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Drivers of regional decarbonisation through 2100: A multi-model decomposition analysis

Adriana Marcucci[a,*], Panagiotis Fragkos[b]

[a]*ETH Zurich, Center of Economic Research, 8092 Zurich, Switzerland*
[b]*National Technical University of Athens, Department of Electrical and Computer Engineering, 15773 Athens, Greece*

Abstract

This study explores short and long-term drivers of alternative decarbonisation pathways in four major economies (China, India, Europe and USA), using a multi-model decomposition analysis. The paper focuses on determining the energy system transformations that drive the changes in carbon emissions and identifying the model characteristics that lead to differences in the decarbonisation strategies. First, we compare the decomposition over time of near-past carbon emissions and near-future model projections as a methodology to validate baseline scenarios. We show that a no-policy baseline scenario is in line with historical trends for all regions except China, where all models project higher improvements in energy and carbon intensity than the near-past historical development. Second, we compare regional decarbonisation drivers across models in a scenario with moderate policy targets that represents the current fragmented international climate policy landscape. The results from the different models show that energy efficiency improvements represent the main strategy in achieving the moderate climate targets. Finally, we develop an LMDI decomposition analysis to determine the additional energy system changes needed to achieve a global GHG concentration target of 450ppm compared to the moderate policy case. In all models, reducing regional carbon intensity of energy is the major decarbonisation strategy after 2030. In the long-term (after 2050), most of the models find that negative carbon emissions are critical in such scenario, emphasizing the key role of biomass with CCS. However, the level of contribution of the decarbonisation factor varies significantly across models, due to the large uncertainty in the availability of renewables and the development of CCS technologies. Overall, we find that the main differences in the decomposition results across models are due to assumptions concerning availability of natural resources and variety of backstop technologies.

Keywords: Regional decomposition analysis, model inter-comparison, climate change mitigation pathways, backstop technologies

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*Corresponding author. Tel: +41 44 6327045

Email addresses: `madriana@ethz.ch` (Adriana Marcucci), `central@e3mlab.eu` (Panagiotis Fragkos)

JEL: Q47, Q41, Q43

1. Introduction

Climate change mitigation is one of the major global policy challenges, as it is increasingly recognized that unabated climate change can lead to large environmental, social and economic impacts on human societies. Limiting greenhouse gas (GHG) emissions has been the subject of international negotiations for more than two decades. Due to the persistent lack of a comprehensive global agreement on GHG emissions reduction, several studies based on individual or multi-model results have analysed the effect of delayed and unilateral climate change mitigation policy action. For instance, the 22nd Energy Modeling Forum (EMF-22) analysed the consequences of delayed action (Bosetti et al., 2009; Krey & Riahi, 2009; van Vliet et al., 2009); unilateral climate change mitigation policies have been studied concerning policy effectiveness, carbon leakage and border carbon adjustment (Böhringer et al., 2012; Bosetti & De Cian, 2013; Böhringer et al., 2014). Moreover, the role of the European Union, which has taken the lead in climate change mitigation policy, has been investigated (For instance in the EMF-28, see De Cian et al. (2013) and Knopf et al. (2013)). Recently, the AMPERE modelling comparison project[1] analysed three different aspects of climate change mitigation: (1) The consequences of following the Copenhagen Accord and the Cancun Agreement until 2030 for the achievement of long-term global stringent mitigation objectives (Eom et al., 2015; Riahi et al., 2015); (2) the implications of moderate regional climate policies and the consequences of unilateral first-mover action in the EU and China (Kriegler et al., 2015b; Bauer et al., 2015; Marcucci & Turton, 2015; Schwanitz et al., 2015; Paroussos et al., 2015); and (3) European decarbonisation pathways under alternative technological choices to achieve the climate targets of the EU Roadmap 2050 (Capros et al., 2014).We develop in this paper a multi-model decomposition analysis of a subset of the global AMPERE scenarios. This decomposition analysis helps identifying the contribution of different drivers, such as energy efficiency of GDP and carbon intensity of energy, to changes in CO_2 emissions from the combustion of fossil fuels and industrial applications.

The objective of decomposition analysis is to quantify the relative contribution of different pre-defined factors to the change of one explained variable. The decomposition methods used in the 1970's and 1980's were based on the Laspeyres index, which measures percentage change of a factor while holding the other decomposition factors constant (Ang, 2004). At the end of the 1980s, Boyd et al. (1988, 1987) proposed

[1] The AMPERE project is a collaborative effort among 22 institutions in Europe, Asia and North America, funded by the European Commission, FP7 (http://ampere-project.eu/web/). AMPERE aims for a broad exploration of mitigation pathways and associated mitigation costs under real-world limitations while offering insights into the differences across models and the relation to historical trends.

the use of the Divisia index to decompose energy intensity as an alternative to the Laspeyres index. The Divisia index is a "weighted sum of logarithmic growth rates, where the weights are components' shares in total value" (Ang, 2004). One frequently used method is the Log-mean Divisia index (LMDI), introduced by Ang & Liu (2001). The LMDI can be used to decompose energy demand or emissions between two end points into separate sectoral contributions (Ang, 2005). The LMDI method has been further developed to analyse energy intensity (Choi & Ang, 2012) and both energy and emissions (Su & Ang, 2012).

After being introduced in 1970, decomposition analysis has become a well-known analytical tool for supporting policy making in energy and environmental issues, as shown in Ang & Zhang (2000) where more than 100 decomposition studies are presented. In 1990, Kaya (1990) introduced a method to decompose emissions into key drivers, like population, GDP per capita, energy intensity of GDP and carbon intensity of energy. Kawase et al. (2006) expanded the Kaya identity in order to incorporate more drivers for carbon emissions and applied the extended method to a set of national emission scenarios for Japan, Germany, the U.K. and France. Many studies have evaluated the role of key drivers for historical changes in emissions or energy intensity, for example Baldwin & Sue Wing (2013) decompose the evolution CO_2 emissions in the period 1963-2008 in the US in five driving factors: the emission intensity of energy use, the energy intensity of economic activity, the composition of states' output, per capita income and population; Alves & Moutinho (2013) use the complete decomposition technique originally developed by Sun (1998) to examine the evolution of CO_2 emissions intensity in 16 industrial sectors in Portugal in the period 1996 to 2009; Voigt et al. (2014) analysed energy intensity trends between 1995 and 2007 in 40 major economies using the LMDI method to attribute efficiency changes to either changes in technology or changes in the structure of the economy.

Decomposition analysis has also been used to analyse future model-based energy scenarios, including analyses from the IEA (IEA, 2004; Ang & Liu, 2007a; IEA, 2012) and the assessments prepared for use by the IPCC[2] (Nakicenovic et al., 1998; Hanaoka et al., 2006, 2009). Moreover, Riahi et al. (2007) project the evolution of global energy intensity of GDP and carbon intensity of energy until 2100; Agnolucci et al. (2009) decompose future energy scenarios for the UK; Kesicki & Anandarajah (2011) decompose global and regional future energy-emissions scenarios using the Times Integrated assessment model; and Fisher-Vanden et al. (2012) apply a new decomposition technique to the results of a multi-region, multi-sector CGE model. While all these studies are based on a single model, more recently, the decomposition analyses have been focused on the comparison of the results from different models to determine robust patterns across them. For instance, Bellevrat (2012) analyses the Chinese future energy and carbon

[2] Intergovernmental Panel on Climate Change

emissions scenarios using results from different models; Blanford et al. (2012) developed a decomposition analysis of baseline scenarios for Asia comparing different models; Förster et al. (2013), as part of the EMF-28, and Capros et al. (2014), as part of AMPERE, developed multi-model decomposition analyses of alternative European climate policy scenarios by 2050; and van Sluisveld et al. (2013) present a multi-model decomposition analysis of the emissions in five major economies using the Kaya identity in the period 2020-2050.

Following the approach used in Bellevrat (2012) and Förster et al. (2013), in this paper we develop the first multi-model decomposition analysis of short- and long-term regional carbon emissions, which allows the analysis of differences and synergies in regional decarbonisation strategies. We analyse four major economies, including both developed (USA, EU-27) and developing regions (China, India), all of which are projected to play a critical role in global climate policies in the long term. The analysis compares the results of a subset scenarios from ten well-established global energy-economy integrated assessment models (IAMs) that participated in the AMPERE project. The analysis focuses on the regional energy system transformations required to mitigate energy-related CO_2 emissions[3] including reductions in energy intensity of GDP and carbon intensity of final energy. This paper contributes to the literature by means of: (1) the decomposition of near-past historical carbon emissions and near-term modelling projections as an alternative to validate baseline scenarios; (2) the identification of regional decarbonisation strategies to achieve moderate and stringent climate change mitigation objectives; and (3) determining the main assumptions and model characteristics that drive significant deviation from the average results in the carbon decomposition analyses.

First, integrated assessment modelling of climate change aims to analyse the behavior of the future energy-economy-climate system by evaluating alternative scenarios of the system's future development. IAMs commonly use a (no climate policy) baseline scenario that provides the benchmark for the evaluation of the impacts of alternative climate policies on the evolution of the energy system and economic development. We propose the comparison of the decomposition of the historical carbon emissions of the period 1990-2010 with the near-term model results to validate the assumptions of the baseline scenario.

