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Energy substitution by sector: technological flexibility and the impact of mitigation policy

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Table of content

EU climate policy up to 2030: reasoning around timing, overlapping instruments and cost effectiveness

List of tables and figures

Elasticity of substitution in capital-energy relationship: a sector-based panel estimation approach

A sensitivity analysis of a dynamic climate-economy CGE model (GDynE) to empirically estimated energy-related elasticity parameters

EU climate policy up to 2030: reasoning around timing, overlapping instruments and cost effectiveness

Introduction

The impact of climate mitigation policies on economic activity is a longstanding controversial issue justifying the large strand of literature analysing the effect of climate change policies in terms of environmental and economic costs, also in light of the numerous international agreements and negotiations. Starting with the constitution of the Intergovernmental Panel on Climate Change (IPCC), through the 1992 United Nations Framework Convention on Climate Change (UNFCCC), the international community has ratified the Kyoto Protocol (KP) assigning greenhouse gas (GHG) reduction targets for Annex I countries compared to 1990 levels. From then to the current climate policy agenda approved by the European Union in October 2014, mitigation of climate change still constitutes a challenging long term objective at the global level, and it is particularly relevant for the European Union.

These concerns justify the interests in the assessment of climate change impacts given that mitigation costs are an essential input to policy decisions. One of the driving criteria of the KP is explicitly directed toward a minimisation of the overall costs associated with emission reduction and, given both the global scale of the problem and the differences in marginal abatement costs, the KP allows domestic emission reduction efforts to be complemented by various flexible mechanisms, including permit trading. To this purpose, the sole existing permit market under the KP umbrella is the European Union Emission Trading Scheme (EU ETS), started in 2005 as a core instrument within the overall EU climate strategy.

Moreover, given the global scope of environmental policies in an open economy and considering environmental quality as global public good (as the controversial international Post-Kyoto negotiations on reduction targets prove), a second aspect to carefully account for is the regional distribution of those costs. In addition, changes in relative energy costs across countries not only influence industrial and energy competitiveness but also economic competitiveness, and energy-intensive sectors are more and primarily affected by increases in energy prices.

In this context, it is not surprising the comprehensive use of applied models representing the global economy, the relations between the economic, social and technological dimension, across countries and the economic sectors. Models may differ in purpose and perspective, depending on the short or long-term time horizon, focussing on a single country or globally, analysing unilateral or coordinated measures. Recently, great efforts have been directed to link bottom-up technology models into partial or general equilibrium models to provide a better representation of the key energy system in more details.

In this light, the current work is structured in three main parts. The first is an analysis of the energy substitutability in the context of capital-energy relationship, centred on a sector-based panel estimation approach. Several types of impact forecasting tools for the assessment of economic impacts of climate actions have been developed based on top-down, bottom-up or integrated approaches. In particular, Computable General Equilibrium (CGE) models, which have been extensively employed to analyse policy incidence and forecast economic impacts of climate actions, are extremely sensitive to exogenous assumptions on such energy-related elasticity parameters. Indeed, one specific issue under investigation is the role of behavioural parameters in influencing climate models' results. This part of the work specifically addresses the computation of capital-energy substitution elasticity values in ten manufacturing sectors for OECD countries considering different time horizon and aggregation level. Firstly, the long run elasticities are estimated at aggregate level for the whole manufacturing sector as well as for single sectors during the time span between 1970 and 2008 for a panel of 21 OECD countries with a panel cointegration technique. We then focus on the elasticity of substitution between capital and energy, at the aggregate manufacturing level (1970-2008), distinguishing ten manufacturing sectors (between 1990 and 2008, and for separate sub-periods), and comparing several alternative econometric estimation methods. These results can inform climate-economic models in order to assess more precisely the reaction of the economic system to the implementation of climate policies, in terms of both overall abatement costs and their distribution across different sectors.

The second part presents a sensitivity analysis of a dynamic climate-economy CGE model (GDynE), where we specifically focus on testing the effect of changing the values for the elasticity parameters. In fact, Computable General Equilibrium (CGE) models are especially suitable to analyse the effect of carbon-abating policies considering they can capture the linkages between regulated and non-abating countries in terms of competitiveness through trade channel, but also through investment dynamics in the long run. However, these models need be improved and validated with detailed information on technological and energy modules in order to produce more reliable results. As far as CGE models are concerned, this kind of information is represented by elasticities, or behavioural parameters, which regulate the substitution processes in response to changes in relative prices. Those behavioural parameters represent a component of the technology information and regulate how the model responds to exogenous policy shock, and, in particular, the elasticity of substitution between energy and capital is a measure of technological flexibility related to energy use. Thus, we shall conduct a sensitivity analysis considering three different sets of elasticity parameters: the standard GTAP version; the parameters derived from Koetse *et al*. (2008) on energy-capital elasticity of substitution and from the meta analysis by Stern (2012) on interfuel-substitution; and the sector-specific KE elasticity parameters econometrically estimated in the previous part.

Finally, in the third part the focus is on the climate policy strategy of the European Union to 2030 that was discussed in October 2014. This so called EU2030, as the previous strategy EU2020, combines several tools and different objectives, and the assessment of the mitigation costs needs also to consider the potential trade-offs or complementarities among simultaneous policies. This framework defines three goals to be achieved by 2030: a 40% GHG reduction with respect to 1990 levels, the EU target of at least 27% for the share of renewable energy and a 27% increase in energy efficiency. The main instrument to reduce GHG emissions is the European Emission Trading System (EU ETS), which covers the energy and industry sectors. The renewable energy goal does not set binding national targets and leaves each Member States free to choose which types of supporting framework to implement (*e.g.*, feed-in tariff and premium, green certificates or quota system). Hence, in the light of the recent debate around the effectiveness and the optimality of complex policy mix, especially in the case of environmental and innovation public support, the EU approach to climate change represents an interesting case study to be investigated, both in term of complementarity among policy measures and timing of the abatement targets. This last part of the work relies on a simple theoretical approach and on the GDynE, the dynamic CGE climate-economic model considered in the previous part. The aim is to suggest some reflections upon potential trade-offs or complementarity among different policy instruments within a complex climate policy mix, with particular attention to the mechanisms behind prevailing effects in terms of cost effectiveness, economic competitiveness and optimal taxation.

Elasticity of substitution in capital-energy relationship: a sector-based panel estimation approach

1. Introduction

Climate change mitigation policies promote the abatement of greenhouse gases (GHG) through the reduction of energy consumption from fossil fuels, the production of renewable energy and the diffusion of low carbon technologies. Starting with the constitution of the Intergovernmental Panel on Climate Change (IPCC), through the 1992 United Nations Framework Convention on Climate Change (UNFCCC), the international community has ratified the Kyoto Protocol (KP) assigning GHG reduction targets for Annex I countries compared with 1990 levels. One of the driving criteria of the KP is explicitly directed toward a minimisation of the overall costs associated with emission reduction and, given both the global scale of the problem and differences in marginal abatement costs, the KP allows domestic emission reduction efforts to be complemented by various flexible mechanisms, including permit trading. To this purpose, the sole existing permit market under the KP umbrella is the European Union Emission Trading Scheme (EU ETS), started in 2005 as a core instrument within the overall EU climate strategy.

In this context, increased interest in analysing the role that energy plays in production processes is more than justified given that the potential impacts, in economic and environmental terms, of climate policies are strongly influenced by several factors. Few examples are the specific energy mix, the energy intensity of the production process, energy prices and responses by the markets, together with the technological opportunities to be exploited when facing binding constraints in energy consumption.

According to the IEA (2013), the impact of changes in energy prices (especially considering the existence of regional disparities) on economic and industrial competitiveness has been addressed since higher the share of energy cost on total production costs, more vulnerable the economic activity is to changes in energy prices. At the same time, more an economy is based on energy intensive activities, and more severe the consequences of an increase in energy prices can be.

In addition, even considering the possibility of technological advancements that can make production processes more energy efficient, concerns about the possible negative impacts of climate policies still rise, in terms of firm profitability and distribution across sectors of the associated costs.

Given the characteristics of supply and demand for energy and the relevance of the distribution of the policy impacts, the analysis of climate change policies has been largely done using energy economic modelling and literature in this regard is longstanding. Impact forecasting assessment tools are based on both top-down or bottom-up approaches, or are integrated as Integrated Assessment Models (IAMs). Whatever modelling approach is chosen, the specific energy-related behavioural parameters are crucial in influencing results. In particular, Computable General Equilibrium (CGE) models have been extensively employed to analyse policy incidence and forecast economic impacts (see Antimiani *et al.*, 2013a for a review).

Results in the assessment exercise for abatement costs with respect to the role played by the energy mix, energy prices and technological opportunities are all influenced by behavioural parameters that, in applied models, are exogenously given most of the time. In this sense, the criticism to these models is due to the fact that the results can be highly dependent on the value of the behavioural parameters (or elasticities), which are not always validated enough (Okagawa and Ban, 2008). In other words, as Böhringer (1998) has pointed out, these models need to be improved with the inclusion of more detailed technological information that is indeed represented by elasticity parameters.

In particular, the economic impact of abatement policies is strongly sensitive to the values assigned to the elasticity of substitution between capital and energy in the industrial sector (Antimiani *et al.*, 2013b; Nijkamp *et al.*, 2005). Concerns arise mainly when the inter-sector distribution of abatement costs is under scrutiny, since energy-intensive sectors will face more challenging efforts to be compliant (Borghesi, 2011; Hoel, 1996; OECD, 2003, 2005). The strong heterogeneity of the reaction of different industrial sectors to the same abatement policy produces uncertainty about the distributive effects, thus reducing the potential role of CGE models in supporting policy design. This is, for instance, a major alarm in the assessment of the potential impact of the EU ETS on the competitiveness performance of energy intensive industries, as emphasized in the growing debate on potential carbon leakage and trade policy reactions (Kuik and Hofkes, 2010).

To increase the reliability of the model and its results, the introduction of econometric estimated values for the parameter in the model, driven from historical data, is a first step to ensure that the model will not incorrectly represent the effect of exogenous shocks (and the policy conclusions driven by the results).

Furthermore, the introduction of sector specific parameters is especially relevant for the improvement in the assessment of abatement costs and, above all, sector-based capital-energy elasticity values are key factors when alternative mitigation policies are under scrutiny. In fact, energy-intensive and capital-intensive sectors are characterised by different input shares and different degree of technological content and this imply differences in potentials and cost effectiveness in the responses to energy reduction policies among industries.

In this respect, the debate is still open on whether or not (and if so in which measure) the introduction of climate change policies could have a detrimental effect on competitiveness and economic performances, where particular regard is focused on energy-intensive industries. Moreover, it has also to be noted that the relative importance of the different sectors can vary substantially across countries and regions, in term of both economic value added and employment, and this regional differentiation will also benefits from a more detailed sectoral representation.

The uncertainty given by behavioural exogenous parameters used in forecasting models mainly derives from the absence of a consensus on empirical estimations, or by the scarce availability of punctual estimated values. To this end, the purpose of this work is to partially fill this gap by proposing an empirical framework able to reduce uncertainty in the estimation of elasticity of substitution parameters in capital-energy relationships.

More specifically, the novelties of the work with respect to the existing literature are: i) energy-output elasticities are computed for disaggregated manufacturing sectors for a long time span (1970-2008) for a panel of 21 OECD countries; ii) capital-energy substitution elasticity is estimated at aggregate level for the whole manufacturing sector for the same panel of countries; iii) substitution elasticities are also accurately estimated for 10 distinguished manufacturing sectors for the same time span and panel of countries; iv) average substitution values at sector level are computed by comparing several alternative econometric estimation methods; v) average substitution values at sector level are also computed for separate sub-periods in order to trace the dynamics over time of these behavioural parameters.

The rest of the work is structured as follows. Section 2 provides a detailed literature review on how the concept of elasticity of substitution between capital and energy has evolved in the last decades. Section 3 gives a description of different methodological approaches used for empirical estimation, Section 4 describes the methodology adopted in this paper for empirical estimation, Section 5 contains empirical results and Section 6 concludes the paper.

2. Elasticity of substitution between capital and energy: relevance and interpretation

Understanding the substitution possibilities between energy (E) and capital (K), as well as those between different fuels such as renewables, fossil fuels and electricity, has been a longstanding issue of interest in energy economics literature. In fact, considering a production side approach, "the adoption of energy-saving technologies can be represented by substitution of capital for energy" (Koetse *et al.*, 2008, p. 2237) and the elasticity of substitution between E and K is crucial for policies aimed at reducing energy consumption and the concentration of polluting emissions.

It is not surprising if a large strand of literature is trying to assess the magnitude of these substitution possibilities. Bounds on energy supply, rising energy prices and emission reduction targets can induce changes in the composition of input and energy mix and the impact of these changes strongly depends on the undergoing level of substitutability.

The elasticity of substitution can be defined as the reaction of an economic system to substitute one input with another where the higher the magnitude is (the absolute value assumed by the elasticity parameter), then the stronger the changing effect will be, whereas the positive or negative sign is used to distinguish between substitution or complementarity. This behavioural parameter reflects the role that an input plays in production processes by considering how it is combined with the others. Considering the specific context of interest of this work, it gives information on the scope for new intervention to reduce energy consumption, and, to some extent, represents the overall (production) conditions influencing how difficult or costly it is to reduce energy consumption through the introduction of new capital (*e.g.,* new and less energy requiring machinery), or any other investment able to modify the production process.

Given a certain target for emission reduction, if the elasticity between E and K is low, then the costs for being compliant will be higher. As Golub (2013) points out, the elasticity of substitution between E and K basically measures the degree of *technological flexibility*: the lower the level then, *ceteris paribus*, the higher will be the reduction in output required to achieve the established target for cutting emissions. This is an *energy-related* level of technological flexibility that, together with capital accumulation, rate of technical progress and changes in the sectoral composition of output, describes the technology in CGE models.

Early research questions were mainly focused on investigating the nature itself of the relationship between K and E and whether it indicates complementarity or substitutability. The nature of the relationship is quite crucial in assessing the impact of alternative policy design. If the inputs are complement, they will respond to price changes moving in the same direction, thus promoting innovation and diffusion of less energy-requiring technologies will be more appropriate instruments to reduce energy consumption. On the other hand, if they are substitute, as a consequence of a change in relative prices, the share of energy will be reduced but the level of capital will increase, and a carbon tax could be less harmful than the former case (Tovar and Iglesias, 2013).

In the same line of reasoning, while complementarity and substitutability should be ascribed to a short run view, a parallel strand of literature has also investigated the nature of causal relation between energy and economic output in the long run. Besides the impact it has if combined with capital, energy also has a direct contribution on output and energy-output elasticity has therefore been largely investigated, both in CGE literature and in terms of causality relationships. In this second case, starting from an analysis of the causal direction, the magnitude, sign and significance of these parameters have also been investigated (Ortuz, 2010). Also in this case, by implementing sector-specific estimations, the reliability of parameter values will improve substantially (Costantini and Martini, 2010). Nonetheless, the level of disaggregation for sector-based analyses is not deep since only macro sectors (e.g., residential, commercial, industry) have been used for long run causality estimations.

Later contributions on capital-energy substitution elasticity moved from the issue of complementarity/substitutability to refining the econometric design in order to obtain more realistic estimations to be used in energy forecasting models. In these models, the elasticity parameters measure how sensitive economic agents are to price changes (as for instance how responsive the demand for a good is with respect to changes in relative prices or income) and determine the size of the demand adjustments. It is a crucial parameter in many energy-related models because it is a means through which changes in energy prices affect, differently according to magnitude, the supply and demand for energy, the level of capital investment and output, and the distribution of the associated costs among different sectors and countries. Thus, econometric evaluations from historical data will increase the reliability of the model results because if the parameter values are misspecified, the model will incorrectly represent the effect of exogenous shocks and policy conclusions will not be reliable (Beckam *et al.*, 2011).

While at the general level elasticities of substitution are crucial parameters influencing the results induced by policy shocks, in selected forecasting models, and specifically in CGE models, the computation method may not support complementarity conditions (Böhringer, 1998). This is the main explanation for increasing interest in econometric estimations of the substitution between energy and capital imposing restrictions in order to obtain a positive estimated value.

Several examples available in the international scientific literature reveal the crucial role of elasticity of substitution between K and E. Just to quote a few, Jacoby *et al.* (2004) analyse the effect of technological change in reducing GHG emissions and find that capital-energy substitution elasticity is the key parameter in the MIT EPPA model given that changes in its magnitude determine large variations in costs associated to a "Kyoto forever" scenario for USA. Antimiani *et al.* (2013b) and Burniaux and Martin (2012) study the impact on carbon leakage assessment and their results show that when elasticities are higher, the level of carbon leakage is also higher. The relevance of the elasticity has also been studied in rebound effect literature, as can be seen in the works of Saunders (2000, 2008) and the review from Broadstock *et al.* (2007). Okagawa and Ban (2008) estimate the substitution elasticities between energy and capital at the sector level for a panel of OECD countries and their results show that, compared with the new parameter scenario, in the former specification the carbon price required to reach the objective is overestimated by 44% (and the distribution of the reduction efforts is also different). Lecca *et al.* (2011) analyse the impact of different separability assumptions among inputs on elasticity values and CGE model results. They therefore conclude that the inclusion of energy in different nesting structures produces significant differences in the estimation results and that capital-energy elasticity, in particular, determines a large variation in energy use, economic growth and other macroeconomic indicators.

Most of these models, however, assume the same values for these parameters in all sectors and regions since empirical estimations for deeper disaggregation at sector level are not reliable.

Hence, the reliability of impact assessment of abatement costs will largely benefit from the implementation of model settings with sector-based capital-energy elasticity values. The reasons behind this requirement can be synthesized as follows. First, the assumption of equal values for energy-intensive and capital-intensive sectors means that the reaction capacity of these sectors will be the same with respect to energy reduction policies whereas the cost shares for single inputs will be substantially different. Second, it is implicitly assumed that the degree of technological content of the production function is equal whereas the capacity of energy-intensive sectors to rapidly reduce their own energy content is rather lower than for other industries.

These features are at the basis of fears regarding the reduction in competitive performance of energy-intensive industries which is misunderstood if equal elasticity values are included in model settings. More importantly, given the different economic structures across regions, a more detailed sectoral representation will also result in a more accurate regional differentiation in terms of the distribution of abatement costs.

3. Literature review

3.1. Early studies: substitution or complementarity between energy and capital

Early studies investigating the linkages between non-energy inputs, technology structure and economic output in terms of energy substitutability took advantage of the works on flexible possibility frontiers, which made the substitution possibilities between production factors the aim of further econometric studies. The Trascendental Logarithmic Function (or Translog) from Christensen *et al*. (1973, 1975), in particular, has been one of the most popular because setting only a few constraints on the input-output relationship allows for unrestricted elasticities.

Bernd and Wood (1975) analysed industrial demand for energy focusing on the cross-substitution between energy and non-energy inputs in the US manufacturing industry during the period 1947-1971. They used the time series data to test a Translog cost function with four inputs (capital, labour, energy and materials, *i.e.* the KLEM model) and the results showed energy and capital to be strong complement (negative elasticity of substitution ranging from -3.2 to -1.4). In this case, an increase in energy prices can have a negative impact not only on the demand for energy but also on capital investments, making structural adjustments more difficult.

On the other hand, Griffin and Gregory (1976), using the same methodology on a KLE model, studied the manufacturing sector in nine industrialised countries (in the period 1955-1969)[1] focusing on the cross section variation and using a sample of four benchmark years. In this case, the elasticities were always positive (around 1), implying substitutability between capital and energy. Following this line of research, many other studies tried to assess the elasticity of substitution (or complementarity) between energy and capital, *e.g.* Hudson and Jorgenson (1974), Pindyck (1979), Hunt (1984), Thompson and Taylor (1995), Nguyen and Streitweiser (1997) (see Table 1). Although there are a large number of empirical estimates, no unanimous conclusion has been reached yet, both in terms of sign and magnitude (Apostolakis, 1990; Thompson, 2006).

Two main differences between these works were the central issues of the initial debate, and these are the use of *time series* or *cross section* data and a KLEM instead of a KLE model. Cross section studies, capturing long run factor adjustments, usually found that capital and energy were substitutes whereas time series cases typically represented the (short run) complementarity between them. Time series data reflect dynamic adjustments to technical changes and external shocks whereas cross section data capture structural differences between regions, hence large inter-country variation in pooled models has been ascribed to differences

[1] Belgium, Denmark, France, Italy, Netherlands, Norway, UK, USA, West Germany.

in national policies (Roy *et al.*, 2006).

Table 1 - Early empirical studies on capital-energy substitution and complementarity

Authors	Model	Type of elasticity	Data type	Regions	Time period	Complementarity /Substitutability
Berndt-Wood (1975)	Translog (KE)(LM)	AES	TS	USA	1947-71	C
Griffin-Gregory (1976)	Translog (KLE)M	AES	CS	9 industrialised countries	1955, '60, '65, '70	S
Fuss (1977)	KLEM			Canada manufacturing	1961-71	C
Berndt-Wood (1979)	Translog (KE)(LM)	AES	TS	Canada, USA	1961-71, 1947-71	C
Pindyck (1979)	Translog KL(E) [1]	AES	CS	10 industrialised countries [2]	1963-73	S
Hunt (1984)	Translog KLE	AES, CPE	TS	UK	1960-80	C
Hunt (1986)	Translog KLE [3]	AES, CPE	TS	UK	1960-80	S
Nguyen-Streitweiser (1997)	Translog KLE	AES, CPE, MES	CS	USA	1991	S

Notes: AES: Allen Elasticity of Substitution. CPE: Cross Price Elasticity. MES: Morishima Elasticity of Substitution. TS: Time Series. CS: Cross Section. [1] The nest E includes 4 types of fuels: solid fuel, liquid fuel, gas, electricity. [2] Canada, France, West Germany, Italy, Japan, Netherlands, Norway, Sweden, UK, USA. [3] Non-neutral technical change

Considering models with three or four inputs (KLE or KLEM, respectively), the choice of including or excluding material inputs (M) implies different assumptions about the *separability* of the factors within production processes and, therefore, generates differences in cost shares. Indeed, as pointed out by Frondel and Schmidt (2002), the magnitude of *cost shares* is crucial in determining the sign for the energy price elasticity (especially in Translog estimations): higher cost shares would be more likely to determine substitutability; whereas for small cost shares it is easier to have smaller or negative elasticities (factors may be complements). As far as the *aggregation* level is concerned, most of the studies have focused on the aggregate (whole economy) level or on the industrial sector. In this regard, it should be stressed that the higher the level of aggregation and the more severe the argument will be according to which elasticity will not distinguish the pure substitution effect among factors from change in the sectoral composition of output and a shift in input demand. In fact, the measurement of elasticity of substitution assumes that there is a change in input mix keeping the level of output, which is however a homogeneous and constant product.

3.2. *Energy and economic output: from Granger causality to Fully Modified OLS*

Together with an analysis of short run capital-energy substitution elasticity at the aggregate level, a large strand of literature has also tried to assess the nature of the relationship between energy consumption and economic performance in the long run. Starting from Kraft and Kraft (1978), at first the goal of this line of research was to establish the direction of the causal relationship between energy consumption and output, usually measured by Gross Domestic Product (GDP), at the national level in a bivariate framework. Further econometric developments also allowed testing for non-stationarity of time series, cointegration in a multivariate setting and better controlling for omitted variables bias. Moreover, the application of panel cointegration techniques and Vector Error Correction Models (VECM) allows controlling for countries' heterogeneity and cross-sectional interdependency. Although the improvements in empirical analysis, results are still mixed and unambiguous conclusions about the direction of the causality have not yet been reached (see Ozturk, 2010 and Payne, 2010a for a review).

Investigating the role of energy in economic system in terms of direction of the causal relationship has relevant policy implications, especially considering the debate on the potential negative impact of energy and climate regulations on economic performance. The different possibilities are usually expressed in terms of four hypotheses. The *neutrality hypothesis* holds if no causal relationship is found between energy and economic output and suggests that energy policies have no significant impact on economic growth. On the other hand, for bi-directional causality (*feedback hypothesis*) energy and economic output need to be considered as interdependent because they affect each other. Considering uni-directional causality, the *conservation hypothesis* is verified when the level of economic activity Granger-causes energy consumption and, in this case, energy policies setting constraints on energy supply are considered not too harmful since the demand for energy may be mainly driven by the level of production processes or income, thus market-based measures and regulatory instruments could be used to reduce energy demand (Coers and Sanders, 2013). Finally, the *growth hypothesis* is verified if causality is running from energy consumption to economic output and, in this case, energy (together with other inputs) can be seen as a limiting factor in production processes.

If the growth hypothesis is verified, measures of intervention aimed at reducing energy consumption could negatively affect economic output while policies fostering the adoption of low carbon technologies and easier access to sustainable and clean energy supply should be preferred (Coers and Sanders, 2013). In this latter case, in particular, understanding the sign and the magnitude of the impact that energy has on the economic performances is of particular interest (Apergis, 2013). Considering, in fact, that energy conservation policies are growing both in scope and relevance, it is crucial to determine the role that energy plays in the economic system in order to understand the potential impact of energy in different economic activities and whether energy policies can provide a positive impulse to the economic system or if they are harmful.

These studies not only apply different econometric techniques, but also cover different time periods and account for different countries, which are some of the reasons behind the diverging results. Differences in the results may also arise because countries are heterogeneous in terms of structural and development characteristics and because of the different level of aggregation analysed. In addition, there is a wide range of variables on which the analyses are performed, especially in multivariate models, and this aspect also partly justifies the diverging conclusions (Gross, 2012).

The economic variable is usually represented by GDP (in absolute value or in per capita terms) but in some cases a production index is used as an economic growth variable (Ewing *et al.,* 2008). On the other hand, energy is usually accounted for in terms of total final energy consumption. In some cases primary energy consumption is used (as in Bowden and Payne, 2009), but several works also deal with particular energy resources, especially electricity (see Payne, 2010b for a review) but also coal, natural gas and fossil fuel (Ewing *et al.* 2009), or distinguish between renewable and non-renewable energy sources (Tugcu *et al.*, 2012). Finally, some authors (Oh and Lee, 2004; Stern, 2000; Warr and Ayres, 2010) highlight the relevance of the composition of the energy input mix.

The level of aggregation can be seen as a further source of mixed results and contrasting outcomes may hold between the national and sectoral level analysis (Gross, 2012). In the energy-GDP cointegration analysis literature, attention has been mainly focused at the national level and only a few works investigate the relationships considering a more detailed sectoral disaggregation. Examples of country-specific studies exploring the energy-growth link at a lower aggregation level are: Bowden and Payne (2009), Ewing *et al.* (2009), Gross (2012), Soytas and Sari (2007), Tsani (2010), Zhang and Xu (2013), and Ziramba (2009). On the other hand, examples of multi-countries sectoral investigations are Costantini and Martini (2010), Liddle (2012), and Zachariadis (2007). However, these works usually only distinguish between residential, industry, services and transport sectors (see Table 2), and only Liddle (2012) conducts the analysis at a more disaggregated level, considering five energy intensive sub-sectors of the manufacturing industry.

Table 2 - Summary of literature review on disaggregated sectors

Study	Methodology	Period	Country	Sectors	Industrial sector results
Zachariadis (2007)	VECM, ARDL, TY [bivariate]	1960-2004	G7	Total, residential, industry, services, transport	different for country [1]
Soytas -Sari (2007)	VECM [multivariate]	1968-2002	Turkey	Manufacturing	E→Y [2]
Ewing *et al.* (2008)	VDC [multivariate]	2001-2006	US	Industry	different for energy sources
Bowden-Payne (2009)	TY [multivariate]	1949-2006	US	Total, residential, commercial, industrial, transport	E→Y [3]
Ziramba (2009)	TY [multivariate]	1980-2005	South Africa	Manufacturing	different for energy sources
Costantini-Martini (2010)	VECM [bivariate and multivariate]	1970-2005	71 countries (26 OECD and 45 non-OECD)	Total, residential, industry, services, transport	different [4]
Tsani (2010)	TY [multivariate]	1960-2006	Greece	Total, industrial, residential, transport	bi-directional
Gross (2012)	ARDL [multivariate]	1970-2007	US	Total, industry, commercial, transport	E→Y short run
Liddle (2012) [5]	FMOLS	1978-2007	OECD countries	5 manufacturing sectors	
Zhang-Xu (2013)	VECM [multivariate]	1995-2008	China	Total, industry, service, transport, residential	different [6]

Notes: Methodology: VECM Vector Error Correction Model, ARDL Autoregressive Distributed Lag, TY Toda-Yamamoto, VDC Variance Decomposition; G7 countries: Canada, France, Germany, Italy, Japan, UK, US; [1] more Y→E than E→Y; [2] Electricity→Value Added; [3] negative sign; [4] Bivariate model: Y→E in the short run, E→Y in the long run only for OECD sample; Multivariate model: Y→E; [5] Liddle (2012) has estimated the long-run elasticities for five manufacturing sectors and for the whole panel, using a panel FMOLS to estimate the parameters from a production function model; [6] Y→E in the short term while a bi-directional relationship is found in the long term.

In this case, determining not only the direction of the causal relationships but also the sign and magnitude of the effects that each variable has on the others is of particular importance. In fact, results can also been used to derive technological parameters to be used in empirical models (as highlighted in previous sections). The contribution by Liddle (2012) adopts the long-run relationship estimation using the *Fully Modified OLS* (FMOLS) estimator developed by Pedroni (2000) for heterogeneous cointegrated panel data. If the panel series are non-stationary and cointegrated, the FMOLS estimator generates asymptotically unbiased estimates of the long-run coefficients in a relatively small sample. In this case, the direction of the relationship between energy and output is assumed to be that of a production function (E→Y), thus generating results that can be directly interpreted in elasticity terms. More importantly, these elasticities represent a first assessment of the potential negative impact on economic output due to energy conservation policies in the *growth hypothesis*, providing country and sector specific assessment of the required complementary actions to be implemented to ensure energy availability (such as the adoption of low carbon technologies and easier access to sustainable and clean energy supply).

3.3. Measuring the elasticity of substitution between energy and capital at sector level

With the increasing attention that energy modelling has gained in an analysis of climate change policies, the focus of the estimations of the elasticity of substitution have moved from the complementarity or substitutability debate to econometric estimations to be implemented in applied models, so that the economy-wide structural adjustments following a change in energy price can be assessed. Although there is a long line of research in this respect, there is still no consensus on the positive or negative sign of the elasticity between energy and capital or on its magnitude. In fact, besides the theoretical assumptions exposed in the previous section, elasticity remains a relative concept (Tovar and Iglesias, 2013) and differences in the estimations are also due to different formulation models, data characteristics and estimation methods (Table 3).

