# A Multi-Model Regional Decomposition of $CO_2$ Emissions: Socio-Economic Developments vs Energy Efficiency and Carbon Intensity Improvements

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**Abstract**

This study explores the regional distribution of total $CO_2$ emissions.
Kaya and Yokoburi (1997) decompose carbon dioxide emissions into 4 components, namely Population, GDP per capita, Energy Efficiency and Carbon Intensity. Using the Long Mean Divisia Index (LMDI) and the Refined Laspeyres Decomposition (RLD), the purpose of the paper is to quantitatively analyze how those components affect total $CO_2$ emissions for different regions of the world, over time and across different socio-economic scenarios. In particular, socio-economic scenarios considered to perform this analysis are the 5 SSPs developed by National Center for Atmospheric Research (NCAR).
The reason of that is to determine the implications of each of the 4 drivers in evaluating the impacts of climate policies on global and regional economic systems and exploring the differences between short-term (2010-2030), medium-term (2010-2050) and long-run (2010-2100) effects.
By drawing data from the IIASA Database, this study considers 6 Integrated Assessment Models used to analyze climate mitigation and impact of different policies in regional economic systems, i.e. AIM-CGE, REMIND, MESSAGE, GCAM, IMAGE and WITCH and by making use of the Principal Component Analysis it evaluates their performances in explaining regional $CO_2$ variations, and in which degree they differ.

The main findings of this study are the following:
- Index Decomposition Analysis suggests a convergence and eventually divergence in total $CO_2$ emissions for developing countries with respect to the advanced economies. This is mainly due to more robust GDP per capita and Population growth rates relatively to those shown by the USA and Europe.
- GDP per capita and Population are shown to have a positive impact on total $CO_2$ emissions, in particular for developing regions. Energy Efficiency, in contrast, is the main determinant in dragging down total $CO_2$ emissions variations across different economic scenarios. This is valid for all regions considered expect for Latin America Countries in which decarbonization plays the biggest role.
- While the impact of Energy Efficiency is more stagnant over time, the pattern shown by the Carbon Intensity Effect suggests an increasing trend over the course of the years. Nevertheless the implications of such components differ from region to region and scenario considered.

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- Principal Component Analysis suggests that although the 6 models achieved a considerable degree of homogeneity, the main source of difference stems from the components of Primary Energy(i.e. Fossil, Biomass, Nuclear and Non Biomass Renewables), while showing a similar pattern for Carbon Intensity, Population and GDP per capita. In particular IMAGE and MESSAGE incorporate more optimistic assumptions on total $CO_2$ variation in the short-term relatively to WITCH, GCAM, AIM and REMIND.

# 1. Introduction

The classification of different economic scenarios has always been a crucial point in comparing macroeconomic models which have as main purpose that to evaluate the impact of climate policies on global and regional economic systems and to analyze the optimal response of these economies to climate change.

In particular the SRES scenarios have so far been used widely in climate modeling. They are the basis for assumptions of future development in the two latest publications by IPCC (TAR, 2001 and AR4, 2007). For the Fifth assessment report (AR5, due in 2014) new types of scenarios have been developed, called the SSP and RCP scenarios, respectively.

The SRES scenarios are described in the IPCC Special Report on Emission Scenarios (2000). There are 40 different scenarios, each making different assumptions for future greenhouse gas pollution, land-use and other driving forces. Assumptions about future technological development as well as the future economic development are thus made for each scenario. These emissions scenarios are organized into families, A1, A2, B1, B2, which contain scenarios that are similar to each other in some respects.

*The four main SRES categories. A2 and B2 were the main scenarios used in the IPCC Third Assessment Report (TAR, 2001) and later A1B has been the most common scenario. A1FI is the most extreme scenario regarding emission rate.*

The A1 storyline and scenario family describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity building and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil-intensive (A1FI), non-fossil energy sources (A1T) or a balance across all sources (A1B) (where balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end use technologies).

The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing population. Economic development is primarily regionally oriented and per capita economic growth and technological change more fragmented and slower than other story lines.

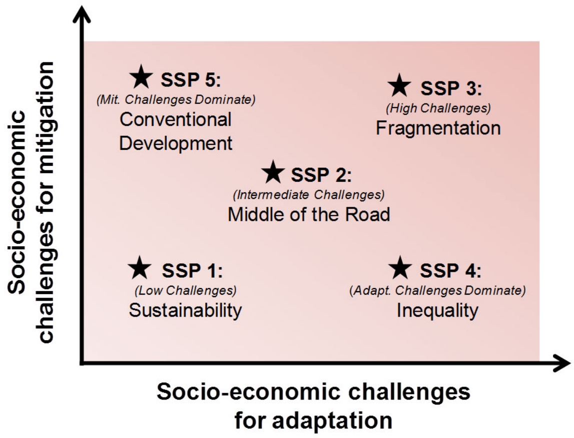
The B1 storyline and scenario family describes a convergent world with the same global population, that peaks in mid-century and declines thereafter, as in the A1 storyline, but with rapid change in economic structures toward a service and information economy, with reductions in material intensity and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social and environmental sustainability, including improved equity, but without additional climate initiatives.

The B2 storyline and scenario family describes a world in which the emphasis is on local solutions to economic, social and environmental sustainability. It is a world with continuously increasing global population, at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 story lines. While the scenario is also oriented towards environmental protection and social equity, it focuses on local and regional levels. The SRES scenarios do not include additional climate initiatives, which means that no scenarios are included that explicitly assume implementation of the United Nations Framework Convention on Climate Change or the emissions targets of the Kyoto Protocol.

## 1.1 SSP and RCP scenarios

The RCP (Representative Concentration Pathways) scenarios are a new set of scenarios defined in terms of radiative forcing. They work both forwards towards climate modeling and backwards to analyse what future world development is needed to achieve a certain level of anthropogenic influence on the climate. They are associated with Shared Socioeconomic Pathways (SSPs) matrix wise.

The new SSPs are stretched again along two major development axes, as conceptualized in the graph below. For SSPs these axes correspond to the intensity of climate policies that will be necessary in the future, either to prevent a certain level of climate change (mitigation on the vertical axis), and/or to cope with a certain level of climate change (adaptation on the horizontal axis). These SSP in turn are driven or at least affected by Shared Policy Assumptions (SPAs). Climate policy scenarios are derived by combining an SSP and SPA (e.g. a set of climate policies designed to achieve a given RCP level), and, possibly, climate change projections. Because GDP and other variables would be affected by the climate policies and climate change impacts, model outputs would replace reference SSP assumptions when and where they were significantly different.




As with the RCPs, IIASA is hosting the SSP database. The five narratives are:

SSP1 (Sustainability). A world making relatively good progress toward sustainability, with ongoing efforts to achieve development goals while reducing resource intensity and fossil fuel dependency. It is an environmentally aware world with rapid technology development, and strong economic growth, even in low-income countries.

SSP2 (Middle of the road). This business-as-usual world sees the trends typical of recent decades continuing, with some progress toward achieving development goals. Dependency on fossil fuels is slowing decreasing. Development of low-income countries proceeds unevenly.

SSP3 (Fragmentation). A world that is separated into regions characterized by extreme poverty, pockets of moderate wealth, and a large number of countries struggling to maintain living standards for a rapidly growing population.

SSP4 (Inequality). A highly unequal world in which a relatively small, rich global elite is responsible for most of the greenhouse gas emissions, while a larger, poor group that is vulnerable to the impact of climate changes, contributes little to the harmful emissions. Mitigation efforts are low and adaptation is difficult due to ineffective institutions and the low income of the large poor population.

SSP5 (Conventional Development). A world in which conventional development oriented toward economic growth as the solution to social and economic problems. Rapid conventional development leads to an energy system dominated by fossil fuels, resulting in high greenhouse gas emissions and challenges to mitigation.

For what concerns the regions chosen, these are 5, namely R5ASIA[1], R5MAF[2], R5LAM[3], EUROPE and the USA.

Finally the 6 models which we have taken into consideration are AIM/CGE (henceforth AIM), a general equilibrium model with technology explicit modules in power section, it is developed by the National Institute for Environmental Studies of Kyoto University Fujimori et al. (2011) ; Global Change Assessment Model (henceforth GCAM) a dynamic-recursive model with technology-rich representations of the economy, energy sector, land use and water linked to a climate model of intermediate complexity that can be used to explore climate change mitigation policies including carbon taxes, carbon trading, regulations and accelerated deployment of energy technology, Edmonds et al. (1997); IMAGE, a bottom-up integrated assessment simulation model covering energy, land use and water, it is developed by the PBL Netherlands Environmental Assessment Agency of Utrecht University, Rotmans (1990); REMIND a hybrid model developed by the Postdam Institute for Climate Impact Research which couples an economic growth model with a detailed energy system model and a simple climate model, Leimbach et al. (2010); MESSAGE, a hybrid model developed by the IIASA that can be best described as an energy engineering partial equilibrium model soft-linked to general equilibrium model, Strubegger et al. (2004); and WITCH, an economic optimal growth model which includes a bottom-up energy sector and a simple climate model, embedded in a game theoretic setup, Bosetti et al. (2006).

As previously clarified this study aims are manifold.

In particular the first objective is that to explore in a descriptive way the contribution of Population, Gross Domestic Product per capita, Energy Efficiency and Carbon Intensity in explaining the average growth rates of total $CO_2$ from 2010 to 2100 for the five aforementioned regions of the world and for each of the five socio-economic scenarios.

[1]The region includes most Asian countries with the exception of the Middle East, Japan and Former Soviet Union states. Afghanistan, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, China, Hong Kong SAR, Macao SAR, Democratic People's Republic of Korea, Fiji, French Polynesia, India, Indonesia, Lao People's Democratic Republic, Malaysia, Maldives, Micronesia (Fed. States of), Mongolia, Myanmar, Nepal, New Caledonia, Pakistan, Papua New Guinea, Philippines, Republic of Korea, Samoa, Singapore, Solomon Islands, Sri Lanka, Taiwan, Thailand, Timor-Leste, Vanuatu, Viet Nam

[2]This region includes the countries of the Middle East and Africa. Algeria, Angola, Bahrain, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Cte d'Ivoire, Democratic Republic of the Congo, Djibouti, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Iran (Islamic Republic of), Iraq, Israel, Jordan, Kenya, Kuwait, Lebanon, Lesotho, Liberia, Libyan Arab Jamahiriya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mayotte, Morocco, Mozambique, Namibia, Niger, Nigeria, Occupied Palestinian Territory, Oman, Qatar, Rwanda, Runion, Saudi Arabia, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Syrian Arab Republic, Togo, Tunisia, Uganda, United Arab Emirates, United Republic of Tanzania, Western Sahara, Yemen, Zambia, Zimbabwe

[3]This region includes the countries of Latin America and the Caribbean. Argentina, Aruba, Bahamas, Barbados, Belize, Bolivia (Plurinational State of), Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, French Guiana, Grenada, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Jamaica, Martinique, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, United States Virgin Islands, Uruguay, Venezuela (Bolivarian Republic of)

After gaining a first insight on what affects what, we then aim at exploit the conclusions drawn by Foster, De Cian et al.(2013) across different regions, models and economic scenarios.
In particular Foster, De Cian et al.(2013) by utilizing a LMDI for European mitigation scenarios, conclude that Energy efficiency is the most important factor in explaining the emission variations over time, while Carbon intensity has a crucial role in the long term.

By extending those results we also compare the emissions trends across different regions of the world and show a clear convergence/divergence pattern between developing regions and advanced ones while studying the determinants of such a convergence.

Additionally we evaluate the performance of each of the model considered in our analysis by making use of the Principal Component Analysis. In particular we also study their differences in evaluating each of the 2 endogenous variables (Carbon Intensity and Energy Efficiency)

To answer to the questions discussed above, the study is structured as follows: Section 2 sets up the IPACT identity in which $CO_2$ is decomposed into 4 components, namely Population, GDP per capita, energy intensity and carbon efficiency. Moreover, a discussion over the Decomposition Methods used is provided. In Section 3 the Log Mean Divisia Index (LMDI) decomposition of $CO_2$ variations over time, across the five regions and SSPs is explained. Section 4 analyses the conclusions that can be drawn from the LMDI for all five socio economic scenarios. Moreover a robustness check is performed by making use of the RLD method, Ang and Liu (2001) . In Section 5, we deal with the use of Principal Component Analysis in order to quantitatively assess the main source of uncertainty among the six models considered. Finally section 6 concludes the paper highlighting the contribution of each factor in explaining $\Delta CO_2$ over time and across socio economic scenarios. And a general overview over the similarities and differences among models in assessing the components of Primary Energy Consumption is provided.

