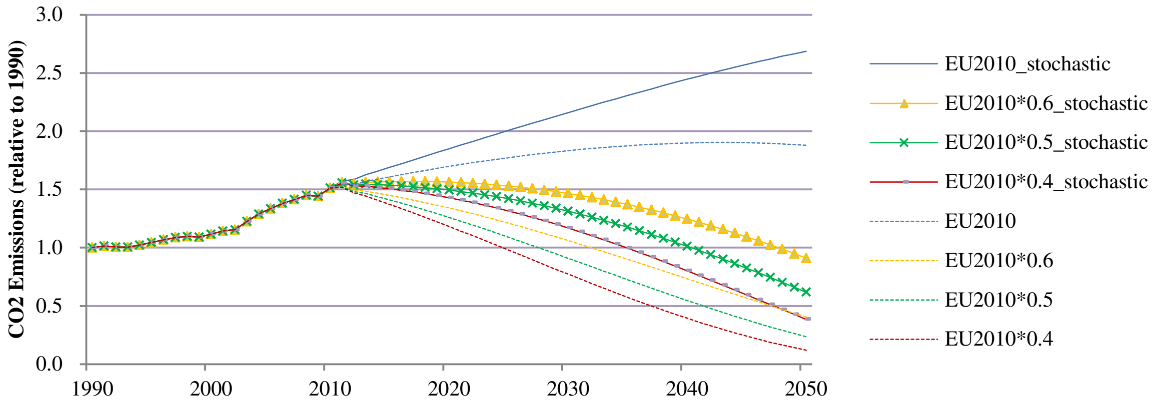


Figure 5 Comparison of emissions-projections. Stochastic refers to the case where the stochastic Kaya model is applied, whereas the others refer to the case for the deterministic model.

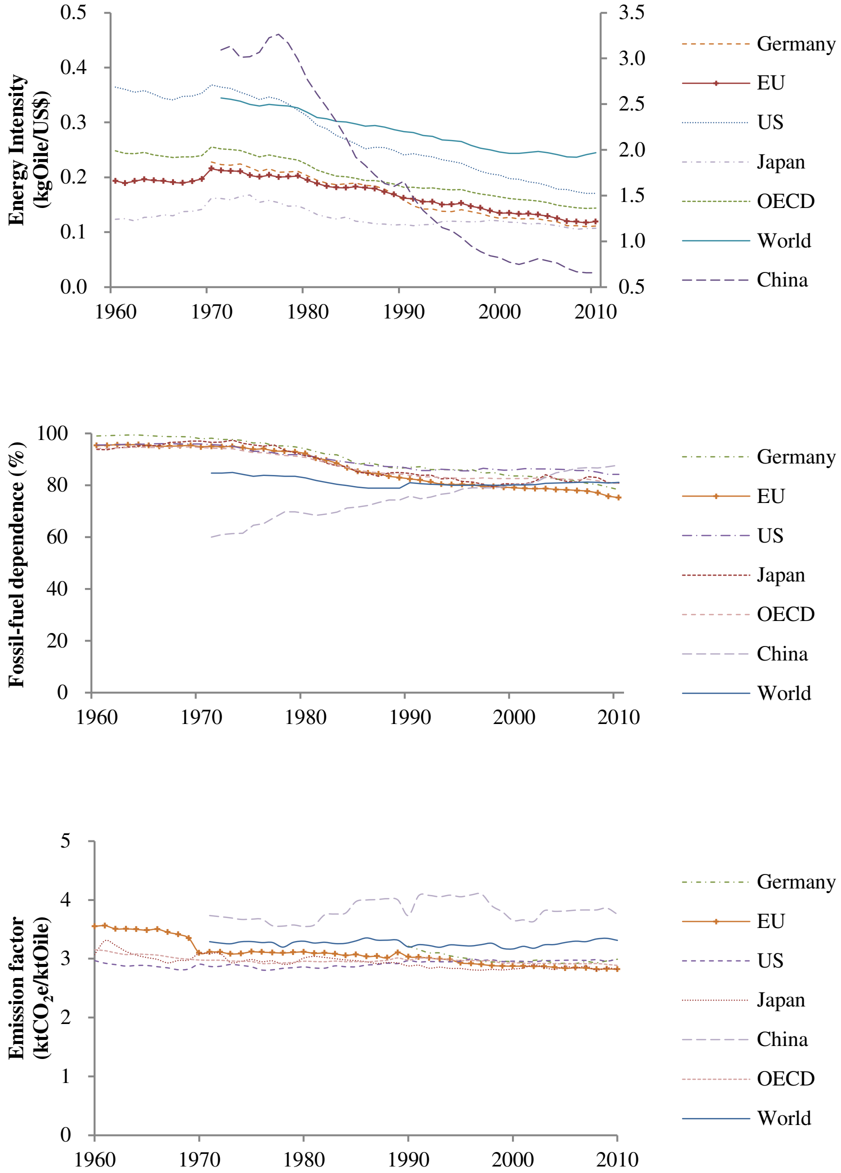
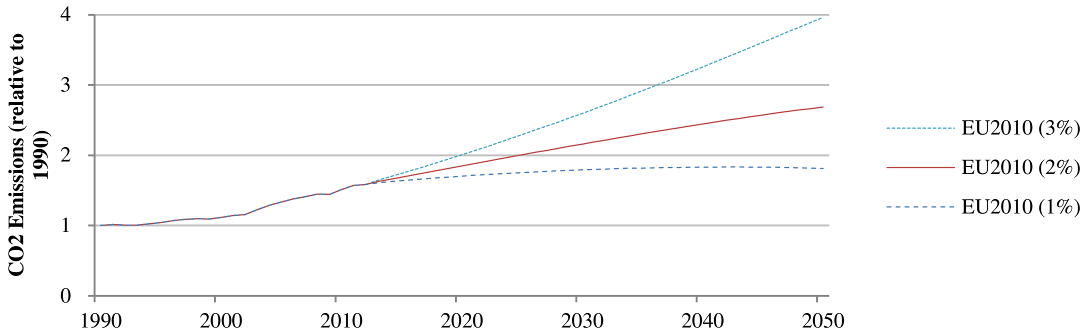