Firstly, considering differences in the model formulation, there are four aspects to take into account: the number of production factors, the functional form, the formulation of the elasticity of substitution and the treatment of technological change. In relation to the former issue, and following the discussion between early works of Bernd and Wood (1975) and Griffin and Gregory (1976), empirical studies analysing substitution possibilities between energy and capital, generally take into account three or four inputs, thus distinguishing KLE and KLEM models.

Considering then the choice between different functional forms, three functions have been extensively employed in empirical analysis on capital-energy substitution: the Cobb-Douglas, the *Constant Elasticity of Substitution* (CES) and the Translog formulations.[2] Translog production (or cost) functions, in particular, have been considered in the majority of econometric works because they have the advantage of being more flexible and, without imposing restrictions on substitutability, are more suitable when the number of inputs is greater than two. In other cases, authors have analysed CES production functions, which are a generalisation of a Cobb-Douglas form, where the elasticity of substitution is constant and not necessary equal to one but can vary between 0 and infinity. A further aspect to consider in CES functions is related to the separability assumptions, which imply different nesting structures. Differences in the aggregation of inputs can have relevant on the magnitude of substitution elasticities and, in some cases, the aim of the analysis has been an investigation into which nesting structure would best fit the data and consequently, the most appropriate elasticities estimations were selected (Kemfert, 1997).

Moreover, there are several formulations of the elasticity of substitution and, starting from

[2] Further studies attempt to verify the possibility of zero substitution among inputs, according to the Leontief function (which assumes that the elasticity of substitution is close to zero and implies that production factors need to be used in fixed proportions) or take into account Generalized Leontief functions (see Tovar and Iglesias, 2013).

the original two Hicks-type elasticity of input substitution, three main generalisations have been developed for cases with three or more factors. The *Cross Price Elasticity* (CPE) is at the basis of the distinction between gross and net substitution introduced by Berndt and Wood (1979) and is strictly linked with the separability conditions assumed in the model. In particular, in KLEM models, taking E and K as separable from L and M, the CPE is an asymmetric *one-factor-one-price* elasticity that represents the net substitution between E and K and measures the relative change in use of one factor (K) given a change in the other factor's price (E), keeping output and other input prices fixed. It is the sum of the positive gross price elasticity (which measures the change in E and K demand, holding EK composite input fixed) with the negative expansion elasticity, whose magnitude depends on the cost share of K (in this case output is fixed but the demand for the composite input EK can vary in response to changes in relative prices). Complementarity or substitutability depends on which of the two effects is larger, and the cost share of the two factors have a crucial role, thus changes in energy or capital prices will have different consequences also due to the fact that the capital cost share is usually higher than the energy one.

The *Allen Elasticity of Substitution* (AES) has been widely used in empirical studies and, as for the CPE, a positive value implies an increase in the use of one factor as a consequence of the increase in the price of another factor, and corresponds to the substitutability case among inputs. Contrary to CPE, it is a symmetric *one-factor-one-price* formulation that measures the effect of changes in price *i* on the demand for input *j,* taking into account the share of input *j* in output value. Indeed, it can also be derived by dividing the CPEij by the cost share *j* (Broadstock *et al.*, 2007).

The *Morishima Elasticity of Substitution* (MES) is an asymmetric measure of substitution between production factors and, in contrast to AES and CPE, is a *two-factor-one-price* elasticity that represents the change in the ratio of factor quantities given a change in one factor prices. It is positive in almost all cases and the sign is therefore not very useful for distinguishing substitution from complementarity. Moreover the cost share *i* will decrease relatively to *j* (following a rise in p_j) only when MES>1. Blackorby and Russel (1989) show that the MES_{ij} can be calculated as the difference between the CPE_{ij} and the own price elasticity for input j (CPE_{jj}). As far as AES is concerned, if two inputs are Allen substitutes they will also be MES substitutes, but when AES is negative it is still likely to have positive MES.

A further aspect to take into account, which has already emerged in the early debate, is the way technological change is treated. Generally represented in the Hicks-neutral form, technical change can also be represented as non-neutral or factor saving, as in Hunt (1986), Kemfert (1997), Morana (1998), Su *et al*. (2012), and van der Werf (2008). Moreover, in some cases, non-constant returns to scale are implemented, and Koetse *et al*. (2008) show that including returns to scale parameters has a positive and significant impact on MES and CPE. In other studies, as in Popp (1997), a time trend is used to approximate the effect of a general technological change, but it cannot be specifically related to innovations fostering specific forms of energy efficiency. It is also worth noting that non-exogenous technical change can be derived from both factor substitution, as a response to changes in price or income, and capital accumulation, representing innovation embedded in new production machines. Moreover, factor substitution at the aggregate level can be seen as a change within the same technology but, at the process-engineering lower level, it still implies a shift in technologies (Jacoby *et al.*, 2004).

Estimates also vary according to the data characteristics, in term of regions*,* sectors and time periods selected. In some cases, analysis is focused on a single country, US and UK above all (Broadstock *et al.,* 2007), while in others a sample of countries is analysed, in a cross-section or panel framework. Different results can also arise from different time horizons considered, especially when the time period is quite long and includes some *structural breaks* that could have modified economic behaviour with regard to energy demand and consumption. Examples of this are oil shocks from the '70s or the introduction of policies able to substantially affect economic activities as far as capital-energy substitution is concerned.

A further source of variation can also be ascribed to the way production factors are measured. In particular, most works consider aggregate energy consumption whereas in other cases specific energy fuels or electricity are distinguished. Moreover, a consequent and relevant argument in the elasticity debate concerns the substitution possibilities at a lower level than the capital-energy nest, or rather between different types of energy inputs, such as electricity, fossil fuels or renewable energy, as in Halvorsen (1977) and Morana (1998). In this regard, Bacon (1992) and Stern (2012) proposed, respectively, a review and a meta-analysis on inter-fuel substitution. As far as capital input is concerned, different types of measure can be accounted for. Tavor and Iglesias (2013), for example, distinguish capital input in buildings from machinery and equipment, whereas Kim and Heo (2013) account for two forms of capital, the first increases the electricity demand while the second does not, while energy is divided into electricity and fuels (they calculate specific capital-fuel elasticity and find evidence of asymmetric substitution).[3]

[3] Energy substitution for capital is greater than the inverse case, i.e. capital do not substitute for energy in the manufacturing sector, especially for fuel.

Table 3 - Review of aggregate capital-energy elasticity of substitution estimates

Authors	Data	Model	Functional form	KE e.s.	Other e.s.	Technology
Chang (1994) [1]	Taiwanese manufacturing	KLE	CES	0.87 2.17 (AES)	0.42 KL-E	n.a.
Thompson and Taylor (1995) [2]	Manufacturing [Review]	KLE KLEM		0.17 (AES) 1.01 (MESe) 0.76 (MESk)		Non-neutral technical change, returns to scale
Kemfert (1998)	German Industry 1960-93	KLE	CES	0.653	0.458 KL-E 0.146 EL-K	Technical progress (independent)
Christopoulos (2000)	Greek Manufacturing 1970-90	KL(E) [3]	Translog	0.25 (AES)	0.03 (Pe) 0.14 (Pk)	Hicks non-neutral technical change
Jaccard and Bataille (2000)	Canadian industry [4]	KLE	Translog	0.17		Technology evolution (simulation model)
Roy et *al.* (2006)	4 countries Manufacturing 1980-93 [5]	KLEM	Translog	6.15 (AES)	0.28 (Pke) 1.13 (Pek) [6]	Productivity improvements, technical change
Markandya and Pedroso-Galinato (2007)	208 countries	K, H, E, L	CES	0.37, 1.57		[7]
Koetse et *al.* (2008)	Meta Analysis	KLE KLEM	Translog	from 0.178 to 1.074 (CPE, MES) [8]		Non-neutral technical change, returns to scale
Okagawa-Ban (2008)	14 countries Manufacturing 1995-2004	KLE	CES	0.102 [9]	0.529 KL-E	n.a.
Su et *al*. (2008) [1]	Chinese industry 1980-2000	KLE	CES		2.59 KL-E 0.07 KL	n.a.
Lv et *al.* (2009) [1]	Chinese industry 1980-2006	KLE	CES	0.47	0.84 KE-L	n.a.
Su et *al.* (2012)	China 1979-2006 [10]	KLE	CES	0.67	0.76 KL-E 0.71 EL-K	Increasing technological change rate
Shen and Whalley (2013)	China 1979-2006	KLE	CES	0.55 [11]	0.69 KL-E 0.58 EL-K	Hicks neutral technical change, returns to scale

Notes. [1] Estimations from Su et *al*. (2012); distinctions between E.S formulations not available. AES values are derived from Markandya-Pedroso Galinato (2007). [2] The review analyses several studies different for KLE or KLEM model, functional forms. MES_i represents the Morishima E.S. when the price of input *i* alters. [3] Price index of energy (E) is constructed aggregating Electricity (EL), Diesel (D), Crude oil (M). Results in table are, Allen E.S. and Price elasticity corresponding to a change in price of factor *i (Pi).* [4] Pseudo data. They also estimate aggregate EK elasticities for commercial 0.34, residential 0.21, Canada total 0.24. [5] The study includes 3 developing countries (South Korea, Brazil, India) and USA. [6] Results in table are, Allen E.S. and Price elasticity, relative to *country pooled* estimates. AES excluding Brazil is 4.72. [7] Produced capital (K), Human capital (H) measured as Intangible capital residual (HR) or human capital related to schooling (HE), Energy (E) including oil, natural gas, hard coal and lignite, Land resources (L). Results in table are from the four-factors (KEH)L model using HR and HE. Estimate for the two-factors model with capital and energy using HR is -0.48 but not significant. Estimates using HR (HE) in the three-factors (KE)L model is 0.65 (0.17). The authors did not consider technology, but they include indicators for institutional development and efficiency of economic organization and use non-linear estimation method to estimate the CES function. [8] Different for: Long and short run, Europe and North America, pre-1973, post-1973 and post-1979, MES or CPE. The range reported in Table 3 includes only significant estimates. [9] Result in table is for manufacturing industry, for sector specific elasticities see Table 4. [10] Elasticities for different time periods are, respectively, for 1953-1978 period and 1953-2006: KE 0.2152 and 0.2826; KL-E 0.2553 and 0.2599; EL-K 0.3177 and 0.3329. The authors use nonlinear regression carried on different optimization methods. [11] Results in table are the average elasticities calculated from estimations with constant and non-constant returns to scale for both (K, HL, E) and (K, L, E) models. The authors use grid search based non-linear estimation procedures.

Finally, different data characteristics require different (econometric) estimation methods, especially considering the increasing number of panel data studies. Differences in results can also be due to: linear or non-linear methods, static or dynamic models, non-stationarity and cointegration in time series, correlation between regressors and error components, endogeneity, omitted variable bias[4] or the choice of panel estimators (pooled OLS, Fixed or Random Effects, Between estimators).

Koetse *et al.* (2008) present a meta-analysis on capital-energy substitution elasticity (focusing on CPE and MES) to explain the heterogeneity between different studies and also calculate short and long run elasticities for different regions and time periods. If the exclusion of materials[5] (KLE function) and the inclusion of non-neutral technical change do not seem to significantly affect estimation results, the assumption of non-constant returns to scale has a significant and positive effect. Moreover, cross section data (long-run elasticity) and, for CPE, also aggregate data (in contrast with 2- or 4- digit manufacturing data) produce higher elasticities[6]. With respect to regions and time period, estimations for Europe tend to be lower than the US and systematic differences seem to arise from data before or after the two oil crises (1973, 1979). Aggregate measures of inputs (with respect to CPE) can also lead to underestimating the substitution possibilities since both coefficients for energy fuels and machinery (instead of aggregate E and K) are significant and positive whereas electric energy has a negative coefficient. Given all these possible sources of differences, in order to define a reference range of variation for the capital-energy elasticity of substitution, studies with similar characteristics of interest have to be picked. Here, the research focus is on the level of disaggregated sectors in manufacturing industry and previous attempts studying the substitution elasticity between E and K in this respect are presented in Table 4.

Kemfert (1998) analyses data for industry in West Germany from 1960 to 1993, also accounting for 7 sectors in manufacturing industry (1970-1988)[7], and tests which nesting structure of a CES function with three inputs would best fit the data (using non-linear estimation methods). For the aggregate industry the (KE)L nesting form gives the highest R-sq whereas for all industrial sectors (except for food), the (KL)E structure seems more appropriate. Considering both capital-energy elasticity from the first nesting structure and (KL)E elasticity from the second, energy and capital are substitutes for all sectors with ranges of variation going, respectively, from 0.04 to 0.93 and from 0.35 to 0.97.

[4] Most relevant omission bias can be ascribed to a lack of information on the technology status and even the inclusion of a (deterministic) time trend is just an approximation.

[5] Also Roy *et al.* (2006), studying a KLEM Translog function without imposing any separability assumptions and then testing different restrictions, find weak evidence in this respect.

[6] Higher elasticity values from cross section data, and lower ones for time series cases, was the argument proposed by Griffin and Gregory (1976) and also adopted by Koetse *et al*. 2008 to calculate (cross section) long-run and (time series) short-run elasticities.

[7] Chemical industry, Stone and earth, Non-ferrous, Iron, Vehicle, Paper and Food.

Okagawa and Ban (2008) estimate substitution elasticities to be implemented in a CGE model considering a three level nested CES function (KLEM). They focus their attention on two main structures, the KE-L and KL-E forms, using data from 14 countries[8] and 19 industries (within which there are 10 manufacturing sectors)[9], from 1990 to 2004. From the former model they obtain EK elasticities ranging from 0.04 to 0.45 (where the assumed pre-existing parameters were 0.10 or 0.20), while in the latter, the (KL)E elasticities go from 0[10] to 0.64 (while the pre-existing parameters were equal to 0.4 for all sectors)[11]; they also find higher KE elasticities for energy-intensive industries. The comparison of results from a GAMS/MPSGE static CGE simulation with the estimated parameters shows that, in order to cut CO_2 emissions by 13% in Japan, in the (KE)L form the carbon tax required is 44% lower than with the original parameters.

Van der Werf (2008) conducts an empirical analysis on 12 OECD countries (1978-1996) accounting for the manufacturing industry and 6 sub-sectors[12], along with the construction industry, and estimates (sector and country specific) substitution elasticities to be implemented in dynamic climate change models. Considering industry specific results, in the (KL)E structure the elasticity between energy and aggregate input (in this case KL) varies between 0.17 and 0.64, in the (LE)K case from 0.18 and 0.50 whereas in the (KE)L form, values for capital-energy elasticity of substitution are significantly higher and around unity (from 0.96 to 1.00).

Tovar and Iglesias (2013), using data from 8 UK manufacturing industries[13] from 1970 to 2006, estimate capital-energy cross price elasticities (CPE) from two flexible forms, *i.e.* Translog and Generalized Leontief functions, and account for technological change by introducing a time trend. They account for 5 production factors: labour, energy, materials and two types of capital input, buildings and machinery and equipment. In the Translog KLEM model, energy and capital are complements in each sector (elasticities for buildings are higher in absolute value), but when materials are dropped (KLE model) estimates are only significant and negative for machinery. When using the GL function (however, in the Translog model, the goodness of fit is higher), capital-energy elasticities in the long-run are all negative and, in particular, chemical, machinery, textile and food sectors show higher absolute values while short-run values are

[8] Austria, Belgium, Denmark, Finland, France, Germany, Japan, Italy, Luxembourg, Netherlands, Spain, Sweden, UK and US.

[9] Manufacturing sectors considered in the analysis by Okagawa and Ban (2008) are: Food, Textile, Wood, Pulp and paper, Chemical, Other non-metallic mineral, Basic metals, Machinery, Electrical equipment and Transport equipment.

[10] For Chemical sector the (KL)E substitution elasticity reported in the Appendix is negative (-0.065) but in the result section is reported as 0.

[11] To resume, previously assumed elasticities were: for KE-L model 0.80 (KL-E) and 0.10 or 0.20 (KE); for KL-E model 0.40 (KL-E) and 1.00 (KL).

[12] Basic metal products, construction, food and tobacco, textiles and leather, non-metallic minerals, transportation equipment, and the paper, pulp and printing industry

[13] Basic metals, chemical and petrochemical, non-metallic minerals, transport equipment, machinery, textiles, food and paper industries.

slightly positive but not statistically robust.[14]

Table 4 - Review of sector capital-energy elasticity of substitution for manufacturing industries

KE elasticity	Kemfert (1998)	Okagawa-Ban (2008)	van der Werf (2008)	Roy *et al.* (2006)	Tovar-Iglesias (2013)	Tovar-Iglesias (2013)
Model	CES [1]	CES [1]	CES [1]	Translog AES	Translog CPE [2]	GL CPE [2]
Chemical and petrochemical	0.93	0.04			-0.05	-0.07
Electric machinery		0.25				
Food	0.85	0.39	0.99		-0.63	-0.25
Machinery		0.12			-0.13	-0.10
Basic metals	0.19 [3]	0.29	0.88	1.90	-0.07	-0.07
Non-metallic minerals	0.48	0.35	0.99		-0.03	-0.05
Pulp and paper	0.33	0.37	0.97	2.55 (0.50) [4]	-0.06	-0.06
Textile		0.17	0.99		-0.08	-0.08
Transport equipment	0.61	0.09	0.99		-0.07	-0.06
Wood		0.05				

Notes: [1] Specific formulations for substitution elasticities not specified. [2] Results in table for TCF are from KLEM model using machinery as a measure of capital. The reported estimates from GL model are long-run elasticity between energy and capital (machinery). [3] Basic metal elasticity is calculated as average between Iron and Non-ferrous sectors. [4] Value in brackets is AES excluding Brazil.

4. Empirical analysis

4.0 Empirical strategy

As already mentioned, the estimations of elasticity parameters are relevant in the validation processes of climate-economic models, especially for CGE ones. In this regard, according to Sancho (2010), CGE models are rich in describing the economic structure, but have weaker statistical basis and cannot be econometrically tested. However, "by selecting appropriate values for the elasticities, we are able to efficiently use the same model structure to mimic (two) different views of the world" (Sancho, 2010, pag. 2932). Thus, data-driven elasticities are instruments to make CGE models (used, as in the present case, to evaluate costs of abatement of GHG emissions policies) more reliable with respect to real world economy.

In defining the estimated model, the first choice is about the selection of the KLE (over the KLEM) model because, as already mentioned in section 3.3, the exclusion of the fourth input (material) do not seem to bias results significantly and the smaller data requirements would allow to use a wider database in term of time and country coverage.

[14] Cross price elasticities from GL model in the short-run are low positive but non-statistical significant.

The second step is the choice among the alternative functional forms. Here, the higher level of flexibility and the absence of restrictions on the substitutability between different factor inputs drive the adoption of a Translog production function (over CES or Cobb Douglas forms). Although, most of GCE models use CES functions, the Translog is a functional form on its own but also a second-order Taylor approximation to CES[15]. Moreover, Translog functions have the advantage of being linear and can be estimated using linear econometric techniques. In contrast, CES functions are non-linear and require non-linear optimization techniques, which may be problematic in term of implementation and convergence and also involve assumptions on the values of other parameters included.

A further relevant aspect is the formulation of the elasticity of substitution adopted, which in this case is the Allen elasticity (AES). Although the AES has been extensively used in empirical works in production literature, it is not free of criticisms. A first criticism came from Blackorby and Russel (1989) that argued that the Morishima formulation (MES) is superior to AES, because it represents the real curvature of the isoquant and the effects of changes in price or quantity ratios on the relative factor shares. More recently, Frondel (2011) has shown that cross price elasticity (CPE) is at the basis for the calculation of both AES and MES and should be favored also over MES, given that it is more relevant in term of economic content[16]. However, most of CGE models use a symmetric measure of substitution, while both MES and CPE are asymmetric measures of substitutability (meaning that substitution between two inputs assumes a different value depending on which is the input whose price is changing). Consequently, it would not be possible to integrate the CPE or MES value without making arbitrary assumptions about which elasticity (out of the two possibilities) integrate in the models. On the other hand, Allen elasticities, even if do not add more information to that already contained CPE, are symmetric and more suited for empirical GCE models.

Finally, as far as the econometric approach is concerned and given the data availability (almost 40 years), the work is conducted following an approach depending on the stationarity of the time series. Whenever the series are non-stationary and cointegrated, the estimations were developed using FMOLS estimator, which was specifically developed by Pedroni (2000) to evaluate common long run relationships (allowing a considerable degree of short run heterogeneity) in cointegrated panels. When those conditions do not apply and when the time series cover a shorter time interval, different panel econometric estimators are taken into

[15] In the formulation known as Kmenta approximation, Translog functions can be divided in two parts: the first represents a linearized Cobb-Douglas form while the second embodies the correction due to the departure of the substitution elasticity from one (Kmenta, 1967).

[16] “The ultimate reason for this conclusion is that cross-price elasticities measure the relative change of only one factor due to price changes of another input, whereas HAES, MES, and SES measure the relative change of a factor ratio due to price changes of these two factors” (Frondel, 2011, pag. 4603). In the same work is argued that the relative change of a factor ratio seems less important for many applications.

consideration.

In the perspective of incorporating the resulting estimated elasticities in applied energy CGE models, the best solution would be having sector and country specific values. However, given the data constraints, this is not possible and it seems more relevant to focus on the sectoral dimension for two reasons. Firstly, the panel database in use in this work includes only developed OECD countries, whose internal economic structures are expected to be quite homogeneous and would probably end in similar substitution values (of course, if also developing countries and emerging economies are considered, the country dimension will be more interesting). On the other hand, in a CGE framework sector-specific elasticity values, through the aggregation process, will also determine a better representation of each country.

Given the relevance of both short and long-run energy-economy relationships, as well as the crucial role of carrying empirical estimations at more detailed sector-based level, the econometric estimations developed in this paper aim to fill this gap by: i) calculating long-run output elasticities between energy and value added for 10 disaggregated sectors; ii) calculating short run substitution elasticities between K and E for the same 10 manufacturing sectors in the whole time span here considered; iii) computing dynamic changes in short run elasticities over different sub-periods.

4.1. Dataset analysis

The dataset used in this work has been built by collecting disaggregated data on 21 OECD countries[17] from 1970 to 2008. In particular, the focus is on the manufacturing industry divided in 10 sub-sectors which, based on ISIC Rev. 3 classification, are: Food, beverages and tobacco (D15-16); Textiles, textile products, leather and footwear (D17-19); Wood and product of wood and cork (D20); Pulp, paper, paper product, printing and publishing (D21-22); Chemical, rubber, plastics and fuel product (D23-25); Other non-metallic mineral products (D26); Basic metals and fabricated metal products (D27-28); Machinery and equipment (D29-33); Transport equipment (D34-35); Manufacturing n.e.c. and recycling (D36T37)[18]. Summing up the overall potential number of observations is given by: i = countries ($\forall i = 1, \dots, N, with\ N = 21$); j = sectors ($\forall j = 1, \dots, M, with\ M = 10$); t = years (with different time spans according to the type of analysis carried) with a maximum length equal to 39 years (1970-2008).

Considering that the adoption of a KLE or KLEM function does not seem to affect

[17] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, UK and USA.

[18] For the sake of simplicity, hereafter the sectors may be referred to as: Food, Textile, Wood, Paper, Chemical, Minerals, Basic Metals, Machinery eq., Transport eq., Other manufacturing.

econometric estimates of capital-energy elasticity of substitution, and given the poor availability of sector-based data on inputs used in the production function apart from energy (M), we here adopt a KLE version of the production function in order to have the highest data availability at sector level.

In a KLE production function materials are assumed as separable from other factors (capital, energy and labour), and they can affect both the value of cost shares of inputs and the value of energy-capital elasticity. According to Broadstock *et al*. (2007), in about half of the studies a KLE production function is adopted and, compared to KLEM cases, KLE empirical estimations tend to find more evidence of substitutability between energy and capital. Moreover, van der Werf (2008) compares 10 models used to analyse climate policies and only in three cases materials are included in the production structure. Finally, among the individual studies reviewed in the meta-analysis by Koetse *et al*. (2008), 20 out of 36 cases adopt a KLE model, and even if this modelling choice might be biased, they show that excluding materials does not produce a systematic effect.

Thus, the current paper focuses on four variables of interests: economic output (Y), capital stock (K), labour(L) and energy consumption (E). With the exception of the energy consumption variable, data are taken from the OECD-STAN Database for Structural Analysis. The variables collected are: Value Added (VALU), Gross Fixed Capital Formation (GFCF), both in national currencies at current prices, and Total Employment, in terms of the number of persons engaged (EMPN). For Australia and Japan only, and limited to the GFCF variable, data are from the EU KLEMS database from 1970 to 2007 and 2006 respectively,[19] and from the World Input Output Database (WIOD). All data on VALU and GFCF have been deflated to 2005 US dollars, and transformed into constant Purchasing Power Parity (PPP). The fourth variable is energy consumption, measured in terms of total final consumption in Ktoe and data used are from the Energy Balances provided by the IEA, available for the period 1975-2008 and at the sector base.

While some authors, such as Lee (2005) and Soytas and Sari (2007) have used investment data as a proxy for capital stock, in the majority of cases, the Perpetual Inventory Method (PIM) is applied to derive capital stock from data on investment flows (Braun *et al*., 2010; Coe and Helpman, 1995; Ek and Söderholm, 2010). Following the latter approach, capital stock for the first year is calculated by dividing the annual GFCF (I = investment flow) by a factor given by the sum of a constant depreciation rate (d=0.15) and the average annual sector and country specific growth rate (g) of GFCF variable from the overall time period as expressed by eq. (1)[20]:

[19] This database is on Growth and Productivity Accounts, where KLEMS stands for capital (K), labour (L), energy (E), materials (M) and services (S) factors. This is a European Commission research project from 6th Framework Programme, Priority 8 "Policy Support and Anticipating Scientific and Technological Needs".

[20] An alternative way of applying PIM to GFCF is to calculate the initial capital stock at time t as a function of the sum of the investments in previous years.

$$K_{ij(t0)} = I_{ij(t0)}/(g + d) \quad (1)$$

Then, capital stock at each time *t+1* is the sum of the capital stock at the previous year, discounted by the depreciation rate of 15%, with the investment at year *t+1* as given by eq.(2):

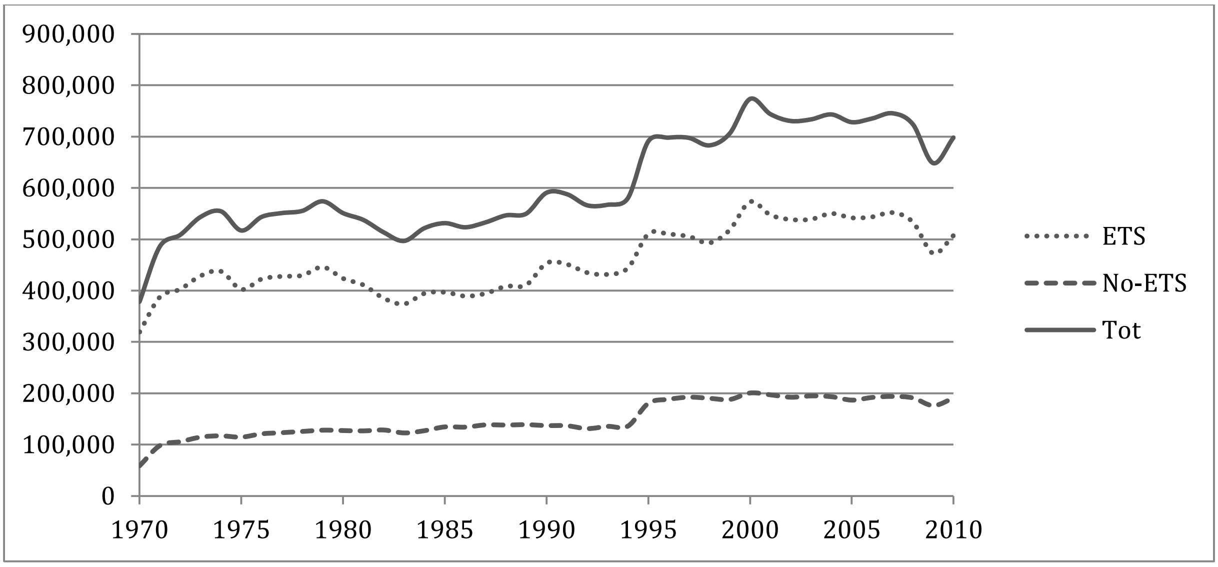
$$K_{ij(t)} = K_{ij(t-1)} \cdot (1 - d) + I_{ij(t)} \quad (2)$$

In Figure 1 trends for total final energy consumption in manufacturing sectors are reported for the period 1970-2010 for selected OECD countries. Here we present aggregated values for two industry groups, namely ETS and non-ETS sectors. This classification between ETS and non-ETS activities is based on the European Emission Trading Scheme that covers only the most energy intensive sectors, which are (limited to manufacturing): Pulp and paper; Chemical, plastics and fuels products; Non-metallic mineral products; Basic metals.

In this way, it is worth noting how energy-intensive industries behave differently from less energy-intensive ones. We can see how the trend for aggregate manufacturing is mainly driven by those four sectors that account for the great majority of the whole energy consumption. By looking at Figure 2, representing the distribution of production factors and economic output among the 10 manufacturing sectors considered (as overall average of the panel sample), we can see that the energy intensive sectors cover more than 60% of overall energy consumption whereas the shares associated with capital, labour and value added are significantly lower. Energy costs are particularly relevant in the chemical and petrochemical sector and these activities cover more than 20% of total manufacturing energy consumption.