# 2. Methodology

In this section we study regional patterns of $CO_2$ emissions explained by each model.

We conduct a decomposition of $CO_2$ emissions making use of the IPACT identity that Ehrlich and Holdren (1972) introduced.
First we explain the significance of the identity and each of its drivers:

- I, that is the variable on the left hand side of the identity represents the environmental impact, in our case the emissions of $CO_2$. The dimensions of the left hand side must be identical to those of the right hand side.
- P stands for Population and therefore evaluates the effect of the number of people on total emissions of $CO_2$.
- A represents Gross Domestic Product per person (for a particular region of the world or for the entire world). This measures the environmental impact of what each person produces over a defined period of time.
- C is the intensity of energy usage per total GDP. In other words this tells us how much energy is consumed with a unit of GDP.
- T implies the ratio of environmental impact to the amount of energy consumed. This ratio is named 'Carbon Efficiency' since engineers and industries can affect the this force by producing, inventing and patenting new technologies which affect the total carbon emission given 1 unit of energy consumed.

Therefore we have 4 different *forces*, namely *population*, *economy*, *energy intensity* and *carbon efficiency* that are represented as follows:

$$CO_2 = POP * \frac{GDP}{POP} * \frac{PE}{GDP} * \frac{CO_2}{PE}$$

Theoretically a difference in an aggregate indicator can be decomposed into the sum of the effects by differences in explaining factors and residual terms Ang (2000). Therefore changes of $CO_2$ between time $t$ and $t-n$ is defined as the sum of the differences of each of the drivers and a residual term:

$$\begin{aligned} CO_{2_t} - CO_{2_{t-n}} = (POP_t - POP_{t-n}) + \left(\frac{GDP_t}{POP_t} - \frac{GDP_{t-n}}{POP_{t-n}}\right) + \\ + \left(\frac{PE_t}{GDP_t} - \frac{PE_{t-n}}{GDP_{t-n}}\right) + \left(\frac{CO_{2_t}}{PE_t} - \frac{CO_{2_{t-n}}}{PE_{t-n}}\right) + (res_t - res_{t-n}) \end{aligned}$$

That can be rewritten as follows[4]:

$$\Delta CO_2 = \Delta POP + \Delta\left(\frac{GDP}{POP}\right) + \Delta\left(\frac{PE}{GDP}\right) + \Delta\left(\frac{CO_2}{PE}\right) + \Delta res$$

As mentioned, a wide range of methodologies are available to perform an Index Decomposition Analysis, Ang and Zhang (2000). One of the most crucial choices is to determine the most suitable

[4]According to index decomposition theory, there are two different ways to express such a difference: the additive and multiplicative methods, Ang (2004). The RLD method has only been studied with an additive method. While in the multiplicative method, a difference is given by $\Delta CO_2 = \frac{CO_{2_t}}{CO_{2_{t-n}}} = \frac{\sum_i^n CO_{2_t i}}{\sum_j^n CO_{2_t j}} = \Delta POP \Delta \frac{GDP}{POP} \Delta \frac{PE}{GDP} \Delta \frac{CO_2}{PE}$. Since the approaches between the two methods are similar we will focus only on the additive method.

decomposition formula. Hence we will briefly go over the methods available and their respective advantages and disadvantages.

In particular the methods that are used to perform a decomposition analysis can the grouped in the non-exhaustive[5] following list:

- Refined Laspeyres Decomposition (RLD)
- Paasche index
- Simple average divisia method (arithmetic mean or Trnqvist formulation)
- Fischer Ideal
- Parametric Divisia Method I (PMD I) and II (PMD II)
- Log Mean Divisia Index (LMD)

Ang and Zhang (2000) explain the fundamental idea behind the Index Decomposition Analysis, i.e. that to compute the impact determined by each factor on the dependent variable. In our case, the factors that have positive numbers impose positive effects on the difference of total variation of $CO_2$ emissions.

The following Table summarizes the main characteristics of the aforementioned methods:

| INDEX | PERFECT DECOMPOSITION | EASINESS TO UNDERSTAND |
|---|---|---|
| Refined Laspeyres Method (RLD) | YES | YES |
| Paasche Index | NO | NO |
| Simple Average Divisia Method | NO | YES |
| Fischer Ideal | YES | NO |
| Pareametric Divisia Method I (PMD I) and II (PMD II) | NO | NO |
| Log Mean Divisia Index (LMD) | YES | YES |

More specifically a decomposition method without a residual term is described to be 'perfectly decomposable' i.e. $\Delta_{res} = 0$.
Among the above listed methodologies, RLD developed by Sun(1998) and the LMDI by Ang and Liu(2001) are the ones with a residual term equal to zero, in other words 'perfectly decomposable' as in Ang (2004).

The decomposition methods used to perform the analysis are the Log Mean Divisia Index (LMDI) and the Refined Laspeyres Decomposition Method (RLD). We have chosen them since their easiness to use, for allowing the easy interpretation of results and for being perfectly decomposable, meaning

[5] Since Ang and Zhang (2000) listed more than 100 decomposition methodologies in energy and environmental studies

that the residual effect is null (Ang 2004).
In particular, the Refined Laspeyres Index (RLD) method has been only used through an additive approach so far Ang (2000).

As regard to the RLD the quantitative contribution of each factor to the difference in $CO_2$ emissions between two different vintages ($t$ and $t-n$) is given by:

$$\Delta CO^j_{2_{ti}} = CO^j_{2_{ti}} - CO^j_{2_{(t-n)i}} = \left( POP^j_{ti} \frac{GDP^j_{ti}}{POP^j_{ti}} \frac{PE^j_{ti}}{GDP^j_{ti}} \frac{CO^j_{2_{ti}}}{PE^j_{ti}} \right) - \left( POP^j_{(t-n)i} \frac{GDP^j_{(t-n)i}}{POP^j_{(t-n)i}} \frac{PE^j_{(t-n)i}}{GDP^j_{(t-n)i}} \frac{CO^j_{2_{(t-n)i}}}{PE^j_{(t-n)i}} \right) \tag{1}$$

Where $i$ stands for the region of the world considered and $j$ for the socio-economic scenario in the decomposition analysis.

Therefore rewriting $X_t - X_{t-n} = \Delta X$ the RLD can be stated as follows:

Concerning the LMDI, Sato (1976) and Vartia (1976) independently introduced a new weight formula which gives to the index some desirables properties. This formula uses the logarithmic mean function, which is represented as follow.

$$L(a,b) = \left( \frac{a-b}{ln(a) - ln(b)} \right)$$

It is a symmetrical function whose properties are presented in detail in Sato (1976) therefore the LMDI adopted to our specific framework is described in the following formula for each region $i$ and scenario $j$:

$$\Delta CO^j_{2i} = \Delta POP^j_i + \Delta \frac{GDP^j_i}{POP^j_i} + \Delta \frac{PE^j_i}{GDP^j_i} + \Delta \frac{CO^j_{2i}}{PE^j_i} \tag{2}$$

where each factor is contributing to the $CO_2$ variations over time as follows:

$$\Delta POP^j_i = \left( \frac{CO^j_{2_{ti}} - CO^j_{2_{(t-n)i}}}{ln(CO^j_{2_{ti}}) - ln(CO^j_{2_{(t-n)i}})} \right) \frac{ln(POP^j_{ti})}{ln(POP^j_{(t-n)i})} \tag{3a}$$

$$\Delta \frac{GDP^j_i}{POP^j_i} = \left( \frac{CO^j_{2_{ti}} - CO^j_{2_{(t-n)i}}}{ln(CO^j_{2_{ti}}) - ln(CO^j_{2_{(t-n)i}})} \right) \frac{ln\left(\frac{GDP^j_{ti}}{POP^j_{ti}}\right)}{ln\left(\frac{GDP^j_{(t-n)i}}{POP^j_{(t-n)i}}\right)} \tag{3b}$$

$$\Delta \frac{PE^j_i}{GDP^j_i} = \left( \frac{CO^j_{2_{ti}} - CO^j_{2_{(t-n)i}}}{ln(CO^j_{2_{ti}}) - ln(CO^j_{2_{(t-n)i}})} \right) \frac{ln\left(\frac{PE^j_{ti}}{GDP^j_{ti}}\right)}{ln\left(\frac{PE^j_{(t-n)i}}{GDP^j_{(t-n)i}}\right)} \tag{3c}$$

$$\Delta \frac{CO^j_{2_i}}{PE^j_i} = \left( \frac{CO^j_{2_{ti}} - CO^j_{2_{(t-n)i}}}{ln(CO^j_{2_{ti}}) - ln(CO^j_{2_{(t-n)i}})} \right) \frac{ln\left(\frac{CO^j_{2_{ti}}}{PE^j_{ti}}\right)}{ln\left(\frac{CO^j_{2_{(t-n)i}}}{PE^j_{(t-n)i}}\right)} \tag{3d}$$

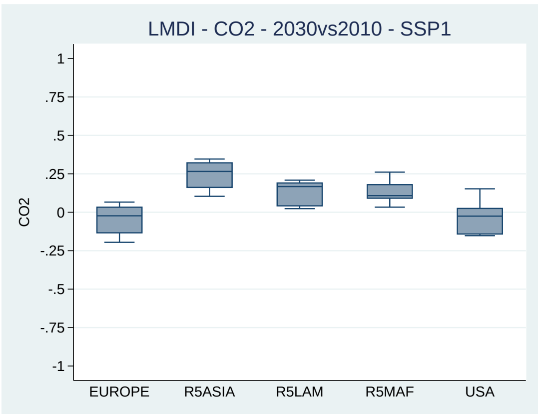
## 3. $CO_2$ regional variation decomposition: over time and across scenarios

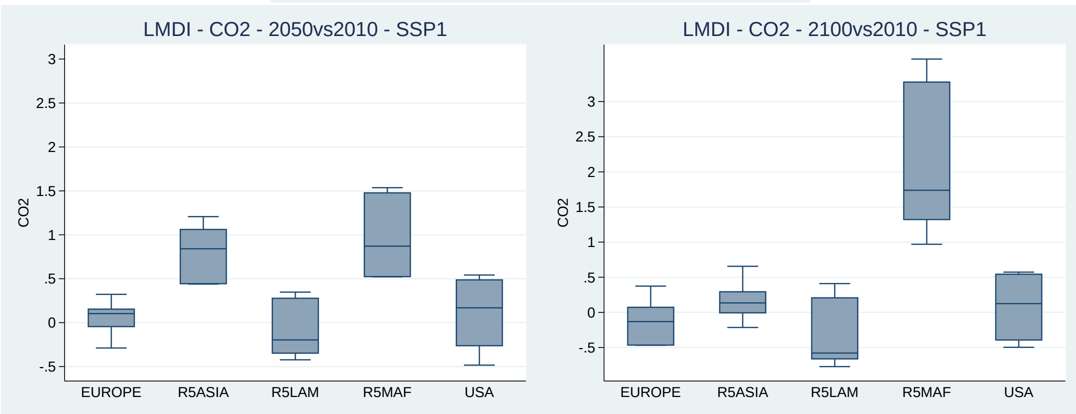
### 3.1. SSP1 - 2030 vs 2010, 2050 vs 2010 and 2100 vs 2010

First of all we study the contribution of each driver of the IPACT identity in explaining the regional difference over time, considering all the 6 models as a whole.