Second, we study a scenario with moderate climate change mitigation policies, where the impacts of regional pledges from the Copenhagen COP are analysed. This moderate climate policy scenario aims to conceptualize the current regionally fragmented climate policies providing important insights to the climate policy discussion concern-

[3]The IAMs use in this paper have different sectoral resolution, from a very aggregate economy in the optimal growth models (1-3 sectors) to a detailed sectoral disaggregation (up to 23 sectors) in the computable general equilibrium models. Therefore, we focus on the analysis of energy-related CO_2 emissions at the aggregate level of economy.

ing the required regional changes in energy efficiency and carbon intensity of energy to achieve the Copenhagen-Cancun pledges. Moreover, we analyse a strong mitigation scenario that results in negative carbon emissions by the end of the century. We present an LMDI decomposition analysis of the changes in emissions in this case compared to the moderate policy scenario to identify the additional efforts needed to realize a stringent mitigation target by 2100 and especially the important role of negative carbon emissions in the second half of the century.

Furthermore, the third contribution of the paper is the identification of the assumptions and model characteristics that lead to different decomposition results in both the moderate and the stringent climate policy scenarios.

The rest of the paper is organized as follows: in the next section we describe the integrated assessments models used in the multi-model decomposition analysis, the analysed scenarios and the decomposition methodologies used in the paper; in Section 3 we present the index decomposition analyses of both the no-policy baseline and the moderate reference policy scenario; Section 4 discusses the regional LMDI decomposition analysis in the case with a global ambitious climate change mitigation target; and finally we discuss the main conclusions and policy implications of the analysis.

2. Methodology

In this paper, we develop a multi-model decomposition analysis of CO_2 emissions to determine the main regional energy system transformation that drive alternative mitigation pathways in diverse energy-economy integrated assessment model.

2.1. Global integrated assessment models

The multi-model decomposition analyses include ten integrated assessment energy-economy models (IAMs) that participated in the AMPERE model inter-comparison project (Table 1 summarizes the main characteristics of the models used in this paper and for a more detailed description see Kriegler et al. (2015b)). The compared models can be broadly grouped according to the modelling approach into three distinct categories: (1) Computable general equilibrium (CGE); (2) Ramsey-type optimal growth models (OG); and (3) partial equilibrium energy system (PE) models. CGE models determine the market equilibrium in every period with exogenous assumptions on population, improvements in labour and total factor productivity or production technologies. OG models maximize intertemporal welfare subject to equilibrium constraints and, in most cases, assume perfect foresight about future production and consumption. Both CGE and OG models represent the whole economy with different sectoral resolution (larger in the CGE models) and are able to quantify the macroeconomic implications of alternative energy and climate policies. PE models represent the market and technology development in the energy sector with a wide portfolio of energy technologies and options for emissions reduction. PE models typically minimize production costs (or maximize consumer and producer surplus) in the energy sector but do not model endogenously the evolution of economic activity. The diversity of energy technologies (in the supply and demand side) varies among models as well as the assumptions concerning future development and availability of low carbon options. To characterise the variety of low carbon energy supply technologies in the models we use the 3-sector Shannon- Wiener index (normalized in the interval [0,1]) estimated by Kriegler et al. (2015a). 1 indicates a large variety of electricity and non-electric energy technologies that reduce CO_2 emissions. CGE models have the lowest low-carbon technology variety while most of the PE and OG models have a large diversity of energy technologies. Besides this indicator, Table 1 presents whether the models include or not biomass technologies with carbon capture and storage (CCS). The last indicator included in Table 1 reflects how responsive the models are to climate policies. It is calculated in Kriegler et al. (2015a) and it encompasses different aspects of the models, including: variety of low carbon technologies, technology costs and technology learning, regional renewable potentials and fossil fuel endowments, assumptions on early retirement of technologies, limits on growth rates and on shares of certain type of intermittent energy sources, among others. The differences in model structure, theoretical foundations, sectoral coverage, representation of GHGs, technological details in the energy sector and assumptions reflect different choices of modellers on how to best approach the analysis of mitigation pathways. The model flexibility for technological substitutions, the potential for radical energy system restructuring and the variety of low carbon options included in the modelling framework have a large impact on model results and therefore in the decomposition analysis. For instance, van Sluisveld et al. (2013) and Förster et al. (2013) found that general equilibrium models have different behaviour relative to technologically-rich energy system models, with the latter opting for reducing carbon intensity of energy rather than energy demand in case of strong climate policies.

Table 1: Characterisation of integrated assessment energy-economy models included in the analysis. PE: Partial equilibrium, CGE: Computable general equilibrium and OG: Ramsey-type optimal growth model

Name	**Modelling approach**	**Time horizon**	**Variety of low-carbon supply tech.**	**Biomass CCS**		**Response to climate policies**
				Elect.	**Non-elect.**	
DNE21+	PE	2050	0.79	Yes	Yes	Low
GCAM	PE	2100	0.93	Yes	Yes	High
GEM-E3	CGE	2050	0.36	No	No	Low
IMACLIM	CGE	2100	0.65	Yes	No	Low
IMAGE	PE	2100	0.92	Yes	Yes	High
MERGE-ETL	OG	2100	0.89	Yes	Yes	High
MESSAGE	OG	2100	0.92	Yes	Yes	High
POLES	PE	2100	0.92	Yes	Yes	Medium
REMIND	OG	2100	0.89	Yes	Yes	High
WITCH	OG	2100	0.57	Yes	No	Low

All the models have global coverage with different disaggregation of world regions. We analyse climate change mitigation policies in four major economies: the EU, USA, China and India, which jointly accounted for 60% of global carbon emissions in 2010. All models adopted harmonised assumptions on population and potential economic growth[4]. The harmonisation was developed at the country or geopolitical level[5] and mapped by each model to the corresponding native regions (details on the harmonisation are provided in Supplementary Online Material of the study (Kriegler et al., 2015b)). The definition of the regions is not harmonised across models, which results in differences in the regional population and potential GDP. For instance, some models define a broader EU region that includes, besides the current EU-28 member states, Turkey and the EFTA countries. Therefore, to improve comparability in the multi-model decomposition analysis, we exclude the results of those models in which the regional population in 2010 has a deviation greater than 10% compared to the UN Population data (United Nations, 2013). Thus, the MESSAGE model has been excluded from the analysis for EU, USA and India, while GCAM and IMACLIM are not taken into account for the EU region.

2.2. Description of analysed scenarios

The target of the decomposition analysis is to explore the changes in Kaya identity factors under alternative and highly contrasting climate policy regimes. The analysis is based on a set of scenarios that assume different stringency levels of global climate change mitigation policies presented in Table 2 (see Kriegler et al. (2015b) and Marcucci & Turton (2015) for a more detailed description of the analysed scenarios). The *Base* scenario models a counterfactual case in which no climate change mitigation policies are pursued. The *RefPol* case aims to conceptualize the current policy landscape including fragmented climate change and technology policies with regional moderate targets. The 2020 mitigation targets are based on the low-end of the (unconditional) Copenhagen-Cancun pledges. After 2020, it is assumed that countries will maintain their mitigation effort with climate policies that lead to improvements in emissions intensity per unit of GDP comparable to the period 2005-2020. Finally, we consider a scenario with an ambitious global target of stabilising the atmospheric concentration of GHGs at 450ppm by the end of the 21st century. The target in this scenario is modelled as a global cap on cumulative CO_2 emissions between 2000 and 2100. Models have full "when" and "where" flexibility, that is, they decide on the optimal timing and distribu-

[4]As an input to the models we use a potential GDP pathway that represents economic output in a hypothetical case with constant prices. General equilibrium and optimal growth models determine endogenously the realized GDP, accounting for changes in the prices due to different scenario assumptions. For instance, climate policies will lead to an increase in energy prices which will reduce the realized economic output compared to the no climate policy Baseline scenario.

[5]USA, Japan, EU15, EU12, Russia, Middle East, China, India, Sub-Saharan Africa, Latin America, Southeast Asia, Sub Saharan Africa, Korea, Eastern Europe, Turkey, Australia and New Zealand, Taiwan, Pakistan, EFTA (Norway, Switzerland and Iceland), North Africa, Indonesia, Mexico and Brazil.

tion among regions and sectors of the GHG mitigation effort, which leads to an efficient distribution of the carbon abatement effort through the equalisation of marginal abatement costs across regions and sectors.

Table 2: Analyzed scenarios

Name	Description	Targets	
		GHG mitigation	Technology
Base	Counterfactual scenario without climate change mitigation policies	None	None
RefPol	Moderate climate change mitigation policy scenario that represents the current policy landscape including regional policies on emissions reduction and technology deployment	**2020**: Low-end of unconditional Copenhagen-Cancun pledges: EU and USA: 15% and 5% reduction in GHG emissions from 2005 levels, respectively. China and India: 40% and 20% reduction in GHG intensity relative to 2005, respectively **After 2020**: Emission intensity targets following the stringency of the Copenhagen pledges	Regional targets on deployment of renewable and nuclear technologies by 2020. They are represented as installed capacity targets or a minimum share in the electricity production[a]
450	Immediate global climate change mitigation policy	Global target aiming to stabilize the concentration of GHGs at 450ppm by 2100. This target is implemented by imposing a cumulative CO_2 emissions budget in the 2010-2100 period	*RefPol* targets

[a]See Kriegler et al. (2015b) and Marcucci & Turton (2015) for a detailed description of the targets.

Figure 1a presents the models results (mean and ranges are shown) for global CO_2 emissions in the three analysed scenarios. Even though the climate change mitigation policies assumed in the *RefPol* scenario are moderate, global CO_2 emissions from fossil fuels are significantly reduced compared to the *Base* scenario, from an average of 100 $GtCO_2$ in 2100 to 44.8 $GtCO_2$, although the short-term effects (until 2030) are rather limited. The global climate stabilization target in the *450* scenario results in a further

[6]This is valid in all the box plots in this paper.