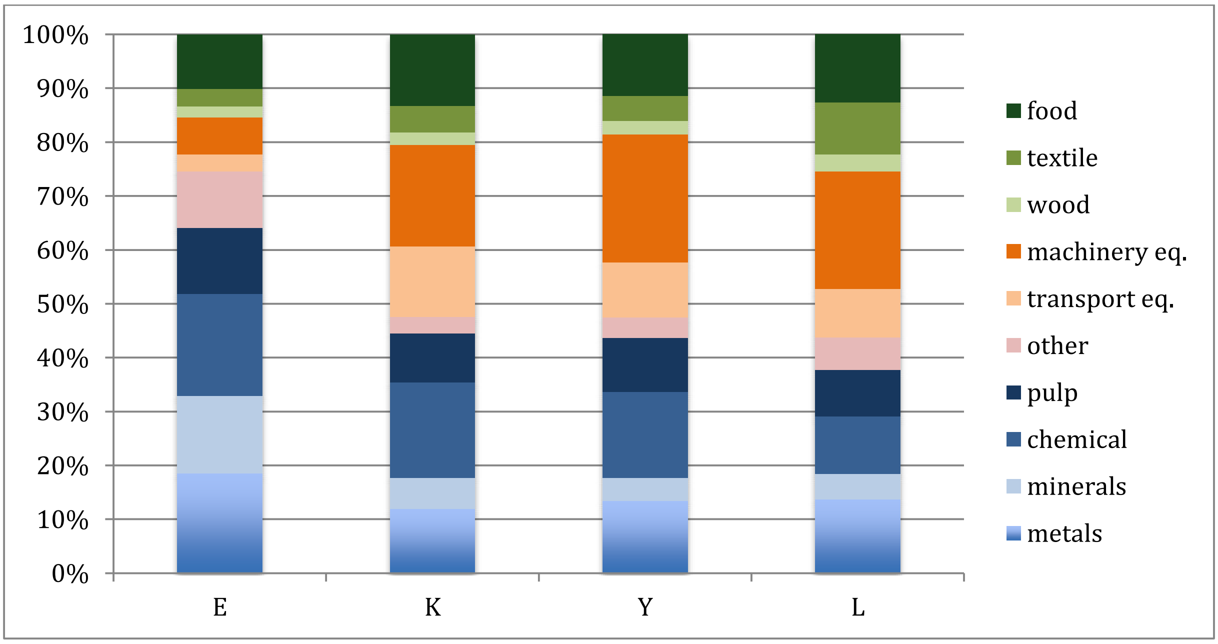
This evidence is also more pronounced at the global level, where energy-intensive sectors are responsible for 70% of industrial energy use, 20% of industrial value added and 25% of industrial employment, focusing particularly on the chemical industry, given that in some activities energy costs are around 80% (IEA, 2013).

Figure 1 - Total final energy consumption by macro-sector in manufacturing (Ktoe)



Source: own elaboration on IEA data (2012). ETS sectors are Pulp and paper; Chemical; Non-metallic mineral products and Basic metals.

Figure 2 - Distribution of factors and output share by sector (average on 1975-2008)



Source: own elaboration on IEA data (2012).

4.2. *Long run relationships between energy and economic dimensions at sector level*

Given the availability of long time series (1970-2008) and the relevance of long-run energy elasticity for the assessment of alternative climate and energy policy options, the first step is to look at this relation both at the aggregate manufacturing level as well at the sub-industry one. In particular, following a panel cointegration approach, the long-run energy elasticity parameters are estimated in a multivariate framework, both for the aggregate manufacturing industry as well as for the 10 sub-sectors[21].

Cointegration analysis and an estimation of the long-run elasticity parameters is performed in a panel framework considering a Cobb-Douglas production function with constant return to scale, because this functional form benefits from the fact that is can be easily analysed in log-linear form where the estimated coefficients represent input elasticities, and it needs less data requirements than more complicated functional forms. The logarithmic formulation of the Cobb-Douglas production function we consider can be written as:

$$lnY_{ijt} = \alpha_{ij} + b_t + \beta_K \cdot lnK_{ijt} + \beta_L \cdot lnL_{ijt} + \beta_E \cdot lnE_{ijt} + \varepsilon_{ijt} \tag{3}$$

where a_{ij} is the country-sector specific fixed effect and b_t is a term representing a deterministic trend (if included).

There are standard steps developed by the scientific literature to be followed: i) when dealing with long time series, the order of integration of each of them needs to be investigated using panel unit root tests; ii) if evidence of non-stationarity emerges, cointegration tests for heterogeneous panels are performed to establish if a stationary relationship between variables exists; iii) allowing for possible parameter instability, we also account for the presence of structural breaks and test for multiple unknown breakpoints in the data series; iv) the long-run relationships are estimated using the *Fully Modified OLS* (FMOLS) estimator developed by Pedroni (2000) for heterogeneous cointegrated panel data.

One of the advantages of working with a longitudinal dataset is that it allows the long run information to be pooled and, at the same time, allows short run dynamics and fixed effects to be heterogeneous across individual members. The first step is to conduct panel unit root tests and identify the order of integration in time series variables. In fact, if the variables are non-stationary, standard regression methodologies are biased and an appropriate approach is the identification of a stationary combination of the series to analyse the long-run relationship together with the short-run dynamics.

Later developments in econometric techniques for panel unit root tests include Levin *et al.* (2002) (LLC), Im *et al.* (2003) (IPS), Breitung (2000), Hadri (2000) and the Fisher-type tests by Maddala and Wu (1999) and Choi (2001). These tests are considered more powerful because, unlike the traditional Augmented Dickey-Fuller (ADF) or Phillips-Perron (PP) tests that account

[21] Even if results on the direction of the causality relationship between energy and value added of economic activities are still conflicting, the growth hypothesis is statistically more likely to be found in more advanced countries, compared with low-middle income countries, especially in multivariate rather than bivariate models (Apergis, 2013).

for non-stationarity only on individual time series, they take advantage of the panel characteristics.

The basic autoregressive model results as follows:

$$Y_{ijt} = \rho_{ij} \cdot Y_{ij,t-1} + \beta_{ij} \cdot x_{ijt} + \varepsilon_{ijt} \tag{4}$$

where *ij* and t stand for the cross-section dimension (which might be sector-specific or for the whole manufacturing sector according to *j*) and the time period, respectively, x_{ijt} are the exogenous variables in the model and ρ is the autoregressive coefficient, which is equal to 1 if the series contain unit roots.

The LLC-test assumes homogeneity in the AR(1) autoregressive coefficients for all panel members and thus assumes that a common unit root exists for all *i*. The individual processes are independent in the cross-section dimension and no cross-sectional correlation in panels is considered (as in the Breitung and Hadri tests). It can be seen as a pooled ADF test and under the null hypothesis the series contains a common unit root whereas the alternative hypothesis implies stationarity. The Breitung test, like the LLC, restricts the first order autoregressive coefficients to being the same for all individuals, and the lag order of the first difference term can vary across individuals (Karimu and Brännlund, 2013). As in the previous cases, the null hypothesis assumes the presence of unit root. On the other hand, the Hadri (2000) test can be used as a check on results because, unlike the previous tests, it considers the null of stationarity and extends the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) procedure in a panel framework. The Hadri test also assumes cross sectional homogeneity and common persistence parameters, and allows the case of heterogeneous disturbance terms across units (Ciarreta and Zarraga, 2010).

The IPS test, as well as the Fisher-ADF and Fisher-PP tests, are considered more powerful because they allow for individual unit roots and autoregressive coefficients that can vary in the cross section dimension. In these cases, individual unit root tests are used to derive panel-specific statistics. The IPS test, in particular, considers a separate ADF regression for each cross-section and takes the average of the t-statistics of the autoregressive coefficients to build the panel statistics. Under the null hypothesis each series has a unit root (ρ is equal to 1 for all *i*) whereas under the alternative it allows at least one individual series to be stationary, allowing heterogeneity of the autoregressive coefficients ($\rho < 1$ at least for one *i*). The Fisher type tests are also based on individual unit root tests and allow, under the alternative hypothesis, some cross-sections to be stationary. The approach proposed by Maddala and Wu (1999) and by Choi (2001), based on Fisher (1932), uses the individual p-values from unit root test on each cross-section to derive the panel test. The main advantage over the IPS test is that it is a more general approach and improves the estimation if the panel is unbalanced (Liddle, 2012).

If time series are integrated of order one (I(1)), following Engle and Granger (1987), the next step is to test for cointegration. In particular, the panel cointegration tests developed by Pedroni (1999, 2000) account for individual heterogeneity in fixed effects and dynamics but also the cointegrating vectors can vary across members, where these are the vectors of coefficients that make the combination of the individual I(1) series stationary. The main advantage of this technique is that, although the common long-run relationship is derived, the cointegrating vectors can still vary in the cross-section dimension.

There are seven different statistics in the Pedroni test, four of which are *panel* cointegration statistics and three *group* mean panel cointegration statistics. They all test the null of no cointegration and are estimated by pooling residuals from individual members' estimation of the cointegrating relationships as in eq. (5):

$$\varepsilon_{it} = \gamma \cdot \varepsilon_{i,t-1} + u_{it} \tag{5}$$

The panel statistics pool the autoregressive coefficients of the estimated residuals (γ_i) along the *within* dimension. Under the null hypothesis of no cointegration the residuals are I(1) and γ_I is equal to 1 for all *i*, while if the alternative holds and the series are cointegrated, then the autoregressive coefficient is the same for all the individuals ($\gamma_i=\gamma$ and lower than 1 for all *i*). The four panel cointegration statistics are: a non-parametric variance ratio (*v*-statistics), the panel version of two non-parametric statistics analogous, respectively, to the Phillips and Perron (PP) ρ-statistic and *t*-statistic and, finally, a parametric statistics analogous to the augmented Dickey-Fuller *t*-statistic, which is the closest to the LLC panel unit root statistics on the residuals of a cointegrating regression (Pedroni, 1999).

On the other hand, the *group* mean panel cointegration statistics are less restrictive and allow for individual first-order autoregressive coefficients to vary across the cross-sections. There are three tests that are analogous to the PP ρ and *t*-statistics and to the augmented Dickey-Fuller *t*-statistic, which is the closest to the IPS group mean unit root statistics. These *between* dimension statistics are based on estimators that do not assume a common value for all *i* but allow for an additional source of heterogeneity: they average the individual estimated coefficients for each member in the panel so that under the alternative hypothesis γ is lower than 1 for all *i*.

According to Pedroni (2004), in very small panels which are more likely to be characterised by size distortion, cointegration can be relatively confidently accepted if the *group*-ρ statistics rejects the null of no cointegration whereas in fairly large panels, the *panel-v* statistic performs better; moreover *panel*-ADF and *group*-ADF tests are considered to have better small sample properties (Lee *et al.*, 2008; Pedroni, 1999).

Another aspect to consider is the possible presence of structural breaks in the series. In fact, as stressed by Coers and Sanders (2013), if these effects exist but are not taken into account, a series can be mistaken for a non-stationary process whereas the actual causes may be (single or multiple) structural breaks. Moreover, this is also a way to test for parameter stability and avoid erroneous estimation of the model coefficients.

If the panel series are non-stationary and cointegrated, a linear combination of the pooled variables, which represents the long-run relationship, cannot be estimated using an OLS estimator because it is biased and inconsistent. The FMOLS estimator, on the other hand, generates asymptotically unbiased estimates of the long-run coefficients in relatively small sample (Pedroni, 2000). The FMLOS is a group mean estimator (or between group) that allows a high degree of heterogeneity in the panel and has the advantage, compared with the within dimension pooled estimator, of allowing more flexible representations. Indeed, the cointegrating vectors, as well as the short-run deviations in terms of serial correlation, can differ across individual members (Pedroni, 2000). In presence of heterogeneous residual dynamics, this estimator does not suffer from size distortion like the pooled panel FMOLS (in this case the second order bias arising from endogeneity is not eliminated asymptotically). The FMOLS estimator uses a semi-parametric correction for endogeneity of the regressors and residual autocorrelation and produces long-run estimates that are asymptotically unbiased and efficient and have normally distributed standard errors.

4.3 Translog production function and Allen Elasticity of Substitution

The Translog function introduced by Christensen *et al.* (1973) is often used in empirical studies because, without imposing restrictions on the substitutability between inputs, it allows both return to scale and elasticity of substitution to vary. This form is a second order Taylor approximation of a general production function and one of its main advantages is that it is flexible, especially if compared with Cobb-Douglas and CES functions (Hoff, 2004; Roy *et al.*, 2006; Saunders 2008).

The following expression represents the general formulation of a Translog production function:

$$lnY = \alpha_0 + \sum_{p=1}^{n} \alpha_p \cdot lnx_p + \frac{1}{2}\sum_{p=1}^{n}\sum_{q=1}^{n} \alpha_{pq} \cdot lnx_p \cdot lnx_q \qquad (6)$$

where Y is the production output while x_p and x_q are the quantities of the n inputs employed in the process. The terms α_p and α_{pq} are the distribution and substitution parameters respectively, where the latter measures the effect that a change in relative prices has on input cost shares through factor substitution, while α_0 is the term representing the technology level (exogenously determined).

In the specific case under analysis, we adopt a KLE production function and calculate the *Allen Elasticity of Substitution* (AES) formulation. Thus, the Translog production function assumes the following specification[22]:

$$lnY_{ijt} = \alpha_0 + \beta_K \cdot lnK_{ijt} + \beta_E \cdot lnE_{ijt} + \beta_L \cdot lnL_{ijt} + \\ + \frac{1}{2}\left[\beta_{KK} \cdot \left(lnK_{ijt}\right)^2 + \beta_{EE} \cdot \left(lnE_{ijt}\right)^2 + \beta_{LL} \cdot \left(lnL_{ijt}\right)^2\right] + \\ + \beta_{KL} \cdot \left(lnK_{ijt} \cdot lnL_{ijt}\right) + \beta_{KE} \cdot \left(lnK_{ijt} \cdot lnE_{ijt}\right) + \beta_{LE} \cdot \left(lnL_{ijt} \cdot lnE_{ijt}\right) + \varepsilon_{ijt} \tag{7}$$

As far as the formulation for the elasticity of substitution is concerned, the AES is a *one-factor-one-price* measure that represents the effect that a change in one factor's price has on the quantity employed of the second factor, given that prices of output and other inputs remain constant. Considering the Translog production function in eq. (7), the AES can be calculated as:

$$AES_{pq} = \frac{\sum_{p=1}^{n} x_p \cdot f_p}{x_p \cdot f_p} \cdot \frac{|F_{pq}|}{|F|} \quad \forall p, q \tag{8}$$

where x_p is the quantity of input *p-th*, f_p is the partial derivative of the production function with respect to x_p, $|F|$ is the determinant of the bordered Hessian matrix associated to the production function and $|F_{pq}|$ is the determinant of the co-factor associated to the f_{pq} element of matrix *F.* Considering a three-input Translog production function, the AES can be estimated using the following formulation:

$$AES_{pq} = \frac{|H_{pq}|}{|H|} \tag{9}$$

where at denominator and numerator there is, respectively, the determinant of the symmetric matrix H and of the co-factor associated with the *pq-th* element (Nguyen e Streitwieser, 1997).

[22] Without imposing the *symmetric condition.* the Translog formulation would have been the following: $lnY_{ijt} = \alpha_0 + \beta_K \cdot lnK_{ijt} + \beta_E \cdot lnE_{ijt} + \beta_L \cdot lnL_{ijt} + \frac{1}{2}\left[\beta_{KK} \cdot \left(lnK_{ijt}\right)^2 + \beta_{EE} \cdot \left(lnE_{ijt}\right)^2 + \beta_{LL} \cdot \left(lnL_{ijt}\right)^2 + \beta_{KL} \cdot \left(lnK_{ijt} \cdot lnL_{ijt}\right) + \beta_{KE} \cdot \left(lnK_{ijt} \cdot lnE_{ijt}\right) + \beta_{LE} \cdot \left(lnL_{ijt} \cdot lnE_{ijt}\right)\right] + \varepsilon_{ijt}$.

The bordered Hessian matrix H in the KLE function is the following:

$$H = \begin{bmatrix} 0 & h_K & h_L & h_E \\ h_K & h_{KK} & h_{KL} & h_{KE} \\ h_L & h_{KL} & h_{LL} & h_{LE} \\ h_E & h_{KE} & h_{LE} & h_{EE} \end{bmatrix} \quad (10)$$

and its elements are constructed from the estimated parameters of the Translog function and the actual factor cost share. In particular, assuming constant returns to scale:

$$h_p = S_p$$
$$h_{pp} = \beta_{pp} + S_p^2 - S_p \quad (11)$$
$$h_{pq} = \beta_{pq} + S_p \cdot S_q$$

where the cost share of input *i* is calculated in the following way:

$$S_p = \beta_p + \sum_{p=1}^{3} \beta_{pq} \cdot lnx_q \quad (12)$$

The main criticism of this elasticity is that it is symmetrical, therefore the direction of the substitution cannot be distinguished, and that it is dependent on the size of cost shares. This could constitute a substantial limiting issue if the composition of the input mix were to change dramatically over time, thus changing the cost shares of single inputs while assuming symmetric reactions. On the other hand, the AES estimation is much simpler than CPE and MES since it requires less information than the others. A potential solution to this limit could be given by dynamic estimations, carried out in different temporal spans in order to catch variability in cost shares in the input mix more carefully. If the AES values largely vary across time spans, this could be a first sign of the instability of AES estimations and one simple way to reduce strong variance could be to calculate an average value across time spans instead of computing a single value for the whole period.

5. Empirical results

5.1. Results of stationarity and cointegration analysis

In Table 5 results from unit root tests are reported for each variable, both in levels and first differences. When accounting for the variables in level, the time period considered is 1970-2008, except for energy consumption for which it is 1975-2008. As far as lag lengths are considered for stationarity tests, for Y and L there are no lags selected, while for K lags are equal to two and for E automatic selection of maximum lags was based on the Modified Akaike Information Criterion (MAIC). This heterogeneity in lag selection has been chosen on the basis of the following criterion: for each variable we tested several lag structures and we adopted the structure revealing non-stationarity with the most stringent assumptions[23].

With the only exception of PP-Fisher *t-stat* for K, unit root tests on level variables confirm that the series are non-stationary. When considering the first differences, the null of unit root is strongly rejected at the 1% significance level for all series and this leads to the conclusion that the series are non-stationary and integrated of order one. As a robustness check, the Hadri unit root test was also performed since it tests the null of stationarity. In this case, the Hadri test on variables in levels is always significant at 1% level and rejects the null of stationarity, thus the series contain unit roots.

Table 5 - Unit root tests

TEST	Y	ΔY	K	ΔK	E	ΔE	L	ΔL
LLC	8.65 [1.00]	-54.03*** [0.00]	16.50 [1.00]	-42.00*** [0.00]	3.22 [1.00]	-111.16*** [0.00]	3.87 [1.00]	-36.82*** [0.00]
Breitung t-stat	29.19 [1.00]	-20.29*** [0.00]	0.95 [0.83]	-3.71*** [0.00]	6.42 [1.00]	-24.50*** [0.00]	16.47 [1.00]	-12.01*** [0.00]
IPS	17.87 [1.00]	-52.23*** [0.00]	6.15 [1.00]	-41.01*** [0.00]	4.54 [1.00]	-89.59*** [0.00]	8.49 [1.00]	-35.95*** [0.00]
ADF - Fisher	328.63 [1.00]	3864.34*** [0.00]	479.56 [0.99]	3092.99*** [0.00]	569.36 [1.00]	10747.6*** [0.00]	416.02 [1.00]	2622.80*** [0.00]
PP - Fisher	391.12 [1.00]	6301.46*** [0.00]	2363.63*** [0.00]	3624.76*** [0.00]	993.24 [0.00]	14323.2*** [0.00]	538.88 [0.89]	3120.75*** [0.00]

Notes: Newey-West automatic bandwidth selection and Bartlett kernel. Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. Exogenous variables: Individual effects, individual linear trends. H_0: Unit Root (LLC and BREITUNG tests assume common unit root process; IPS, ADF and PP Fisher assume individual unit roots). *, **, *** significant at 10%, 5%, 1% level; p-values reported in brackets.

Given that the variables are I(1), cointegration analysis is required in order to test the existence of a long-run relationship between the series, and heterogeneous panel cointegration

[23] All results on different lag structures for the stationarity test are available upon request.

tests developed by Pedroni are applied (Table 6). Two time periods were considered, from 1970 (cases a and b) or 1975 (case c). Both panel and group ADF statistics always reject the null of no cointegration; moreover *panel-v* statistic also confirms cointegration between the variables in all cases but one. Thus, the existence of a cointegrating vector can be accepted and long-run elasticities can be derived using the FMOLS estimator.

Table 6 - Pedroni Panel Cointegration Test

	(a)		(b)		(c)	
	Statistic	Weighted Statistic	Statistic	Weighted Statistic	Statistic	Weighted Statistic
Panel v-Statistic	-2.15	-7.36	2.31**	-1.15	2.29**	-1.13
Panel rho-Statistic	-0.16	-0.62	2.61	2.60	2.89	2.67
Panel PP-Statistic	-3.25***	-5.00***	-0.30	-2.88***	1.37	-1.52*
Panel ADF-Statistic	-4.04***	-4.50***	-3.06***	-5.93***	-1.64*	-4.35***
Group rho-Statistic	5.60		9.10		8.63	
Group PP-Statistic	-8.01***		-6.64***		-6.94***	
Group ADF-Statistic	-11.03***		-9.12***		-9.81***	

Notes: Newey-West automatic bandwidth selection and Bartlett kernel; Lag length selection based on SIC. H_0: No cointegration. Alternative hypothesis: Panel statistics assume common AR coefficients (*within-dimension*); Group statistics assume individual AR coefficients *(between-dimension*). Series: VALU, K STOCK, ENE, EMPL. (a) 1970-2008; No deterministic intercept or trend; (b) 1970-2008; No deterministic trend; (c) 1975-2008; No deterministic intercept or trend. *, **, *** significant at 10%, 5%, 1% level. Standard errors reported in brackets.

Considering the Cobb-Douglas production function from eq. (3), Tables 7 and 8 present results for long-run output elasticities at the aggregate manufacturing level and by sector, respectively, while Table 9 summarises the results for long-run energy-output elasticities both at the aggregate manufacturing level and by sector.

Table 7 - Long-run elasticities from panel FMOLS for whole industry (1975-2008)

	(2)	(1)
K	0.215*** [0.005]	0.143*** [0.005]
E	0.037*** [0.004]	0.015*** [0.003]
L	0.536*** [0.007]	0.657*** [0.006]
B_82		0.012*** [0.003]
B_98		0.106*** [0.002]
No. Obs	4,667	4,667
Rsq	0.993	0.995
Adj.Rsq	0.993	0.993
S.E	0.176	0.176

Notes: B_1982 and B_1998 are dummy variables representing breakpoint years that were selected by Bai Multiple breakpoint test. *, **, *** significant at 10%, 5%, 1% level. Standard errors reported in brackets.

Long-run elasticities of value added with respect to energy consumption (Table 7) are low but significant at the aggregate manufacturing as well as at the sector level and in line with previous studies[24]. In particular, it is worth noting that for energy-intensive sectors (chemicals, basic metals, non-metallic minerals, and pulp and paper, which correspond to the regulated activities under EU ETS), the associated coefficients assume the highest (and statistically robust) values. The results confirm that, with respect to manufacturing industry, these industrial sectors are the most energy intensive and, above all, the most vulnerable with respect to increase in energy price or stringent targets in emission abatement. Consequently, the potential impact of those measures will be different among countries and region depending on the internal economic structure: more relevant the energy intensive industries are within the national economy, and more vulnerable the country will be to energy and climate change policies. As further consequence, these issues would also determine differences among countries with respect to the willingness to accept commitments in term of emission abatement, as the deadlock in the current international negotiations shows.

The first implication we can derive from these preliminary findings is that the technological content and input mix of these energy-intensive industries are strongly dependent on the availability of affordable energy inputs, and they require specific complementary interventions in the form of stringent energy conservation policies in order to be compliant with emission targets. As a consequence, by comparing the elasticity for E at the aggregate level with the sector-specific ones, it is worth noting that sector-based empirical estimations are absolutely necessary in order to disentangle differentiated impacts and consequent sector-specific policy actions.

Moreover, this heterogeneity in the energy-output relationship for distinguished manufacturing sectors suggests that when top-down or bottom-up models are used to assess economic impacts of climate mitigation policies, a distinction in behavioural parameters for sectors that behave differently, but share the same climate stringency target, is needed to obtain reliable abatement cost evaluations. In the following we therefore adopt an AES approach in order to calculate input-specific elasticities in the production function of the 10 manufacturing sectors.

[24] Liddle (2012), for example, finds similar results when considering aggregate energy consumption (as here), while energy coefficients are higher when computed from *energy indices* that allow controlling for energy mix quality.

Table 8 - Long-run elasticities from panel FMOLS for sub-sectors (1975-2008)

Sector	*Variables*	*Coefficient*	*Sector*	*Variables*	*Coefficient*
Food	K	0.195*** [0.023]	Minerals	K	-0.004 [0.020]
	E	-0.018 [0.021]		E	0.159*** [0.016]
	L	0.516*** [0.051]		L	0.840*** [0.034]
	No Obs.	489		No Obs.	485
	R-sq	0.998		R-sq	0.998
	Adj.R-sq	0.998		Adj.R-sq	0.998
	S.E	0.106		S.E	0.093
Textile	K	0.338*** [0.020]	Basic metals	K	0.208*** [0.024]
	E	0.047*** [0.015]		E	0.151*** [0.022]
	L	0.597*** [0.034]		L	0.572*** [0.039]
	No Obs.	451		No Obs.	489
	R-sq	0.998		R-sq	0.998
	Adj.R-sq	0.997		Adj.R-sq	0.998
	S.E	0.099		S.E	0.094
Wood	K	0.344*** [0.034]	Machinery eq.	K	0.282*** [0.025]
	E	0.021 [0.014]		E	-0.026* [0.011]
	L	0.774*** [0.055]		L	0.670*** [0.038]
	No Obs.	449		No Obs.	483
	R-sq	0.991		R-sq	0.998
	Adj.R-sq	0.989		Adj.R-sq	0.998
	S.E	0.140		S.E	0.097
Paper	K	0.159*** [0.026]	Transport eq.	K	0.182*** [0.029]
	E	0.166*** [0.019]		E	-0.021 [0.020]
	L	0.630*** [0.060]		L	0.877*** [0.050]
	No Obs.	520		No Obs.	447
	R-sq	0.997		R-sq	0.996
	Adj.R-sq	0.996		Adj.R-sq	0.996
	S.E	0.116		S.E	0.138
Chemical	K	0.007 [0.021]	Other manuf.	K	0.412*** [0.025]
	E	0.065*** [0.020]		E	0.022*** [0.006]
	L	-0.105*** [0.017]		L	0.693*** [0.039]
	No Obs.	402		No Obs.	452
	R-sq	0.998		R-sq	0.998
	Adj.R-sq	0.998		Adj.R-sq	0.998
	S.E	0.108		S.E	0.089

B_1982 and B_1998, dummy variables representing breakpoint years were also included in the estimation. *, **, *** significant at 10%, 5%, 1% level. Standard errors reported in brackets.

Table 9 – Energy long-run elasticities from panel FMOLS for sub-sectors (1975-2008)

Sector	*Coefficient*
Machinery eq.	-0.026* [0.011]
Transport eq.	-0.021 [0.020]
Food	-0.018 [0.021]
Other manufacturing	0.022*** [0.006]
Wood	0.021 [0.014]
Textile	0.047*** [0.015]
Chemical	0.065*** [0.020]
Basic Metals	0.151*** [0.022]
Minerals	0.159*** [0.016]
Paper	0.166*** [0.019]
Manufacturing	0.037*** [0.004]

5.2. Capital-energy Allen Elasticity of Substitution

As a complement of the long-run output elasticity estimation, Table 10 shows the Translog long-run estimations of the elasticities of substitution for the aggregate manufacturing industry and sub-sectors. As before, considering the reference time period of almost 40 years, the FMOLS was applied and results show that the coefficients are statistically robust at 1% level. Starting from the estimated coefficients, applying the computation methodology described in Section 4.3, we calculated the capital-energy elasticity of substitution at the aggregate manufacturing level, which is equal to 0.27, in line with previous empirical findings.

As a second step, we computed sector-based estimations of capital-energy elasticity of substitution. A few methodological issues should be noted. First, the sub-sector estimates using the FMOLS as described in Table 10 are rather distant from the average value (0.27) calculated for the aggregate manufacturing sector and can not be considered fully reliable. Bearing in mind that when non-stationary and cointegrated series are used for a multivariate estimation, if dynamic models such as FMOLS cannot be used, the time series have been restricted in order to reduce non-stationarity problems. Hence the time dimension of the panel is reduced and in this case only observations from 1990 are included. Nonetheless, this data-driven computational choice is also theoretically coherent with the purpose of providing sector-specific capital-energy elasticity of substitution for energy-related forecasting models.