We perform the decomposition by using the LMDI method. In particular, below we show the results of the pairwise comparison: 2030 against 2010, 2050 against 2010 and 2100 against 2010 for SSP1.
The SSP1 is considered as a socio economic scenario which predicts a more sustainable path, and it is characterized as follows:

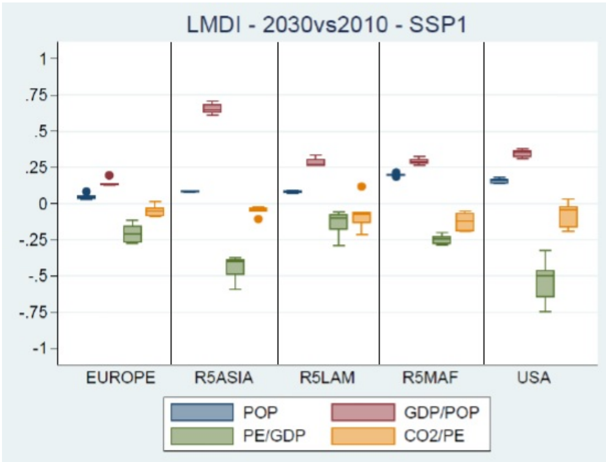
- Most Optimistic Scenario in terms of Challenges to Mitigation and Adaptation
- Rapid Technology
- High Environmental Awareness
- Low Energy Demand
- Medium-High Economic Growth
- Low Population

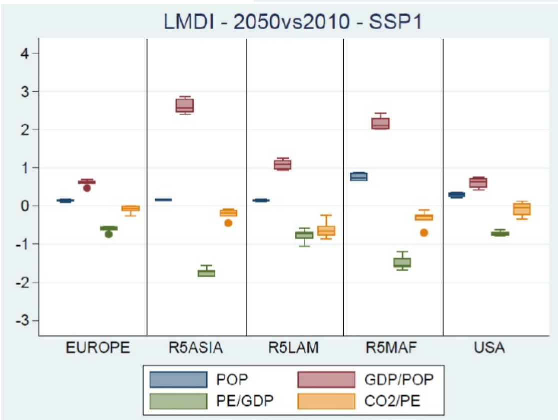


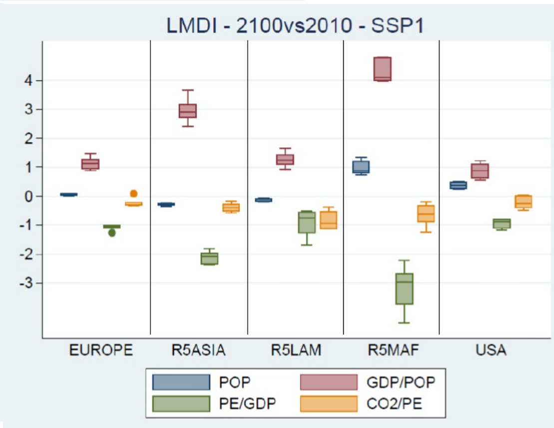




From the analysis of regional $\Delta CO_2$ over time, we deduce that R5MAF countries will experience a greater increase in $CO_2$ emissions over time than the other regions considered. This is largely due to an increase in GDP per capita.
Moreover Europe, USA and R5LAM will manage, in this socio economic scenario, to keep $CO_2$

emissions constant over time. This is partially due to a slow population growth amd GDP per capita. Lower growth of primary energy demand relatively to that of GDP will also play a large role on pushing down $CO_2$ emissions for R5LAM.
Below we also report the LMDI regional decomposition which show the contribution played by each factor in describing the total $CO_2$ emissions variations.




Firstly we notice that although developing regions will be more energy efficient and less carbon intensive during the next 50 years, the fast growing GDP per capita and Population will lead to a substantial increase in total $CO_2$ emissions.
These relatively high rates of economic indicators suggest a convergence first and a divergence later in terms of $CO_2$, with emissions in developed countries set to increase substantially more relatively to those that advanced regions will experience.

To show that, we compute the growth rate of $CO_2$ and its drivers relatively to those of the USA over the period 2010-2050.

Divergence Decomposition relatively to USA 2010-2050

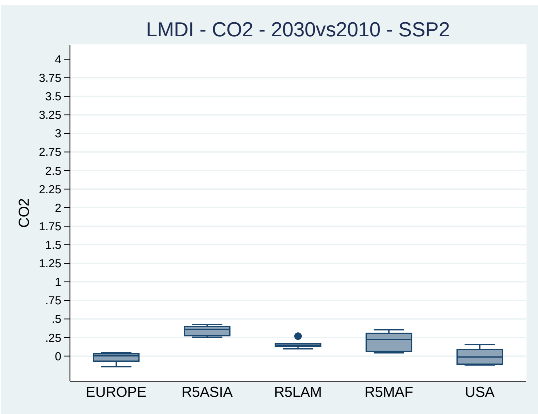
| Country | Total | POP | GDP/POP | PE/GDP | CO2/PE |
|---|---|---|---|---|---|
| R5 ASIA | 0.6323554 | -0.14871 | 1.30221746 | -0.4354228 | -0.08573 |
| R5 MAF | 0.7266159 | 0.286576 | 0.90378093 | -0.2902565 | -0.17348 |
| R5LAM | -0.2126018 | -0.12533 | 0.48114518 | -0.0907106 | -0.4777 |

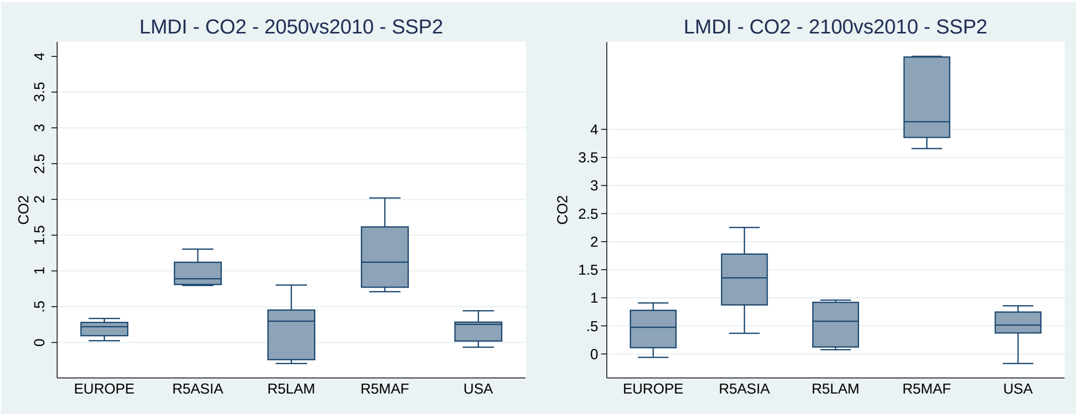
More in particular, R5ASIA and R5MAF regions show an increase in growth rates of $CO_2$ relatively to that of USA for the period 2010-2050, this is mainly due to an increase of GDP per capita in these regions which doubles that of the USA, while they will experience Energy improvements and less intensity of Carbon.
However this is not the case of the other developing region, namely R5LAM which thanks to a relative high rate of carbonization and less GDP per capita growth will show a minor average growth of total $CO_2$ emissions with respect to that of the USA.

### 3.2. SSP2 - 2030 vs 2010, 2050 vs 2010 and 2100 vs 2010

We perform the decomposition by using the LMDI method. In particular, below we show the results of the pairwise comparison: 2030 against 2010, 2050 against 2010 and 2100 against 2010 for SSP2.
The SSP2 scenarios is considered as the middle of the road and often used to perform comparative studies. It is indeed characterized as follows:

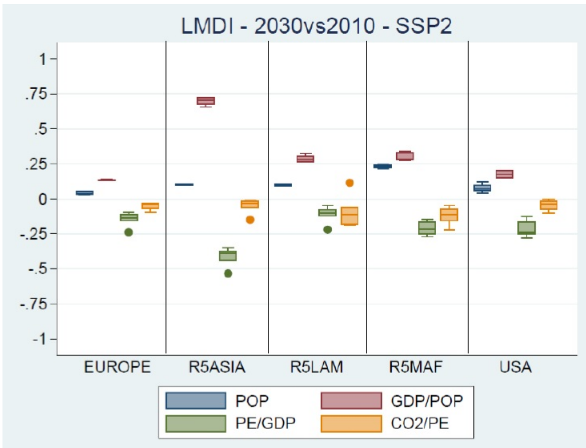
- Medium Technology Growth
- Environmental Awareness
- Medium Energy Demand
- Medium Economic Growth
- Medium Population Growth

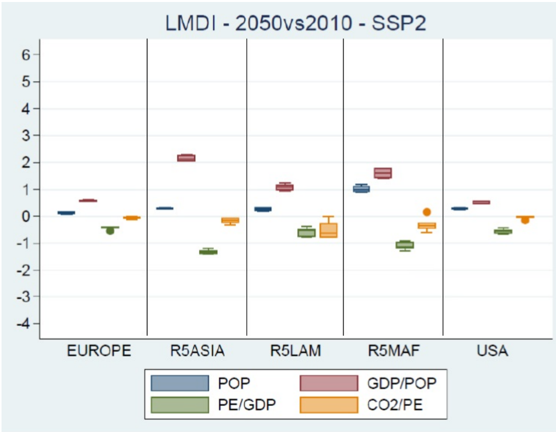


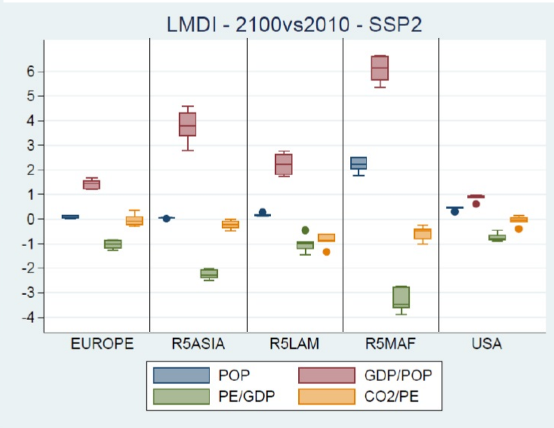



In such framework, R5ASIA and R5MAF countries will experience the same $\Delta CO_2$ for the period 2010-2050. After 2050 a divergence is shown, largely due to a greater impact of Population growth (+100% on 2010) and GDP per capita (+200% on 2010) on R5MAF carbon dioxide emissions.
Europe, USA and R5LAM $\Delta CO_2$ will once again manage to keep, in this socio economic scenario, $CO_2$ emissions constant over time. This partially due to a slow population growth and GDP per capita.
Finally, Energy Efficiency will play the largest role in pushing $CO_2$ emissions down over time, while Population growth will be modest especially in Europe where the number of inhabitants in 2100 is set to be same of 2010.

Below we also report the LMDI regional decomposition which show the contribution played by each factor in describing the total $CO_2$ emissions variations.





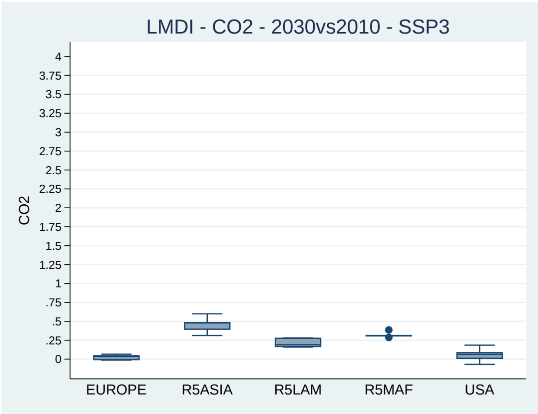


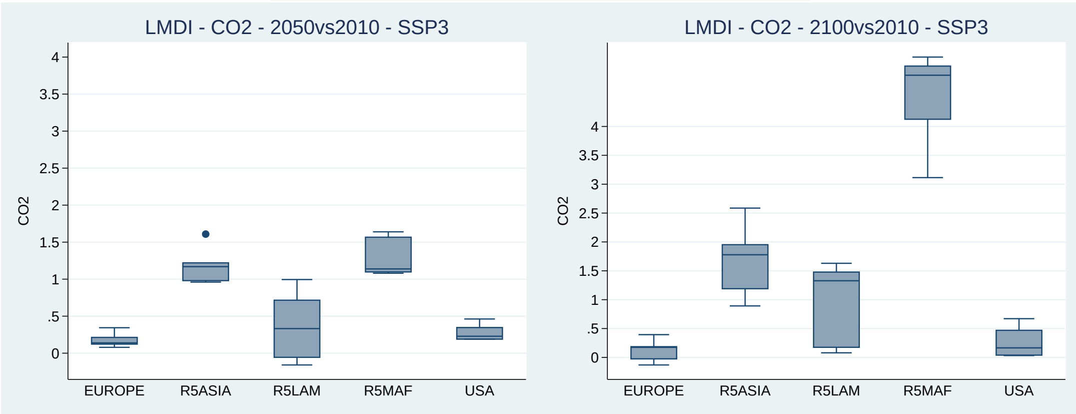

Note that in this framework R5ASIA will be the most energy efficient among the regions considered. This is largely due to a remarkable increase in GDP per capital while at the same time controlling Primary Energy Consumption over time.
On the other hand very little it will be done in terms of Carbon Intensity. This is shown by the fact that USA, Europe and R5ASIA in 2100 will pollute the same amount of $CO_2$ 0f 2010 relatively to the Primary Energy Consumed.