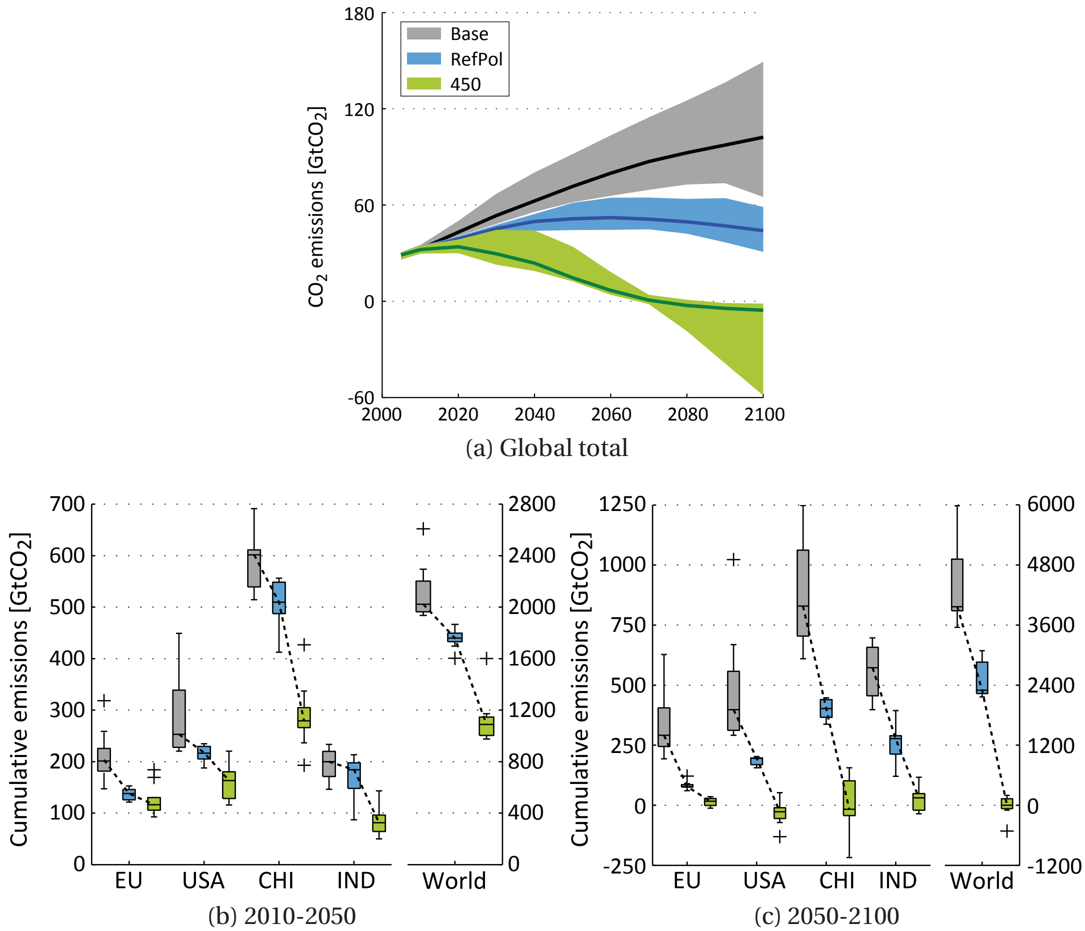


Figure 1: CO_2 emissions from fossil fuels and industry (excluding LULUCF) in *Base*, *RefPol* and *450* scenarios: (a) Global emissions and regional cumulative CO_2 emissions in (b) 2010-2050 and (c) 2050-2100. In (a) the dark line represents the mean across the models; and in (b) and (c) the central mark is the median, the edges of the box are the 25th (q_1) to the 75th (q_3) percentiles, the error bars extend to the minimum and maximum data points not considered outliers, and the outliers (+) are defined as those points that are outside the range $\left[q_1 - 1.5\left(q_3 - q_1\right), q_3 + 1.5\left(q_3 - q_1\right)\right]$[6]. Note the different y-axes.

reduction of energy-related CO_2 emissions to an average of -12.3 $GtCO_2$ by 2100. All the models present a similar behavior with a significant reduction of carbon emissions in the first half of the century and slightly negative emissions after 2060, except for GCAM, whose optimal pathway implies a relatively low effort until 2050 and a high development of biomass technologies with CCS in the second half of the century, leading to large negative emissions in 2100 (-59 $GtCO_2$). CO_2 is the major contributor to total GHG emissions, accounting for around 85% of GHGs in the *Base* scenario in 2100.

Figures 1b and 1c compare the regional cumulative CO_2 emissions in the periods 2010-2050 and 2050-2100, respectively. The assumptions in the *RefPol* scenario are particularly stringent in the EU with an average reduction of cumulative emissions of 27% until 2050 (and 83% in 2050-2100) compared to the *Base* scenario, while in the other regions the reduction in this same period is around 10% (and around 50% in 2050-2100).

In the *450* scenario, all regions reduce their cumulative CO_2 emissions to around zero (median of models) in the second half of the century. This stringent scenario results in important regional differences with, China and India undertaking the largest emissions reduction efforts in the period 2010-2050 (an average reduction of 50% compared to the *RefPol* case) and a relatively low additional carbon abatement in the EU (compared to the *RefPol* scenario).

The climate outcome of the different scenarios depends on the global cumulative GHG emissions in the 2010-2100 period. Models results show an increase in global mean temperature by 2100 relative to pre-industrial levels of 4.1-5.3°C in the *Base* case; 3.2-3.8°C in the moderate reference policy; and 1.7-2.2°C in the *450* scenario (Kriegler et al., 2015b).

2.3. The Kaya identity

A useful tool to analyze the model differences in terms of the determinants of the reductions in CO_2 emissions[7] reductions is the Kaya identity (Kaya, 1990) that decomposes carbon emissions into the main underlying factors:

$$CO_2 = GDP \times \underbrace{\frac{FE}{GDP}}_{EI} \times \underbrace{\frac{\mathrm{CO_2}}{FE}}_{CI} \tag{1}$$

where CO_2 represents the total carbon emissions, *GDP* is the gross domestic product, *FE* is the final energy consumption, *EI* represents the final energy intensity of GDP and *CI* is the carbon intensity of final energy. The three components of the above decomposition formula are interpreted as follows:

1. Economic activity: A reduction of the economic activity (measured as a reduction in GDP) leads directly to a decrease in the energy demanded by final consumers that in turn leads to lower carbon emissions both in final energy demand sectors and in the power generating sector.

2. Energy intensity of GDP (*EI*): A reduction in energy intensity (the ratio of final energy demand to GDP) can be attributed to energy efficiency improvements (better insulation in buildings, more efficient technologies such as household appliances or hybrid/electric vehicles, etc.) promoted via policies or standards, structural changes of the economy away from energy intensive industrial sectors (e.g. ferrous and non-ferrous metals, chemicals, cement etc.), consumers' reaction to high energy prices or behavioral changes of energy consumers[8].

[7] CO_2 emissions from fossil fuel combustion and industry are considered. Emissions from the LULUCF sector (Land Use, Land Use Change and Forestry) are excluded from our analysis.

[8] Energy efficiency improvements can be caused by structural changes in economic production, e.g. de-industrialization process as GDP increases. However, most global IAMs used in the study do not represent multiple sectors and thus the structural economy effect cannot be studied in the AMPERE framework.

3. Carbon intensity of energy (CI): A reduction in the carbon intensity of energy (rate of CO_2 emissions to final energy) corresponds to changes in the energy mix, including substitution within the fossil fuel mix (natural gas replaces coal and oil), the use of renewable-based alternatives, deployment of nuclear power plants or technologies with carbon capture and storage (CCS) in the power generation sector and in industrial applications.

Partial equilibrium energy-system models have exogenous assumptions on GDP. Moreover, according to Kriegler et al. (2015a), in the CGE and OG models the variation across scenarios in the effect of changes in GDP to changes in CO_2 emissions is significantly lower than the effect from changes in energy intensity of GDP and carbon intensity of energy. Therefore, in this analysis we focus on regional energy system transformations (energy intensity of GDP and carbon intensity of energy) driven by alternative climate policies. Another factor that is often included in the decomposition of emissions is the population growth, since an increase in the population leads directly to higher energy demand and hence higher emissions. In this analysis we have not included the influence of population in the changes of CO_2 emissions since it is an exogenous harmonised parameter to all the models and it is kept constant across scenarios, and therefore, does not provide additional insights to the decomposition analysis.

2.4. Decomposition methodology

We use two distinct approaches for the decomposition analysis: the index analysis and the additive log mean Divisia index (LMDI I). We use the first technique to develop an intertemporal analysis of the changes in carbon emissions compared to a reference year because it allows a straightforward interpretation of the decomposition results. We use the LMDI approach to analyse the changes in emissions in the scenario with the stringent climate target. This methodology has some advantages compared to other decomposition approaches, for instance, it gives a perfect decomposition (no unexplained residuals), it can handle zero values in the data set and it is relatively easy to formulate (does not depend on the number of factors used) (Ang, 2004).