Table 10 - Translog estimation for aggregate manufacturing industry and sub-sectors in FMOLS (1975-2008)

Variable	*Manuf. ind. tot.*	*Food*	*Textile*	*Wood*	*Pulp and paper*	*Chemical*	*Minerals*	*Basic metals*	*Machinery and Eq.*	*Transport eq.*	*Other manuf.*
K	4.639***	1.620***	-9.496***	-4.623***	2.866***	1.619***	0.905**	-0.897	8.956***	-1.815***	5.566***
	[0.008]	[0.401]	[0.306]	[0.369]	[0.198]	[0.164]	[0.301]	[0.392]	[0.250]	[0.227]	[0.143]
E	-3.587***	-9.113***	0.018	0.042	-1.111***	-0.954***	-2.889***	1.865***	-7.819***	0.160***	0.298***
	[0.009]	[0.277]	[0.237]	[0.263]	[0.170]	[0.105]	[0.340]	[0.231]	[0.299]	[0.270]	[0.046]
L	-3.576***	7.844***	5.080***	2.917***	1.865***	1.466***	-3.784***	-2.149***	4.161***	5.319***	-6.120***
	[0.017]	[0.359]	[0.141]	[0.384]	[0.188]	[0.124]	[0.226]	[0.233]	[0.219]	[0.198]	[0.145]
KK	-0.164***	0.142***	0.299***	0.149***	-0.027***	0.006	-0.065***	0.029*	-0.165***	0.059***	-0.235***
	[0.001]	[0.014]	[0.009]	[0.016]	[0.007]	[0.006]	[0.010]	[0.011]	[0.008]	[0.009]	[0.006]
EE	-0.012***	-0.198***	-0.059***	-0.046***	0.080***	0.047***	-0.033**	0.078***	-0.110***	-0.086***	-0.008***
	[0.000]	[0.012]	[0.007]	[0.002]	[0.005]	[0.004]	[0.016]	[0.007]	[0.007]	[0.010]	[0.001]
LL	0.234***	0.608***	0.005	-0.068*	0.226***	0.159***	0.307***	0.047***	0.293***	-0.304***	-0.090***
	[0.001]	[0.021]	[0.008]	[0.025]	[0.009]	[0.005]	[0.014]	[0.011]	[0.014]	[0.020]	[0.008]
KE	0.295***	0.501***	-0.05**	-0.075***	0.121***	0.038***	0.290***	-0.128***	0.536***	-0.172***	-0.010***
	[0.001]	[0.019]	[0.015]	[0.019]	[0.010]	[0.008]	[0.023]	[0.013]	[0.022]	[0.019]	[0.004]
KL	0.035***	-0.953***	-0.244***	-0.10***	-0.201***	-0.188***	-0.004	0.072***	-0.369***	0.013***	0.418***
	[0.002]	[0.026]	[0.010]	[0.037]	[0.014]	[0.008]	[0.012]	[0.015]	[0.015]	[0.022]	[0.012]
EL	-0.233***	0.008	0.145***	0.189***	-0.237***	-0.051***	-0.269***	0.013	-0.267***	0.400***	0.003***
	[0.001]	[0.025]	[0.012]	[0.015]	[0.007]	[0.010]	[0.032]	[0.014]	[0.012]	[0.018]	[0.005]
B_82	0.111***	0.025***	0.017***	-0.003	0.059***	0.089***	0.094***	0.090***	0.125***	0.058***	0.009***
	[0.002]	[0.006]	[0.005]	[0.007]	[0.005]	[0.006]	[0.005]	[0.006]	[0.006]	[0.007]	[0.005]
B_98	0.227***	0.006	0.103***	0.114***	0.134***	0.174***	0.128***	0.086***	0.176***	0.199***	0.131***
	[0.002]	[0.005]	[0.005]	[0.007]	[0.005]	[0.004]	[0.004]	[0.004]	[0.005]	[0.006]	[0.005]
No. Obs.	4,667	489	451	449	520	402	485	489	483	447	452
Rsq	0.744	0.994	0.996	0.986	0.995	0.996	0.997	0.995	0.997	0.996	0.998
Adj.Rsq	0.599	0.993	0.995	0.983	0.994	0.995	0.996	0.994	0.996	0.994	0.998
S.E	1.375	0.171	0.128	0.172	0.154	0.152	0.129	0.157	0.142	0.158	0.106
KE-AES	*0.27*	*-0.04*	*-0.16*	*-0.54*	*-0.19*	*-0.77*	*-1.24*	*-0.57*	*0.45*	*0.15*	*0.10*

Notes: *, **, *** significant at 10%, 5%, 1% level. Standard errors reported in brackets; B_1982 and B_1998 are dummy variables representing breakpoint years that were selected by Bai Multiple breakpoint test.

Considering that AES is a symmetric measure of substitution elasticity, it is strongly affected by the relative share on each input in the production function. By adopting more recent data, we partially reduce this specific problem by using input mix information that is consistent with what is included in most energy-related forecasting models and obtaining sector-based substitution elasticities that better represent current behavioural parameters regarding the current state of technology.[25]

Moreover, the panel database can be considered as a generalization of time-series and cross-section and different econometric estimators can capture different properties of the data. Stern (2012) in a meta-analysis on inter-fuel substitution draws a detailed picture of econometric issues and possible bias in estimations of long-run elasticity. Although the adequacy of estimators depends on specific characteristics of the analysed data, he shows that theoretically the between estimator (BE) is particularly adequate for empirical analysis of long-run elasticities. If the real process determining the observed data is characterized by a dynamic path, BE is the most consistent estimator if there is no correlation between regressors and the error term in non-stationarity (but strictly exogeneity) cases since it is less affected by measurement errors. Moreover, if omitted and explanatory variables are correlated, BE is consistent when there is correlation with respect to remainder disturbance whereas it can be more affected than OLS, panel FE and RE when there is correlation with individual effects. Nonetheless, Stern (2012) cites results of Monte Carlo simulations on the impacts of measurement errors and omitted variables on panel estimators performed by Huak and Wacziarg (2009). Their conclusion is that BE has minimum bias compared to FE, RE and some GMM formulation because it is consistent in non-stationarity cases (even with misspecified dynamics and heterogeneous coefficients), although explanatory variables may be correlated with individual effects.

The computation of capital-energy substitution elasticities at sub-sector level has therefore been carried out in two steps. The first step is to conduct BE econometric estimation on the time sample from 1990 to 2008 for each sector. Secondly, elasticities are also estimated by dividing the time period in 4 sub-samples of 5 years each. In this specific case, for each sector and time period together with BE estimations, Translog parameters and elasticities of substitution are also estimated using different panel estimators (FE, RE, IV and GMM). Then, given that the sector-based substitution elasticities here computed should be mainly used as behavioural parameters in climate and energy models, only estimations providing values within the interval (0,1) have been considered.

Values for the capital-energy elasticity of substitution are presented for each sector (Table 11), both from the BE 1990-2008 estimations and for the 5 year sub-periods, as the mean of all values that are positive and lower than 1 (together with the 4 periods mean).

[25] For details on dynamics over time for capital and energy intensity for the 10 manufacturing sectors, see Tables A1 and A2 in the Appendix.

Starting with the BE estimator, capital-energy elasticities are different by sector and clearly lower than 1, with the only exception of the *Other manufacturing industries* (the corresponding 0.98 elasticity can be biased as a result of the fact that this sector aggregates less homogeneous production activities). As a result, climate and energy models applying the same value for substitution elasticity to all sectors may be highly misspecified. A second issue to be noted is that the Food sector is the only one for which the BE estimator does not produce estimations so that the corresponding elasticity is positive and lower than 1.[26]

At the same time, looking at the sub-period results, it is worth noting that the Food sector is the only one out of the 10 here investigated for which the 4 periods means are always within the target range and almost constant. On the other hand, for Textile and Wood sectors, the values show an increasing trend[27] whereas for five industries (Chemical, Minerals, Basic metals, Machinery and equipment, and Other manufacturing industries), as well as the overall mean, values follow a U shape over time.

Focusing on columns (5) and (6) in Table 11, in both cases, lower values for KE substitution elasticity seem to be associated with the Wood sector (0.16 and 0.13), whereas the Textile sector shows higher substitutability between energy and capital (0.47 and 0.44). Excluding the Food sector, for which the BE result is not available, and Other manufacturing, where the 0.97 value from BE is clearly too high[28], elasticity from BE is lower than the mean of period-by-period results in five cases. For the Pulp and paper and Machinery and equipment sectors, the relation is the opposite whereas in both cases, KE elasticity for Chemical industry is equal to 0.29.

Besides that, the only case in which the two econometric procedures give relative different results is for the Minerals sector. In this specific case, the KE elasticity is 0.12 from BE (the lowest value obtained) and 0.44 as a mean value from the shorter period estimations.[29] Finally, it is worth mentioning that the lowest variance calculated across sectors is associated with the average values obtained by the four time spans calculated over the mean values of the different estimators adopted. Given the strong dependence on different estimators, a different composition of the input mix and different time spans adopted, we can affirm that the average values calculated in the dynamic setting as a mean across the four sub-periods may constitute a robust measure of capital-energy elasticity of substitution at sector-based level.

[26] They were either negative values or values higher than 1.

[27] The Paper and Pulp industry also has an increasing trend, but it is only relative to the last two periods.

[28] Moreover, the corresponding mean value from 5 year estimations of 0.27 is also equal to the FMOLS result from the aggregate manufacturing sector as shown in Table 9.

[29] Specific KE-AES values for each estimator used to compute the average values reported in Table 10 are given in Tables A3-A6 in the Appendix. Full details of single regression outputs are not reported for the sake of simplicity but they are available upon request from the authors.

Table 11 – KE-AES by manufacturing sector

	1990-1994	1995-1999	2000-2004	2004-2008	Mean	BE 1990-2008	Distance from mean in (6)	(6)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food	0.44	0.45	0.46	0.44	**0.45**	1.00	*0.58*	*0.55*
Textile	0.30		0.46	0.64	0.47	**0.44**	0.02	-0.03
Wood	0.03	0.14		0.32	0.16	**0.13**	*-0.29*	-0.03
Pulp and paper			0.37	0.29	0.33	**0.38**	-0.04	0.05
Chemical	0.46		0.04	0.36	0.29	**0.29**	-0.13	0.00
Minerals	0.61	0.01		0.69	**0.44**	0.12	*-0.30*	*-0.32*
Basic metals	0.61	0.12		0.32	0.35	**0.24**	-0.18	-0.11
Machinery eq.	0.51	0.07	0.09	0.43	0.27	**0.32**	-0.10	0.05
Transport eq.	0.28	0.35	0.32		0.32	**0.28**	-0.13	-0.04
Other manufacturing	0.30		0.15	0.35	**0.27**	0.98	*0.56*	*0.71*
Mean	*0.39*	*0.19*	*0.27*	*0.43*	*0.33*	*0.42*		
Variance	*0.035*	*0.029*	*0.031*	*0.021*	*0.009*	*0.066*		

Summing up, in order to provide valuable estimations for CGE models, our conclusions are that estimated values from BE estimator applied to the medium term (1990-2008) are those AES values to be preferred (highlighted in bold in Table 10). For those sectors where AES values are distant from the overall average value (those in italics in Column (7)) we have compared values from Column (6) with those in Column (5) as resulting by differences expressed in Column (8). For those AES values calculated by the BE estimator over the whole time period where the distance from the average in Column (7) is relatively high and the distance from the corresponding AES values calculated as an average across the four sub-periods with alternative estimators is also high (values in italics in Colum (8)), we have replaced AES values obtained by medium-term BE with AES values calculated by the alternative method. As a result, the final sector-based values of AES for the capital-energy relationships are the bold values in Table 10.

It is worth noting that also in this case, even if substantial robustness checks have been carried, a high degree of subjectivity affects this choice and an accurate sensitivity analysis is necessary to be carried in CGE energy-economic models in order to understand to which extent such AES values might influence abatement cost assessment.

6. Conclusion

The aim of this paper is to closely analyse the role that energy plays in manufacturing sectors at a detailed level in order to provide empirically grounded behavioural parameters for the production function. In particular, it provides econometrically estimated capital-energy elasticity of substitution values to be adopted in climate-energy-economic forecasting models.

A preliminary analysis regards the long-run energy elasticity calculated by implementing a FMOLS to I(1) and cointegrated series in a growth hypothesis framework. The elasticity values for specific manufacturing sectors are highly heterogeneous with respect to the elasticity value computed on the aggregate manufacturing sector. More specifically, for energy intensive sectors the associated coefficients assume higher values, revealing that the technological content and the input mix of these industries are strongly dependent on the availability of affordable energy inputs. The first policy implication is thus that these sectors require specific complementary interventions in the form of stringent energy conservation policies in order to be compliant with emission targets. Moreover, this heterogeneity in the energy-output relationship for distinguished manufacturing sectors suggests that when energy forecasting models are used, a distinction in behavioural parameters for sectors that behave differently from the same energy stringency target is necessary to obtain reliable cost evaluations.

According to this first finding, the second and main step of this work consists in computing sector-based capital-energy elasticity of substitution values in order to provide empirically-grounded behavioural parameters that help providing a better representation of the impacts of energy saving policies in terms of the production function. The sector-based elasticity of substitution values better represent the economic impacts of energy saving and low carbon policies especially in terms of international competitiveness, structural change dynamics and emission abatement costs. Substitution elasticities represent the degree of technological flexibility and their magnitude directly affects the costs of achieving emission targets where the negative effect on output will be greater if flexibility is lower. It is also worth noting that the final effect also depends on the energy intensity of economic activities, which determines the higher or lower reduction in energy consumption as a result of an increase in energy prices.

In the elasticity of substitution values, the distinction between energy-intensive and non-energy-intensive sector behaviour is less clear than for long-run output elasticity. This is due to the fact that this parameter does not represent the direct impact that energy has in the production process, but reflects the capital-energy relation and also the energy-oriented characteristics of the overall technological structure. In fact, in addition to the impacts on output reduction, the capital-energy elasticity of substitution has a direct link with the level of capital stock, especially in dynamic climate-energy models. In this case, the degree of technological flexibility may directly affect capital profitability across regions in terms of capital reallocation. This is a further reason why detailed parameters should be included to adequately differentiate structural characteristics between activities in order to obtain a more accurate representation of the consequences of different climate change policies. Since accuracy in econometric estimations of substitution elasticity parameters is strongly affected by divergences in temporal structure of the dataset investigated, as well as by the specific estimator adopted, the proposed methodology developed here tries to reduce this uncertainty by comparing different estimation outputs in terms of both alternative econometric estimators adopted and different time periods analysed.

In this regard, the international scientific community has pointed out that "[changes] in relative energy costs across countries not only affect industrial and energy competitiveness but also economic competitiveness. The extent to which an increase, compared with other economies, in the pre-tax price of energy undermines economic competitiveness depends largely on the extent to which a given country relies on energy-intensive manufacturing, as well as the scope for higher prices to be offset by economically viable investments towards greater energy efficiency" (IEA, 2013, p. 293). Energy-intensive sectors are more (and primarily) affected by increases in energy prices, and the final effect also depends on the degree of flexibility of the production system which can be represented by the capital-energy elasticity of substitution.

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Appendix

Table A.1 - Energy intensity by manufacturing sector

ISIC Rev.3	**Energy intensity**	Mean 1970-71	Mean 2007-08	Variance
C15T16	Food products, beverages and tobacco	0.148	0.775	4.229
C17T19	Textiles, textile products, leather and footwear	0.121	0.982	7.143
C20	Wood and products of wood and cork	0.070	1.392	18.993
C21T22	Pulp, paper, paper products, printing and publishing	0.431	2.371	4.504
C23T25	Chemical and petrochemical	0.427	1.218	1.851
C26	Other non-metallic mineral products	0.737	3.408	3.622
C27T28	Basic metals and FMP	0.592	1.461	1.470
C29T33	Machinery and equipment	0.052	0.234	3.487
C34T35	Transport equipment	0.053	0.188	2.566
C36T37	Manufacturing n.e.c. and recycling	2.943	4.115	0.398

Notes: Sector C20: USA excluded; Sector C23T25: Data from 1980; Sector C36T37: Mean 1970-1971 USA excluded.

Table A.2 - Capital intensity by manufacturing sector

ISIC Rev.3	**Capital intensity**	Mean 1970-71	Mean 2007-08	Variance
C15T16	Food products, beverages and tobacco	0.015	0.032	1.040
C17T19	Textiles, textile products, leather and footwear	0.016	0.016	-0.034
C20	Wood and products of wood and cork	0.020	0.063	2.124
C21T22	Pulp, paper, paper products, printing and publishing	0.022	0.039	0.746
C23T25	Chemical and petrochemical	0.016	0.026	0.624
C26	Other non-metallic mineral products	0.019	0.029	0.534
C27T28	Basic metals and FMP	0.017	0.021	0.191
C29T33	Machinery and equipment	0.013	0.017	0.306
C34T35	Transport equipment	0.017	0.020	0.196
C36T37	Manufacturing n.e.c. and recycling	0.023	0.036	0.590

Note: Sector C23T25: Data from 1980.

Table A.3 – KE-AES by manufacturing sector (1990-1994)

	FE	RE	FEIV	SYS	FE_D	RE_D	BE_D	FEIV_D	REIV_D	GMM_D	*MEAN*	*VAR*
Food		0.21					0.47			0.64	*0.44*	*0.05*
Textile		0.59	0.04				0.29				*0.30*	*0.07*
Wood							0.03				*0.03*	
Paper												
Chemical	0.63						0.28				*0.46*	*0.06*
Minerals					0.46	0.92	0.45	0.62			*0.61*	*0.05*
Basic metals			0.46				0.76				*0.61*	*0.05*
Machinery eq.			0.37	0.64							*0.51*	*0.04*
Transport eq.	0.35	0.36	0.15								*0.28*	*0.01*
Other man.									0.21	0.39	*0.30*	*0.02*

Table A.4 – KE-AES by manufacturing sector (1995-1999)

	FE	RE	BE	FEIV	REIV	GMM	BE_D	SYS_D	*MEAN*	*VAR*
Food						0.45			*0.45*	
Textile										
Wood	0.07	0.21							*0.14*	*0.01*
Paper										
Chemical										
Minerals								0.01	*0.01*	
Basic metals			0.08	0.19			0.08		*0.12*	*0.00*
Machinery eq.			0.07				0.07		*0.07*	*0.00*
Transport eq.			0.53		0.00		0.53		*0.35*	*0.09*
Other man.										

Table A.5 – KE-AES by manufacturing sector (2000-2004)

	FE	RE	FEIV	SYS	FE_D	RE_D	BE_D	FEIV_D	REIV_D	GMM_D	*MEAN*	*VAR*
Food	0.37		0.22		0.38	0.90		0.43				0.46
Textile		0.54			0.21	0.56	0.54					0.46
Wood												
Paper		0.19			0.11		0.19		0.30	0.42	0.97	0.37
Chemical		0.04					0.04					0.04
Minerals												
Basic metals												
Machinery eq.								0.09				0.09
Transport eq.		0.17		0.73			0.07					0.32
Other man.		0.16					0.13					0.15

Table A.6 – KE-AES by manufacturing sector (2005-2008)

	FE	BE	FEIV	GMM	FE_D	RE_D	BE_D	FEIV_D	GMM_D	*MEAN*	*VAR*
Food		0.33		0.76			0.25			*0.44*	*0.08*
Textile		0.68				0.67	0.57			*0.64*	*0.00*
Wood							0.32			*0.32*	
Paper		0.09						0.49		*0.29*	*0.08*
Chemical		0.54					0.18			*0.36*	*0.07*
Minerals		0.33	0.55	0.44	1.00	0.91		0.91		*0.69*	*0.08*
Basic metals									0.32	*0.32*	
Machinery eq.	0.83		0.59	0.57			0.08		0.08	*0.43*	*0.11*
Transport eq.											
Other man.		0.42					0.29			*0.35*	*0.01*

A sensitivity analysis of a dynamic climate-economy CGE model (GDynE) to empirically estimated energy-related elasticity parameters

1. Introduction

The impact of climate mitigation policies on economic activity is a longstanding controversial issue still highly debated by the international literature. Given the global scope of climate policies in an open economy, a crucial aspect to carefully account for is the regional distribution of mitigation costs. These concerns justify the assessment of climate change costs by applying several model types that differ in purpose and perspective, such as, for instance, addressing a short or long term time horizon or focusing on a single country or a global analysis of unilateral or coordinated measures.

Computable General Equilibrium (CGE) models are particularly suitable for analysing the effect of low-carbon policies since they can capture differences between regulated and unregulated countries in term of competitiveness through trade channels, but also through investment dynamics in the long term. However, these models need to be improved and validated with detailed information on behavioural parameters on the technology and energy sides in order to produce more reliable results . As far as CGE models are concerned, this kind of information is mainly represented by elasticity values that regulate the substitution processes in response to changes in relative prices.

In this regard, we analyse the sensitivity of a dynamic version of the GTAP-E model (GDynE) and test different sets of energy-related elasticity parameters.

The rest of the work is structured as follows. Section 2 provides a literature review of the relevance of sensitivity analysis in applied models to validate results and the reasons why detailed behavioural parameters are crucial to the robustness of simulation results. Section 3 illustrates the GDynE model and describes simulation scenarios. Section 4 reports quantitative results and Section 5 outlines the main conclusions.

2. Literature Review

The impact of policies on economic systems can be analysed by taking advantage of different applied models that can assess how the economy will react to any exogenous shock. Examples of shocks are the imposition or cutting of tariffs on imports, export subsidies, trade liberalisation, the impact of an increase in the price of a particular good or changes in supply for strategic resources such as fossil fuels. There are many examples of simulation of economic scenarios through bottom-up, top-down or integrated assessment models, especially in the fields of international trade, agriculture and land use, and climate change policies. Whatever approach is selected, and depending on the issue under investigation, a particular aspect that must be taken into account is the role of the behavioural parameters that regulate the responsiveness of economic agents and, consequently, the effects of the modelled policy scenarios.

In particular, applied general equilibrium (AGE) or CGE models are an analytical representation of the interconnected exchanges that take place between all the economic agents based on observed data. The advantages of this kind of analysis are that they can evaluate direct as well as indirect costs, spillovers and economic trade-off effects in a multi-region and inter-temporal perspective. A CGE model usually includes a detailed database, in the form of Input-Output (IO) matrices or Social Account Matrices (SAMs), and a set of equations linking variables through behavioural parameters (or elasticities). Different elasticity values strongly determine responses to a given shock, but there are often no empirically estimated values for these elasticities. This is a source of large criticism for CGE models. Accordingly, model validation needs accurate estimations of crucial behavioural parameters.

For this purpose, the sensitivity of CGE models has been tested for instance with regard to the elasticity of substitution between goods or the Armington elasticity, which measures the degree of substitution between domestic and imported goods. Hertel *et al*. (2003) investigate how the elasticity of substitution across multiple foreign supply sources influences the economic impacts of free trade agreements. By using econometric estimations for behavioural parameters that are crucial to trade relationships, they conclude that there is great potential for improving the reliability of results when empirically estimated parameters are adopted. Németh *et al*. (2011) estimate Armington elasticities for seven sectors in the GEM-E3, which is a CGE model on the interactions between economy, energy and environment in Europe. They find significant differences in model results due to the different elasticity values between domestic and imported goods as well as between imported goods from different countries, both in the short and long term. More generally, Hillberry and Hummels (2013) state that the elasticity of substitution is one of the most important parameters in modern trade theory since it captures both the own-price elasticity of demand and the cross-price elasticity of demand by measuring how close goods are in the product space.

In climate change models used for policy modelling, there are two main classes of behavioural parameters: i) the elasticity of substitution between energy (E) and other inputs (I) in the production function, hereafter referred to as σ_{EI}; ii) the elasticity between different types of energy sources (inter-fuel substitution). As far as the former is concerned, it directly affects the costs associated with reduction target policies and represents one of the aspects characterising the technology embodied in the model (the others being, for example, the level of capital accumulation and the rate of technical change). It is crucial because changes in energy prices have a direct effect on supply and demand for energy, but also an indirect one on total output and welfare driven by changes in the intensity of other inputs, but mediated through the magnitude of the substitutability between inputs in the production function.

These behavioural parameters represent a component of technology information and regulate how the model responds to exogenous policy shocks. The value of σ_{EI}, in particular, is a measure of technological flexibility related to energy use. More precisely, a lower value for such elasticity corresponds, ceteris paribus, to higher rigidity in the whole economy and, consequently, to higher abatement costs to be sustained for a given climate mitigation policy (Golub, 2013).

Empirical studies analysing elasticity of substitution in the production function generally take into account three or four inputs, thus distinguishing KLE and KLEM models (where K, L, E, M refer to capital, labour, energy and materials, respectively). The functional form usually adopted in a CGE model corresponds to a Constant Elasticity of Substitution (CES) function. This means that, according to the separability conditions specifically assumed, in order to respect the specific nesting structure adopted by the CGE model, differences in the aggregation of inputs should be carefully detected since they can strongly influence the magnitude of substitution elasticities (Kemfert, 1998). Based on the GDynE structure, in this work we consider elasticity values empirically derived from CES or Translog functions, keeping in mind that the Translog is a second-order Taylor approximation of a CES.

In particular, GDynE is structured as a KLEM model, taking E and K as separable from L and M. Accordingly, the main relation where energy is involved is a symmetric substitutability with capital stock. Thus, the value assumed by the elasticity of substitution between energy and capital (σ_{KE}) has a crucial role in shaping abatement costs when low-carbon policies are assessed.

The relevance of values adopted for σ_{KE} in GTAP-related models has been only partially addressed by scientific contributions. Beckman *et al*. (2011) note that values for energy substitution and demand elasticity parameters are too high in the static GTAP-E model and suggest replacing them with more reliable econometrically specified values available in the recent literature.[30]

In many cases, elasticity parameters have proved to be crucial when studying energy policies, especially with regard to carbon leakage effects (Antimiani *et al*., 2013b; Burniaux and Martin, 2012; Kuik and Hofkes, 2010), abatement costs (Antimiani *et al*., 2014; Borghesi, 2011; Nijkamp *et al*., 2005), impact of technological progress (Jacoby *et al*., 2004) and the rebound effect (Broadstock *et al*., 2007).

Nonetheless, an accurate analysis on how sensitive CGE results are to alternative σ_{KE} values is still lacking, especially if the CGE model works in a dynamic framework. When capital dynamics in a recursive approach is shaped, the role of capital, and its substitutability with energy, assumes primary importance. In fact, international capital mobility may expand or reduce the shift in trade patterns and ignoring these issues could seriously understate or overstate the effects of climate policies (Springer, 2002). With regard to this last point, an econometric estimation of σ_{KE} is of particular interest for climate change analysis in the long term, where the model allows for international capital mobility. In this context, substitutability between the two primary inputs becomes crucial in understanding the possible consequences of energy-related measures on the amount and distribution of abatement costs and, more generally, on economic competitiveness.

Another important issue is the level of aggregation of the analysis. Alexeeva-Talebi *et al*. (2012), for example, analyse the importance of the heterogeneity of selected energy-intensive and trade-exposed sectors for the implementation of border taxes. The economic impacts for distinguished industries can be highly divergent and a low degree of disaggregation at the sector level produces biased assessment of carbon-related trade measures. Thus, the value added of sector disaggregation is due to a more differentiated representation of production technologies and international trade relationships. This modelling approach requires an improved empirical foundation of substitution and trade elasticities at a more detailed sector-based level. This could therefore provide a more precise sector distribution of impacts, re-assess leakage rates and the effectiveness of border adjustments, and quantify the aggregation bias. Caron (2012) estimates the size of this bias to be large, with considerable differences between sectors, both in sign and magnitude, and shows that it is mainly related to within-sector heterogeneity, which is averaged out at a higher level of aggregation. Lacking precise sector-level elasticity estimates will not account for a crucial source of unobserved heterogeneity.

Following uncertainty in the computation of parameter values, there are several examples of sensitivity analysis performed to identify the sources of output variation, each adopting different points of view. As a first more general example, Siddig and Grethe (2014) study the mechanisms driving the transmission of international prices to domestic markets in a CGE approach. They formulate several assumptions on the

[30] In the same vein, Okagawa and Ban (2008) estimate that the carbon price required to satisfy a given abatement target is overestimated by 44% if standard σ_{KE} values are adopted instead of empirical estimates.

determinants of price transmissions, which include Armington, substitution and Constant Elasticity of Transformation (CET) elasticities. When performing a sensitivity analysis, they consider several values for the elasticity parameters and their results show how different values determine higher or lower price transmissions.

As a second and more interestingly contribution, Lecca *et al*. (2011) investigate the impacts on a CGE model due to different nesting structures, according to different separability assumptions in the KLEM function (EM-KL or EK-L model). They also consider the impact of changes in the values of substitution elasticities (in the range 0.2 – 1.2) and perform a sensitivity analysis with regard to GDP and total energy use in production. In particular, in the nesting structure EK-L (which is the closest to the structure adopted in the GDynE here used), the σ_{KE} parameter is particularly relevant and is likely to have a high impact on model results, especially with regard to macroeconomic variables.

There are several methods of performing a sensitivity analysis and identifying the sources of output variation for different elasticity values. Local (or limited) sensitivity analysis considers the impact that changing one parameter has on the model's output to be assessed, keeping all others fixed, without taking into account interactions with other parameters. The differential sensitivity analysis (or direct method), one-at-a-time measure and sensitivity index are examples of methods to perform sensitivity on single parameters (Hamby, 1994). Global sensitivity analysis, on the other hand, considers all parameters simultaneously and, accounting for the entire parameter distribution, identifies which combination is more likely to affect output variability and what is the effect on output of changes in the value of parameters. These methods use parameters error analysis or random sampling methods to generate input and output distribution such as the Monte Carlo analysis, the Gaussian Quadrature methods, regression (parametric methods) or variance based approaches (Saltelli *et al*., 2008). In some cases, a preliminary screening procedure is applied to identify key and non-influential elasticities among all the parameters defining the model's result; then sensitivity analysis is performed only on the most relevant according to, for example, the elementary effect (Quillet *et al*., 2013) or the Monte Carlo filtering procedure (Mary *et al*., 2013). While local analysis tests the sensitivity of the model to small variations in parameters, global analysis also accounts for parameter interactions, but can become time consuming and computationally expensive as the number of parameters rises (Cariboni *et al*., 2007).

In our analysis, we are interested in a limited number of behavioural parameters, all of which are included in a narrow area of the model (energy and fuel substitutability). There is a long line of research on the estimation of energy-related parameters and their relevance to a model's results. This leads the current work to focus on the impact that empirically estimated energy-related elasticities have on abatement costs.

3. Model

3.1 Model description

The model we adopt here is a combination of the dynamic version of the GTAP (Global Trade Analysis Project) model (named GTAP-Dyn) and the static energy version GTAP-E (Burniaux and Truong, 2002; Hertel, 1997; McDougall and Golub, 2007; Golub, 2013; Ianchovichina and McDougall, 2000).

Firstly, this is a top-down model whose main novelty is the introduction of a specific energy module that includes energy data and ad hoc modelling of energy sub-nests in a very detailed multi-region multi-sector model with complex bilateral relationships. Energy demand is explicitly specified and substitution between energy sources appears both in the production and consumption structure. As far as the demand side is concerned, the GTAP-E model separates energy and non-energy composites within a nested-CES function for both private and government consumption (thus admitting substitution between the two groups). Finally, the household demand function is a constant difference of elasticities (CDE) functional form with substitution elasticity equal to one. The production structure, on the other hand, is characterised by a multistage CES function whose top level includes the value added nest and intermediate inputs. In particular, energy enters the production structure as a good within the energy-capital composite in the value added nest, together with labour and land. At the lower level, the module presents the energy-capital composite and, following the energy commodities line, is separated into electricity and non-electricity groups. The nesting structure continues first dividing the non-electricity sources into coal and non-coal and then dividing the latter into oil, oil products and natural gas. According to this structure, each level is characterised by a different substitution parameter so that the model can distinguish between inter-factor and inter-fuel substitution. This is particularly significant given the importance that these parameters play in determining aggregate output related to changes in energy and fuel prices. In particular, energy-capital substitution affects the impacts of technology on energy efficiency, the level and distribution of carbon emissions and permit prices as well as capital accumulation.