### 3.3. SSP3 - 2030 vs 2010, 2050 vs 2010 and 2100 vs 2010

We perform the decomposition by using the LMDI method. In particular, below we show the results of the pairwise comparison: 2030 against 2010, 2050 against 2010 and 2100 against 2010 for SSP3.
The SSP3 scenarios is considered as the model that predicts fragmentation, namely a financially troubled world and very low environmental awareness. The latter is characterized as follows:

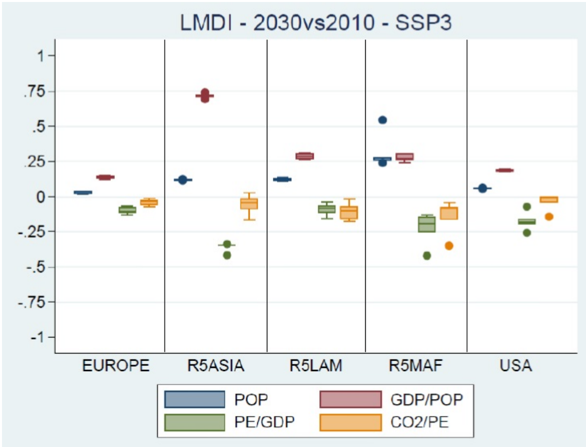
- Worst Scenario in terms of Economic Growth
- Slow Technology
- Little Environmental Awareness
- High Energy Demand
- Low/Negative Economic Growth
- Reduced Trade
- Very High Population

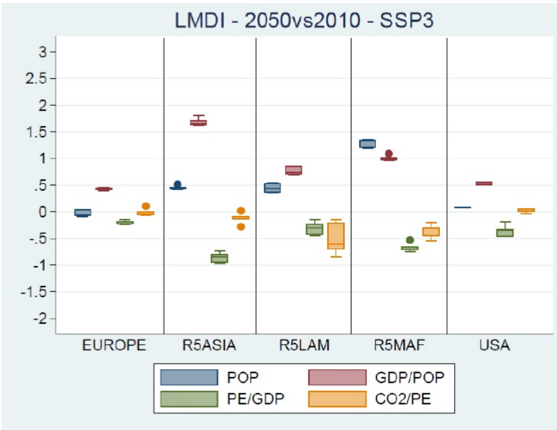


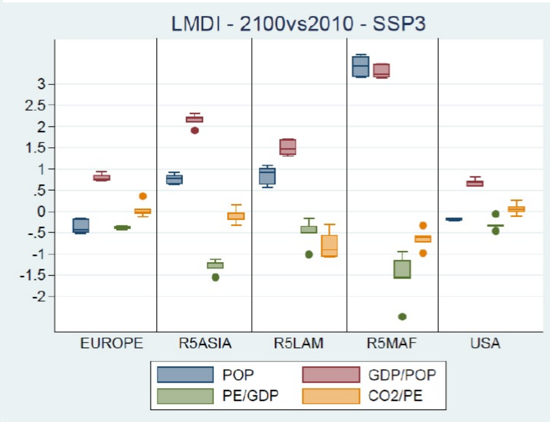




From the analysis of regional $\Delta CO_2$ over time, in this fragmented socio economic scenario, we deduce that in the short run (i.e. until 2030) R5ASIA will experience the greatest growth in terms of $CO_2$ emissions (namely +50% over the emission levels in 2010). On the other hand as we enlarge the time horizon, the same conclusions drawn from the 2 previous SSP is reached: R5MAF will indeed pollute up to 6 times what it pollutes nowadays, while R5ASIA is set to peak between 2030 and 2050 and eventually stabilize its $CO_2$ emissions.
Different patten shown by the Advances Economies (i.e. Europe and USA) whose $CO_2$ emissions are predicted to be stable until 2050 and to grow by 20% over the long run (from 2010 to 2100).
Finally models seem to differ particularly in quantitatively assessing the $\Delta CO_2$ emissions growth of R5LAM over time, which is predicted to be in the range of +20% to +150% relatively to 2010.

Below we also report the LMDI regional decomposition which show the contribution played by each factor in describing the total $CO_2$ emissions variations.



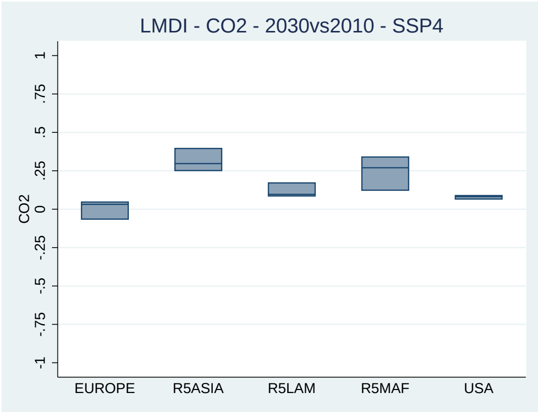

The first consideration about the role played by each factor is again that R5ASIA is predicted to be the most energy efficient region in terms pf primary energy consumption (+150% of $CO_2$ emission growth over the period 2010-2100) relatively to its GDP per capita growth which in 2050 is forecasted to be +150% of $CO_2$ emission growth and in 2100 +200% of its $CO_2$ growth rate relatively to 2010.
Interesting is also the modest role of Population in Advanced Economies in explaining the constant $CO_2$ emission growth over time, where in the Developing Regions the results are the opposite (+120% of $CO_2$ emission growth over the period 2010-2050 for R5MAF, 150% for R5ASIA and +50% for R5LAM).
Finally the region that will perform better in terms of Carbon Intensity will be R5LAM (-80% of $CO_2$ emission growth) over the long run.

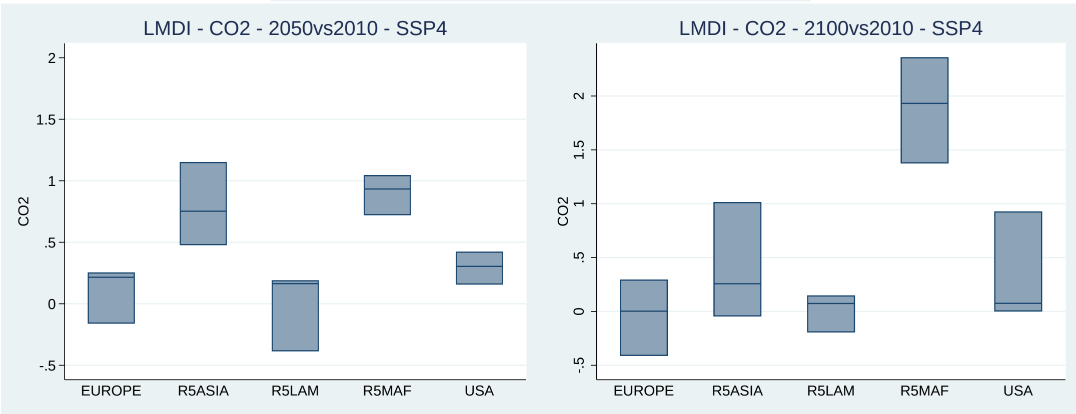
### 3.4. SSP4 - 2030 vs 2010, 2050 vs 2010 and 2100 vs 2010

We perform the decomposition by using the LMDI method. In particular, below we show the results of the pairwise comparison: 2030 against 2010, 2050 against 2010 and 2100 against 2010 for SSP4.
The SSP4 scenarios is considered as the model that predicts inequality, therefore considerably high challenges to adaptation and low challenges to mitigation. The latter is characterized as follows:

- Slow Technology
- High Inequality

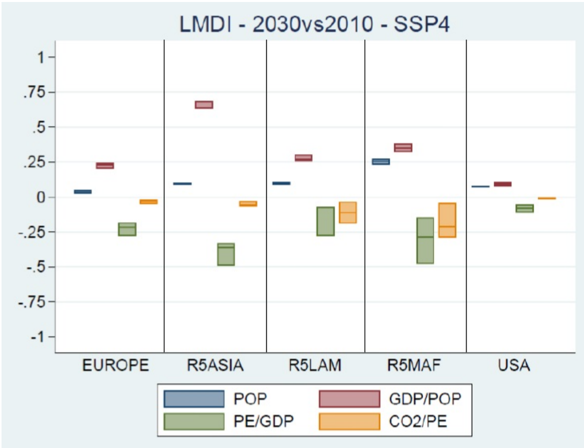
- Low Energy Demand
- Low Economic Growth
- High Population

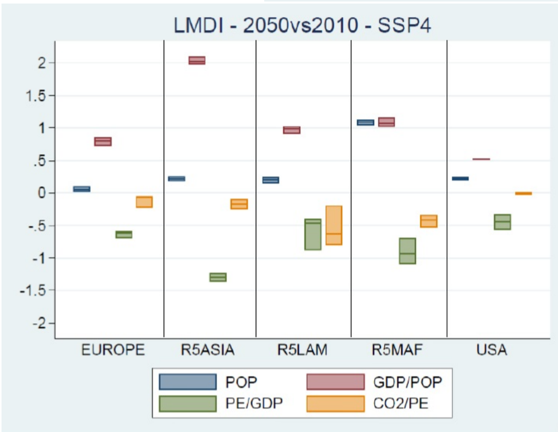


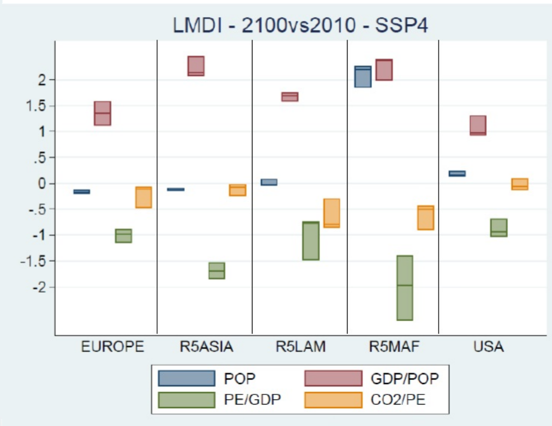




From the analysis of regional $\Delta CO_2$ over time,of this scenario of great inequality, we deduce that over the short time period only Europe will manage to keep the $CO_2$ emission growth close to zero, while the developing countries will experience an early remarkable pollution growth (+25% in 2030 with respect to the levels of 2010).
Over the medium term (2010-2050) and long term (2010-2100) worth of note is the prediction for R5LAM on one side and the USA on the other side, since R5LAM is set to pollute in 2100 the same level experienced in 2010, while for the USA we highlight both the remarkable level of uncertainty of the models and the $CO_2$ emission growth (+50% from 2010 to 2100).
Finally a consideration on the SSP4. The latter is indeed the scenario with the most uncertainty among models in describing the future pattern of $CO_2$ emission over time.

Below we also report the LMDI regional decomposition which show the contribution played by each factor in describing the total $CO_2$ emissions variations.