Figure A.1 Trend of technology indicators for some selected countries: 1960-2010 (Top panel): Energy intensity. The right axis is for China. **(Middle panel):** Fossil-fuel dependence. **(Bottom panel):** Emission factor. For data source see Section 2.



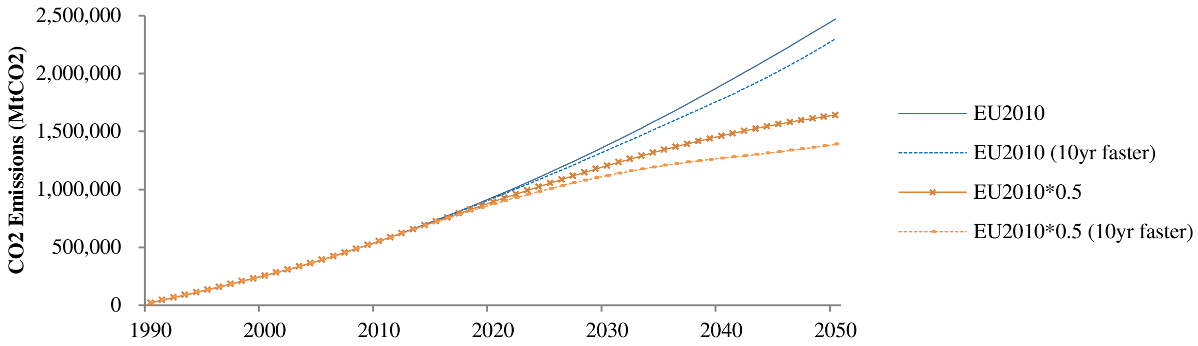


Figure A.2 Global CO_2 emissions trajectory: 1990-2050 (sensitivity analysis) (Top panel): Sensitivity to the growth rate of per capita GDP (3%/yr, 2%/yr, 1%/yr). **(Bottom panel):** Sensitivity to the rate of technological improvements. The growth rate of per capita GDP is assumed to be 2%/yr.