Moreover, the introduction of specific data on carbon dioxide, through SAMs, allows a detailed representation of CO_2 emissions derived from energy consumption at regional level and distinguished by fuels. The model admits the possibility of introducing market-based instruments that can imply changes in the consumption structure such as a carbon tax on CO_2 (with detailed information on the corresponding costs and revenues) and international emission trading among regional blocks.

Given the highlighted characteristics, GDynE is particularly suited for assessing the economic impacts of CO_2 mitigation policies and offers a detailed representation of the consequences in terms of trade analysis, competitiveness and the distribution of the economic costs of climate change measures. It provides a time path for both CO_2 emissions and global economy and allows the impacts of policies on abatement costs as well as on regional and sector competitiveness to be captured.

The GDynE adopted here uses the last version of the GTAP-Database (GTAP-Database 8.1, updated to 2007), together with the latest version of the additional GTAP-Energy data on CO_2 emissions and the arrays in the standard GTAP-Database 8.1. Some modifications are introduced at the general modelling structure level according to recent contributions to the GDynE modelling approach (Antimiani *et al.*, 2013a, 2014). First, updated coefficients have been introduced in order to account for factor productivity growth differentials. In particular, a first coefficient (non-cumulative endowment productivity growth differential) was already introduced in Golub (2013), but only for commodities and regional sets, whereas we also model it for sub-products, endowments and tradables, which represent all the commodities demanded by firms.

Second, we develop a different specification for household saving behaviour in the investment-capital module. In the standard design, a saving rate is given for each region as a fixed proportion of income. Consequently, the net regional foreign position can grow without boundaries, where regions with higher growth rate face an excess in savings and investments and a consequent fall in the rate of return on capital. In the new specification adopted here, the propensity to save is not fixed but the saving rate in each region is endogenously determined as a function of the wealth to income ratio.[31]

3.2 Alternative sets of elasticity of substitution parameters

The first set is given by standard values available from the GTAP Database here named as Case A (first column in Table 1). The second set is derived from an analysis by Koetse *et al.* (2008) on the energy-capital elasticity of substitution values empirically estimated in past contributions (ELFKEN elasticity in GTAP jargon) and by an analysis carried out by Stern (2012) on the inter-fuel elasticity of substitution values (ELFENY, ELFNELY, ELNCOAL in GTAP jargon), synthesised as Case B (second column in Table 1). The third set replicates Case B, but the ELFKEN parameters are sector-specific econometrically estimated values for ten manufacturing sectors, as provided in the previous part of the work. The criterion adopted for selecting empirically estimated values is based on the availability of a comparison of different estimation techniques and values. Considering that estimated values for elasticity parameters are strongly volatile, strictly depending on assumptions for the specific empirical strategy, the only way to reduce bias in this sense is the choice of values taken from a careful comparative work. In this sense, values included in Case B derive from two contributions based on a meta-analysis approach (Koetse *et al.*, 2008; Stern, 2012),

[31] See Appendix A in Golub (2013) for further details.

which allows a large number of different estimated values in past literature to be compared. As far as Case C is concerned, sector-specific σ_{KE} values provided for manufacturing sectors are built as average values from different econometric estimation techniques applied to the same panel dataset and validated by comparing them with already existing values available for selected sectors.

Table 1 - Values of alternative substitution elasticities in energy-related nests

Elasticity	Case A	Case B	Case C
Capital and energy (ELFKEN)			
Food	0.50	0.38	0.45
Textile	0.50	0.38	0.44
Wood	0.50	0.38	0.13
Pulp and paper	0.50	0.38	0.38
Chemicals	0.50	0.38	0.29
Minerals (non-metal)	0.50	0.38	0.44
Basic metals	0.50	0.38	0.24
Machinery eq.	0.50	0.38	0.32
Transport eq.	0.50	0.38	0.28
Other manufacturing	0.50	0.38	0.27
Agric., Electricity, Transport, Services	0.50	0.38	0.38
Coal, Oil, Gas, Oil products	0	0	0
Electricity and non-electricity (ELFENY)	1.00	0.81	0.81
Non-electricity energy sources (ELFNELY)	0.50	0.57	0.57
Non-coal energy sources (ELNCOAL)	1.00	0.41	0.41

3.3 Baseline and policy scenarios

Consistently with existing scenarios, the GDynE in use extends the time horizon to 2050 in order to perform long term analysis of climate change policies in a world-integrated framework. In order to calibrate the baseline, existing scenarios have been compared according to two main criteria defining the scenarios: i) the degree of ambition in terms of stringency of instruments to mitigate climate change; ii) the degree of convergence among countries and regions which represents to what extent countries achieve multilateral agreements.

The baseline scenario corresponds to a Business as Usual (BAU) scenario calibrated with respect to the CO_2 projections provided by alternative international sources.

The World Energy Outlook (WEO) 2013 (IEA, 2013) provides different emission projections according to the state of the art in terms of policy implementation and distinguishes among the Current Policies scenario, the New Policies scenario and the 450PPM scenario. The Current Policies scenario takes only into account the effects of the policies that had been implemented by mid-2013; the New Policies scenario embodies all policy commitments that have already been adopted as well as those that have been announced and, finally, the 450PPM scenario establishes the goal of limiting the concentration of greenhouse gases in the atmosphere to around 450 parts per million of CO_2 equivalent (CO_2-eq PPM).

Furthermore, the IPCC in the Fifth Assessment Report (IPCC, 2013) describes a set of future emission pathways: the Representative Concentration Pathways (RCPs). They consist of a set of projections on greenhouse gas concentration where radiative forcing by 2100 is an input for climate modelling (van Vuuren *et al*., 2011).[32] The two scenarios we are interested in are the RCP 6.0 that corresponds to a status quo view and the RCP 2.6, which broadly corresponds to a concentration path comparable with the 450PPP scenario (Table 2).

The projections provided by the Global Change Assessment Model (GCAM), which is an integrated assessment tool developed to analyse cost-effective pathways for the transition to a low-carbon economy (Capellán-Pérez *et al*., 2014), are also coherent with the WEO 2013 and the IPCC Report. The "Do-nothing" scenario represents low ambition and convergence in climate policies, resulting in CO_2 trends comparable with the Current Policy and RCP 6.0 scenarios. On the opposite, the "Global deal path" scenario represents a path with high ambition and high convergence that corresponds to the 450PPM and RCP 2.6 scenarios. Although the sets of scenarios use different criteria, it is possible to establish a comparison among them based on the concentration of greenhouse gases (CO2-eq PPM) by 2100.

Table 2 - Relation between IEA and IPCC Scenarios based on CO_2-eq PPM

IEA Scenarios	CO_2-eq PPM in 2100 [1]	IPCC Scenarios	CO_2-eq PPM in 2100 [2]
Current Policies	950	RCP 6.0	~850 (at stabilization after 2100)
New Policies	Over 700	RCP 4.5	~650 (at stabilization after 2100)
450PPM	450	RCP 2.6	Peak at ~490 before 2100 and then declines

Notes: [1] World Energy Outlook 2012 (IEA, 2012); [2] Moss *et al*. (2010).

In this work, we refer to a BAU scenario based on the definition of a Current Policies approach where projections for exogenous variables such as GDP, population and labour force are taken from major international organizations. GDP projections are taken from the comparison of the reference case from

[32] Radiative forcing is a cumulative measure of human emissions of GHGs from all sources expressed in Watts per square meter and is defined as the change in the balance between radiation coming into and going out of the atmosphere because of internal changes in the composition of the atmosphere. Thus, positive radiative forcing tends to warm the Earth's surface.

four main sources: the OECD Long Run Economic Outlook, the GTAP Macro projections, the IIASA projections used for the OECD EnvLink model, and the CEPII macroeconomic projections used in the GINFORS model. Population projections are taken from the UN Statistics (UNDESA). Projections for the labour force are taken from the International Labour Organization (ILO).

In order to calibrate CO_2 emissions in the baseline, we projected macro variables by using the set of elasticity parameters given by Case C. Assuming that econometrically estimated behavioural parameters are more reliable than standard ones, the calibration procedure has been developed on Case C and then applied to Case A and B. This means that we have three baseline scenarios depending on the set of parameters adopted.

The calibration procedure is commonly developed, whatever set of parameters is adopted, on the basis of standard steps. First, an autonomous energy efficiency improvement parameter (AEEI) was modelled in the baseline as an exogenously given input augmenting technical change. This is a common parameter in bottom-up energy-technology models (de Beer, 2000). The AEEI is modelled here as an input augmenting technical change with an approximate value corresponding to an increase in energy efficiency per year of 1%. This is an average value within the feasible range indicated by the literature where AEEI estimations vary from 0% to 2% per annum (Grubb *et al*., 1993; IPCC, 2013; Löschel, 2002). Second, projections provided by WEO 2013 (IEA, 2013) on fossil fuel availability in terms of reserves are internalised by giving growth constraints to the primary energy commodity supply (coal, oil and natural gas).

Obviously, by applying the same calibration procedure to the same baseline macro projections working on different sets of behavioural parameters, we obtain three baselines that are slightly different in terms of CO_2 pathways. Although this may appear to be a procedure that produces baselines that are not fully comparable, it is worth mentioning that we need to retain differences in economic behaviours due to different parameters. If different calibration techniques are applied with the aim of achieving exactly the same CO_2 baseline path, we lose the effective mechanisms behind economic relationships, thus invalidating the entire sensitivity analysis.

With regard to the policy scenarios, we simulate the 450PPM scenario for stabilizing concentrations of GHGs to 450 part per million of CO_2 equivalent, helping the global mean temperatures not to exceed 2°C, here considered as an upper bound case with the most challenging (but technically feasible) abatement targets developed by international climate models.

In order to ensure that the world will be on track with the 450PPM scenario, we adopt two alternative mitigation policy instruments: a domestic carbon tax (CTAX) and an international emission trading system (IET). In the former, every country or region reduces its own emissions *internally*, and the corresponding carbon tax revenue (CTR) is added to their equivalent variation (EV), resulting in an additional component of domestic welfare, mitigating the costs of abatement efforts[33].

On the other hand, with international emission trading, all countries can trade allowances to emit and the domestic carbon tax levels are all equalised to the permit price. In the IET case we set the same abatement targets as for the CTAX scenario, but the trading option allows the same objective to be reached at lower costs, ensuring a higher level of efficiency. While they are both market-based instruments, the CTAX case represents the upper bound of abatement costs and IET is the cost-effective (or lower bound) one. In the same light of comparability, as previously mentioned, we use the same CO_2 shocks in all three baselines, setting a given quantity of target emissions for each region.

In this case, we assume that all regions participate in international emission trading to achieve the 450PPM goal. This is clearly far from being achieved in the current negotiations. However, an IET where all countries cooperate can be seen as a benchmark in terms of cost effectiveness in achieving abatement targets, while the inclusion of less developed countries in those participating in the carbon market can help analysing the global costs of internationally debated climate change options. The adoption of a global deal allows side effects, such as a pollution haven or carbon leakage, to be excluded which may complicate or bias the interpretation of the results in terms of sensitivity to alternative elasticity values.

As far as country and sector coverage is concerned, we consider 20 regions and 20 sectors. With regard to the former, we distinguish between Annex I (Canada, European Union, Former Soviet Union, Japan, Korea, Norway, United States, Rest of Annex I) and non-Annex I countries (Brazil, China, India, Indonesia, Mexico, African Energy Exporters, American Energy Exporters, Asian Energy Exporters, Rest of Africa, Rest of America, Rest of Asia and Rest of Europe). The distinction between Annex I and non-Annex I countries derives from the approach adopted by the Kyoto Protocol for defining countries subject to abatement targets (Annex I) and countries excluded (non-Annex I), as the only international binding climate rule in force. In the non-Annex I aggregate, we consider single countries (the main emerging economies with strong bargaining positions in the negotiations and eligible to emission cut commitments) as well as aggregates. Finally, considering a geographically-based rule (Africa, America and Asia), we divide both the energy exporter country group and all remaining ones (Rest of) into three groups each. It is important to analyse the impact of abatement policies on economies rich in natural resources, but it is also crucial to compare it with the effect on countries in the same area with less resource availability, and across macro regions.

With regard to sector aggregation, we consider 20 industries with a special focus on the manufacturing industry. Manufacturing sub-sectors are: Food, beverages and tobacco; Textile; Wood; Pulp and paper; Chemicals and petrochemicals; Non-metallic minerals; Basic metals; Machinery equipment; Transport

[33] In the GDYnE carbon taxation is modelled as a standard lump sum in welfare computation and is built as an ad valorem on energy commodities (thus, when energy efficiency reduces energy prices, the carbon tax level is also lower).

equipment; Other manufacturing industries. The other non-manufacturing sectors are: Agriculture, Transport, Services, and Energy commodities (disaggregated in Coal, Oil, Gas, Oil products and Electricity).

4. Results

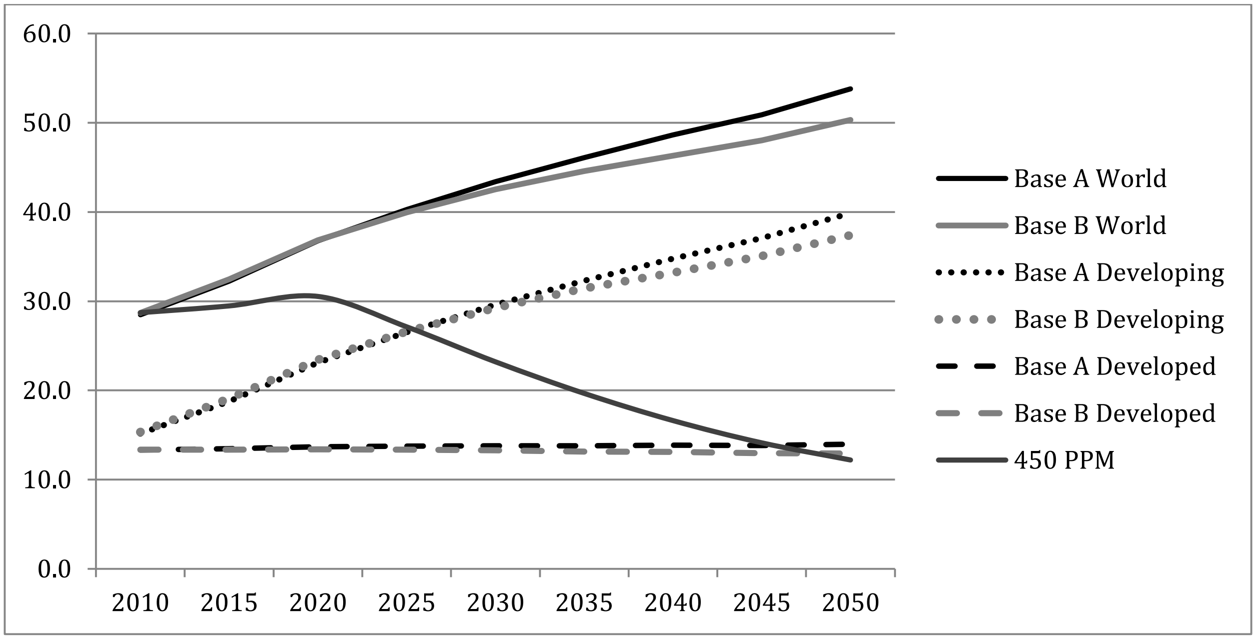
4.1 Comparison between standard and empirically-based elasticity parameters (Case A vs. Case B)

When describing the results, we will proceed in two steps: first, we analyse at the aggregated macro level the differences between the model with standard parameters (Case A) and the model with econometrically estimated elasticities from meta analyses presented in Case B. We then focus on the impact of sector-specific σ_{KE} values for the manufacturing industries, looking at the differences between Case B and Case C (Section 4.2).

Figure 1 depicts the trends of CO_2 emission pathways obtained in the two baselines (Case A and Case B), together with the path of global emissions that should be achieved according to the 450 PPM scenario. In both cases, we distinguish between Annex I and non-Annex I countries because, although the parameters assume the same values in all regions, the overall impact is different across countries depending on the internal economic structure. Emissions from baseline A are higher than in case B (there is a gap of 3 Gt CO_2 in 2050), meaning that the introduction of empirically-based behavioural parameters, which are lower than in the standard case, makes the overall system less flexible and the substitution between energy and capital less easy. The gap between Case A and B is mainly due to the difference in emissions from non-Annex I countries. This is partly due to the higher growth rate these regions are characterised by, but is also a clear sign that the parameters sets are country sensitive. In fact, it is also worth noting that, because the elasticities have the same values in all regions and countries, the deviation between case A and B can also be explained by the different impacts that the parameters have on each country given its internal economic structure. In particular, the distinction between Annex I and non-Annex I countries highlights the crucial role played by energy-intensive activities and the fact that changes in inter-fuel and energy-capital elasticities can produce differentiated impacts depending on the internal structure of the country. For example, in the non-Annex I countries, China is responsible for a reduction in CO_2 emissions (in Case B compared with Case A) that is higher than for all the other non-Annex I countries put together.

Moreover, given that the exogenous shock to GDP is the same in both cases (A and B), the differences in energy elasticities generate a different impact on overall regional efficiency and on the consumption of fossil fuels. The endogenously determined factor augmenting technical change is higher in B than in A for all sectors and is particularly high for the fossil fuel sectors.

Figure 1 - CO_2 trends in 450PPM and BAU, Case A vs. Case B



Source: our elaboration on GDynE results.

In order to better check for differences derived from alternative behaviours, as a preliminary analysis we control for local sensitivity by distinguishing between the two groups of elasticity, inter-fuel and capital-energy, in order to capture whether one out of the two types of elasticities is more responsible for changes in results. In other words, we test the sensitivity of the model changing only the inter-fuel elasticities (available from Case B), but leaving the energy-capital substitution at the standard level of Case A (we refer to this version as Case A1). Hence, we compare Case A, Case A1 and Case B (Table 3).

In particular, we compare the differences between the CTAX scenarios and their respective BAU. In terms of average carbon tax level, the differences between Case A and Case B are equally explained by the variation in the two types of parameters, meaning that both of them are relevant in explaining differences in abatement costs. Moving on to the differences in terms of GDP and looking at long term variation, we find that the highest losses for non-Annex I and Annex I countries are in Case B and Case A, respectively. Interestingly, the associated losses in Case A1 for both regions stand in between these previous cases. This relation is not confirmed only in equivalent variation (EV) given that the welfare losses are higher in Case A1 on a global scale. However, while for non-Annex I countries there are no great differences in the results of the three cases, the main source of change at the world level comes from the introduction of a lower value for the energy-capital elasticity in Annex I. Although the energy-capital parameter assumes the same value in all sectors, it generates impacts of different magnitude among regions, depending on the internal economic structure, and it seems to be highly relevant to the regional distribution of policy impacts. This first result gives rise to the need for further research efforts to be made in finding robust empirical estimations of behavioural parameters at the country level.

Table 3 – Comparison between Cases A, A1 and B applied to CTAX

		2015	2020	2025	2030	2035	2040	2045	2050	Cumulated
					Weighted average Carbon Tax level in CTAX (USD/ton of CO_2)					
Case A	World	11	17	55	109	172	242	362	488	
	Non-Annex I	10	13	40	82	153	232	364	508	
	Annex I	13	23	82	163	211	263	356	438	
Case A1	World	11	17	57	114	182	259	391	530	
	Non-Annex I	10	13	42	86	164	252	398	557	
	Annex I	12	23	85	169	219	275	375	465	
Case B	World	11	17	58	118	191	273	422	570	
	Non-Annex I	11	14	44	92	176	272	439	608	
	Annex I	11	21	84	171	222	277	383	477	
					Differences in GDP between CTAX and BAU (Bln USD)					
Case A	World	-45	-162	-590	-1,563	-3,114	-5,344	-8,417	-12,311	-31,546
	Non-Annex I	-48	-175	-473	-1,055	-2,181	-3,970	-6,583	-10,195	-24,680
	Annex I	3	13	-117	-508	-932	-1,374	-1,834	-2,116	-6,865
Case A1	World	-45	-162	-603	-1,612	-3,245	-5,626	-8,956	-13,230	-33,479
	Non-Annex I	-46	-174	-478	-1,087	-2,298	-4,261	-7,179	-11,245	-26,768
	Annex I	1	11	-125	-526	-947	-1,364	-1,777	-1,985	-6,712
Case B	World	-44	-156	-580	-1,553	-3,140	-5,438	-8,776	-13,172	-32,859
	Non-Annex I	-55	-216	-572	-1,256	-2,600	-4,737	-8,021	-12,673	-30,130
	Annex I	12	60	-8	-296	-540	-700	-755	-499	-2,726
					Differences in EV between CTAX and BAU (Bln USD)					
Case A	World	-117	-193	-1,410	-3,335	-6,000	-9,489	-11,415	-14,930	-46,889
	Non-Annex I	-83	-207	-1,075	-2,328	-4,441	-7,274	-8,772	-11,673	-35,854
	Annex I	-33	14	-335	-1,006	-1,559	-2,215	-2,643	-3,257	-11,035
Case A1	World	-108	-177	-1,414	-3,414	-6,198	-9,919	-12,092	-15,902	-49,225
	Non-Annex I	-77	-199	-1,073	-2,377	-4,594	-7,684	-9,478	-12,741	-38,223
	Annex I	-32	22	-341	-1,037	-1,604	-2,235	-2,614	-3,162	-11,002
Case B	World	-99	-102	-1,249	-2,954	-5,281	-8,212	-9,739	-12,980	-40,616
	Non-Annex I	-78	-206	-1,060	-2,251	-4,311	-7,194	-8,962	-12,449	-36,513
	Annex I	-20	104	-189	-703	-970	-1,017	-777	-531	-4,103

Source: our elaboration on GDynE results.

We can now analyse the differences between Case A and Case B considering the effects that different elasticities produce in two alternative policy measures, namely carbon tax and international emissions trading. First, we focus on the average level of domestic carbon tax and the international permit price and notice that in both policy options, the values are higher in Case B than Case A (Table 4). In particular, when referring to the 2050 values, the carbon tax level is 17% higher in B than in A, and there are differences in distribution among regions. Changes in elasticities increase the average carbon tax by 100USD (almost 20%) in non-Annex I countries, whereas in Annex I regions the increase does not even reach half of that value. This aspect can also be highlighted by looking at the differences between regional and world tax level in both cases. In Case A the carbon tax level in Annex I countries is 10% lower and in non-Annex I 4% higher than the global average respectively. Introducing Case B parameters makes these differences even more accentuated (-16% and 7%). Finally, when comparing domestic carbon tax level and international permit prices, the percentage change at world level remains stable between A and B (-16% and -17%). On the other hand, in Case B the carbon tax in Annex I countries is only 1% higher than the permit price in the IET scenario (7% in Case A), whereas in non-Annex I countries, the corresponding percentage change is 29% (24% in Case A).

Table 4 - Carbon tax level and permit price in 450PPM, Case A vs. Case B (USD/ton CO_2)

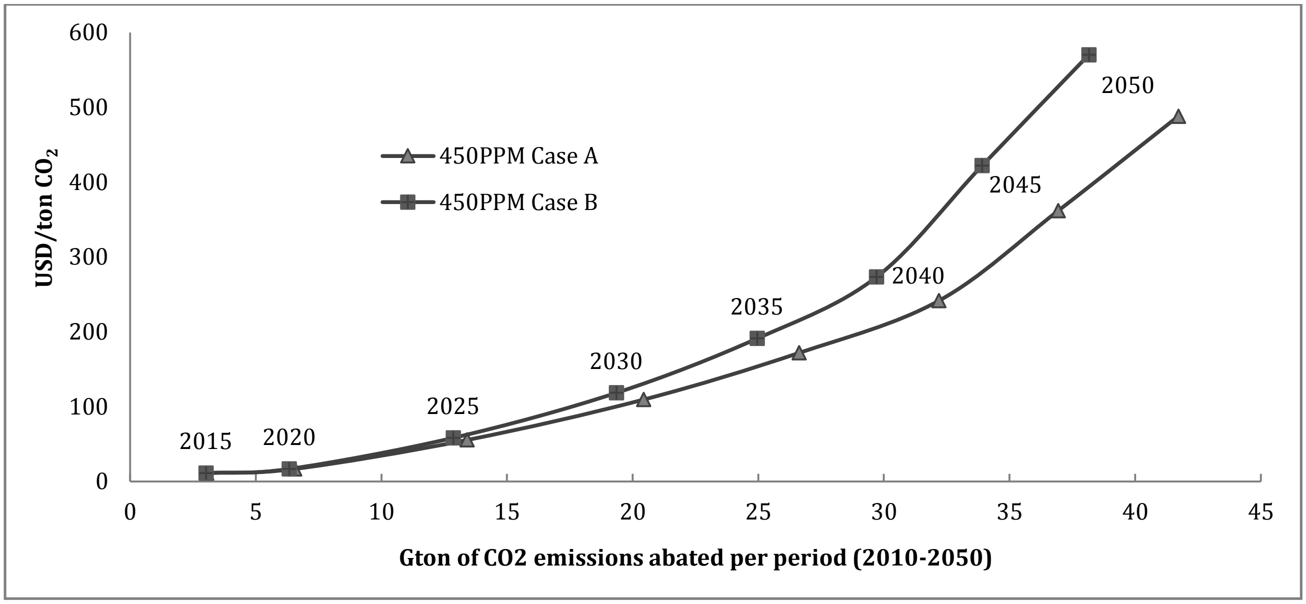
		2015	2020	2025	2030	2035	2040	2045	2050
					Weighted average domestic carbon tax (CTAX)				
Case A	World	11	17	55	109	172	242	362	488
	Non-Annex I	10	13	40	82	153	232	364	508
	Annex I	13	23	82	163	211	263	356	438
Case B	World	11	17	58	118	191	273	422	570
	Non-Annex I	11	14	44	92	176	272	439	608
	Annex I	11	21	84	171	222	277	383	477
					International permit price (IET)				
Case A	World	7	11	46	104	170	225	320	410
Case B	World	7	11	48	113	187	249	364	471

Source: our elaboration on GDynE results.

In addition to these relative changes, it is worth noting the link between the value of domestic carbon tax (or permit price) and the actual amount of CO_2 emission abated in each 450PPM scenario compared with the BAU case. Considering that the level of emissions in the baseline is higher in Case A and the 450PPM targets are the same irrespective of the elasticity values, although the amount of CO_2 abated in Case B is lower, the costs per ton of emission are higher than in Case A.

These differences can be explained considering that in Case B, the overall system is less flexible with regard to energy and fuel substitutability, which implies that every additional reduction of energy consumption needs to be compensated with a higher amount in capital investment. Thus, the achievement of a particular emission target, irrespective of the emission level, is more expensive given the increased rigidity in Case B, and this is confirmed by the marginal abatement cost (MAC) curves derived from different IET simulations (Figure 2).

Figure 2 – Marginal Abatement Cost curves at the world level in IET scenario, Case A vs. Case B



Source: our elaboration on GDynE results.

The effect of the different elasticity parameters from CTAX scenario is also coherent with the results from the IET scenario (see Table 5). The cumulated number of transactions in the emission trading system is higher in B than in A, meaning that the increased rigidity in energy substitution possibilities makes emission reduction within production processes more expensive and thus results in higher access to the permits market in order to ensure compliance with abatement targets. Looking at regional difference in emission trading revenue, countries such as EU and USA, which are net permit buyers, and non-Annex I countries such as India and Energy Exporters, which are net permit sellers, have a gain in Case B. On the other hand, there are regions such as Brazil and China that have a deterioration in their emission trading balance with parameters B.

Moreover, by comparing IET and CTAX, we can also look at the differences in terms of the contribution to allocative efficiency of the two policy options together with the differences in EV as a welfare measure (Table 6). As expected, the contribution to allocative efficiency is higher in emission trading, in both Cases A and B[34], denoting that in a partial equilibrium perspective, IET is the most cost-effective solution among the available mitigation policies. However, considering the general equilibrium effects at the cumulate level, as indicated by the EV differences, only non-Annex I countries have net gains from emission trading policy, whereas at the world level, the negative effect experienced by Annex I countries prevails resulting in a net loss and the gap increases with Case B.

[34] This is also coherent with differences in GDP given that losses in emission trading are lower than in a domestic carbon tax case, in both cases A and B (see Table A.7 in Appendix).

Table 5 – Emission Trading Balance in IET scenario, Case A vs. Case B (Mln USD)

	2015	2020	2025	2030	2035	2040	2045	2050	Cumulated
					Emissions Trading Balance Par. A				
EU	-470	-2,164	-17,266	-53,835	-90,993	-105,654	-120,742	-119,290	-510,414
USA	-54	-451	-12,169	-47,581	-70,219	-65,489	-66,672	-64,161	-326,797
FSU	-16	207	1,924	11,046	32,675	63,421	106,997	140,941	357,195
Rest of Annex I	-755	-2,978	-16,911	-42,242	-65,941	-73,047	-78,907	-71,848	-352,630
Brazil	-67	-231	-1,864	-4,698	-3,516	2,068	10,955	24,078	26,726
China	2,275	9,256	58,283	134,053	143,988	57,152	-68,341	-219,115	117,552
India	1,062	4,544	29,184	73,806	123,184	159,025	203,418	222,416	816,641
Energy Exporters	-1,072	-4,399	-19,878	-23,054	2,172	53,859	134,739	227,301	369,668
RoW	-902	-3,785	-21,304	-47,494	-71,350	-91,335	-121,447	-140,322	-497,938
Number of transactions	3,337	14,008	89,392	218,906	302,019	335,525	456,109	614,737	2,034,031
					Emissions Trading Balance Par. B				
EU	-296	-1,309	-12,753	-45,717	-81,700	-95,825	-111,801	-109,978	-459,379
USA	148	601	-6,940	-39,547	-59,663	-51,313	-48,932	-43,039	-248,686
FSU	-8	165	1,367	11,700	38,457	75,583	132,008	175,362	434,634
Rest of Annex I	-737	-2,898	-17,346	-43,685	-67,665	-72,251	-76,641	-66,934	-348,157
Brazil	-99	-357	-2,808	-6,944	-6,260	-73	9,701	24,253	17,412
China	2,033	8,125	54,330	127,270	126,709	17,474	-148,689	-347,717	-160,464
India	1,150	4,765	31,518	80,355	134,282	171,765	225,707	249,046	898,589
Energy Exporters	-1,163	-4,823	-22,424	-27,276	-659	57,854	155,537	272,064	429,111
RoW	-1,028	-4,270	-24,943	-56,157	-83,502	-103,215	-136,891	-153,058	-563,065
Number of transactions	3,331	13,656	87,215	219,326	299,449	322,677	522,954	720,725	2,189,333

Source: our elaboration on GDynE results.