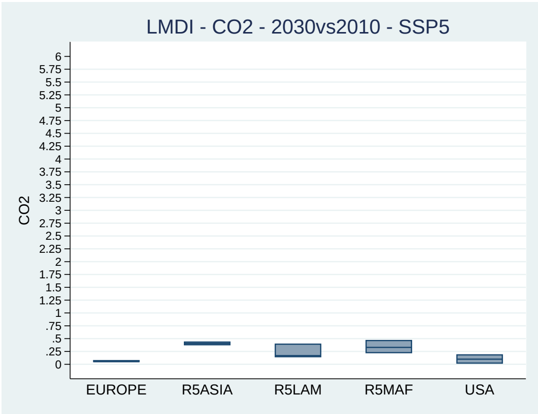

Finally, from the IPACT identity factor decomposition we notice that although developing regions will be more energy efficient and less carbon intensive during the next 50 years, the fast growing GDP per capita and Population will lead to a substantial increase in total $CO_2$ emissions. the opposite behavior is shown by Europe and the USA which will also be more energy efficient but little to no improvements will be made im term of Carbon Intensity. The main reasons of that are to be searched in the substantial better economic conditions although population growth will play a negligeable effect on total $CO_2$ emission growth.
These relatively high rates of economic indicators suggest a convergence first and a divergence later in terms of $CO_2$, with emissions in developed countries set to increase substantially more relatively to those that advanced regions will experience.

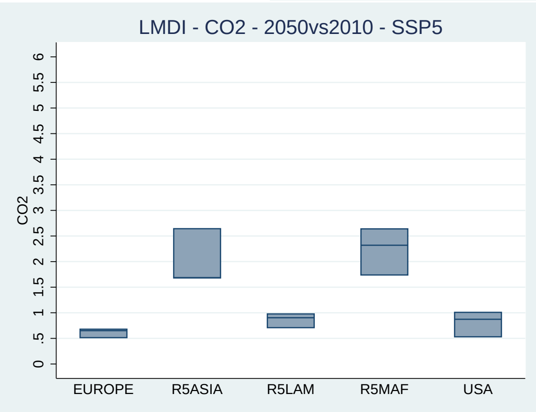
### 3.5. SSP5 - 2030 vs 2010, 2050 vs 2010 and 2100 vs 2010

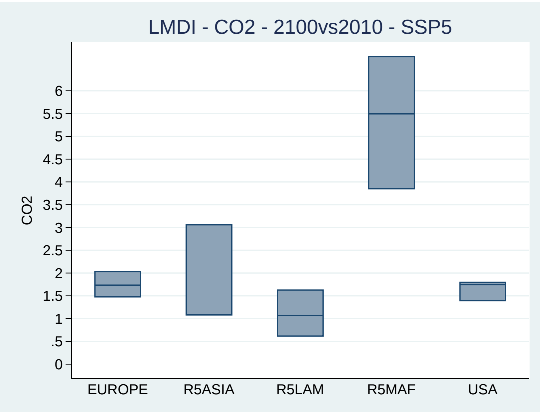
We perform the decomposition by using the LMDI method. In particular, below we show the results of the pairwise comparison: 2030 against 2010, 2050 against 2010 and 2100 against 2010 for SSP5.
The SSP5 scenarios is considered as the model that predicts conventional optimistic economic forecasts determining considerably high challenges to mitigation and low challenges to adaptation. The latter is characterized as follows:

- Worst Scenario in terms of $CO_2$ Emissions
- High Level of Challenges to Mitigation, but Low Level of Challenges to Adaptation

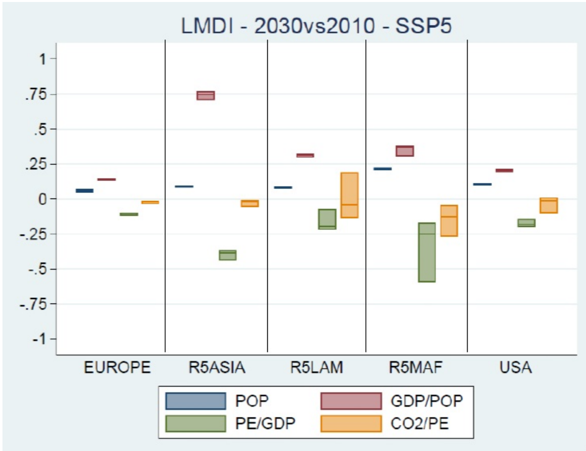
- Rapid Technology for Fossil
- High Energy Demand
- High Economic Growth
- Low Population

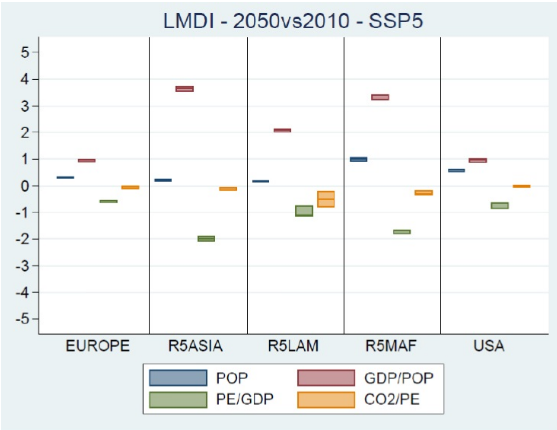


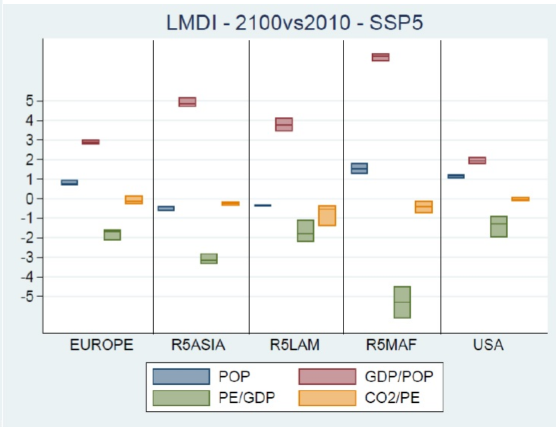




Firstly as one may notice SSP5 is the best scenario in terms of economic growth, and even population will be an important factor (relatively to the case of the prvios models).
Nevertheless SSP5 will also be the most polluted scenario. Mostly due to an excessive and uncontrolled economic development along with very little environmental awareness.
From the analysis of regional $\Delta CO_2$ over time, we deduce that all the 5 regions of the world except for Europe, will experience an early substantial increase of $CO_2$ emissions in the air (e.g. for R5ASIA, R5LAM and R5MAF $CO_2$ emissions will grow by nearly 40% over th next 15 years). In particular R5MAF countries will experience a greater increase in $CO_2$ emissions over time than the other regions considered (in the range of +400% to +600% in 2100 with respect to 2010).
Moreover Europe, USA and R5LAM will not manage, in this socio economic scenario, to keep $CO_2$ emissions constant over time.
Below we also report the LMDI regional decomposition which show the contribution played by each factor in describing the total $CO_2$ emissions variations.




Firstly we notice that although developing regions will be more energy efficient and less carbon intensive during the next 50 years, the fast growing GDP per capita and Population will lead to a substantial increase in total $CO_2$ emissions.
These relatively high rates of economic indicators suggest a convergence first and a divergence later in terms of $CO_2$, with emissions in developed countries set to increase substantially more relatively to those that advanced regions will experience.

## 4. General Conclusions for LMDI analysis of SSPs

The decomposition analysis described above let us gain a first insight over the regional differences in $CO_2$ emissions over time according to different predicted socio economic scenarios.
In particular, considering all the 5 SSPs, as a general consideration we can deduce that over the period 2010-2050 R5ASIA and R5MAF will pollute more than the rest of the regions of the world considered, namely Europe, the USA and R5LAM. While in the long run (i.e. from 2050 to 2100) R5MAF will experience a less controlled increase of $CO_2$ emissions, R5ASIA will keep $CO_2$ emissions at the same level of 2050 in the worst case scenario (i.e. SSP5) and will control its emissions down to the same level of 2010 in the best case scenarios (i.e. SSP1 and SSP4). This is mainly due to a decrease of population and more efficient use of primary energy.

### 4.1. Limitations of LMDI decomposition method - Average Yearly Growth Rates Decomposition

A limitation of the Decomposition is that it does not take into account the *YEARLY* growth rates of the total $CO_2$ emissions and in turn those of its main factors. Thus we consider the *Yearly* Growth Rate Decomposition in order to explain which component affects the growth rate of $CO_2$ the most for each region and model.

The scenario considered is the SSP2 since it is defined as the '*middle of the road*'.

We compute the growth rate decomposition of the Kaya Identity as following:

$$log(1 + g_{CO_2}) = log(1 + g_{POP}) + log(1 + g_{\frac{GDP}{POP}}) + log(1 + g_{\frac{PE}{GDP}}) + log(1 + g_{\frac{CO_2}{PE}})$$

where $g_x$ stands for the average growth rate of of the variable $x$ over a fixed time period. Specifically:

$$g_x = \left(\frac{x_{t+n}}{x_t}\right)^{\left(\frac{1}{(t+n)-t}\right)} - 1$$

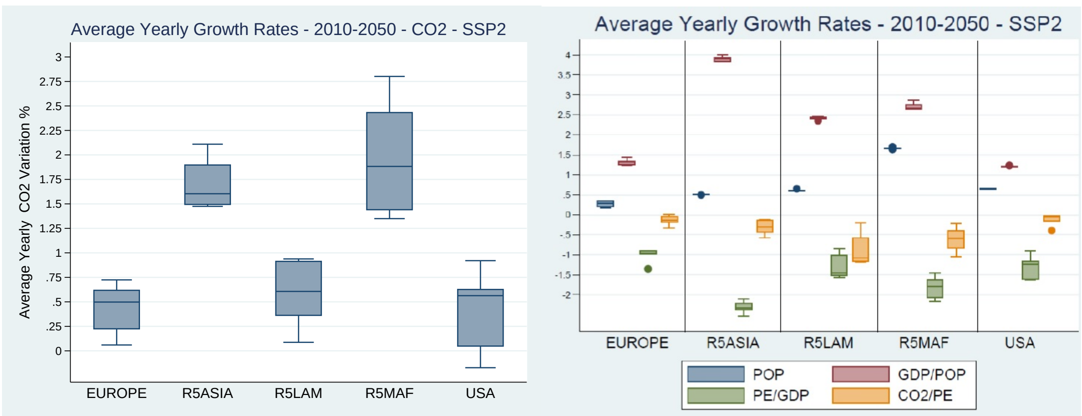
That translated into the Kaya Identity gives the $CO_2$ average yearly growth rate from 2010 to 2050 as:

$$g_{CO_2} = \left(\frac{CO_{2(2050)}}{CO_{2(2010)}}\right)^{\left(\frac{1}{40}\right)} - 1$$

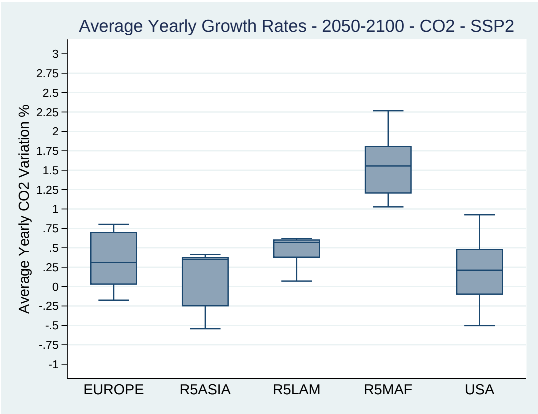
For small values of $x$ we obtain

$$g_{CO_2} = g_{POP} + g_{\frac{GDP}{POP}} + g_{\frac{PE}{GDP}} + g_{\frac{CO_2}{PE}}$$

The graph to the left shows the average yearly growth rates of $CO_2$ for the period 2010-2050 for all 5 regions, while the graph to the right shows the contributions of each factor to the $CO_2$ yearly growth.




The graph below instead, shows the average yearly growth rates of $CO_2$ for the period 2050-2100 for all 5 regions.




From the calculation of the growth rates of $CO_2$ we draw 3 main results:

- As shown by the LMDI analysis less developed regions will experience a faster increase in total $CO_2$ emissions mainly due to GDP per capita and Population.
- And the role played by Energy Efficiency and Carbon Intensity in offsetting the positive effects played by GDP per capita and Population on total variation of $CO_2$.
- The degree of homogeneity of the 6 models in assessing the contribution of each of the 4 drivers on the average growth of total emissions during the period 2010-2050.