2.4.1. Index decomposition methodology

In the index analysis the future evolution of carbon emissions and the related Kaya decomposition factor in future periods (t) are compared to values in the base period (0):

$$\frac{CO_{2t}}{CO_{20}} = \frac{GDP_t}{GDP_0} \times \frac{EI_t}{EI_0} \times \frac{CI_t}{CI_0}$$

Thus, the change in emissions in period t relative to the reference period (period 0) relates to the changes in the underlying factors as follows:

$$\ln\left(\frac{CO_{2t}}{CO_{20}}\right) = \ln\left(\frac{GDP_t}{GDP_0}\right) + \ln\left(\frac{EI_t}{EI_0}\right) + \ln\left(\frac{CI_t}{CI_0}\right). \quad (2)$$

2.4.2. LMDI decomposition methodology

With the second approach we decompose changes in carbon emissions into Kaya factors (Equation 1) using the LMDI methodology (Ang & Liu, 2001; Ang, 2005). This technique determines the contribution of individual factors to changes in emissions in one scenario over time and across scenarios at a specific year. In the analysis over time, the changes in emissions are measured with respect to a reference year[9], while the decomposition across scenarios quantifies the changes with respect to a reference scenario used as the benchmark. Following Ang (2005), the index decomposition of the change in CO_2 emissions between a reference period 0 and a period t is defined as the sum of the activity growth (ΔGDP), energy intensity (ΔEI) and carbon intensity (ΔCI) effects, thus,

$$\Delta CO_2 = \Delta GDP + \Delta EI + \Delta CI \tag{3}$$

where the contribution of each factor F (GDP, EI or CI) is determined as:

$$\Delta F = \frac{CO_{2t} - CO_{20}}{\ln CO_{2t} - \ln CO_{20}} \ln\left(\frac{F_t}{F_0}\right).$$

Similarly, the decomposition of emissions between two scenarios x and y is given by Equation 3 with

$$\Delta F = \frac{CO_{2y} - CO_{2x}}{\ln CO_{2y} - \ln CO_{2x}} \ln\left(\frac{F_y}{F_x}\right). \tag{4}$$

Equation 4 is used to decompose changes in carbon emissions between scenarios with different climate policy assumptions. CO_2 emissions in the less ambitious scenario[10] (scenario x) provide the benchmark point for the evaluation of the more stringent scenario y.

2.4.3. LMDI Decomposition methodology for negative emissions

The LMDI decomposition approach as presented above cannot handle negative carbon emissions and thus it cannot be used directly to decompose changes in carbon emissions in the *450* scenario (scenario y) relative to *RefPol* (scenario x) because, as shown in Figure 1a, he IAMs project negative carbon emissions by 2100 in the *450* case. However, Ang & Liu (2007b) present an analytical approach to deal with negative values in the data set, which we apply to decompose emission changes into Kaya factors. Since the factor that changes from positive to negative is the carbon intensity of energy, following their proposal, we define an intermediate point *mid* (such that $CI_{mid} = 0$ and GDP_{mid}, $EI_{mid} > 0$) and separate the interval into two parts: first from the initial positive point in the *RefPol* scenario (GDP_x, EI_x, CI_x) to the intermediate point *mid* (GDP_{mid}, EI_{mid}, CI_{mid}); and then from *mid* to the final negative point in the *450* scenario (GDP_y,

[9]In the LMDI analysis in this paper we use 2005 as the reference year since it is the latest year to which all models in the AMPERE project are calibrated (Note that a subset of models is also calibrated to 2010).

[10]In terms of climate policies

EI_y, CI_y). Hence, the contribution of each factor F (activity growth, energy efficiency, carbon intensity) to a change in emissions from scenario x to scenario y is given by:

$$\begin{aligned}\Delta F = & \lim_{CI^{-}_{mid}\to 0^{-}} \frac{CO_{2y} - CO^{-}_{2mid}}{\ln CO_{2y} - \ln CO^{-}_{2mid}} \ln\left(\frac{F_y}{F^{-}_{mid}}\right) \\ & + \lim_{CI^{+}_{mid}\to 0^{+}} \frac{CO^{+}_{2mid} - CO_{2x}}{\ln CO^{+}_{2mid} - \ln CO_{2x}} \ln\left(\frac{F^{+}_{mid}}{F_x}\right)\end{aligned}$$

where CI^{-}_{mid} and CI^{+}_{mid} are a small negative and positive numbers, respectively. Solving the limits we obtain the following contribution of the underlying factors to the LMDI decomposition of CO_2 emissions:

$$\begin{aligned}\Delta GDP &= 0 + 0 \\ \Delta EI &= 0 + 0 \\ \Delta CI &= CO_{2y} - CO_{2x},\end{aligned}$$

which means that the carbon intensity of final energy accounts for 100% of the change in emissions from the *RefPol* scenario to the *450* case in the periods in which CO_2 emissions become negative.

3. Historical trends, baseline and moderate policy scenarios

3.1. No-policy baseline vs. moderate policy: baseline scenario validation

Integrated assessment models represent the behaviour of the future energy, economic and climate systems. Given that the future evolution of key energy/economic and climate variables cannot be predicted, the validation of IAMs constitutes a complicated task because the results cannot be compared with real data, and the system behaviour in the past does not necessarily represents the future. For the same reason, integrated assessment modelling focuses on the analysis of scenarios where different alternatives of future developments are evaluated (Schwanitz, 2013). In general, IAMs use a counterfactual baseline scenario as the benchmark to compare the results of alternative climate change mitigation policies and to estimate the cost of abating GHGs emissions. In this section, we use the index decomposition analysis (see Section 2.4.1) of historical emissions and near-term modelling results to evaluate baseline scenarios and to identify assumptions or model characteristics driving significant deviation from the average results. This analysis follows the proposal in Schwanitz (2013) of using stylized facts as one option to diagnose the behaviour of IAMs. Following the same idea, one could expect that the decomposition of the near-future carbon emissions in the baseline scenarios does not diverge significantly from the near past trends. We compare the index decomposition of carbon emissions in the counterfactual no-policy baseline

(*Base*), the moderate policy scenario (*RefPol*) and the historical data of the period 1990-2010[11]. Table 3 presents the logarithm of the 2030 factor change (following Equation 2) in the four analysed economies using 2005 as the reference year . The first factor driving changes in carbon emissions is economic growth. As shown in Table 3, changes in GDP account for a significant part of the changes in emissions, especially in India and China. However, given that the GDP projections in all regions are harmonized in the baseline and that energy system models have exogenous GDP assumptions, the dispersion across models is very limited, with exception of IMAGE (in China and India) and IMACLIM (in India). The IMAGE model has higher GDP projections in India and China due to a different approach used to convert GDP MER to PPP[12]. IMACLIM assumes in India infrastructure policies that aim at controlling the long-term dynamics of transport-related emissions as well as measures to enable more flexible labour markets.

Table 3: Logarithm of 2030 factor change using 2005 as reference year; the values correspond to the average and the standard deviation in parenthesis

Factor	EU		USA		China		India	
	Base	*RefPol*	*Base*	*RefPol*	*Base*	*RefPol*	*Base*	*RefPol*
C	0.08	-0.28	0.13	-0.12	0.99	0.9	1.24	1.17
	(0.22)	(0.07)	(0.24)	(0.1)	(0.1)	(0.09)	(0.28)	(0.3)
GDP	0.42	0.42	0.46	0.46	1.91	1.92	1.99	2.01
	(0.005)	(0.001)	(0.01)	(0.01)	(0.08)	(0.08)	(0.11)	(0.1)
EI	-0.33	-0.43	-0.37	-0.43	-0.95	-0.96	-0.88	-0.93
	(0.04)	(0.09)	(0.12)	(0.13)	(0.15)	(0.15)	(0.18)	(0.16)
CI	-0.01	-0.27	0.03	-0.15	0.03	-0.05	0.13	0.09
	(0.19)	(0.03)	(0.14)	(0.07)	(0.14)	(0.15)	(0.27)	(0.29)

The limited dispersion across models in the changes in economic growth allow us to focus our analysis on the changes in energy and carbon intensity. Figure 2 presents the 10 year growth rate of energy intensity from 1990 to 2030. Most of the models project in both scenarios short-term improvements in energy efficiency consistent with the near-past historical rates for the four analysed regions. However, GEM-E3 (in EU-*RefPol*, USA-*RefPol*, India-*Base* 2020-2030); IMACLIM (in USA); and MERGE-ETL (in EU-*Base*,

[11]The historical data used in this paper are derived from: UN database (United Nations, 2013) for population, World Bank for GDP (World Bank), the IEA statistics for final energy (IEA, 2013) and the CDIAC database for CO_2 emissions (Boden et al., 2013). The EUROSTAT database (European Commission) has been used to provide historical data for the EU region.

[12]As highlighted in Kriegler et al. (2015a), in the AMPERE context models assumed a constant PPP to MER ratio (i.e. PPP growth rates = MER growth rates). However, IMAGE used a dynamic PPP to MER conversion ratio and thus MER growth in developing regions is significantly higher than PPP growth.