Considering only non-Annex I countries, in 2025 and 2030, the contribution to allocative efficiency is higher in the CTAX case, (the differences are negative) and this is due to the increasing stringency in the abatement targets (especially for China and India). Nonetheless, the emission trading is still more cost effective at the global level than the carbon tax measure. Considering the entire time period up to 2050, an emission trading scenario seems to induce a strong restructuring of economic processes that starts immediately until the abatement target becomes binding. On the other hand, in the CTAX case, losses in allocative efficiency due to the reallocation of production factors are lower during the initial periods, but determine higher losses in the long term.

Table 6 – Comparison in allocative efficiency and EV, Case A vs. Case B (Bln USD)

		2015	2020	2025	2030	2035	2040	2045	2050	Cumulated
		Differences in Allocative efficiency between Emission Trading and Carbon Tax								
Par. A	World	8,311	19,766	84,005	162,320	171,158	217,659	356,311	523,886	1,543,415
	Non-Annex I	3,911	1,534	-7,191	-29,551	49,582	147,435	316,579	508,318	990,616
	Annex I	4,400	18,232	91,196	191,871	121,575	70,224	39,731	15,568	552,798
Par. B	World	7,606	15,582	79,437	162,763	185,190	264,051	458,141	694,868	1,867,638
	Non-Annex I	4,393	2,498	-1,959	-18,773	80,640	217,597	447,682	702,896	1,434,975
	Annex I	3,214	13,083	81,396	181,536	104,550	46,454	10,459	-8,028	432,663
		Differences in EV between Emission Trading and Carbon Tax								
Par. A	World	32,680	-14,798	226,587	55,798	-487,293	-942,386	-898,006	-218,473	-2,245,892
	Non-Annex I	13,424	-78,172	-60,099	-384,177	-573,053	-369,547	509,518	1,732,313	790,207
	Annex I	19,256	63,374	286,685	439,975	85,760	-572,839	-1,407,524	-1,950,786	-3,036,098
Par. B	World	23,200	-53,120	209,497	52,319	-495,837	-969,803	-907,112	-31,886	-2,172,743
	Non-Annex I	14,169	-67,021	-19,736	-346,998	-555,399	-263,208	841,977	2,476,046	2,079,831
	Annex I	9,030	13,901	229,233	399,317	59,561	-706,595	-1,749,088	-2,507,932	-4,252,574

Source: our elaboration on GDynE results.

Focusing on emission trading scenarios, in Table 7 we highlight the results and analyse the differences generated by the elasticity changes in Case B compared with Case A in terms of GDP, looking at the deviation between the policy and baseline results. At the world level, GDP losses in IET scenarios compared with the BAU level are quite similar in both Cases A and B. However, there are specular differences across regions, and the introduction of Case B parameters generates higher losses in non-Annex I countries that are compensated by gains in Annex I regions. In fact, while in non-Annex I countries the GDP losses are higher in B and increasingly over time, for Annex I countries results go in the opposite direction. They have GDP gains up to 2030 with Case A, but with Case B the benefits are higher and last up to 2035; from 2040, in both Cases A and B, Annex I countries have GDP losses, even though they are lower in B. Despite the fact that in Case A there is a greater amount of CO_2 emissions to be reduced, the lower overall flexibility in the system associated with parameters B makes the economic impact of the abatement policies greater and also affects the distribution of costs across regions, in this case penalising non-Annex I countries.

Table 7 - Differences in GDP between Case A and Case B in IET scenario (Mln USD)

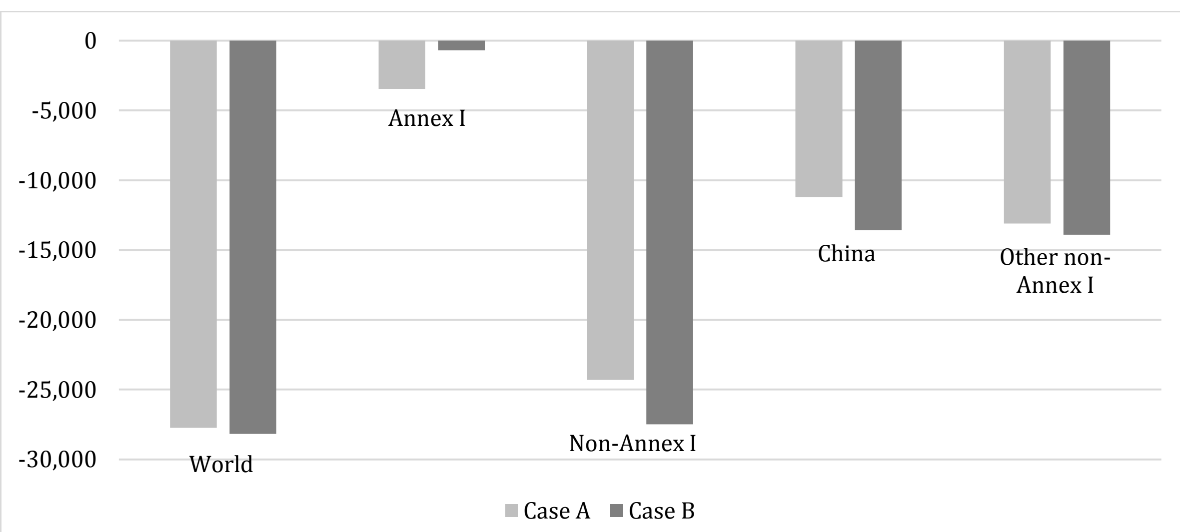
	2015	2020	2025	2030	2035	2040	2045	2050	Cumulated
					Differences in GDP (IET w.r.t. BAU) Case A				
World	-27	-91	-395	-1,212	-2,697	-4,822	-7,609	-10,896	-27,749
Non-Annex I	-42	-166	-541	-1,328	-2,568	-4,215	-6,361	-9,078	-24,299
Annex I	15	75	146	117	-129	-607	-1,249	-1,818	-3,450
					Differences in GDP (IET w.r.t. BAU) Case B				
World	-29	-91	-392	-1,208	-2,706	-4,828	-7,714	-11,196	-28,164
Non-Annex I	-43	-177	-583	-1,455	-2,854	-4,702	-7,210	-10,466	-27,490
Annex I	15	86	191	247	148	-126	-504	-730	-674

Source: our elaboration on GDynE results.

However, leaving aside the differences between these two macro regions, the impact of different elasticity values is heterogeneous when also considering single countries. As far as non-Annex I countries are concerned, half of the overall loss is due to the GDP reduction originated in China and in Case B this effect is even more evident, with an increase in losses in Chinese GDP of 21% in B compared with A, whereas for all other non-Annex I countries the corresponding variation is only 6% (Figure 3).

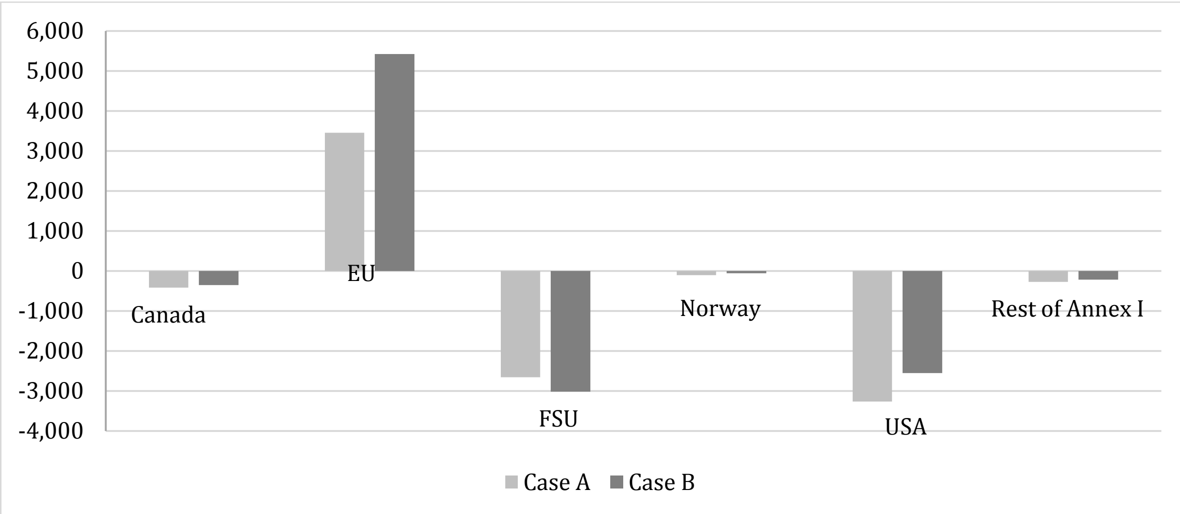
Moreover, also within the Annex I regions, differences in GDP losses are quite heterogeneous. The only region that benefits from IET mitigation policy is the EU, which also has an increase in GDP gains in Case B compared to A (Figure 4). On the other hand, both FSU and USA are subject to GDP losses with regard to baseline level but, whereas for the former the introduction of Case B elasticities worsens this loss, USA takes advantage in terms of a lower reduction of GDP with regard to the baseline.

Figure 3 – Differences in GDP between IET and BAU, Case A vs. Case B (Bln USD)



Source: our elaboration on GDynE results.

Figure 4 - Differences in Annex I GDP between IET and BAU, Case A vs. Case B (Bln USD)



Source: our elaboration on GDynE results.

Given that one of the main advantages of Case B is the introduction of econometric based inter-fuel elasticities of substitution, we are now going to analyse the difference in energy mix in terms of world total consumption of energy commodities and highlight the differences between Case A and Case B in emission trading policy.

Considering the structure of the production function, the upper nest describes the substitution between electricity and non-electricity energy sources and the value of the corresponding elasticity parameter (ELFENY) goes from 1 (Case A) to 0.81 (Case B). At the lower aggregation level, coal can be substituted with three other non-electricity fuels (oil, oil products and natural gas) through the non-electricity elasticity of substitution parameters (ELFENELY) which slightly increased from A to B (0.50 and 0.57, respectively). Finally, the non-coal elasticity of substitution (ELFNCOAL), which determine the substitution between oil, oil products and natural gas, drops from the value of 1 in Case A to 0.41 in Case B.

When introducing less flexible elasticity parameters (Case B), we impose even more stringent boundaries on the model. Therefore, there are differences in the percentage change between 2010 and 2050 in the baselines where the increase (decrease) in energy consumption with Case B is lower (higher) than in Case A (see Table 8). These variations determine changes in regional and sectoral energy demands also in the IET scenario. In particular, the increase in electricity consumption is lower with Case B than with standard parameters (Case A) at the world level, and the effect is particularly evident for non-Annex I countries.

Indeed, when looking at the shares of each fuel in the energy mix, we compare the differences (in term of percentage change) between the emission trading scenarios with regard to the baseline in both Cases A and B (see Table 9).

Table 8 – Changes in fuel mix between 2010 and 2050 (Case A vs. Case B)

		Coal	Oil	Natural gas	Oil products	Electricity	Total
BAU Case A	World	58%	-16%	57%	115%	181%	75%
	Annex I	-42%	-47%	0%	31%	39%	-1%
	Non-Annex I	107%	21%	137%	217%	361%	153%
IET Case A	World	-79%	-66%	-70%	-21%	93%	-36%
	Annex I	-90%	-76%	-80%	-47%	-20%	-62%
	Non-Annex I	-74%	-53%	-55%	11%	237%	-9%
BAU Case B	World	39%	-19%	50%	107%	155%	63%
	Annex I	-52%	-50%	-6%	24%	28%	-8%
	Non-Annex I	84%	18%	130%	207%	315%	136%
IET Case B	World	-79%	-67%	-68%	-24%	71%	-40%
	Annex I	-90%	-78%	-79%	-52%	-26%	-65%
	Non-Annex I	-73%	-54%	-53%	11%	193%	-14%

Source: our elaboration on GDynE results.

Table 9 – Differences in fuel mix shares between IET and BAU, Case A vs. Case B

	2015	2020	2025	2030	2035	2040	2045	2050
Difference in shares of the energy mix IET w.r.t. BAU Case A								
Coal	-12%	-22%	-38%	-50%	-56%	-60%	-62%	-64%
Oil	5%	9%	19%	26%	27%	23%	17%	10%
Natural Gas	1%	0%	-6%	-16%	-24%	-33%	-41%	-48%
Oil Products	5%	9%	18%	24%	23%	16%	9%	0%
Electricity	3%	6%	12%	20%	32%	50%	68%	87%
Difference in shares of the energy mix IET w.r.t. BAU Case B								
Coal	-12%	-21%	-37%	-48%	-54%	-56%	-58%	-58%
Oil	5%	9%	18%	25%	25%	20%	15%	9%
Natural Gas	1%	1%	-5%	-13%	-21%	-29%	-36%	-43%
Oil Products	4%	9%	17%	22%	21%	14%	7%	0%
Electricity	3%	6%	11%	19%	30%	47%	63%	81%

Source: our elaboration on GDynE results.

Given the abatement constraints and the fact that electricity is the only non-emitting source, its share increases between the baseline and policy scenario, but in B at a lower rate than in A. The increase is more evident in non-Annex I countries than in Annex I, as Table A.8 in the Appendix shows. With regard to the nesting structure, at the lower nest level, coal is the most carbon-intensive source and, given the abatement target, is substituted by other non-coal energy sources. At the lowest level, we reduce the substitution elasticity from a value of 1 to 0.41, making the system much less flexible than in standard parameters (Case A). We note an increase in the consumption of oil, driven by an increasing demand for oil products, which is mainly due to a growing demand especially in non-Annex I countries (see Table A.7), whereas for natural gas there is a (residual) lower demand (although it is the less carbon-intensive energy source).

4.2 Comparison in model results between economy-wide and sector-specific elasticity parameters

We now focus on the differences in model results when introducing sector-specific values for σ_{KE} (comparing Case B with Case C). Climate change mitigation policies induce a reduction in energy consumption and the costs of achieving a reduction in energy intensity is strongly influenced by the flexibility of each sector in substituting energy with other inputs. Therefore, by using specific σ_{KE} values, the distribution of mitigation costs may vary substantially across different sectors.

First, we report in Table A.9 in the Appendix the carbon intensity of manufacturing sectors which are those where σ_{KE} values have changed from B to C. In particular, we specify the 2010 carbon intensity (which is common to every scenarios) together with the 2050 level, and distinguish between Case B and Case C, as well as between IET and BAU scenarios.

Results from BAU show that the most carbon-intensive sectors are the Non-metallic minerals, Basic metals, Chemicals and Paper industries, but are also characterised by the most significant differences between the two regions considered in this analysis (Annex I and non-Annex I). Given that the abatement targets are the same in both Cases B and C, results from policy scenarios are more homogeneous and we can focus on the specific differences induced by the different elasticity sets by looking at the percentage changes between the results from IET and BAU scenarios in 2050. In this case, at the world level the reduction in carbon intensity with Case C values is higher (lower) for all sectors where σ_{KE} has increased (decreased) compared with Case B. The greatest reductions in carbon intensity are in the Food and Textile sectors, with a quite homogeneous difference across regions. On the other hand, there are significant positive changes in the Wood and Other manufacturing sectors, mainly for Annex I countries, and in the Basic metals sector, especially in non-Annex I regions.

It is worth mentioning that in the Paper sector, whose σ_{KE} has the same value in B and C, we note a negative difference for non-Annex I countries and at the world level, while in the Annex I region, the difference is almost zero. Moreover, it is interesting to look at changes in Chemicals sector: there is a negative change in Annex I region (-0.17) and a positive one for non-Annex I countries (1.16), resulting in a positive variation at the world aggregate level. In this case, it is clear how differences in flexibility in energy use may generate different impacts depending on the internal economic structure. In fact, if we look at the results for the whole manufacturing sector, in Annex I countries we found a negative change (whose value corresponds to -0.45) whereas the same relation in non-Annex I countries highlights a positive difference (0.43). This leads to the fact that, although the changes in parameters are the same for all countries, there are regional differences and the reduction in carbon intensity has been relatively greater for Annex I economies with Case C (if compared with Case B), while the opposite holds for non-Annex I countries. Thus, at the aggregate level, in the sectors where the σ_{KE} parameters in C are higher than in B (meaning greater technological flexibility), the carbon intensity is always lower than in corresponding sectors with Case B. However, at a more disaggregated regional level, an increase in substitutability is not necessarily linked to a reduction in carbon intensity and a different distribution of abatement costs occurs.

Table 10 shows the differences in carbon intensiveness compared with the differences in the σ_{KE} value, as a ratio between the percentage change in CO_2 intensity between Case C and B (in year 2050 for IET scenario) and the percentage change in the values of σ_{KE} parameters. As a first general remark, at the world level, in each sector where σ_{KE} has increased in Case C with respect to Case B, the relative CO_2 intensity is lower, while the same conclusion does not hold for sectors where elasticity has decreased. This means that changes in carbon intensity are not predictable with regard to changes in elasticity values, since sector-specific production structure induces different reactivity to behavioural parameters. As a second result, it is worth mentioning that there are significant differences in region-specific results. Given the same differences in parameter values, the impact on CO_2 intensity is always positive (higher in C than in B) in Annex I countries and negative in non-Annex I ones.

Furthermore, the sector-specific σ_{KE} values generate changes in the level of the domestic manufacturing output differentiated by regions. In this case, we look at the baseline results because the changes between Case B and Case C already influence the value of the sectoral output in the BAU scenarios and explain most of the differences in the policy cases. Hence, Figures 5 and 6 represent the differences between the values of output (Case C vs. Case B) in BAU for Annex I and non-Annex I regions, respectively. It is worth noting that in the long term the variations for Annex I countries are lower in magnitude (and begin only after 2030) than those in the other group. Moreover, there are interesting differences concerning which sectors have increased (or decreased) the production level in the two regions.

Table 10 – Differences in carbon intensity w.r.t. changes in σ_{KE}, Case C vs. Case B

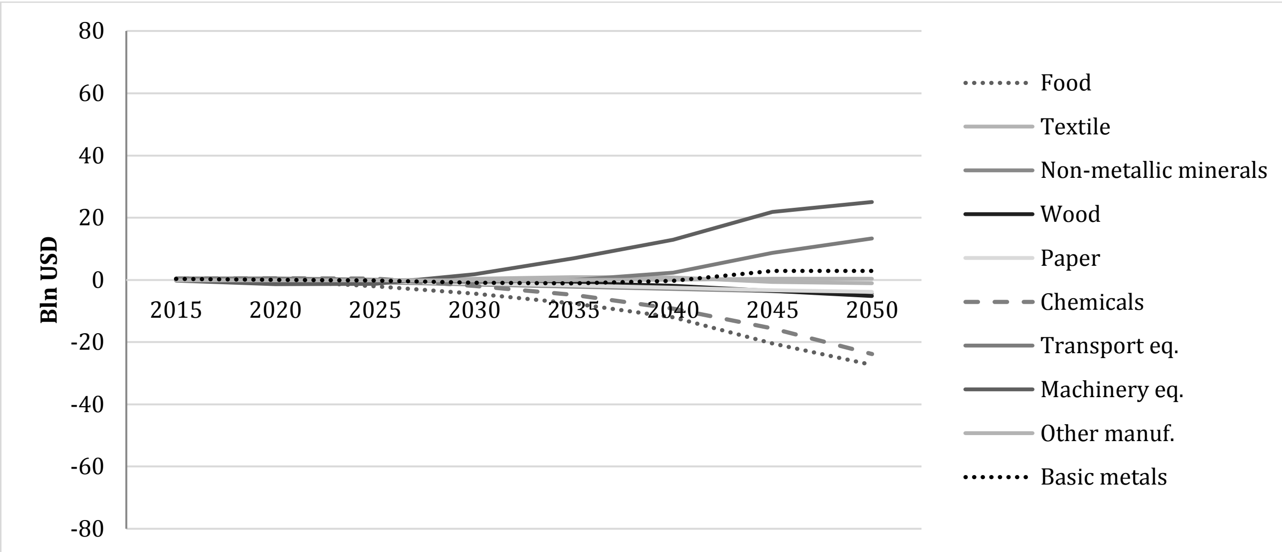
	(1) % change CO_2 intensity (IET scenario, 2050) Case C vs Case B			(2) % change EK_sub	(1) / (2)		
	World	Annex I	Non-Annex I		World	Annex I	Non-Annex I
Food	-1.44	3.83	-3.52	18.4	-0.08	0.21	-0.19
Textile	-1.35	3.05	-2.53	15.8	-0.09	0.19	-0.16
Non-metallic minerals	-3.53	0.72	-4.24	15.8	-0.22	0.05	-0.27
Wood	-0.85	-15.01	11.32	-65.8	0.01	0.23	-0.17
Paper	-0.09	0.00	-0.14	0.0			
Chemicals	-0.59	-6.10	1.83	-23.7	0.03	0.26	-0.08
Basic metals	4.00	-2.72	4.69	-36.8	-0.11	0.07	-0.13
Transport eq.	2.67	-5.87	4.33	-26.3	-0.10	0.22	-0.16
Machinery eq.	2.81	-3.69	3.27	-15.8	-0.18	0.23	-0.21
Other manuf.	2.33	-0.97	2.79	-28.9	-0.08	0.03	-0.10

Source: our elaboration on GDynE results.

When introducing sector-specific elasticities, in Annex I countries the two sectors showing the highest increase are Machinery equipment and Transport equipment. On the other hand, in the non-Annex I region, the two sectors showing the most significant increases in the value of output (Case C w.r.t. Case B) are Basic metals and Chemical industries, which are also characterised by the greatest differences in the percentage change in prices (Table 11). Furthermore, for both country groups, the same sectors have also the highest percentage change in the IET scenario with respect to Case B (see also Table A.10 in Appendix). These results are coherent with development patterns where non-Annex I countries modify their economic structures promoting energy-intensive industries, while in more advanced regions there is an increase in more technology-reliant industrial activities.

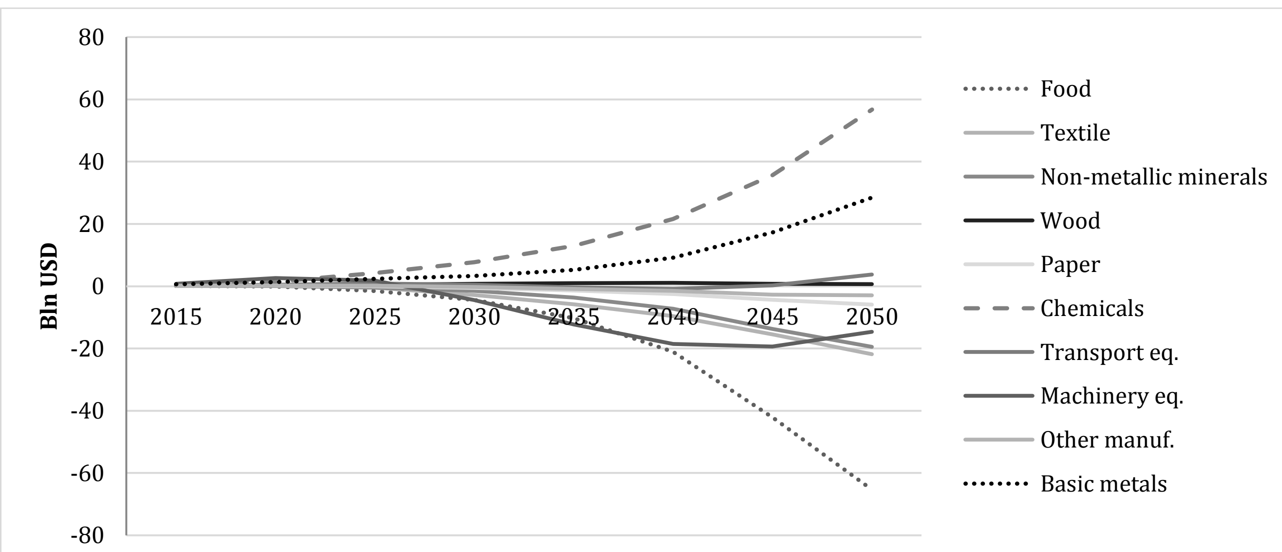
Additionally, when considering a mitigation policy scenario such as the IET, there is still high variability between the two macro-regions especially in the selected sectors shown in Figure 7 (Basic metals and Chemical industries, but also less energy-intensive ones). In non-Annex I countries, the two sectors whose values of output have the most relevant increase (Case C vs. Case B), are still Basic metals and Chemicals. On the other hand, the only two sectors where the Annex I region experiences an increase in the output value are Machinery and Transport equipment. Chemicals, Basic metals and Machinery equipment are also sectors where the changes in elasticity parameters (Case C vs. Case B) produce the greatest variation in terms of carbon intensity between non-Annex I and Annex I countries with regard to the global result.

Figure 5 – Differences in output in BAU for Annex I countries, Case C vs. Case B



Source: our elaboration on GDynE results.

Figure 6 – Differences in output in BAU for non-Annex I countries, Case C vs. Case B



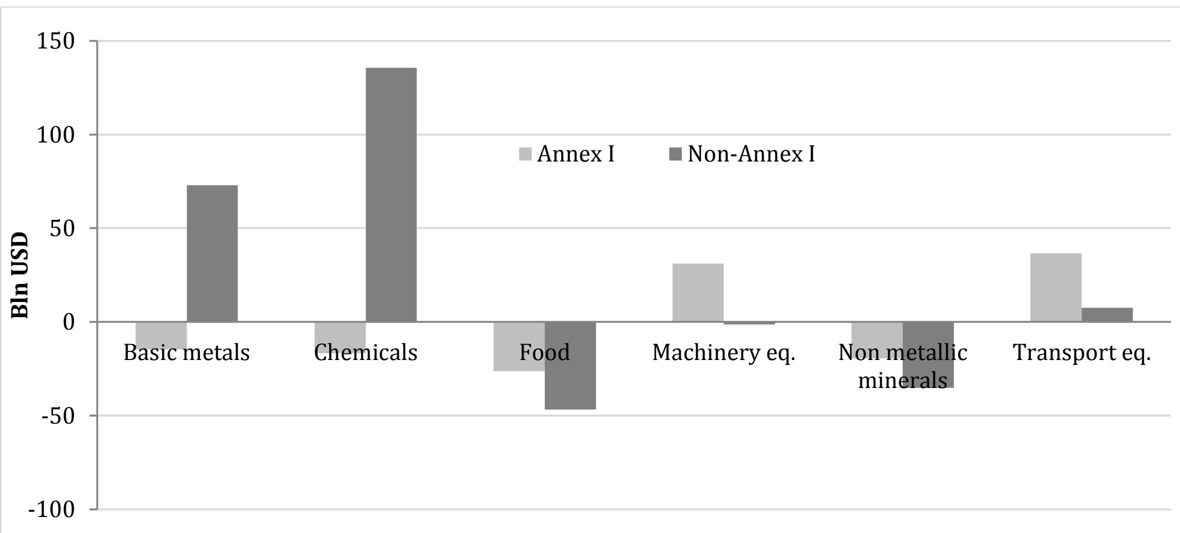
Source: our elaboration on GDynE results.

Table 11 – Differences in price changes in BAU, Case C vs. Case B (2050)

	Case B (% change)*		Case C (% change)*		Diff. Case C – Case B	
	Annex I	Non-Annex I	Annex I	Non-Annex I	Annex I	Non-Annex I
Food	9.89	8.44	9.84	8.37	-0.05	-0.07
Textile	3.10	4.13	3.07	4.09	-0.02	-0.04
Non-metallic	-0.02	1.45	-0.08	1.39	-0.06	-0.06
Wood	7.37	7.96	7.41	7.94	0.04	-0.02
Paper	2.90	1.74	2.93	1.74	0.03	0.00
Basic metals	-4.17	-0.53	-3.99	-0.42	0.19	0.11
Chemicals	-2.94	-2.93	-2.74	-2.75	0.20	0.18
Transport eq.	0.90	-0.41	0.94	-0.34	0.04	0.07
Machinery eq.	0.89	-0.43	0.93	-0.38	0.04	0.05
Other manuf.	3.42	1.58	3.46	1.65	0.05	0.07

Source: our elaboration on GDynE results. *Note: The % changes are expressed in relation to the 2045 level.

Figure 7 – Differences in output in IET (cumulated 2010-2050), Case C vs. Case B

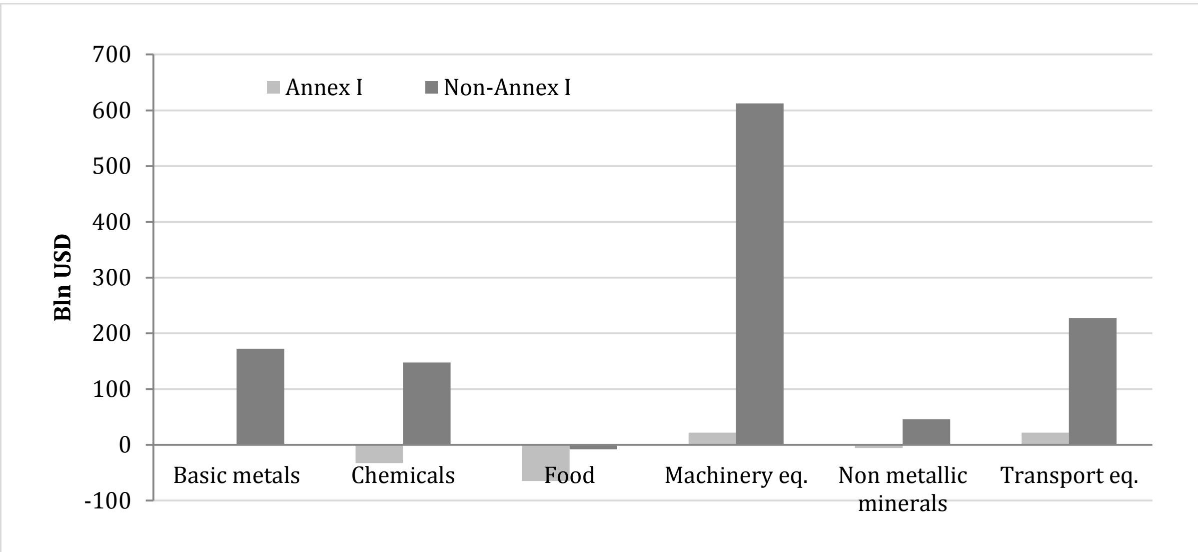


Source: our elaboration on GDynE results.