The aforementioned results let us gain a first insight both on the role of each driver on total variation of $CO_2$, and the differences of the models in quantitatively assess the latter.

In particular the 6 models that we have considered in our analysis assume GDP per capita and Population to be exogenous variables, while Energy Efficiency and Carbon Intensity are treated as endogenous variables.

Our next questions consist of explaining how each model studies the impact of the 2 endogenous variables and in what they differ.
In other words we want to address the following questions:

- What is the endogenous driver (i.e. Energy Efficiency and Carbon Intensity) that has the main impact on $CO_2$ emissions ***across different models*** and scenarios?
- Do these models substantially differ from each other and if so in which measure?

This will allow us to shed light on performance of the aforementioned 6 models. We do it over time (i.e by comparing 2020 against 2010 and 2050 against 2010) and across the 5 socio-economic scenarios considered, in particular we compare SSP1 against SSP3. The reason of such a choice is simple: as learned from the introduction, SSP1 is defined as the best socio-economic scenario among the 5, consisting in a rapid technology, a high environmental awareness, a low energy demand of the world population and industries, therefore a relative low growth rates of population along with a medium-high economic growth; while SSP3 is defined as the worst scenario thus consisting in a slow technology development, a reduced amount of trade a very high increase in population and therefore a high energy demand but a pessimistic view on the economic conditions.

We utilize the Log Mean Divisia Index (LMDI).

## 5. Performance of models in assessing regional $\Delta CO_2$ differences over time and across SSPs

### 5.1. Principal Component Analysis and Model Comparison

While in the previous section we study the performance of each model, in the present section we quantitatively assessed the difference across them. And the procedure used to perform the statistical analysis is the Principal Component Analysis (PCA)

PCA is a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the graphical representation is not available, PCA is a powerful tool for analyzing the data.
The other main advantage of PCA is that once one has found these patterns in the data, one can *compress* the data without considerable loss of information. This statistical technique first developed by Pearson(1912) is widely used in many disciplines.

The main steps to compute the PCA are the following:

- Calculate the Covariance Matrix of the data
- Calculate the eigenvectors and their associated eigenvalues.
  The meaning of the eigenvectors and eigenvalues of the covariance matrix is crucial for PCA, indeed they show the pattern of the data. The reason is that the eigenvector with the highest eigenvalue goes through the middle of the points, like drawing a line of best fit. That eigenvector is showing us how the data sets are related along that line. The second eigenvector gives us the other, less important, pattern in the data, that all the point follow the main line, but are off to the side of the main line by some amount.
  Hence, by this process of taking the eigenvalues and their respective eigenvectors of the variance-covariance matrix we have been able to extract lines that characterize the data. The rest of the steps involves transforming the data so that it is expressed in terms of their lines.
- Choose the matrix containing the eigenvectors with the highest eigenvalues associated, ignoring teh components of lesser significance. In this process you do lose some information, but this is not considerable as far as the eigenvalues are small.
- Finally, derive the new data set. Once one has chosen the components (eigenvectors) that we wish to keep in our data and formed a featured vector, we simply take the transpose of the vector and multiply it on the left of the original data set, transposed. This will give us the original data solely in terms of the vectors we had chosen.

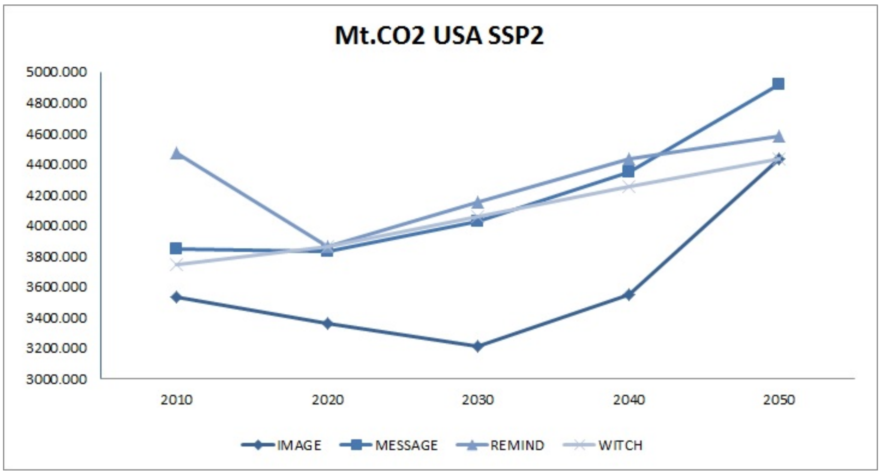
In our case Principal Component Analysis shows that while some differences occur from model to model, in general they assess the $CO_2$ variations in a similar pattern.

We consider data ***for all the components of*** $CO_2$ for 2020, 2050 and for the whole period 2010-2100 for all regions and across scenarios, for each of the 6 models and we find that the first 2 Principal Components account for almost 90% of all variance, with PC1 explaining 70% and PC2 explaining the other 20%.

| YEARS | PRINCIPAL COMPONENTS | PROPORTION EXPLAINED | CUMULATIVE |
|---|---|---|---|
| 2020 | PC1 | 70.5% | 70.5% |
| | PC2 | 18.1% | 88.6% |
| | PC3 | 11.0% | 99.5% |
| 2050 | PC1 | 69.3% | 69.3% |
| | PC2 | 18.9% | 88.3% |
| | PC3 | 11.1% | 99.4% |
| 2010-2100 | PC1 | 65.3% | 65.3% |
| | PC2 | 21.9% | 87.2% |
| | PC3 | 10.8% | 98.0% |

Our findings suggest a considerable degree of homogeneity among models (given by the fact that the values of the eigenvector with the higher eigenvalue associated are all positive and in the range of 0.37 to 0.49 ).
Nevertheless, for PC2 the results are different, in fact the coefficients are all positive except for those associated to IMAGE and MESSAGE which are negative.
This raises doubts over the effectiveness of the homogeneity of the 2 aforementioned models with the rest of them.

An explanation to that difference stems from the results obtained from PCA for the years 2020 and 2050, which remarks the different pattern in $CO_2$ of IMAGE, MESSAGE and REMIND with respect to that of AIM, GCAM and WITCH for EUROPE and USA in early years while fading away over time.




One of the assumptions of these models is that Population and GDP per capita are exogenous variables while Energy Efficiency and Carbon Intensity are endogenous.
The next step involves the evaluation of the performance of the models in considering the endogenous factors only.

#### 5.1.1. PCA for 2020 and 2050 for Energy Efficiency

| YEARS | PRINCIPAL COMPONENTS | PROPORTION EXPLAINED | CUMULATIVE |
|---|---|---|---|
| 2020 | PC1 | 62.4% | 62.4% |
| | PC2 | 23.2% | 85.6% |
| | PC3 | 13.9% | 99.5% |
| 2050 | PC1 | 62.7% | 62.7% |
| | PC2 | 25.3% | 88.0% |
| | PC3 | 9.8% | 97.8% |

The associated Eigenvectors and Eigenvalues for Energy Efficiency are reported below:

Principal Components- Energy Efficiency-2020

| values | vectors.1 | vectors.2 |
|---|---|---|
| 33.084190000 | 0.092788250 | - 0.052404760 |
| 12.299960000 | 0.093521350 | - 0.105285600 |
| 7.375849000 | 0.572593460 | 0.406874030 |
| 0.221795800 | 0.580170420 | 0.409446510 |
| 0.045360380 | 0.556408400 | - 0.797219060 |
| 0.016791110 | 0.092697390 | - 0.131975500 |

Principal Components- Energy Efficiency-2050

| values | vectors.1 | vectors.2 |
|---|---|---|
| 13.956750000 | - 0.164640200 | - 0.325641240 |
| 5.620622000 | - 0.123705900 | - 0.299362720 |
| 2.190924000 | - 0.664687100 | - 0.066111780 |
| 0.313361700 | - 0.647485400 | - 0.088634000 |
| 0.135438800 | - 0.290297800 | - 0.805645280 |
| 0.033226710 | - 0.110776400 | - 0.378217760 |

As reported above the first 2 principal components explain almost 90% of the pattern shown by the data, with PC2 explaining more than 20% of the latter both in 2020 and 2050.
PC1, representing alone more than 60% of the data, suggests homogeneity among models, this is due to the fact that the values have all the same sign (positive in 2020 and negative in 2050); nevertheless PC2 shows a different story in 2020, again between IMAGE and MESSAGE on one side and WITCH, GCAM, AIM and REMIND on the other side. However such a difference is greater in 2020 with respect to 2050, suggesting that the assumptions that models make on Primary Energy consumption are different, while converging over time.

The same reasoning is applied to Carbon Intensity

#### 5.1.2. PCA for 2020 and 2050 for Carbon Intensity

| YEARS | PRINCIPAL COMPONENTS | PROPORTION EXPLAINED | CUMULATIVE |
|---|---|---|---|
| 2020 | PC1 | 74.1% | 74.1% |
| | PC2 | 15.4% | 89.5% |
| | PC3 | 8.5% | 98.0% |
| 2050 | PC1 | 73.1% | 73.1% |
| | PC2 | 23.8% | 96.9% |
| | PC3 | 2.1% | 99.0% |

As shown above the first 2 Principal components explain 90% of the data in 2020 and 97% of the latter in 2050 with PC2 having much less weight in 2020 (15.4% of the data explained) with respect to 2050 (24% of the data explained).
For Carbon Intensity the results are much different from the results obtained for Energy efficiency, indeed both Principal Components show the same sign (positive in 2020 and negative 2050) suggesting that the 6 models considered are performing similarly in evaluating Carbon Intensity.

The associated eigenvectors and eigenvalues for Carbon Intensity are reported below:

Principal Components- Carbon Intensity-2020

| values | vectors.1 | vectors.2 |
|---|---|---|
| 71.268592610 | 0.007698536 | - 0.075698250 |
| 14.864271760 | 0.011198182 | - 0.121494550 |
| 8.140968080 | 0.632452925 | - 0.235192560 |
| 1.087260680 | 0.684097897 | - 0.254556950 |
| 0.788845370 | 0.349308237 | - 0.926976460 |
| 0.065589860 | 0.099057830 | - 0.010426910 |

Principal Components- Carbon Intensity-2050

| values | vectors.1 | vectors.2 |
|---|---|---|
| 42.267486360 | - 0.013302829 | - 0.055283930 |
| 13.772846830 | - 0.026393485 | - 0.128521370 |
| 1.234198420 | - 0.631692025 | - 0.283287640 |
| 0.309424730 | - 0.649279309 | - 0.303075790 |
| 0.162907860 | - 0.422486615 | - 0.898812760 |
| 0.099306720 | - 0.005748267 | - 0.021324880 |

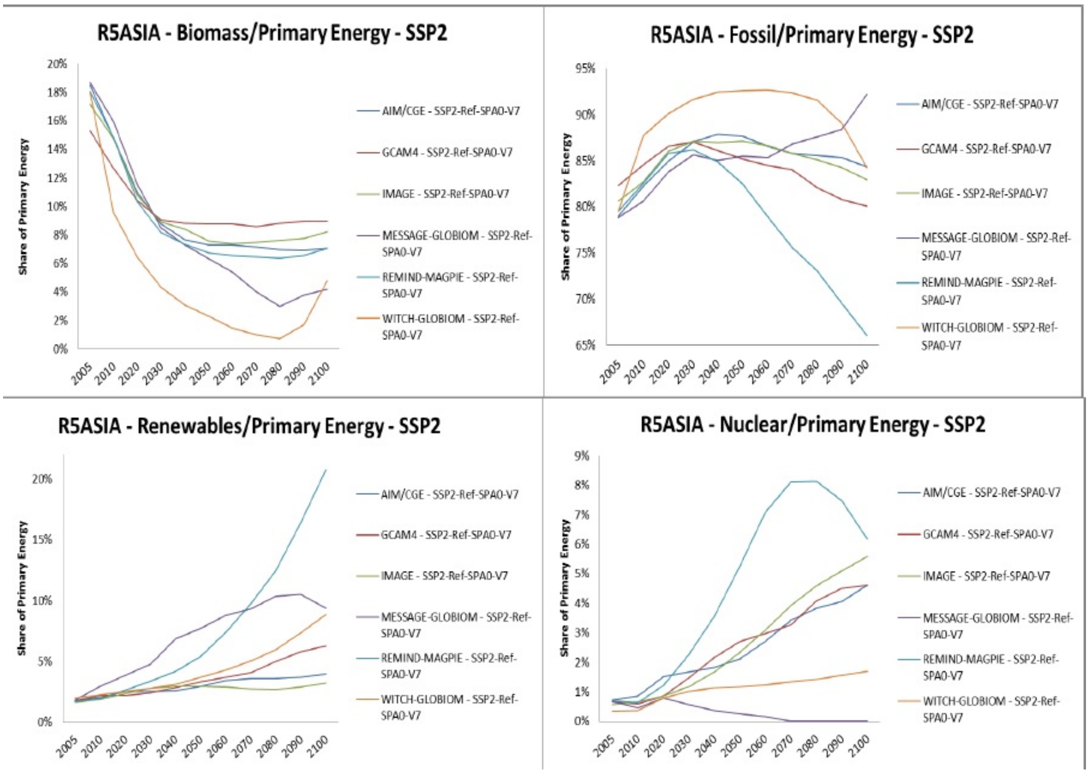
The conclusions that can be drawn from the Principal Component Analysis for both endogenous components of the Kaya Identity are that of the endogenous variables, only Energy Efficiency represents the source of the difference among models in assessing total $CO_2$ variations over time and across scenarios, while as regards Carbon Intensity the models show considerable similarities. In particular IMAGE and MESSAGE incorporate more pessimistic assumptions on Primary Energy than those of the other models.