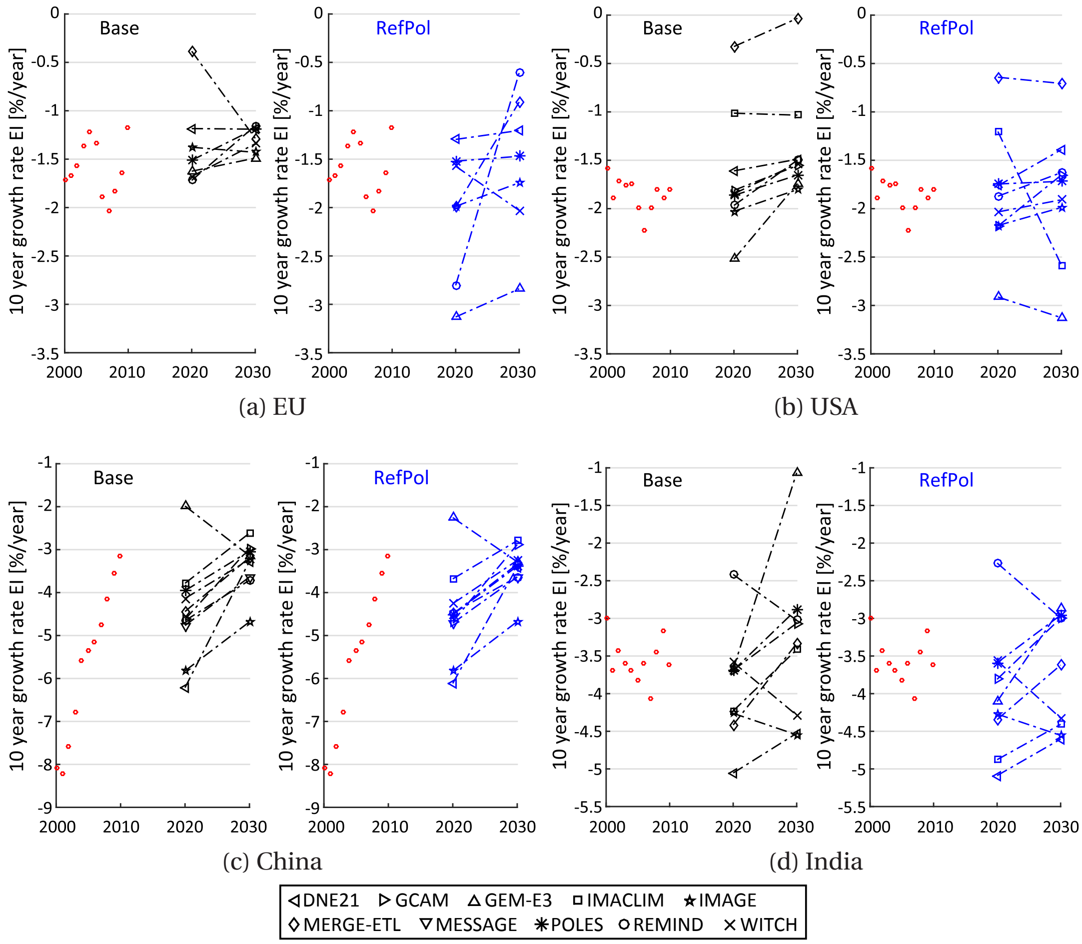


Figure 2: Energy intensity 10-year growth rate: Historical values and model projections. The values correspond to the annual growth rate in the precedent decade.

USA) result in different[13] EI improvement rates. GEM-E3 opts for a larger reduction in energy intensity of GDP because of the limited substitution within the energy mix (especially for the EU and USA). Conversely, GEM-E3 projects higher carbon intensity improvements for India as it assumes reduction of coal input to power plants and thus energy intensity improvements are lower compared to the model average in the *Base* and *RefPol* scenarios. IMACLIM results are directly link to their GDP projections in the US, lower than all the models in the *Base* scenario: A yearly growth rate of 2 and 1.75 %/year in 2020 and 2030, respectively, compared to an average of 2.4 and 2%/year in the other models. In the case of MERGE-ETL, the higher energy intensity in USA results from different assumptions concerning the availability and deployment of coal and nuclear power plants: In the *Base* scenario, a larger deployment of coal-based technolo-

[13]These outliers are defined as those points that are outside the range $[min - 1.2(max - min), max + 1.2(max - min)]$ where max and min correspond to the maximum and minimum 10-year rates from 1995-2005 to 2000-2010.

gies results in higher EI; while in *RefPol* the deployment of nuclear reactors allows the achievement of the moderate climate targets with a higher energy demand compared to the other models.

The greatest dispersion across modelling results (as shown in Table 3) is related to the evolution of carbon intensity of energy. Figure 3 presents the 10-year growth rate of the carbon intensity from 1990 to 2030. In the EU and USA the short-term projection in the *Base* scenario of all models are consistent with the near-past CI improvement rates, except for MERGE-ETL and DNE21 that assume a future energy production that relies largely on fossil fuels (especially coal). In the EU-*Base* the rest of the models include to some extent the already adopted climate policies, such as the Climate and Energy Package for 2020 (European Union 2009). The moderate climate targets in the EU and USA (presented in Table 2) result in a relative decarbonisation of the energy system that leads to CI improvement rates larger than the observed near-past trends, with exception of MERGE-ETL and DNE21, whose projections in RefPol represent a continuation of historical trends. On the other hand, in China and India, the climate target is defined as a reduction in GHG intensity that is already achieved in the *Base* case, as shown in Marcucci & Turton (2015), and the CI improvement is due only to the technology targets (25% share of renewables in China; and 20 GW and 10 GW installed capacity of Wind and solar in India). Therefore, both *Base* and *RefPol* scenarios result in similar CI growth rates, especially in India that has the less ambitious technology targets. In China all models project CI growth improvements larger than the near-past trends, and WITCH, MERGE-ETL and GCAM have the closest results to the historical trends because they project a larger use of coal-based power plants and fossil fuels in the non-energy sector. These results are driven by differences in the models concerning limits in the deployment of coal technologies, technology costs and technology lock-in[14]. In India, all the models project in Base and RefPol an increase in the CI similar to the historical development except the CGE models (GEM-E3 and IMACLIM).

In general, the counterfactual *Base* scenario represents a continuation of historical trends in the EU and US, except for those models with optimistic assumptions on the deployment of coal-based technologies (MERGE-ETL and DNE21), where the *RefPol* scenario projects trends closer to the historical developments. In China, the models project in both scenarios improvements in energy and carbon intensity larger than the historical development; conversely, in India, the two scenarios represent a benchmark with near-future trends close to the near-past development.

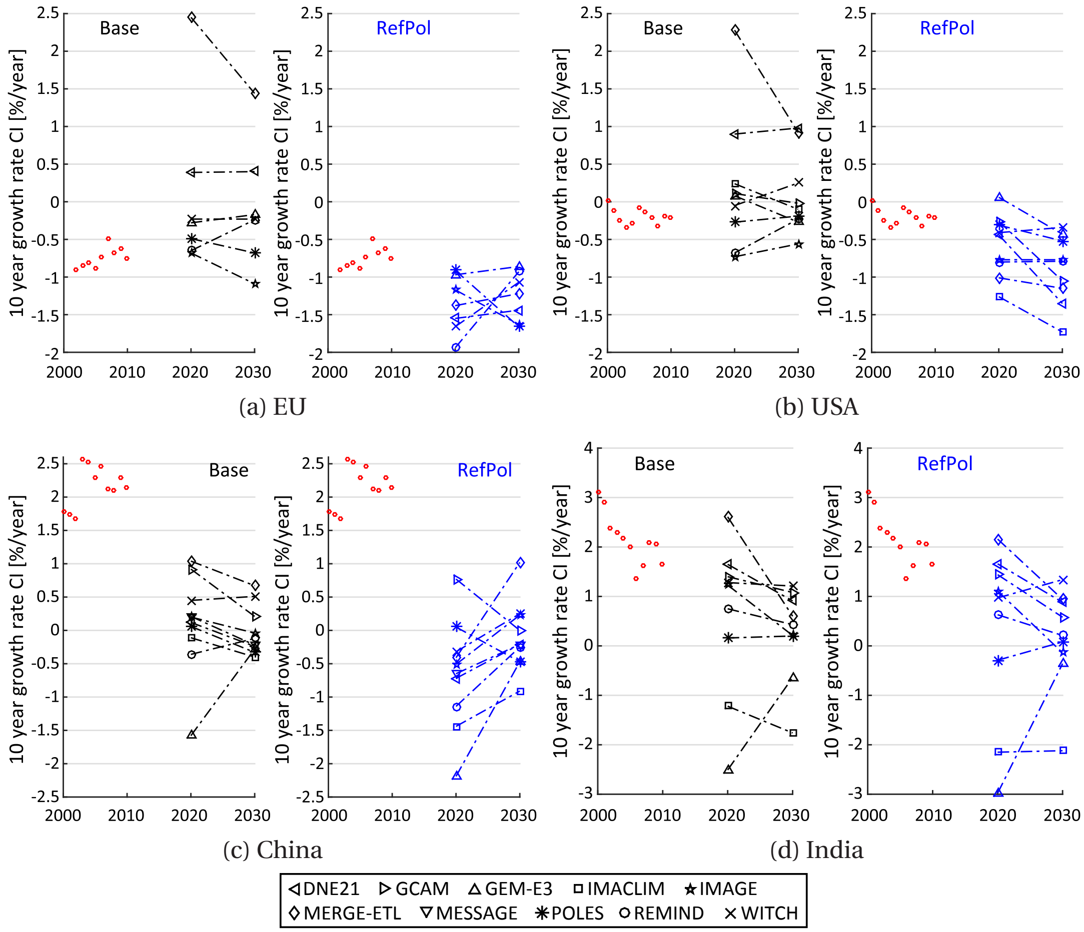


Figure 3: Carbon intensity 10-year growth rate: Historical values and model projections. The values correspond to the annual growth rate in the precedent decade.