It is also worth mentioning that the results in terms of value of export (Figure 8) for energy-intensive sectors, especially Chemicals and Basic metals, are reasonably in line with those on output, whereas there are greater differences for the other sectors due to trade dynamics.

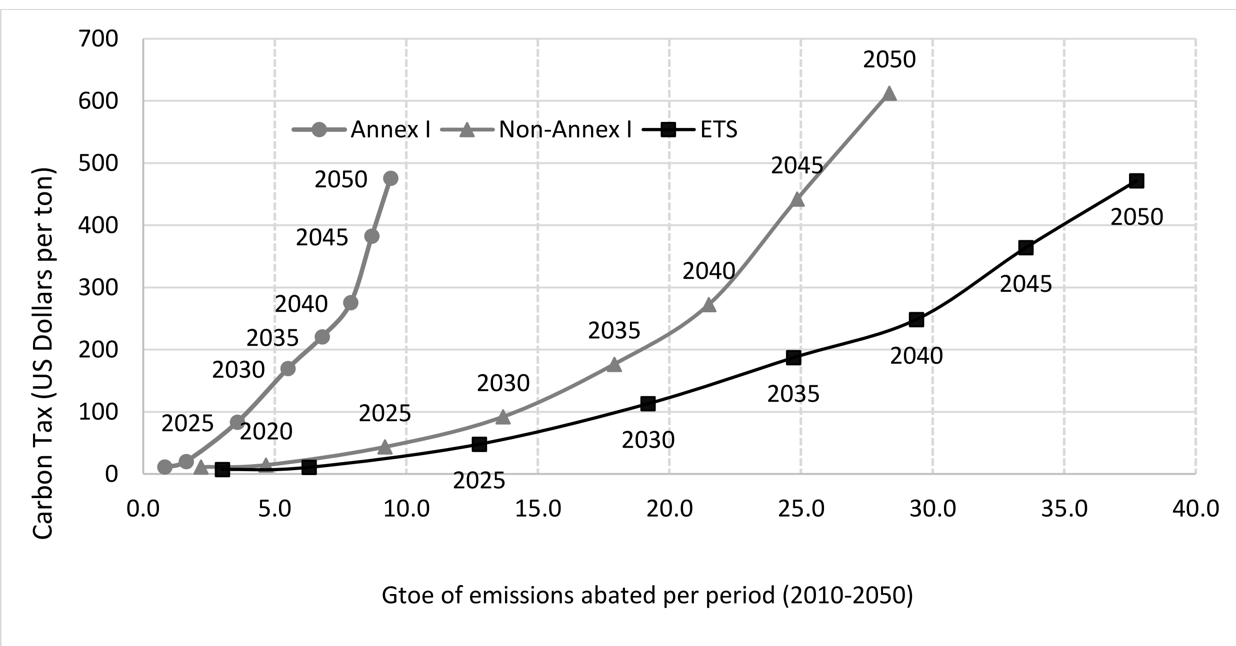
Finally, most of the issues noted, besides the changes in elasticity of substitution, point to the fact that the internal economic structure can intensify the differences induced by the sectoral parameters. In this regard, Figure 9 presents the curves of Marginal Abatement Cost for the two considered regions, in case of Par. C. For a given level of CO_2 emissions abated, the carbon tax needed to achieve the target is higher for Annex I countries than for Non-Annex I. This result confirms that is more expensive to reduce carbon emissions in the former and cheaper in latter, while the corresponding permits price is the lowest among the three curves and the global emission trading scenario is the most cost effective solution to achieve abatement targets.

Figure 8 – Differences in export flows in IET (cumulated 2010-2050), Case C vs. Case B



Source: our elaboration on GDynE results.

Figure 9 – Marginal Abatement Cost curves (Par. C)



Source: our elaboration on GDynE results.

5. Conclusion

The aim of this work was to analyse the sensitivity of the energy dynamic version of the GTAP model (GDynE), a dynamic CGE model that specifically accounts for economic and energy data, where we introduced sector-specific and econometrically estimated values for the elasticity of substitution between capital and energy and among fuels. Although this type of model is notably appropriate for addressing the economic impacts of climate mitigation policies, it also needs detailed and reliable information on technology, energy and emissions linkages in order to improve and validate the results. We focused on two classes of behavioural parameters: the elasticity of substitution between energy and capital and between different types of energy sources (inter-fuel substitution).

We considered three different sets of elasticity parameters: Case A, including standard values available from the GTAP Database; Case B, including elasticity parameters derived from empirically estimated values elaborated by a meta-analysis approach; Case C, including the same values adopted for Case B but introducing σ_{KE} parameters that are sector-specific and econometrically estimated for manufacturing sectors.

We made comparisons between baselines and two alternative mitigation policies, a domestic carbon tax and an international emission trading system, and allowed the target of limiting the concentration of GHGs in the atmosphere to around 450 PPM of CO_2 equivalent by 2050 to reach.

When analysing the sensitivity of the model, we accounted for the impacts of changes in substitution elasticities on abatement costs, the distribution of the effects among countries and sectors and the cost effectiveness of the different policy measures.

First, the two types of parameters are both responsible for the variation in results and the different distribution of impacts. A reduction in the flexibility of energy substitution possibilities makes abatement efforts more expensive. In fact, considering both policy measures, the level of both carbon tax and permit price is higher for Case B with respect to Case A and the upward shift of the MAC curves confirms that, irrespective of the emissions level, the increased rigidity makes the achievement of abatement targets more expensive. The limited possibilities to increase energy consumption, especially for non-Annex I countries, and the consequent changes in fuel mix, justify the greater losses in terms of GDP.

Second, restrictions in substitution possibilities in the energy nests generate changes in the distribution of costs associated to the abatement efforts with regard to the two aggregate regional groups. This finding is confirmed by all the economic impacts analysed such as differences in GDP, allocative efficiency, and welfare levels. With regard to GDP, a restriction in flexibility generates opposite differences across the two regional groups and the higher losses in non-Annex I countries are compensated by gains in the Annex I regions. Within each group, there are also different responses to the same changes in elasticities, as in the case of China and the European Union.

Third, when accounting for the elasticity of substitution between energy and capital differentiated by sector, the model is again sensitive to the introduced changes both considering the climate and economic dimensions. Changes in elasticities have large impacts in terms of distributive effects, given that there are significant differences in carbon intensity and the value of production across sectors and regions. Even if the sector-specific elasticities assume the same values in all countries, the effects between Annex I and non-Annex I regions are rather different. In fact, changes in flexibility in energy use generate different regional impacts and the internal economic structure can intensify the differences induced by the sectoral parameters.

Two main implications follow from this analysis. First, when considering the allocation of abatement targets between different sectors within a country, heterogeneity in the technological flexibilities should also be taken into consideration. Second, it is worth noting that further improvements to this type of model are highly recommended in order to increase the reliability of simulation results. In particular, given the regional differences in reacting to sector-specific elasticity values, which are the same for all regions, there is a need to empirically estimate all energy-related behavioural parameters at the specific sector and country level, at the highest disaggregation compatible with data availability.

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Appendix

Table A.1 - List of GDYnE countries

GTAP code	Code	Country	GTAP code	Code	Country	GTAP code	Code	Country
BRA	bra	Brazil	EU27	mlt	Malta	RAM	gtm	Guatemala
CAN	can	Canada	EU27	nld	Netherlands	RAM	hnd	Honduras
CHN	chn	China	EU27	pol	Poland	RAM	nic	Nicaragua
CHN	hkg	Hong Kong	EU27	prt	Portugal	RAM	pan	Panama
EExAf	xcf	Central Africa	EU27	rou	Romania	RAM	pry	Paraguay
EExAf	egy	Egypt	EU27	svk	Slovakia	RAM	per	Peru
EExAf	nga	Nigeria	EU27	svn	Slovenia	RAM	xca	Rest of Central America
EExAf	xnf	Rest of North Africa	EU27	esp	Spain	RAM	xna	Rest of North America
EExAf	zaf	South Africa	EU27	swe	Sweden	RAM	xsm	Rest of South America
EExAf	xac	South Central Africa	EU27	gbr	United Kingdom	RAM	ury	Uruguay
EExAm	arg	Argentina	FSU	blr	Belarus	RAS	arm	Armenia
EExAm	bol	Bolivia	FSU	rus	Russian Federation	RAS	bgd	Bangladesh
EExAm	col	Colombia	IDN	idn	Indonesia	RAS	bhr	Bharain
EExAm	ecu	Ecuador	IND	ind	India	RAS	khm	Cambodia
EExAm	ven	Venezuela	JPN	jpn	Japan	RAS	kgz	Kyrgyztan
EExAs	aze	Azerbaijan	KOR	kor	Korea	RAS	lao	Lao People's Democratic Rep.
EExAs	irn	Iran Islamic Republic of	MEX	mex	Mexico	RAS	mng	Mongolia
EExAs	kaz	Kazakhstan	NOR	nor	Norway	RAS	npl	Nepal
EExAs	kwt	Kuwait	RAF	bwa	Botswana	RAS	xea	Rest of East Asia
EExAs	mys	Malaysia	RAF	cmr	Cameroon	RAS	xoc	Rest of Oceania
EExAs	omn	Oman	RAF	civ	Cote d'Ivoire	RAS	xsa	Rest of South Asia
EExAs	qat	Qatar	RAF	eth	Ethiopia	RAS	xse	Rest of Southeast Asia
EExAs	xsu	Rest of Former Soviet Union	RAF	gha	Ghana	RAS	sgp	Singapore
EExAs	xws	Rest of Western Asia	RAF	ken	Kenya	RAS	lka	Sri Lanka
EExAs	sau	Saudi Arabia	RAF	mdg	Madagascar	RAS	twn	Taiwan
EExAs	are	United Arab Emirates	RAF	mwi	Malawi	RAS	pak	Pakistan
EU27	aut	Austria	RAF	mus	Mauritius	RAS	phl	Philippines
EU27	bel	Belgium	RAF	moz	Mozambique	RAS	tha	Thailand
EU27	bgr	Bulgaria	RAF	nam	Namibia	RAS	vnm	Vietnam
EU27	cyp	Cyprus	RAF	xec	Rest of Eastern Africa	REU	alb	Albania
EU27	cze	Czech Republic	RAF	xsc	Rest of South African Custom	REU	hrv	Croatia
EU27	dnk	Denmark	RAF	xwf	Rest of Western Africa	REU	geo	Georgia
EU27	est	Estonia	RAF	sen	Senegal	REU	xee	Rest of Eastern Europe
EU27	fin	Finland	RAF	tza	Tanzania	REU	xef	Rest of EFTA
EU27	fra	France	RAF	uga	Uganda	REU	xer	Rest of Europe
EU27	deu	Germany	RAF	zmb	Zambia	REU	xtw	Rest of the World
EU27	grc	Greece	RAF	zwe	Zimbabwe	REU	tur	Turkey
EU27	hun	Hungary	RAF	mar	Morocco	REU	ukr	Ukraine
EU27	irl	Ireland	RAF	tun	Tunisia	ROECD	aus	Australia
EU27	ita	Italy	RAM	xcb	Caribbean	ROECD	isr	Israel
EU27	lva	Latvia	RAM	chl	Chile	ROECD	nzl	New Zealand
EU27	ltu	Lithuania	RAM	cri	Costa Rica	ROECD	che	Switzerland
EU27	lux	Luxembourg	RAM	slv	El Salvador	USA	usa	United States of America

Table A.2 - List of GDYnE commodities and aggregates

Sector	Code	Products	Sector	Code	Products
agri	pdr	paddy rice	wood	lum	wood products
agri	wht	wheat	paper	ppp	paper products, publishing
agri	gro	cereal grains nec	oil_pcts	p_c	petroleum, coal products
agri	v_f	vegetables, fruit, nuts	chem	crp	chemical, rubber, plastic products
agri	osd	oil seeds	nometal	nmm	mineral products nec
agri	c_b	sugar cane, sugar beet	basicmet	i_s	ferrous metals
agri	pfb	plant-based fibers	basicmet	nfm	metals nec
agri	ocr	crops nec	basicmet	fmp	metal products
agri	ctl	bovine cattle, sheep and goats, horses	transeqp	mvh	motor vehicles and parts
agri	oap	animal products nec	transeqp	otn	transport equipment nec
agri	rmk	raw milk	macheqp	ele	electronic equipment
agri	wol	wool, silk-worm cocoons	macheqp	ome	machinery and equipment nec
agri	frs	forestry	oth_man_ind	omf	manufactures nec
agri	fsh	fishing	electricity	ely	electricity
Coal	coa	coal	gas	gdt	gas manufacture, distribution
Oil	oil	oil	services	wtr	water
Gas	gas	gas	services	cns	construction
nometal	omn	minerals nec	services	trd	trade
food	cmt	bovine cattle, sheep and goat meat products	transport	otp	transport nec
food	omt	meat products	wat_transp	wtp	water transport
food	vol	vegetable oils and fats	air_transp	atp	air transport
food	mil	dairy products	services	cmn	communication
food	pcr	processed rice	services	ofi	financial Oth_Ind_serices nec
food	sgr	sugar	services	isr	insurance
oth_man_ind	ofd	Oth_Ind_ser products nec	services	obs	business and other services nec
food	b_t	beverages and tobacco products	services	ros	recreational and other services
textile	tex	textiles	services	osg	public admin. and defence, education, health
textile	wap	wearing apparel	services	dwe	ownership of dwellings
textile	lea	leather products			

Table A.3 - List of GDYnE Regions

GTAP code	Description
CAN	Canada
EU27	European Union
FSU	Former Soviet Union
JPN	Japan
KOR	Korea
NOR	Norway
USA	United States
ROECD	Rest of OECD
BRA	Brazil
CHN	China
IND	India
IDN	Indonesia
MEX	Mexico
EExAf	African Energy Exporters
EExAm	American Energy Exporters
EExAs	Asian Energy Exporters
RAF	Rest of Africa
RAM	Rest of America
RAS	Rest of Asia
REU	Rest of Europe

Table A.4 - List of GDYnE aggregates

Sector	Description
agri	Agriculture
food	Food
coal	Coal
oil	Oil
gas	Gas
oil_pcts	Petroleum, coal products
electricity	Electricity
text	Textile
nometal	Non-metallic mineral products
wood	Wood
paper	Pulp and paper
chem	Chemical and petrochemical
basicmet	Basic metal
transeqp	Transport equipment
macheqp	Machinery and equipment
oth_man_ind	Other manufacturing industries
transport	Transport
wat_transp	Water Transport
air_transp	Air Transport
services	Services

Table A.5 - Baseline GDP Projections to 2050 (Bln constant USD)

	2010	2015	2020	2025	2030	2035	2040	2045	2050	Growth p.a.
Canada	1,424	1,668	1,893	2,092	2,286	2,493	2,707	2,924	3,145	2.1%
European Union	16,489	18,302	20,051	21,451	22,627	23,714	24,823	25,943	27,080	1.3%
Former Soviet Union	1,344	1,589	1,858	2,105	2,346	2,580	2,782	2,937	3,065	2.2%
Japan	4,186	4,575	4,895	5,173	5,379	5,500	5,546	5,592	5,641	0.8%
Korea	1,100	1,316	1,474	1,595	1,686	1,759	1,817	1,863	1,896	1.4%
Norway	393	427	472	522	572	621	672	728	786	1.8%
United States	13,947	15,868	17,779	19,633	21,548	23,565	25,656	27,799	29,986	2.0%
Rest of OECD	1,646	1,861	2,071	2,267	2,459	2,660	2,872	3,099	3,330	1.8%
Brazil	1,474	1,753	2,077	2,421	2,775	3,137	3,500	3,863	4,223	2.8%
China	4,687	7,157	10,602	15,128	20,630	26,893	33,517	40,130	46,321	6.8%
India	1,482	2,091	2,925	4,068	5,591	7,558	9,996	12,872	16,119	7.0%
Indonesia	498	648	848	1,104	1,421	1,802	2,250	2,769	3,361	5.4%
Mexico	995	1,233	1,478	1,733	1,985	2,219	2,432	2,636	2,830	2.8%
African Energy Exp.	889	1,117	1,408	1,785	2,273	2,902	3,702	4,722	6,039	5.4%
American Energy Exp.	801	942	1,126	1,326	1,542	1,772	2,014	2,266	2,525	3.1%
Asian Energy Exp.	1,723	2,092	2,529	3,026	3,559	4,125	4,708	5,297	5,898	3.3%
Rest of Africa	571	733	953	1239	1627	2102	2692	3400	4271	5.7%
Rest of America	753	912	1,087	1,278	1,489	1,750	2,049	2,380	2,746	3.5%
Rest of Asia	1528	1932	2457	3112	3924	4927	6151	7631	9394	5.1%
Rest of Europe	962	1,152	1,379	1,612	1,842	2,063	2,269	2,459	2,638	2.7%
World	56,893	67,366	79,362	92,669	107,560	124,142	142,154	161,311	181,294	3.1%
Non-Annex I	16,364	21,760	28,869	37,832	48,658	61,250	75,279	90,427	106,366	5.3%
Developed	40,529	45,606	50,493	54,836	58,902	62,892	66,875	70,884	74,928	1.6%

Source: our elaboration on GDynE results.

Table A.6 - Baseline CO_2 Projections to 2050 (Gt CO_2)

	2010	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	**% Change 2010-2050**
Canada	0.53	0.58	0.65	0.66	0.66	0.66	0.67	0.68	0.70	30.2%
European Union	3.67	3.52	3.31	3.20	3.12	3.01	2.95	2.86	2.83	-22.7%
Former Soviet Union	1.62	1.70	1.75	1.84	1.89	1.96	2.05	2.06	2.09	28.9%
Japan	1.11	1.11	1.10	1.09	1.08	1.05	1.04	1.02	1.01	-8.7%
Korea	0.48	0.51	0.56	0.57	0.56	0.53	0.51	0.50	0.50	4.1%
Norway	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.07	8.4%
United States	5.36	5.33	5.31	5.29	5.29	5.27	5.27	5.22	5.19	-3.3%
Rest of OECD	0.51	0.54	0.62	0.61	0.59	0.57	0.55	0.53	0.53	2.9%
Brazil	0.35	0.39	0.47	0.52	0.56	0.61	0.65	0.71	0.81	130.9%
China	7.19	9.42	11.58	12.80	13.76	14.33	14.42	14.51	14.78	105.6%
India	1.59	1.93	2.37	3.03	3.62	4.21	4.77	5.28	5.75	261.7%
Indonesia	0.41	0.48	0.54	0.60	0.69	0.75	0.79	0.86	0.95	133.4%
Mexico	0.41	0.41	0.45	0.45	0.45	0.46	0.46	0.47	0.47	15.9%
African Energy Exp.	0.70	0.84	1.04	1.18	1.27	1.39	1.50	1.61	1.76	151.0%
American Energy Exp.	0.41	0.49	0.59	0.67	0.75	0.82	0.88	0.93	0.99	139.9%
Asian Energy Exp.	2.06	2.49	3.07	3.49	3.82	4.13	4.43	4.82	5.28	156.5%
Rest of Africa	0.19	0.20	0.25	0.30	0.36	0.41	0.49	0.58	0.75	300.3%
Rest of America	0.29	0.31	0.38	0.44	0.50	0.50	0.48	0.49	0.52	80.8%
Rest of Asia	1.14	1.45	1.92	2.23	2.49	2.72	3.06	3.44	3.88	240.1%
Rest of Europe	0.63	0.70	0.82	0.87	0.89	0.92	0.96	1.01	1.09	74.0%
World	28.71	32.48	36.84	39.90	42.39	44.38	46.00	47.67	49.95	74.0%
Non-Annex I	15.36	19.13	23.47	26.56	29.14	31.24	32.90	34.72	37.04	141.1%
Developed	13.35	13.35	13.37	13.34	13.25	13.14	13.10	12.95	12.91	-3.3%

Source: our elaboration on GDynE results.

Table A.7 – Differences in GDP between IET and CTAX Scenarios, Case A vs. Case B (Mln USD)

	2015	2020	2025	2030	2035	2040	2045	2050
					Differences in GDP in CTAX scenario			
Case A	-45 403	-161 627	-590 205	-1 562 514	-3 113 651	-5 344 093	-8 416 859	-12 310 735
Case B	-43 765	-155 856	-580 107	-1 552 657	-3 140 162	-5 437 626	-8 776 404	-13 171 580
					Differences in GDP in IET scenario			
Case A	-27 041	-91 241	-394 669	-1 211 828	-2 696 710	-4 822 242	-7 609 288	-10 895 958
Case B	-28 631	-91 171	-391 991	-1 207 987	-2 705 902	-4 828 187	-7 713 837	-11 196 250

Source: our elaboration on GDynE results.

Table A.8 - Differences in fuels mix in IET w.r.t. BAU, Case A vs. Case B (%)

	2015	2020	2025	2030	2035	2040	2045	2050	Cumulated
	Difference in fuels shares in the energy mix IET w.r.t. BAU (Case A)								
	Annex I countries								
Coal	-9%	-17%	-33%	-45%	-49%	-51%	-52%	-53%	-18%
Oil	2%	4%	10%	15%	17%	17%	16%	16%	13%
Natural gas	-1%	-2%	-8%	-17%	-26%	-34%	-41%	-48%	-12%
Oil products	2%	4%	9%	13%	13%	11%	8%	5%	3%
Electricity	1%	2%	5%	9%	16%	26%	37%	50%	7%
	Non-Annex I countries								
Coal	-12%	-21%	-37%	-49%	-55%	-60%	-63%	-65%	-33%
Oil	7%	13%	25%	34%	32%	25%	17%	7%	26%
Natural gas	2%	1%	-7%	-17%	-26%	-34%	-41%	-47%	-15%
Oil products	7%	13%	25%	31%	28%	18%	8%	-3%	10%
Electricity	4%	8%	17%	27%	42%	63%	83%	103%	30%
	2015	2020	2025	2030	2035	2040	2045	2050	Cumulated
	Difference in fuels shares in the energy mix IET w.r.t. BAU (Case B)								
	Annex I countries								
Coal	-9%	-17%	-34%	-44%	-48%	-48%	-48%	-48%	-16%
Oil	2%	4%	9%	13%	14%	14%	13%	12%	12%
Natural gas	0%	-1%	-5%	-13%	-21%	-28%	-35%	-42%	-10%
Oil products	2%	4%	8%	11%	10%	7%	4%	0%	1%
Electricity	1%	2%	5%	10%	17%	27%	39%	51%	7%
	Non-Annex I countries								
Coal	-12%	-20%	-36%	-47%	-53%	-56%	-58%	-60%	-31%
Oil	7%	13%	25%	32%	31%	23%	16%	6%	24%
Natural gas	2%	1%	-7%	-15%	-23%	-30%	-38%	-44%	-14%
Oil products	7%	12%	24%	29%	27%	17%	9%	-1%	9%
Electricity	4%	8%	16%	25%	38%	57%	75%	93%	26%

Source: our elaboration on GDynE results.

Table A.9 – Carbon intensity (Ton/Mln USD, *10,000)

	2010			2050 BAU PAR B			2050 ET PAR B			2050 BAU PAR C			2050 ET PAR C		
	World	Annex I	Non-Annex I	World	Annex I	Non-Annex I	World	Annex I	Non-Annex I	World	Annex I	Non-Annex I	World	Annex I	Non-Annex I
Food	0.62	0.42	0.97	0.13	0.09	0.15	0.04	0.03	0.04	0.14	0.10	0.16	0.04	0.03	0.04
Textile	0.54	0.29	0.74	0.21	0.15	0.23	0.04	0.04	0.04	0.23	0.16	0.25	0.04	0.04	0.04
Non-met. min.	6.65	3.30	10.05	3.98	1.59	4.58	0.53	0.36	0.57	4.18	1.69	4.81	0.51	0.36	0.55
Wood	0.36	0.26	0.61	0.12	0.09	0.14	0.02	0.03	0.02	0.09	0.06	0.11	0.02	0.02	0.02
Paper	1.18	0.80	2.61	0.67	0.33	0.99	0.10	0.08	0.12	0.67	0.33	0.99	0.10	0.08	0.12
Chemical	1.73	1.03	3.09	1.26	0.77	1.54	0.34	0.26	0.40	1.21	0.72	1.49	0.34	0.25	0.40
Basic metals	3.38	1.77	5.39	2.40	0.99	2.64	0.47	0.26	0.51	2.21	0.90	2.43	0.49	0.25	0.53
Transport eq.	0.25	0.13	0.64	0.26	0.07	0.36	0.04	0.02	0.06	0.23	0.06	0.32	0.04	0.02	0.06
Machinery eq.	0.21	0.11	0.40	0.20	0.06	0.22	0.04	0.01	0.05	0.19	0.05	0.21	0.04	0.01	0.05
Other manuf.	0.55	0.16	1.10	0.44	0.09	0.54	0.06	0.03	0.07	0.41	0.08	0.50	0.06	0.03	0.07
Tot. Manuf.	1.20	0.61	2.32	0.72	0.30	0.89	0.15	0.09	0.17	0.71	0.29	0.88	0.15	0.09	0.17
Total	1.50	0.94	2.89	0.60	0.30	0.80	0.21	0.14	0.26	0.59	0.30	0.79	0.15	0.10	0.20

% change 2050 ETS vs. BAU	Case B				Case C				*diff. C-B*			
	World	Annex I	Non-Annex I	ELFKEN	World	Annex I	Non-Annex I	ELFKEN	Diff. ELFKEN	Diff. World	Diff. Annex I	Diff. Non-Annex I
Food	-70%	-67%	-71%	0.38	-73%	-70%	-74%	0.45	0.07	-2.78	-2.88	-2.84
Textile	-81%	-76%	-82%	0.38	-83%	-77%	-84%	0.44	0.06	-1.53	-1.52	-1.53
Non-met. Min.	-87%	-77%	-87%	0.38	-88%	-79%	-89%	0.44	0.06	-1.06	-1.24	-1.07
Wood	-80%	-69%	-84%	0.38	-72%	-57%	-77%	0.13	-0.25	7.84	11.81	7.43
Paper	-85%	-77%	-88%	0.38	-85%	-77%	-88%	0.38	0	-0.03	0.00	-0.04
Chemical	-73%	-66%	-74%	0.38	-72%	-66%	-73%	0.29	-0.09	0.74	-0.17	1.16
Basic metals	-81%	-74%	-81%	0.38	-78%	-72%	-78%	0.24	-0.14	2.53	1.82	2.64
Transport eq.	-84%	-76%	-84%	0.38	-81%	-73%	-81%	0.28	-0.1	2.32	2.26	2.52
Machinery eq.	-80%	-76%	-80%	0.38	-78%	-75%	-78%	0.32	-0.06	1.78	1.06	1.90
Other manuf.	-87%	-64%	-88%	0.38	-85%	-59%	-86%	0.27	-0.11	1.35	5.89	1.28
Tot. manuf.	-80%	-70%	-81%		-80%	-70%	-81%			0.31	-0.45	0.43
Total	-65%	-55%	-67%		-74%	-68%	-75%			-9.20	-12.99	-8.12

Source: our elaboration on GDynE results.

Table A.10 – Differences in output between IET scenarios, Case C vs. Case B (%)

	2015	2020	2025	2030	2035	2040	2045	2050
				Annex I countries				
Food	0.00	0.00	-0.04	-0.06	-0.06	-0.06	-0.08	-0.08
Textile	-0.02	-0.05	-0.04	0.00	0.03	0.06	0.10	0.06
Non-metallic minerals	0.00	-0.02	-0.06	-0.11	-0.17	-0.24	-0.27	-0.28
Wood	0.00	0.00	0.00	-0.01	0.01	0.03	0.03	0.05
Paper	0.01	0.00	-0.02	-0.03	-0.02	0.00	0.01	0.05
Basic metals	0.02	0.01	0.00	-0.05	-0.14	-0.26	-0.28	-0.10
Chemical	0.01	0.02	0.03	0.00	-0.03	-0.07	-0.12	-0.12
Transport eq.	0.01	0.02	0.01	0.02	0.04	0.08	0.13	*0.21*
Machinery eq.	0.00	-0.03	-0.03	-0.01	0.02	0.09	0.23	*0.26*
Other manuf.	-0.02	-0.03	-0.02	-0.02	0.01	0.05	0.12	0.17
				Non-Annex I countries				
Food	0.01	0.00	-0.03	-0.05	-0.05	-0.07	-0.10	-0.14
Textile	0.03	0.04	0.00	-0.04	-0.05	-0.04	-0.05	-0.02
Non-metallic minerals	0.01	0.00	-0.03	-0.06	-0.09	-0.12	-0.14	-0.20
Wood	0.02	0.03	0.05	0.06	0.05	0.04	0.04	0.03
Paper	0.02	0.03	0.00	-0.02	-0.02	-0.02	-0.01	0.00
Basic metals	0.04	0.07	0.08	0.11	0.17	0.24	0.25	*0.26*
Chemical	0.04	0.07	0.14	0.22	0.29	0.37	0.45	*0.55*
Transport eq.	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.03
Machinery eq.	0.03	0.07	0.04	0.00	-0.01	-0.02	-0.02	0.00
Other manuf.	0.03	0.05	0.03	0.01	0.01	0.01	0.00	0.02

Source: our elaboration on GDynE results.

EU climate policy up to 2030: reasoning around timing, overlapping instruments and cost effectiveness

1. Introduction

The Climate and Energy Policy Framework recently approved by the European Union (EU) in October 2014 and briefly addressed as EU2030 (EC, 2014a, 2014b, 2014c, 2014d) constitutes the last challenging long term objective for the EU in the climate change debate. The EU2030 framework follows the previous EU climate agenda, the so-called EU2020 strategy, which was considered as a great effort in improving the quality of the policy strategy in this field. However, it is still not clear to what extent these mid-term targets will allow the EU to stay on track with respect to a long-term reduction pathway to 2050.