### 5.2. Contribution of Primary Energy Components to total Primary Energy Consumption - Model Comparison

In order to see the main source of such a difference between Primary Energy consumption among the 6 integrated assessment models considered in our analysis we show the pattern of the Primary Energy Components:

- Fossil
  - Gas
  - Coal
  - Oil
- Biomass
- Nuclear
- Non Biomass Renewables

Below it is reported an example of how each Primary Energy Component contributes to the total Primary Energy Consumption assessed by each model in order to show where the differences stem from.
As an example we use the SSP2 (i.e. the middle of the road scenario) and R5ASIA as region of the world.


R5ASIA - Biomass/Primary Energy - SSP2
R5ASIA - Fossil/Primary Energy - SSP2
R5ASIA - Renewables/Primary Energy - SSP2
R5ASIA - Nuclear/Primary Energy - SSP2
Share of Primary Energy
AIM/CGE - SSP2-Ref-SPA0-V7
GCAM4 - SSP2-Ref-SPA0-V7
IMAGE - SSP2-Ref-SPA0-V7
MESSAGE-GLOBIOM - SSP2-Ref-SPA0-V7
REMIND-MAGPIE - SSP2-Ref-SPA0-V7
WITCH-GLOBIOM - SSP2-Ref-SPA0-V7
2005
2010
2020
2030
2040
2050
2060
2070
2080
2090
2100

## 6. Conclusions

From the Decomposition of the Kaya Identity(1990), the first section of the study shows a convergence and eventually a divergence in total $CO_2$ for developed economies with respect to advanced regions.
In particular, asian and middle east-african countries although they will achieve a more efficient use of energy and they will be less carbon dependent showed an average growth rate in carbon dioxide emission superior to that of the USA for the period 2010-2050.
The main reason of that convergence/divergence phenomenon stems from a more robust increase in Gross Domestic Product and Population over time. These two components will offset the reduction in Carbon Intensity. However that is not the case of Latin American countries which through a more consistent decarbonization will achieve a more stagnant level of $CO_2$ relatively to that shown by other developing regions.

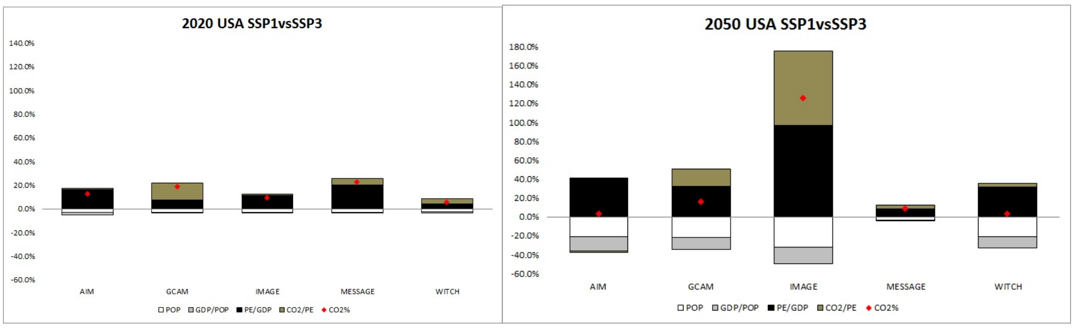
Moreover, from the decomposition analysis carried out over time we conclude that the impact of Carbon Intensity on total $CO_2$ variations is negative, in particular its impact is shown to be greater in 2050 than in 2010. Energy Efficiency has also a negative impact on total emissions in particular in the short-run.

From the analysis of the performance of the 6 models selected, carried out with the Principal Component Analysis we conclude that they show a similar pattern in evaluating the impact of Population, GDP per capita, Energy Efficiency and Carbon Intensity although showing some differences in the short-run (2020) while fading away in the medium/long-run(2050). The main source of this difference stems from changes in assumptions on Primary Energy, in particular IMAGE and MESSAGE are proven to be more optimistic on total $CO_2$ variations in 2020 relatively to WITH, AIM, GCAM and REMIND.

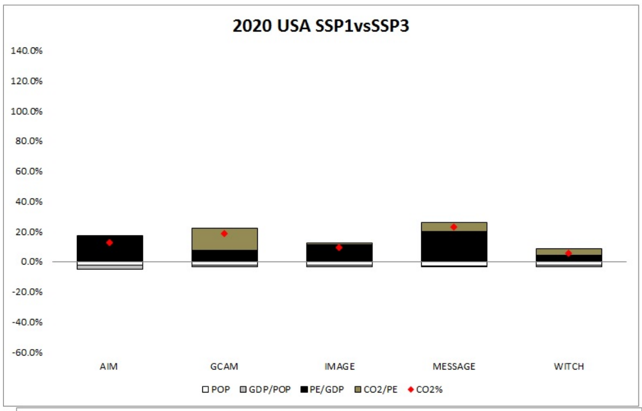
# Appendix 1: LMDI Across SSPs

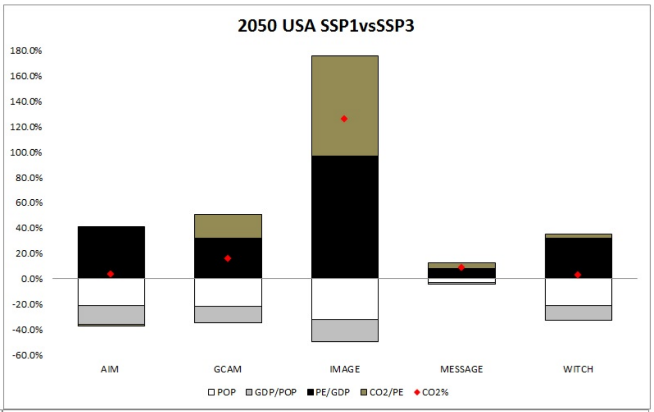
**Model Differences across SSPs**

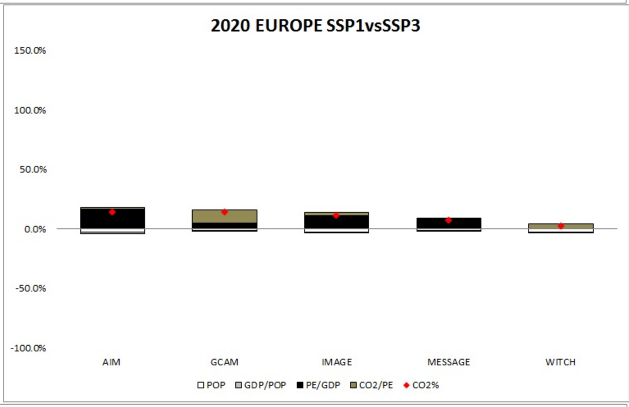
By comparing SSP1 and SSP3 we conclude that Energy Efficiency (i.e. $\frac{PE}{GDP}$ ) and Carbon Intensity (i.e. $\frac{CO_2}{PE}$) have by far, a large impact on $CO_2$ emissions given a particular reference year.

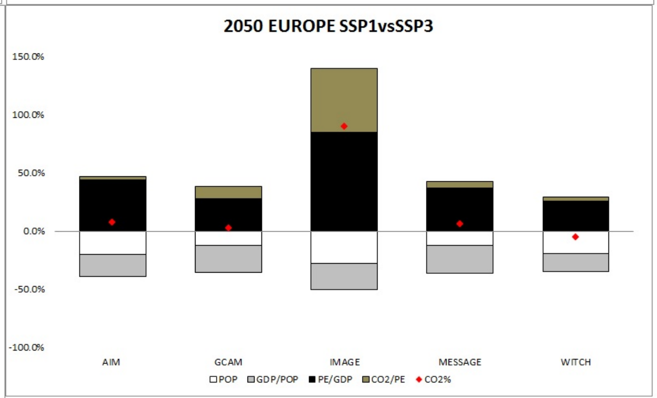


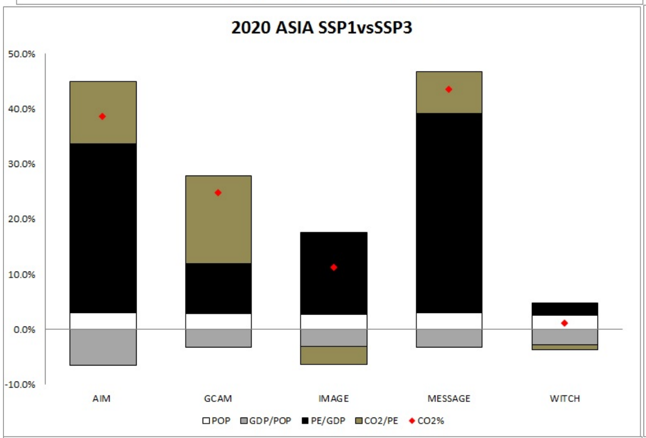

In particular the results from the LMDI across scenarios suggest that the impact of Carbon Intensity (i.e. $\frac{CO_2}{PE}$) on total $CO_2$ emissions between scenarios is greater in 2050 than in 2020 for the majority of the regions considered, therefore suggesting an increasing effect of the latter. Contrasting, the impact of Energy Efficiency (i.e. $\frac{PE}{GDP}$ ) explains on average more that 50% of the total $CO_2$ emissions differences across scenarios, in all periods taken into account in our analysis.