3.2. Regional decarbonisation components in the fragmented policy scenario

The second part of the analysis focuses on decomposing long-term regional carbon emission changes in the *RefPol* scenario relative to base year levels (2005) using the index decomposition analysis described in Section 2.4.1. Table 4 presents the logarithm of the factor change in 2050 and 2100 for the four analysed regions. The decomposition of emissions differs significantly between developing and developed OECD economies concerning: (1) the medium and long-term changes in emissions and (2) the relative importance of the carbon and energy intensity factors. First, while in the EU and USA, the *RefPol* results in a decrease in energy-related carbon emissions relative to 2005, in China and India all models show increasing carbon emissions by 2050, despite the implementation of the (moderate) climate change and technology targets/policies. This

[14] In this context, technology lock-in refers to energy infrastructure being used until the end of its lifetime without the possibility of early retirement. The following models allow early retirement: DNE21, GCAM, MESSAGE and POLES.

Table 4: Logarithm of 2030 factor change using 2005 as reference year; the values correspond to the average and the standard deviation in parenthesis

Factor	EU		USA		China		India	
	2050	2100	2050	2100	2050	2100	2050	2100
C	-0.62	-1.71	-0.28	-0.84	0.84	-0.35	1.49	0.72
	(0.12)	(0.46)	(0.14)	(0.15)	(0.07)	(0.37)	(0.39)	(0.35)
GDP	0.72	1.41	0.83	1.59	2.44	2.97	2.99	3.99
	(0.01)	(0.02)	(0.01)	(0.02)	(0.11)	(0.16)	(0.15)	(0.22)
EI	-0.75	-1.41	-0.76	-1.43	-1.44	-2.26	-1.41	-2.22
	(0.13)	(0.22)	(0.19)	(0.09)	(0.13)	(0.24)	(0.29)	(0.26)
CI	-0.59	-1.71	-0.35	-0.99	-0.16	-1.06	-0.09	-1.04
	(0.12)	(0.52)	(0.11)	(0.13)	(0.13)	(0.38)	(0.44)	(0.39)

difference is mainly due to the large impact of the activity growth effect (ΔGDP). Developing countries are assumed to undergo very high economic growth in the *Base* scenario, with GDP increasing by a factor of 19 and 50 in 2100 from 2005 levels in China and India, respectively, while the increase in the EU and the US is projected to be around 4- and 5-fold, respectively[15]. Second, in China and India the contribution to changes in carbon emissions from CI improvements is significantly lower than the changes in EI (see Table 4), hence the changes in emissions are mainly due to the evolution of economic growth and energy demand. This is consistent with the findings in Blanford et al. (2012), where the changes in income and energy intensity are found to be the main determinants for the variation in emissions in China and India in the baseline projections. The reductions in carbon intensity of final energy become increasingly important in the second half of the century, leading to a significant deceleration in the CO_2 growth in India and to decreasing emissions in China after 2070 (see Figure 4a). On the other hand, in USA and the EU, the joint impact of the energy and carbon intensity reductions more than counterbalances the activity growth effect leading to reductions in carbon emissions relative to 2005. However, there are important differences between the decarbonisation strategies in the EU and USA. In the EU, the reduction in energy intensity is the most important factor until 2050, but all models find that the contribution of changes in the energy mix (away from carbon intensive fuels) increases rapidly in the medium term becoming the leading strategy by the end of the century. On the other hand, in the US, energy efficiency improvements are projected to be the most cost-efficient mitigation option during the whole projection period. This is due to the large potential for demand-side restructuring in the USA, which is characterised by higher energy inten-

[15]Potential GDP under constant prices is harmonized. CGE and OG models determined endogenously the realized GDP but the results do not diverge significantly from the assumed potential economic growth.

sity per unit of GDP compared to other high income OECD economies, like Japan and the EU.

Despite the important effect of GDP growth on the changes in emissions in the long run, we focus our model comparison analysis on the changes in energy and carbon intensity due to the large dispersion across modelling results (see Table 4). Figure 4 presents the changes in carbon emissions, energy intensity of GDP and carbon intensity of energy for the four analysed regions using 2005 as reference year. In the EU and the US the models project significant reductions in energy-related carbon emissions, in particular in GEM-E3 and IMAGE that result in lower carbon pathways. In GEM-E3, these lower emissions are due to a larger reduction in the energy intensity. In IMAGE the difference results from a larger deployment of biomass with CCS in both the electricity and the non-electric sector. IMAGE (van Vuuren et al., 2009) and GCAM (Wise et al., 2009) include a land module with detailed land-use data and competition for land. In general, these two models project the largest deployment of biomass and, in the case of IMAGE, a significant use of biomass with CCS that results in a large reduction in carbon intensity in all the regions. MERGE-ETL is the other model that shows slightly different results in the decomposition of changes in carbon emissions in the EU and USA. Relatively lower investment costs from nuclear and coal-based power plants, due to endogenous technology learning in MERGE-ETL (Marcucci & Turton, 2015), and the assumptions concerning policy support for such technologies determine to a large extent the different decomposition results. For instance, in the EU after 2050, MERGE-ETL assumes an optimistic deployment of coal technologies and a limited production of electricity from uranium[16] that results in a higher production of energy from coal, which in turn leads to a large carbon intensity that is compensated with a reduction in energy intensity. While in the USA, MERGE-ETL has the highest EI due to a larger deployment of nuclear compared to the rest of the models (4.7 PWh in 2050 compared to 2.4, 1.7, 1.44 and 1.36 PWh in DNE21, WITCH, POLES and IMACLIM, respectively).

In China, the IAMs have similar decomposition results except for the decrease in carbon intensity from the CGE models, IMACLIM and GEM-E3, which is significantly higher than in the rest of the models, mainly due to substitutions in the power mix away from coal-based power plants. In India, despite the similar changes in emissions by 2100 in all the models, the pathways have a considerable variation. In India, the model results can be divided in three groups according to the emission reductions: (1) The CGE model IMACLIM that results in the largest reductions; (2) the energy system partial equilibrium models (DNE21 and POLES) and GEM-E3 with an intermediate pathway; (3) and the optimal growth models (REMIND, WITCH, MERGE-ETL) together with IMAGE and GCAM with the largest increase in energy-related carbon emissions. This difference comes mainly from the changes in carbon intensity. Optimal growth models

[16] A maximum share in electricity of 50% from nuclear and no limit on coal, while many of the other models have less optimistic assumptions concerning the deployment of coal in the EU.

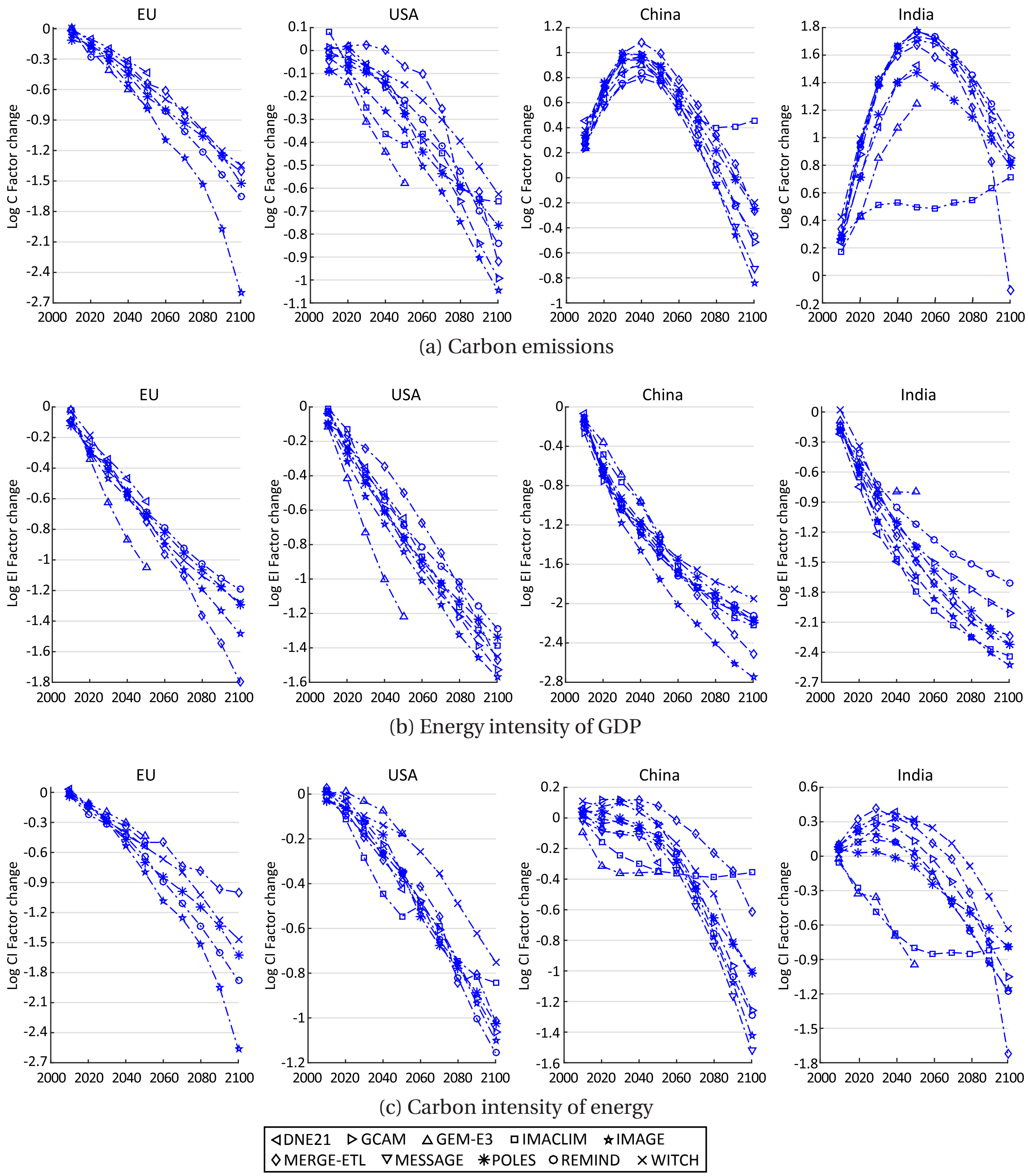


Figure 4: Logarithm of the factor change in the *RefPol* scenario (base year=2005)

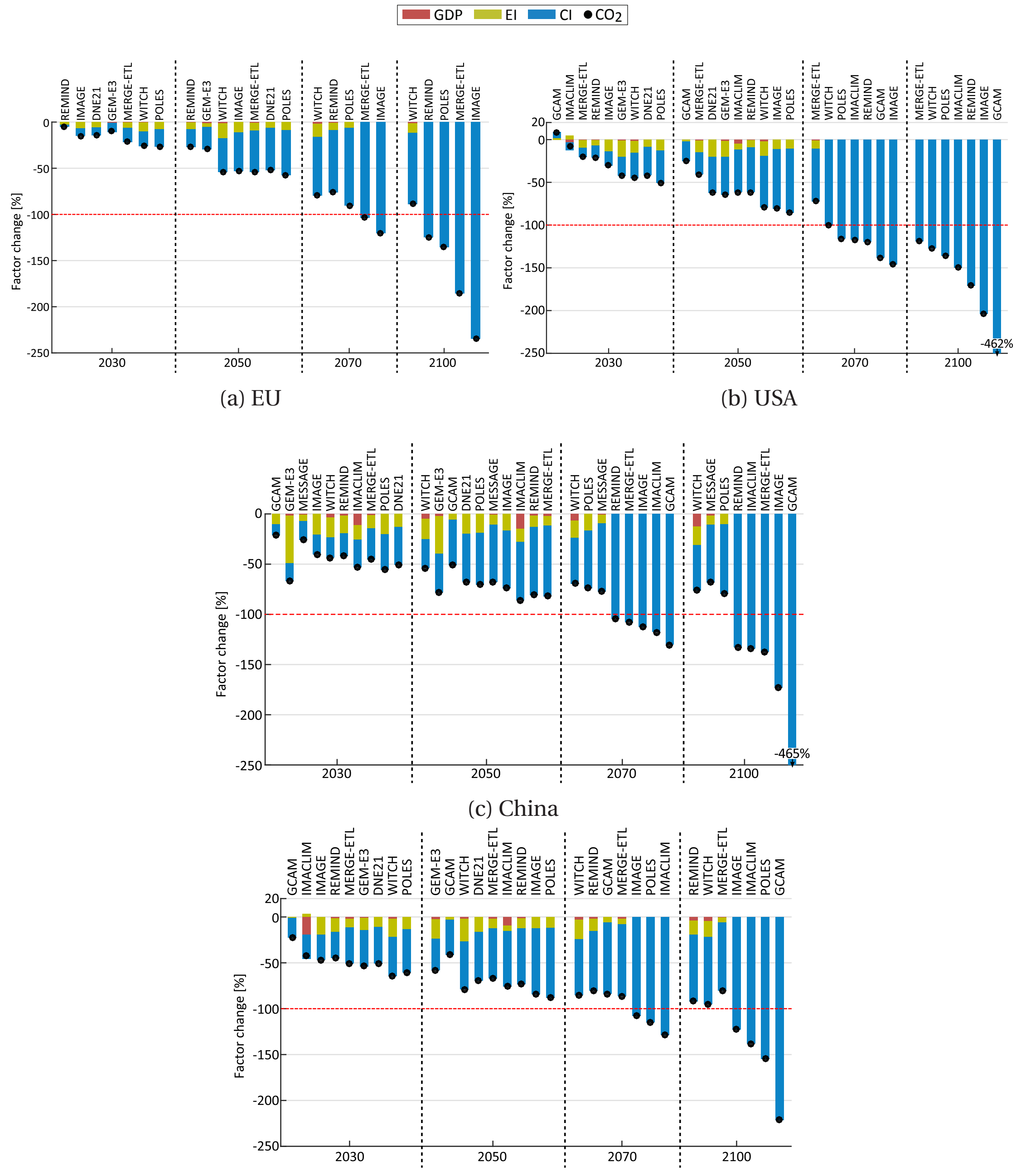
have a less detailed representation of the energy system and model technology lock-in leading to higher increase in carbon intensity until 2050. Energy system models have a large portfolio of energy technologies and carbon abatement options and are characterised by higher substitution flexibility, especially in the case of DNE and POLES that allow for early retirement of technologies. The behaviour of the IMACLIM model is largely due to the low increase in final energy demand in India, driven by assumptions about low urbanisation rate and limited increases in passenger mobility (especially in terms of car ownership rates). GEM-E3 results in a different behaviour with low EI improvements balanced with high reductions in carbon intensity, assuming a reduction in coal-based electricity (as already stated in Section 3.1).

Overall, differences across modelling results in the *RefPol* scenario are largely driven by assumptions concerning resource availability (biomass, for instance); policy support and cost of key technologies such as nuclear and coal power, the availability of low and zero carbon options, the possibility of early retirement of technologies and, to a certain extent, the model type. CGE models do not have a detailed representation of the energy sector, therefore, tend to favour reductions in energy intensity over improvements in carbon intensity. However, especially in China and India, the assumptions employed in CGE models (e.g. cost of coal power plants) have a particularly large effect on the decomposition analysis, leading to the opposite behaviour.

4. The additional effort of a coordinated global climate change mitigation action: The role of negative emissions

The *450* mitigation scenario assumes a global target of stabilizing the atmospheric concentration of GHGs to approximately 450ppm CO_{2e} by 2100. In this case, the models decide on the optimal regional and sectoral emissions reduction pathway needed to achieve this target; thus models are free to choose when and where carbon abatement takes place. As shown in Figure 1a, most of the models find that the optimal global CO_2 emissions path requires both immediate action (from 2015 onwards) and negative carbon emissions in the long term (after 2070). In this Section we develop a multi-model decomposition analysis of the changes in carbon emissions in the *450* scenario (compared to the *RefPol*) in order to determine synergies across models in terms of decarbonisation strategies and to understand the main characteristics in the modelling approaches that lead to different mitigation pathways. We use the LMDI methodology for decomposition across scenarios described in Section 2.4.2 and, in the case of negative carbon emissions, since this methodology cannot be directly applied, we use the analytical approach developed in Section 2.4.3.

Figure 5 presents the LMDI decomposition of the changes in regional carbon emissions in the *450* mitigation scenario relative to *RefPol*. Imposing a 450ppm long-term global mitigation target has significant impacts on global carbon emissions, which are projected to decline globally by 67% and 125% in 2050 and 2100, respectively, compared



(a) EU

(b) USA

(c) China

(d) India

Figure 5: LMDI decomposition analysis of CO_2 emissions in the *450* scenario compared to *RefPol*. Models are sorted from left to right in ascending order of carbon intensity (the model in the left has the lowest changes in CI). Values below -100% (red line) indicate negative emissions

to the *RefPol* case (average of models). All models show a particularly high contribution of the carbon intensity effect in the *450* mitigation scenario both in developed and in developing economies.

The activity growth effect cannot be quantified by energy system models, in which GDP is exogenous and does not change among scenarios. On the other hand, economic activity is endogenous in general equilibrium and optimal growth models and depends on the stringency of climate policies and thus it changes in the alternative examined scenarios. All the IAMs (except IMACLIM and WITCH in China) found that the contribution of changes in GDP to the emissions reduction in the *450* scenario compared to *RefPol* is relatively low (red bars in Figure 5). IMACLIM shows large GDP losses in China and India due to the lack of bottom-up mechanisms for the representation of the energy system, the relatively limited technological coverage and the substitution rigidities in the energy mix that lead to higher carbon price levels compared to other models. In the same way, WITCH is one of the models with the lowest variety of low carbon supply technologies (as shown in Table 1) and, therefore, the model projects in the long-run higher GDP losses to achieve ambitious climate policies.

In the first half of the century, the changes in energy intensity of GDP contribute significantly to the emissions reduction achieved in the *450* scenario compared to *RefPol*, but the contribution is projected to decrease significantly in the second half of the century and to be relatively limited by 2100. Therefore, the additional decarbonisation strategies needed to achieve the global 450ppm target in the four major economies (compared to *RefPol*) shift completely to decreasing the carbon intensity of energy. This means that additional efforts relative to the moderate reference policy scenario focus on the deployment of low, zero and negative carbon technologies. However, this does not mean that reductions in the energy demand are not required to meet stringent emission targets; conversely, they are as relevant as in the reference policy case[17]. Furthermore, in most of the models, the optimal CO_2 emissions pathway after 2070 in the *450* scenario depends totally on the changes in carbon intensity and relies on the development of technologies with carbon capture and sequestration (CCS) and, in particular, biomass technologies with CCS (BECCS) that lead to negative net carbon emissions[18]. BECCS technologies are particularly important in the GCAM model, in which the optimal emission pathway implies less carbon abatement effort in the first half of the century and larger negative emissions in the long term due to the significantly higher potential assumed for the biomass with CCS technology compared to

[17]Note that the decomposition results presented in Figure 5 are relative to the *RefPol* scenario which implies some bias since the *RefPol* already incorporates high energy efficiency improvements (as shown in Figure 4b).