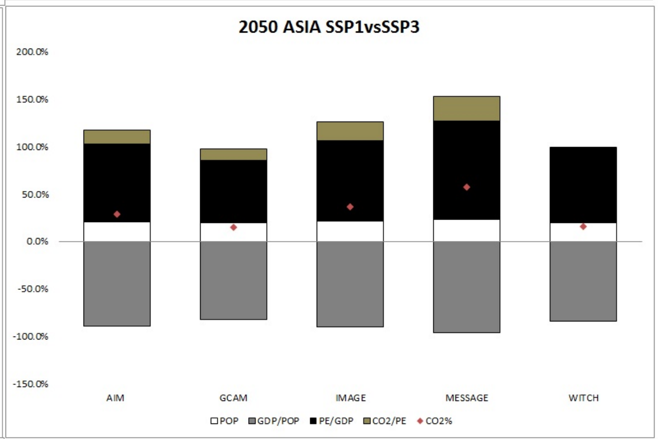

2020 USA SSP1vsSSP3
140.0%
120.0%
100.0%
80.0%
60.0%
40.0%
20.0%
0.0%
-20.0%
-40.0%
-60.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

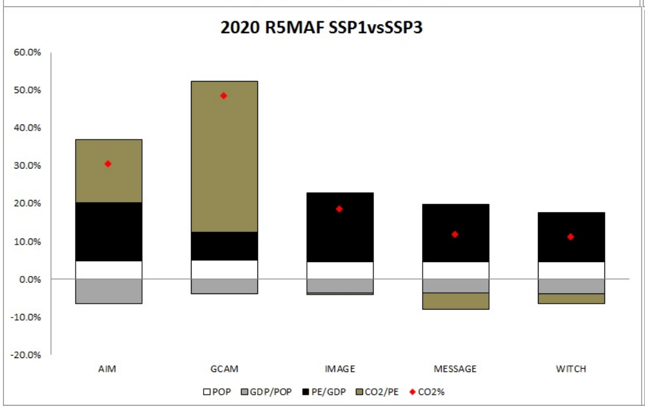

2050 USA SSP1vsSSP3
180.0%
160.0%
140.0%
120.0%
100.0%
80.0%
60.0%
40.0%
20.0%
0.0%
-20.0%
-40.0%
-60.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

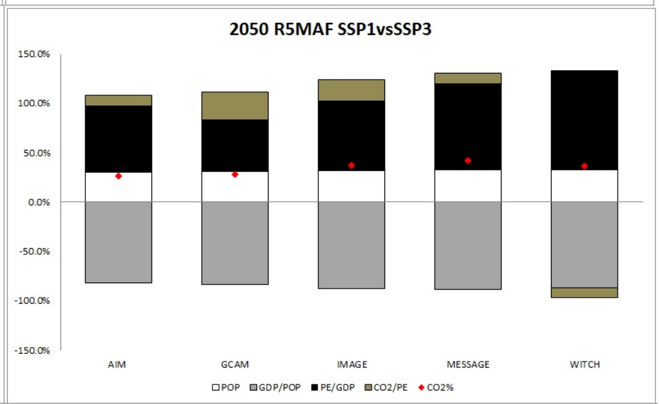

2020 EUROPE SSP1vsSSP3
150.0%
100.0%
50.0%
0.0%
-50.0%
-100.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

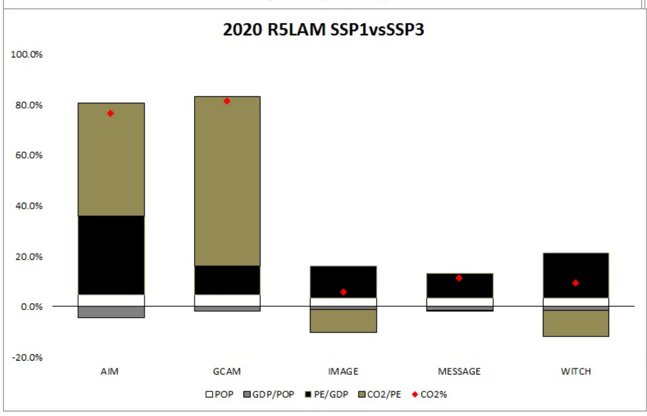

2050 EUROPE SSP1vsSSP3
150.0%
100.0%
50.0%
0.0%
-50.0%
-100.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

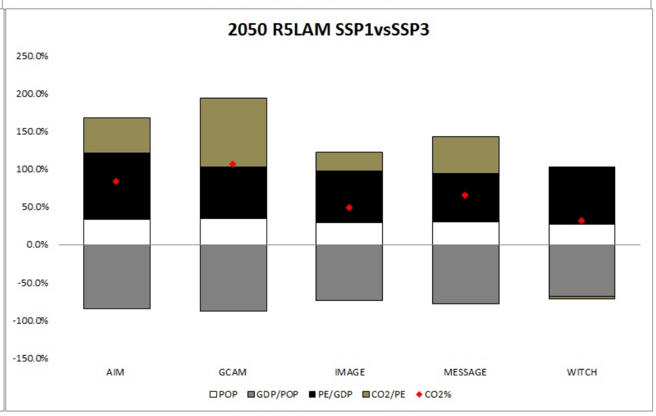

2020 ASIA SSP1vsSSP3
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
-10.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%


2050 ASIA SSP1vsSSP3
200.0%
150.0%
100.0%
50.0%
0.0%
-50.0%
-100.0%
-150.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%


2020 R5MAF SSP1vsSSP3
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
-10.0%
-20.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%


2050 R5MAF SSP1vsSSP3
150.0%
100.0%
50.0%
0.0%
-50.0%
-100.0%
-150.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

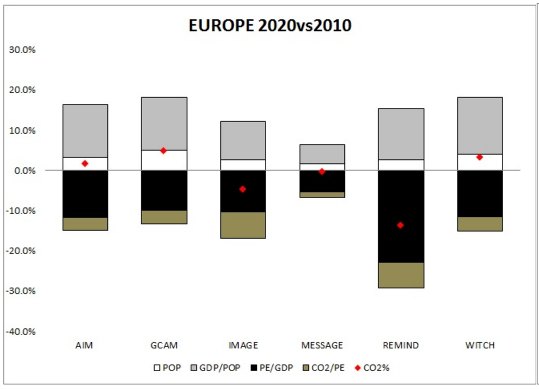

2020 R5LAM SSP1vsSSP3
100.0%
80.0%
60.0%
40.0%
20.0%
0.0%
-20.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

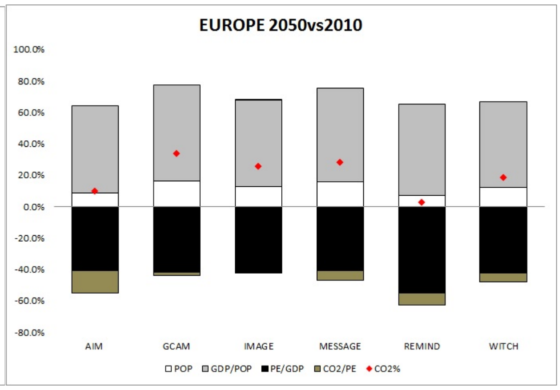

2050 R5LAM SSP1vsSSP3
250.0%
200.0%
150.0%
100.0%
50.0%
0.0%
-50.0%
-100.0%
-150.0%
AIM
GCAM
IMAGE
MESSAGE
WITCH
POP GDP/POP PE/GDP CO2/PE CO2%

# Appendix 2: RLD over time

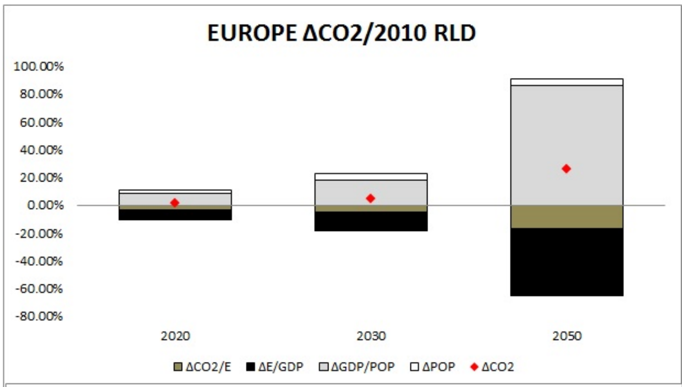
### Model Differences over time

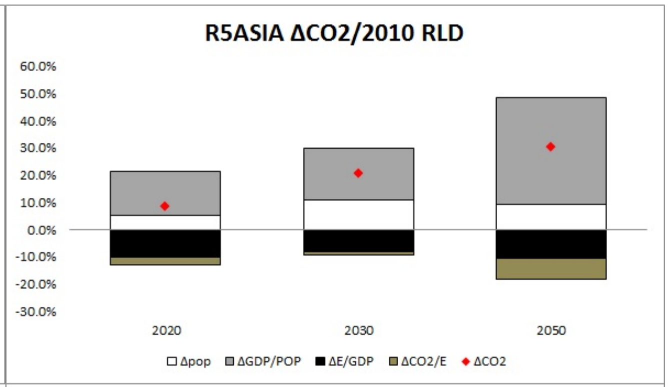
We conduct the same analysis in order to explain which of the drivers of the KAYA Identity are the most significant in determining regional differences over time (i.e. from 2010 to 2030 and from 2010 to 2050)

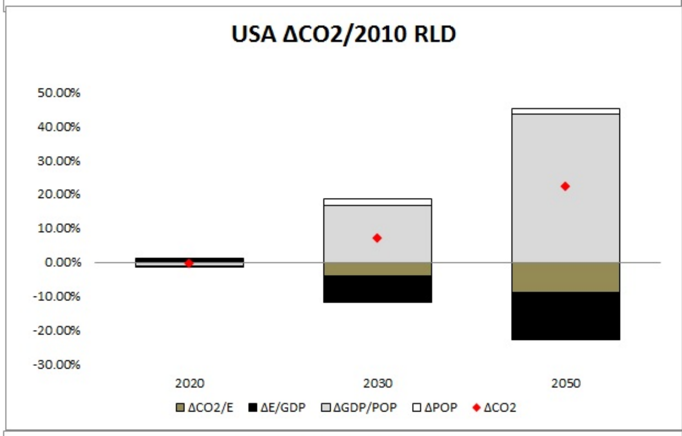


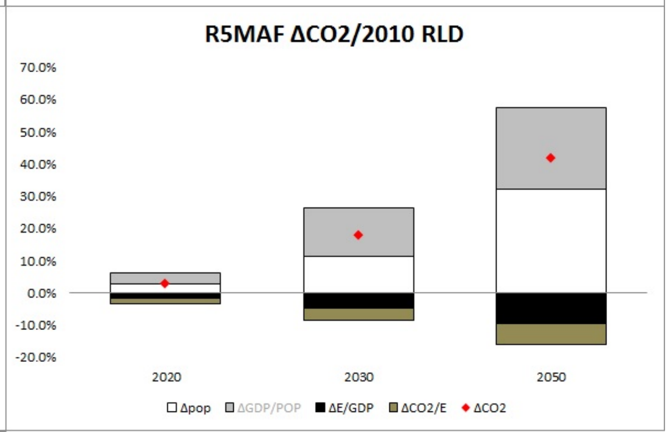



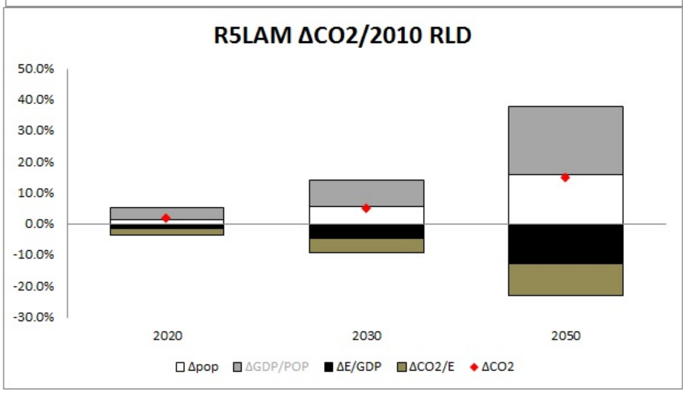

The main findings are as expected opposite to the one obtained from the 'across scenarios' analysis:
Energy Efficiency and Carbon Intensity are the components that bring $CO_2$ emissions down while an opposite effect is caused by GDP per capita and Population across the selected regions of the world. With large differences in weights across regions.


EUROPE ΔCO2/2010 RLD
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
-20.00%
-40.00%
-60.00%
-80.00%
2020
2030
2050
ΔCO2/E
ΔE/GDP
ΔGDP/POP
ΔPOP
ΔCO2


R5ASIA ΔCO2/2010 RLD
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
-10.0%
-20.0%
-30.0%
2020
2030
2050
Δpop
ΔGDP/POP
ΔE/GDP
ΔCO2/E
ΔCO2


USA ΔCO2/2010 RLD
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
-10.00%
-20.00%
-30.00%
2020
2030
2050
ΔCO2/E
ΔE/GDP
ΔGDP/POP
ΔPOP
ΔCO2


R5MAF ΔCO2/2010 RLD
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
-10.0%
-20.0%
2020
2030
2050
Δpop
ΔGDP/POP
ΔE/GDP
ΔCO2/E
ΔCO2


R5LAM ΔCO2/2010 RLD
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
-10.0%
-20.0%
-30.0%
2020
2030
2050
Δpop
ΔGDP/POP
ΔE/GDP
ΔCO2/E
ΔCO2

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