[18]Negative emissions from BECCS technologies are theoretically obtained by coupling a module to capture CO_2 to a carbon-neutral biomass power plant (assuming that the CO_2 capture by the biomass feedstock while growing and at steady state balances the amount emitted during energy production) (Fuss et al., 2014)

other IAMs. However, CCS technologies are still in the demonstration phase without commercial projects being developed yet; and their up-scaling faces important barriers concerning financing, safety, regulatory issues and public acceptance (Lilliestam et al., 2012; Scott et al., 2013; Capros et al., 2014). Moreover, besides the concerns related to the capture and storage of carbon, BECCS technologies face additional challenges including: (1) Physical and technical constraints to the large deployment of biomass due to restrictions in land use and trade-offs with food and water supply and conservation of biodiversity; (2) possible climate risks due to increased N_2O and uncertainty in the behaviour of the carbon cycle in the presence of negative emissions; and (3) uncertainty in the costs of BECCS technologies (Creutzig et al., 2014; Fuss et al., 2014).

Despite the general agreement among the modelling approaches on the regional decarbonisation strategies, the assumptions and characteristics of the models lead to some differences in the decomposition results. One characteristic with a significant impact on the optimal decarbonisation strategies is the variety of low carbon technologies and the availability of backstop technologies with carbon capture and storage. GEM-E3[19] and WITCH are the models with the lowest variety of low carbon technologies (as shown in are in Table 1) and with fewer biomass with CCS options. As a consequence, these models result in optimal regional decarbonisation strategies with lower changes in carbon intensity that are partially compensated by accelerated energy efficiency improvements. This is consistent with the model classification in Table 1 (based on Kriegler et al. (2015a)), in which GEM-E3 and WITCH are classified as low response models with limited availability of low carbon technological options that opt for reducing energy demand rather than switching to clean energy technologies. Conversely, IMAGE and GCAM are in the group of models with highest variety of low carbon technologies (together with MESSAGE, POLES, REMIND and MERGE-ETL) and are the only IAMs in this group with a detailed representation of land use including competition for land. This model of the land-use leads to relatively high biomass potentials and, therefore, changes in the carbon intensity in the long-term are the leading strategy to achieve the 450ppm targets. In particular, GCAM has optimistic assumptions on yield growth, technological improvements of crops and CCS potentials (Wise et al., 2009). Hence, GCAM is the only model that allows for an overshoot in carbon emissions in the beginning of the century that are then compensated by large negative CO_2 emissions after 2050.

Besides the variety of low-carbon technologies represented in the models and the assumptions on biomass potentials, the regional distribution of emissions and the assumptions on regional resource availability have an effect on the decomposition results. The 450ppm target is modelled as a global limit on cumulative GHG emissions,

[19] The CGE models (like GEM-E3) use aggregate CES (constant elasticity of substitution) functions to represent the energy system. The rigidity of CES combined with the limited technological representation implies that CGE models opt for reductions of energy demand rather than changes in the energy mix.

hence, the models decide when and where the abatement takes place. For instance, the MERGE-ETL model shows slightly higher emissions in the USA due to lower changes in the carbon intensity of energy as a result of larger deployment of fossil-based technologies with CCS, due to more optimistic assumptions concerning availability of coal and gas resources in the US. These higher emissions are compensated by lower emissions in other regions, such as Russia and the ROW.

5. Discussion and conclusions

This paper contributes to the literature with a multi-model decomposition analysis of regional carbon emissions under alternative climate policy regimes with the objective of: (1) comparing the behaviour of global energy-economy models under baseline assumptions with historical trends as an alternative approach for validation of baseline scenarios; (2) identifying robust patterns in the regional factors that contribute to the mitigation of carbon emissions; and (3) determining the main model characteristics and assumptions that lead to different decarbonisation pathways.

IAMs use baselines scenarios as a benchmark to compare the consequences of alternative policies. We used the decomposition of near-past carbon emissions and near-term modelling projections as an alternative to validate the baseline scenarios. We found that a counterfactual baseline scenario where no climate change mitigation nor technology policies are pursued (*Base*) is the one that comes closer to a continuation of the historical trends (2000-2010) in terms of energy efficiency and carbon intensity changes in the EU and US, except for the IAMs with optimistic assumptions on the use of fossil-based technologies. In India, both counterfactual and moderate policy scenarios represent a benchmark with near-future projections close to the near-past developments. While, in China, the projections from the models in both cases imply, already by 2020, improvements in energy and carbon intensity significantly higher than the historical trends.

Although it is increasingly recognized that global action would be needed to mitigate the impacts of climate change, the current climate policy landscape is characterized by fragmented regional policies (Copenhagen-Cancun pledges) of moderate ambition and without a global effective and binding agreement in place. We developed a factor decomposition analysis of the changes in carbon emissions in a scenario that conceptualizes the regionally fragmented climate policies compared to the counterfactual no-policy *Base* scenario. We found that the reduction in the energy intensity per unit of GDP is the key factor to achieve the moderate climate change mitigation objectives. This requires, among others, energy efficiency promotion in all demand sectors and regions via dedicated policies or standards, uptake of more efficient energy equipment by consumers, investments in better insulation of buildings and changes in consumer behaviour. However, when the stringency of the climate target increases, the reduction in energy intensity of GDP is not sufficient to achieve the ambitious decarbonisation targets and low-carbon energy technologies have to be widely deployed. This is the especially case for the EU, where the importance of the carbon intensity effect increases over time, becoming the leading driver of decarbonisation in the second half of the century. Moreover, we found substantial differences between developing and developed regions, due mainly to the significantly larger effect of economic growth in India and China, in which a particularly high GDP growth is assumed over the period 2010-2100. The large activity growth effect is only partially compensated by a reduction in energy intensity and, therefore, carbon emissions in China and India are projected to increase significantly until 2050 both in the *Base* and *RefPol* scenarios.

Furthermore, we developed an LMDI decomposition analysis of the changes in CO_2 emissions in a scenario with a global target of stabilizing GHGs concentration at 450ppm by 2100 compared to the moderate policy case. We found that the major additional efforts required to achieve this stringent long-term target are directed towards the reduction of carbon intensity of final energy through the deployment of low carbon technologies, including renewables, nuclear, CCS and electric vehicles. The relative contribution of energy efficiency improvements (compared to *RefPol*) is projected to decline after 2050 and to be relatively low in the long-term. Moreover, most of the models project that realizing the stringent climate target requires negative carbon emissions after 2070 or 2080 in most regions of the world. We showed, using the LMDI methodology, that when carbon emissions become negative the contribution of the carbon intensity effect corresponds to 100% of the changes in emissions. Therefore, biomass technologies equipped with CCS that lead to negative net carbon emissions over their life-cycle are projected to play a critical role in the achievement of the ambitious climate stabilization target. However, the deployment of CCS technologies requires both technological and policy efforts to overcome the barriers on technological development, public acceptance, licensing and regulation that could prevent or delay the commercial uptake and use of CCS technologies. In addition, the large deployment of BECCS might face important challenges concerning changes in land-use and trade-offs with food and water supply and the uncertainty regarding climate risks of negative emissions.

The multi-model decomposition analyses developed in this paper show that, despite the comparable trends in the decarbonisation strategies projected by the IAMs, the specific model assumptions and characteristics lead to important differences across the results from the evaluated models. These model features include: (1) assumptions on resource availability, mainly fossil fuels and biomass; (2) assumptions concerning policy support and cost of key technologies (nuclear and coal power); (3) availability of low-carbon technologies; and (4) model type. First, higher assumptions on the potentials for biomass and BECCS result in significantly larger reductions in carbon intensity in the long-term to achieve the 450ppm target. Second, optimistic assumptions on coal or nuclear technologies result in pathways with higher carbon or energy intensity, respectively. Third, technologically-rich IAMs with a larger variety of low carbon technologies (most of energy system and optimal growth models) opt for higher deployment of low and zero carbon options that leads to reductions in the carbon intensity of final energy rather than energy efficiency improvements to achieve stringent climate change mitigation targets. Conversely, models with relatively limited variety of low-carbon options, such as WITCH and the multi-sectoral CGE models (IMACLIM and GEM-E3) result in larger reductions in energy intensity of GDP. Finally, CGE models opt mainly for energy efficiency improvements rather than reduction in carbon intensity of energy. However, the results in our analysis, show that model type has a lower impact than stated in previous studies (Riahi et al., 2007; Förster et al., 2013; van Sluisveld et al., 2013). In general, the set of assumptions in the CGE models concerning the cost and availability of technologies can lead to the opposite result.

The continuation of moderate climate policies in line with the Copenhagen-Cancun pledges by 2050 is supported by all IAMs at relatively low costs for the major carbon emitting economies. However, the multi-model analysis showed that rapid annual rates of emission reductions combined with radical energy system restructuring towards low, zero and negative carbon technologies are required in all regions in order to achieve the long-term 2°C stabilization target. Optimal decarbonisation strategies differ among regions depending on the current structure of their energy-economy system, the available potential for low cost energy efficiency improvements and the level of ambition of their reference moderate climate policies.

Beyond the scope of the multi-model decomposition analysis presented here, it is important to recognize the differences across sectors in terms of decarbonization strategies. However, most of the models included in this inter-comparison do not generally include a representation of different economic sectors[20]. Thus, the analysis does not seek to identify the impact of structural economic changes or different sectoral behavior on the evolution of carbon emissions under alternative climate policy assumptions. For such analysis alternative decomposition approaches like the one presented in Fisher-Vanden et al. (2012) need to be developed.

Acknowledgments

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