The EU2020 framework defined three goals to be achieved by 2020: a 20% reduction in greenhouse gas (GHG) emissions with respect to 1990 levels, a binding target of 20% of final energy consumption from renewable sources and a 20% increase in energy efficiency to help reducing the primary energy consumption (EC 2009a, 2009b, 2012). The main instrument to reduce GHG emissions is the European Emission Trading System (EU ETS), which mainly covers the energy and industry sectors, but Member States could also define further discretionary measures to achieved the targets in other sectors (above all, transport) such as environmental and energy taxation (de Miera and Rodriguez, 2015). The EU2020 set binding national targets for the renewable energy goal but left each States free to choose which types of supporting framework to implement (e.g., feed-in tariff and premium, green certificates or quota system). Finally, a binding target on energy efficiency was not defined until the 2012 Directive, when national and sectoral targets were identified (especially for energy suppliers) together with several regulatory instruments, although leaving great flexibility to Member States in deciding how to meet the targets.[35]

Indeed, the main novelty of the EU2020 was the explicit combination of the different policy instruments and objectives in a unique coordinated strategy, and the EU2030, besides introducing specific instruments to improve the functioning of the market and avoid the risk of overallocation[36], follows this approach as well. The newly approved agenda set the following goals: a 40% target for domestic reduction in GHG emissions by 2030 compared to 1990 level (where the EU ETS keeps playing the core role); an EU binding target of at least 27% for the share of renewable energy in 2030; and an increase of at least 27% in energy efficiency in 2030.

The three objectives, reducing CO_2 emissions, enhancing energy saving and increasing the share of renewable energies in the energy mix, are strictly connected and the achievement of each goal strongly influences the others, not in a univocal way. There are some controversies in such policy strategy, which may arise at the macro and micro level.

To give an example, if substantial energy efficiency improvements are achieved, energy consumption becomes cheaper, since the reduction in competing energy demand will produce a reduction in market prices, in a well-known rebound effect mechanism (Greening *et al.*, 2000; Bentzen, 2004; Barker *et al.*, 2007; Sorrell, 2007; Saunders, 2008; Gillingham *et al.*, 2013). This reduction in energy prices will increase energy demand, and if it is satisfied by fossil fuels, the CO_2 emission level is more difficult to be reduced. This means that, from one side, improvements in energy efficiency can reduce the costs of achieving abatement targets, but a countervailing effect might arise if cheap energy will induce an increase in consumption. This second effect might produce an increase in the carbon tax level necessary to allow the system to fulfil the abatement target, if the energy mix remains unchanged. A second example is given by the introduction of quotas for renewable energies. If from one side energy efficiency might increase carbon tax level, when introducing renewable energies, the increase in energy demand due to the rebound effect might be satisfied by clean energy, thus reducing the carbon price. Another way of reasoning regards the linkages between energy efficiency and renewable energies in a context of no emission reduction targets. In this case, if energy efficiency does not produce a strong rebound effect, resulting in a final reduction of energy demand, the same share of renewable energies within a lower quantity of demanded energy will result in a reduced amount demanded by consumers. This effect might negatively influence the investors' behaviour, reducing the total installed capacity of renewable energies, thus increasing the final production cost of energy, with a detrimental effect for final consumers. This means that the interaction across different policy tools

[35] Article 7 of Directive 2012/27/EU leaves the Member States free to decide the subjects and sectors to be included, as well the measures to be implemented, such as taxation, standards, a national fund for energy efficiency, voluntary agreements, information and education programs and monitoring activities.

[36] Specifically, the EU2030 framework proposes back-loading of allowances and changes the annual factor to reduce the cap on the maximum permitted emissions from 1.74% to 2.2% from 2021 onwards. Moreover, the market stability reserve is designed with the aim of stabilising the market price and operates through a reduction in the number of the allocated permits in case of over-supply. Rather, whenever the allowances on the market exceed the threshold of 833 million, 12% of the number of the allowances in circulation in the previous two years will be removed from the market (EC, 2014c).

must be investigated in a dynamic setting, since changes of policy objectives over time might correct existing trade-offs and side effects derived from the interaction of the different policy instruments. The extent to which the side effects of each policy can be smoothed or removed by the interaction with other policies is strictly dependent on the case study under scrutiny.

A further aspect to carefully account for is to what extent the newly approved 2030 agenda will allow the EU to stay on track with respect to the long-term 2050 abatement goal. In other words, the cost of achieving the CO_2 abatement targets depends not only on the amount of emissions to be reduced and the alternative ways through which the reduction can be achieved, but also on the timing of the reduction path. The analysis of the EU climate strategy under the lens of potential trade-offs and complementarities among simultaneous policies in a dynamic setting is an optimal case study to be developed both at the theoretical and empirical side.

In this paper, the EU2030 climate strategy will be addressed by considering the effects of alternative mixes of policy tools on selected impacts, as cost effectiveness, economic competitiveness, welfare effects, in a dynamic Computable General Equilibrium (CGE) analytical setting to consider the differences in costs of meeting the emissions targets due to the distribution of reductions through time.

The rest of the work is structure as follows. Section 2 provides the literature review on the relevance of the policy mix strategies and thier the potential trade-offs (especially in the climate and energy economics literature) and the timing of reduction pathways. Section 3 illustrates the model description and simulation scenarios, while Section 4 and Section 5 outline, respectively, main results and conclusions.

2. Literature Review

Among the alternative policy options to mitigate climate change and according to the Kyoto Protocol, the EU has established the biggest market-based ETS as the core mean to achieve the targeted GHG emissions reduction. However, even if the market-based instrument is theoretically addressed as the cost-effective solution to reduce CO_2 emissions, alternative mitigation measures can be implemented and, indeed, from Phase I of EU ETS, the evolution and structure of European climate policy has become more complex. This includes: sector specific goals and technology roadmaps, as for building sector, transport and biofuel; Strategic Energy Technologies Plans (SET Plans) for wind, solar, bioenergy, CCS, electricity grids and nuclear technologies; the electricity market liberalisation; support to RD in clean technologies; activities to support infrastructures, information and labelling programs (Kanellakis *et al*., 2013).

As remarked in the new EU2030, next to the main target of GHG emissions reduction, there are the energy efficiency and renewable energy goals to be reached by 2030. In line with the principle of cost-effectiveness, the EU ETS is the main instrument to achieve the 40% reduction, but also the security of energy supply and economic competitiveness need to be assured. Hence, Members States are allowed to set ambitious national targets for energy efficiency and renewable energy, though, given the intermittent nature of renewable energy, they need to consider the degree of integration in the internal energy market.

In addition to the cost effectiveness issue achievable through the market-based approach, also the impacts in term of distribution of economic costs and competitiveness are crucial. Possible trade off may arise as, for example, the rebound effect and, as Hanley *et al.* (2009) claim, in order to limit the risks, it is necessary to offset the positive impact in term of competitiveness due to the cheaper access to energy input, especially in energy-intensive firms. Thus, they conclude that "what energy efficiency stimuli do create is the potential for energy taxes to be levied without generating any of the adverse effects on economic activity that would otherwise be expected" (Hanley *et al*., 2009, p. 706).

Certainly, if the increase in energy efficiency actually leads to a reduction in energy consumption, the target in term of green quota of renewable energy is easier to be achieved. As in the previous case, also support measures to renewable energy sources have been under scrutiny for their possible interaction with the ETS. Lehmann and Gawel (2013) assert that the introduction of support measures for renewable electricity could result in a reduced demand for allowances (and hence in their price, shifting the emissions to other sectors not covered by the EU ETS) and in welfare losses. However, they conclude that, while in a perfect competitive market the EU ETS would be the only required measure, in real world situations with market imperfections and multiple policy objectives, support schemes for renewable energy may well complement the ETS in the energy mix.

Several examples of studies analysing the economic impacts of mitigation policies are available. Considering the EU2020 policy, Böhringer *et al.* (2009a) evaluate the economic impact of the climate package and compare different policy scenarios to a business-as-usual, as well as alternative baseline projections to 2020. They use the PACE model to investigate the potential for excessive costs in case of market segmentation and green quotas in the EU ETS. Among the alternative approaches used to analyse this climate package, Tol (2012) provides a cost-benefit analysis of the 2020 European targets; Capros *et al.* (2011) use an energy model with non-CO_2 greenhouse gas information to assess the inclusion of renewable targets and other policy options (Clean Development Mechanisms, trade of renewable permits and biofuel use in transport); Böhringer *et al.* (2009b) compare three computable general equilibrium models to evaluate the costs associated to restricted trading across ETS and no ETS sectors and a renewable energy target.

Moreover, with the EU2030 recently being approved, more effort is being directed to the definition of the optimal policy design, considering the potential costs of a complex policy mix and overlapping regulation and few reports are already available. Examples are: a Cost Benefit Analysis conducted by Enerdata (2014) on the additional costs of renewable energy and energy efficiency targets with respect to a market-based GHG reduction; a Briefing Paper by Ecofys with an assessment of ambition of the 2030 targets, also considering the 2050 goals (de Vos *et al*., 2014); the development and evaluation of long-term scenarios for a balanced European climate and energy policy until 2030 by E3MLab using PRIMES model (Capros *et al*., 2014); a Fraunhofer ISI Report (2014) on the estimation of the future costs of the energy system with renewable energy development[37]; an analysis on the interaction between emission trading mechanism and a minimum target for renewable energy sources, considering different electricity demand projections in a partial equilibrium model (Flues *et al.,* 2014).

Considering the long-run perspective to 2050, there are several examples of assessment of alternative solutions to reach the CO_2 abatement targets and their economic effects, as in Hübler and Löschel (2013), Meyer *et al*. (2014) and de Koning *et al*. (2014). Hübler and Löschel (2013), for example, analyse the EU Roadmap to 2050 in a CGE framework considering alternative unilateral and global policy scenarios, eventually including the use Clean Development Mechanism (CDM) and equalization of permits price across sectors (ETS and non-ETS) and world regions. They conclude that RD and new technology options are of crucial importance, that a unilateral European policy has higher costs than a global approach, but they also remark that robust sectoral results are needed.

Moreover, when the inherent coherence of the tools mix of the European climate policy is under scrutiny, there are several trade off to consider. In this respect, beyond the cost effectiveness, there is a fervent debate on the optimality of policy mix, on the interactions between different policy instruments and on possibilities for coordination. Starting from Tinbergen (1952), theory suggests that there should be at least the same number of instruments as there are targets. However, the existence of externalities, market failures and further economic, social or environmental goals may justify additional policy instruments. Accordingly, Böhringer *et al*. (2006, 2009a), Böhringer and Rosendhal (2010) and a report by OECD (2011) find that an appropriate instruments mix to climate change needs to be cautiously designed, otherwise the overlapping regulation may generate additional costs. Böhringer *et al*. (2006), in particular, investigate the potential losses deriving from the application of additional emission taxes in the EU ETS. They conclude that the combination of the two measures can be ineffective and generate efficiency losses (in fact, firms subject to both instruments will abate more than efficiently required, while other firms within the EU ETS will benefit from lower international emission permit prices). Böhringer *et al*. (2009a) provide an impact assessment of EU2020 climate package based on a CGE analysis. Their *first-best* conclusions suggest that the exclusion of non-energy intensive firms from EU ETS generates market segmentation and substantial excess costs with respect to uniform permit pricing. On the other hand, the introduction of green quota for electricity generation within the cap-and-trade system leads to modest additional costs, because the increase in renewable energy production from EU ETS itself is already significant, and the effect of

[37] They use the Green-X model, a specialised model on the future development and deployment of renewable energy sources, and the PowerACE model of the power sector, with the relations with conventional electricity supply and infrastructural prerequisites.

the additional subsidy is low. Moreover, Böhringer and Rosendhal (2010) show that trading system (black quota) and renewables subsides (green quota) end up increasing the production of the most emission-intensive technologies, because in a cap-and-trade system where the emissions are fixed (by the black quota) the introduction of green quota reduces the permits prices, favouring the most emitting firms.

However, given market failures, environmental externalities and additional climate goals than the GHG emission abatement, introducing further policy measures could be justified. Hence, a combination of policies to mitigate concentration of GHG emissions and promoting RD activities, supporting technology or improving energy security may be preferable (Goulder, 2013; Fischer and Newell, 2008). For example, Fischer and Newell (2008) conclude that an optimal portfolio of climate measures (as ETS, performance standard, fossil power tax, green quota and subsidies for renewables energy production and RD) may allow reaching the abatement targets at lower costs than any single policy alone would imply. Furthermore, in presence of market distortions "if differential emission pricing or/and overlapping regulation can sufficiently ameliorate initial distortions then the direct excess costs from a first-best perspective can be more than offset through indirect efficiency gains on initial distortions" (Böhringer *et al*., 2009a, p. S304).

In fact, an efficient EU ETS would also promote the achievement of the further EU2030 targets but, giving the existing imperfections, those targets other than being goals can be considered as instruments aiming to improve the ETS design, reduce market and technology failures, driving change of the economic system toward sustainability. The three EU2030 pillars tend to reduce the consumption of fossil fuels however, while the ETS should increase the market price for energy sources, renewable and energy efficiency support tends to mitigate these increases. The promotion of renewable energy technologies tends to reduce the incentives for energy saving promotion, while investment in energy efficiency (reducing, *ceteris paribus*, the level of fossil fuel demand and, consequently, the carbon price) can have antagonistic effect on renewable energy production (Lecuyer and Bibas, 2012). In case of green quota, energy efficiency measures can facilitate to reach the desired level of renewable energy, especially in case of stringent targets (del Rio, 2010). Hence, the introduction of energy efficiency and renewable energy supports to an existing emission market can improve, respectively, the static and dynamic efficiency of the EU ETS, where the latter represents the ability to promote the diffusion and the locking-out of low carbon technologies (Sorrel, 2003; del Rio, 2008).

Hence, the debate over the optimal policy mix and on the possible consequences of overlapping regulation in term of adverse effects on efficiency and effectiveness is rich and complex. Policy mix can be optimal with respect to economic theory, abatement costs or economic competitiveness, but conclusions derived from applied models should also consider the (partial or general equilibrium) scale dimension. Taking the EU targets as given, the optimality is strictly linked to cost-effectiveness, but it also has to account for a high level of uncertainty (technological, organizational, social) in a dynamic perspective. Görlach (2013), for example, tries to answer to the questions of what 'optimal' means and summarises three criteria to assess the performance of policies: effectiveness, cost-effectiveness and practical feasibility. Accordingly, the optimal solution should be able to induce the required emission reduction, at the least possible cost (with respect to the overall time horizon), accounting for reasonable risks, *e.g.*, the policy not being implemented as designed and the selected tools not being able to deliver the awaited results (political, legal and administrative feasibility). Moreover, as emphasised by Flanagan *et al.* (2011), the definition of the tools adopted in a single policy setting should consider at least three characteristics: variety, consistency and coherence. The overall policy mix needs to be comprehensive, ensuring the extensiveness and exhaustiveness of its elements (variety); the instruments should be synergic, in order to exploit all the potential complementary effects among different policy elements (consistency); and the objective of each instrument should be in line with the others (coherence).

Furthermore, additional questions concern the optimality of the policy mix in a dynamic rather than a static context and, therefore on the timing of introduction of mitigation measures, considering the innovation and diffusion phases of technology. In this respect, when accounting for the possibility of overlapping regulation in a long time horizon, it can occur that a well-designed policy mix can mitigate climate change and generate positive spillover effects on innovation and technology paths (Costantini *et al*., 2014; Corradini *et al*., 2014).

However, even if a well-designed and operating ETS put the system in the right direction (in term of decarbonisation of the economic system and promotion of clean technologies), nothing can ensure that it will also reach the specific targets by the identified year (Lecuyer and Bibas, 2012). Thus, the timing of reduction path is particularly relevant when both short and long-term targets are considered, especially bearing in mind the different reduction potentials of alternative technologies together with the risk of lock-in. The distribution of the reduction costs through time depends on technological progress, which will probably allow decreasing abatement in the future, so that delaying the emissions reduction will allow cheaper abatement but also involve higher risks. Olmstead and Stavins (2012), for example, suggest to set "firm but moderate targets in the short term to avoid rendering large parts of the capital stock prematurely obsolete, and flexible but considerably more stringent targets for the long term to motivate (now and in the future) technological change, which in turn is needed to bring costs down over time" (Olmstead and Stavins, 2012, p. 71). del Rio (2008) states that the ETS is an adequate instrument ensuring the cost-effective abatement solution, but it might not guarantee long-term efficiency in term of incentives toward mitigation technology and RD investment against carbon lock-in. Hence, he suggests integrating the market-based instrument with a more comprehensive technology policy. Moreover, Vogt-Schilb and Hallegatte (2014) investigate the optimal abatement pathway considering marginal abatement cost of different technologies, the corresponding mitigation potentials and their implementation speed. They find that the long-term objectives have strong impacts on the short-term strategies, thus, the inclusion of a 2050 target would change also the optimal strategy to 2020 or 2030. They also suggest that implementing a unique price instruments and introducing, in a sequential order, all those technologies with abatement cost lower than the carbon price may not be the best solutions. In fact, if the long term targets are considered when deciding the short or medium term policy, decision makers would pay more attention to high potential technologies (and not only on cheaper and low potential ones) and the short term effort will be greater with respect to the case where only the short term horizon is taken into account.

Finally, there are few more arguments that may hamper the optimality of EU climate policy. Firstly, a strong international coordination is also crucial because one of the risks of unilateral climate policies is to generate distortive effects at the global scale, affecting world energy prices, international competitiveness and the geographical allocation of carbon intensive production processes, as the carbon leakage argument suggests. Energy intensive sectors, in particular, are more reliable on energy sources and suffer deeper negative impacts from mitigation policies, especially in case of trade-exposed activities. The often-invoked instrument to correct for this carbon leakage effect is the introduction of a boarder carbon tariff, but their potentials for reducing the leakage rate and restoring the competitiveness level are not straightforward (Antimiani *et al*., 2013b). Critics are also directed to mistakes in policy design, as the fact that the introduction of renewable energy sources within the overall ETS cap may have allowed for increasing consumption of coal (Böhringer and Rosendhal, 2010). Moreover, the lack of adequate physical interconnections and competitiveness, especially in the in the European electricity and gas market, have limited the benefits of the EU internal energy market (Helm, 2014).

3. Model

In order to provide a comprehensive analysis of alternative policies, numerous global models combining economic and social data with climate and technology information have been developed. Assessment of the economic impact of the energy and mitigation policies are crucial to policy decisions and can be analysed using different applied models looking at how the economic system will react to an exogenous shock. In particular, applied general equilibrium (AGE) or computable general equilibrium (CGE) models are analytical representation of the interconnected exchanges taking place among economic agents based on observed data. They help analysing alternative climate policy measures and interventions, in a global dimension or across regions and economic sectors, and have the advantages of evaluating direct and indirect costs, spillover and economic trade-off in a multi-region and intertemporal perspective.

The dynamic version (GDynE) of the GTAP (Global Trade Analysis Project) model, in particular, as described in Golub (2013), is an upgrading of the static energy version GTAP-E (Burniaux and Truong, 2002; McDougall and Golub, 2007) in combination with the dynamic GDyn (Ianchovichina and McDougall, 2000).

In the static GTAP-E, energy enters in the production structure as a good within the energy-capital composite in the value added nest, with labour and land. The nesting structure presents the following levels: energy-capital composite, (within energy) electricity and non-electricity nest, (within non-electricity) coal and non-coal, (within non-coal) natural gas, oil, oil products. Energy demand is explicitly specified and there is substitution in both the factors and fuels mix. Data on CO_2 emissions are introduced through social account matrices (SAM) and are region and sector specific and it includes the modelling of market-based instruments, as carbon taxes and emission trading.

The dynamic version GTAP-Dyn is a recursive dynamic model that preserves the standard features of the GTAP and enhances the investment side of the model, allowing a better representation of long-term policies. It introduces international capital mobility, thus regional capital stock includes capital stock physically located within the region as well as financial assets from abroad, and there is a Global Trust acting as the single intermediary for all the international investment. Physical capital is property of firms while households hold financial assets directly in local firms and, through the Global Trust, on equity of foreign firms. On the other hand, households own land and natural resources, and lease them to firms, while the Global Trust hold equity in firms in all regions. Time is an explicit variable in the model equations and dynamic representation of specific evolutions in the global economy can be represented. In particular, in each period the financial intermediary distributes the global funds between regions according to investors' expectation. Hence, capital progressively moves to regions with high (expected) rates of return where the gap between expected and actual rates of return falls period after period. This is particularly relevant given that both the energy efficiency and the renewable targets imply the introduction of a specific form of technical change that is transmitted by capital investment.

In this context, technological change might be modelled alternatively as exogenous or endogenous. In the case of endogenous technical change it is necessary to develop specific modules (as in the case of energy efficiency or renewable energies) in order to simulate also the financial mechanisms of RD activities. In the case of exogenous technical change, it could be modelled only in terms of production function in industrial sectors as a general input or output augmenting technical change, without the possibility to disentangle invention, innovation and diffusion activities

To conclude, the GDynE model merges the dynamic properties of GTAP-Dyn with the detailed representation of energy system from GTAP-E. Therefore, it is appropriate for long-term projections, given the properties of the dynamic model, and it is specifically suited for energy and climate policy analysis, with special attention to energy substitution in production and consumption (Golub, 2013). It provides time path for both CO_2 emissions and global economy, and allows capturing the impacts of policies in term of abatement costs and distributive effects between regions and sectors. It also allows providing an overall assessment of the economic impacts of standard climate policy options and a detailed analysis on the effects in terms of changes in bilateral relationships, with particular focus on those between EU and the rest of the world.

The GDynE adopted here, uses the last version of the GTAP-Database (GTAP-Database 8.1, updated to 2007), together with the latest version of the additional GTAP-Energy data on CO_2 emissions along with the arrays in standard GTAP-Database 8.1.

3.1 Model improvements

The GDynE model adopted for this assessment exercise contains two additional policy options modelled for the evaluation of the EU climate policy mix, including the investments in RD for energy efficiency and renewable energy. The main novelty is that, together with the standard climate policy options represented by market-based instruments (in the form of carbon tax and ETS), we introduce a mechanism to finance directly RD in energy efficiency and renewable sources in the electricity sector, according to Antimiani *et al.* (2014). In this case, we suppose a different use of the revenue from environmental taxation, which directly finance RD activities, in terms of energy efficiency gains and the increase in the share of renewables. Certainly, considering only innovation driven by RD investment (mainly in in the energy sector) is a simplified methodological choice while, among others, spillover effects, technology adoption, sector (and firm) specific characteristics and further external factors affecting innovation should be considered at the aggregate but also at the manufacturing sectoral level (Costantini and Crespi, 2008; Costantini an Crespi, 2013; 2013; Costantini and Mazzanti, 2012; Costantini *et al*., 2013; Corradini *et al*., 2014; Cainelli *et al*., 2015).

In this case, we assume that a portion of the total carbon tax revenue (CTR) is directed to finance RD activities in energy efficiency, in an input-augmenting technical change approach, and investments to increase the installed capacity of renewable energy. In this second case, investment efforts must be interpreted as an output augmenting technical change. In other version of the model, the revenue from carbon taxation is as a source of public budget that directly contributes to domestic welfare and it is usually modelled as a lump sum contributing to the equivalent variation (EV). Indeed, an *Environmental Tax Reform* (ETR), shifting the tax burden to energy and polluting resource (lowering those on capital and labour), could provide the potential for a *double dividend*, where the increase in environmental quality is coupled to economic benefits (see Bosquet, 2000; Goulder, 1995; Patuelli *et al*., 2002; Fernández *et al*., 2011).

The choice of the percentage to be taken from the CTR, collected through a carbon tax or an ETS, and directed towards RD activities is exogenously given, meaning that it is independent from the total amount of CTR gathered. It has to be noticed that in this work, the x% of CTR is not uniformly applied to all regions because this mechanism is active only for EU, while in all the other regions the total amount of the CTR still contributes to the EV.

Obviously, while the x% is exogenous, the total amount of CTR directed to RD activities (CTRD) is endogenously determined by the emission abatement target and the nominal carbon tax level. This means that, when RD activities are transformed into efficiency gains or into an increase in renewable energy, the final effects on the economic system will influence the carbon tax level (for a given abatement target) and consequently the total CTRD amount.

In mathematical terms, the formation of the CTRD is built as follows.

We have modelled the contribution to CTRD as a share of the total CTR[38]. In formulas, total revenue from CO_2 abatement is computed as:

$$CTR = CO_2 \cdot CTAX \quad (1)$$

where CTR is the revenue in EU resulting from a tax on a target level for CO_2 emissions and *CTAX* is the domestic level of carbon tax. Finally, CO_2 is the amount of taxable emissions in EU.

The amount of CTR directed to RD activities is defined as:

$$CTRD = \alpha \cdot CTR \quad (2)$$

where α is the exogenous x% defined by policy makers.

The amount of *CTRD* used for financing RD activities and contributing to domestic welfare has to be detracted from the EV as follows:

$$EVnew = EV - CTRD \quad (3)$$

Having introduced the RD financing mechanism only in the EU, the value of the EV will be unvaried in all other countries except EU, which is the only region where *CTRD* has a value different from zero. Indeed, α will be equal to the x% defined by policy makers in EU and to zero for all the countries of the rest of the wold.

The total amount of CTRD can be used for improving technical change in energy efficiency (CTRDEE) and for improving output augmenting technical change in renewable energies (CTRDRW). The choice of the share of total CTRD to be directed to energy efficiency or renewable energies is exogenously given, as part of the policy options for the climate strategy. The current distribution of total public budget in EU for RD activities in EE and RW (IEA database) is that on average (2003-2010) 55% is directed towards energy efficiency (40% in firms and 15% in households) and 45% to renewable energies.

[38] In the GDYnE model, carbon taxation is modelled as a standard lump sum in welfare computation.

Accordingly:

$$CTRDEE = \beta \cdot CTRD \quad (4)$$

$$CTRDRW = \gamma \cdot CTRD \quad (5)$$

Where $(\beta + \gamma) = 1$.

The relationship between technical change in energy efficiency and CTRDEE is modelled in a very simple way. An elasticity parameter, $R_{EE}(i,j)$, is taken in order to transform RD efforts (millions of US dollars) into technical progress in energy efficiency by using an average elasticity value based on the literature on this topic (Adams and Jaffe, 1996; Griffith *et al.*, 2006; Griliches and Lichtenberg, 1984; Hall and Mairesse, 1995; Lichtenberg and Siegel, 1991).

The final equation for translating RD efforts into technical progress in energy efficiency is thus given by:

$$t_{EE}(i,j) \; = \; R_{EE}(i,j) \; \cdot \; CTRD_{EE} \quad (6)$$

where $t_{EE}(i,j)$ is the technical energy efficiency gain in input *i* as a result of funds allocated to RD in energy efficiency that uniformly influence productivity in all sectors. In this work we have assumed that all RD efforts from the fund are directed towards improvements in energy efficiency in the production function, considering that the diffusion path of technologies is not affected by technical barriers.

The elasticity parameter has been calibrated according to latest reports by Enerdata considering the sectoral efficiency gain (*EE gains*) and the public RD investment in energy efficiency (RD_{EE}) during the last decade, as an average value between industry, residential sector and transport. Such an approach represents a standard modelling choice when sectoral empirical estimates are not given. In mathematical terms:

$$R_{EE}(j,r) = EE\ gains / RD_{EE,t-1} \quad (7)$$

It is worth noting that, by working in a dynamic setting, this is a quite conservative assumption since it could be the case that during the next decade efficiency gains might change among final use and technologies. In order to better shape such dynamic pattern, it will be necessary to link the macro CGE model with bottom-up energy models, which is out of the scope of the current work but it will constitute the next research agenda.

The second technology option is to use CTRD to finance the increasing electricity production from renewable energies. In this case, a share of CTRD devoted to technology options is directed toward financing the output-augmenting production of renewable energies. Here, from a pure modelling approach, what it is affected is not an input augmenting technical change parameter as $t_{EE}(i)$ in energy efficiency, but an improving technical change measure in the electricity sector, given by $el_{RW}(j)$ (we ignore biofuels and other non-electricity renewable sources):

$$el_{RW}(j,r) = R_{RW}(j,r) \cdot CTRD_{RW} \quad (8)$$

where $R_{RW}(j)$ represents the reactivity of the electricity sector to RD investments. In this specific case, the reactivity parameter is calibrated with regard to the investment in RD activities in renewable energies (RD_{RW}) during the last ten years and the corresponding increase in installed capacity in renewable electricity in OECD countries, at the numerator in the following formula (IEA energy Balance dataset available online):

$$R_{RW}(j,r) = \frac{(C_t - C_{t-1})}{C_{t-1}} / RD_{RW\,t-1} \quad (9)$$

3.2 Baseline and policy scenarios

The model is used to conduct an analysis on EU2030 policy mix but extending the time horizon to 2050, in order to perform a long-term analysis of climate change policies in a world-integrated framework and, in this case, the GDynE model presents the EU at aggregate level.

The projections for macro variables as GDP, population and labour force are given by the combination of several sources, in particular projections for exogenous variables are taken as given by major international organizations. GDP projections are taken from the comparison of the reference case for four main sources, the OECD Long Run Economic Outlook, the GTAP Macro projections, the IIASA projections used for the OECD EnvLink model, and the CEPII macroeconomic projections used in the GINFORS model. Population projections are taken from the UN Statistics (UNDESA). Projections for the labour force (modelled here as skilled and unskilled) are taken by comparing labour force projections provided by ILO (which result as aggregate) with those provided by the GTAP Macro projections (where skilled and unskilled labour force are disentangled).

With respect to calibration of CO_2 emissions, in the reference scenario the model presents emissions by 2050 in accordance with the CO_2 projection given by International Energy Agency in the World Energy Outlook 2013 and Energy Information Administration (EIA). In order to have calibrated emissions in accordance with a specific EU perspective, emissions provided by IAM climate models, as GCAM in a "Do-nothing"[39] scenario for EU countries, are also compared with GDynE output.

In the reference case, Current Policies scenario, CO_2 emissions are given as an endogenous output of the model. In fact, we projected the global economy from 2007 to 2010, with CO_2 emissions being

[39] The "Do-nothing" scenario is coherent with IEA Current Policies and the RCP 6.0 from IPCC scenarios.

exogenous in order to replicate the current distribution among regions based on current data. To this purpose, the calibration criteria is built on the maintenance of existing economic and technological trends, including short-term constraints on the development of oil and gas production and moderate climate policies.

When considering the policy options (emission trading or carbon tax, and RD efforts in energy efficiency and renewable energies in electricity production), these are based on the 450PPM scenario developed by IEA (or RCP 2.6 by IPCC) and the EU2030 framework. Indeed, the 450PPM scenario establishes the goal of limiting the concentration of greenhouse gases in the atmosphere to around 450 parts per million of CO_2 equivalent. In the latter, the 2030 target recently adopted by the EU is considered, consisting in a reduction of CO_2 emissions of 40% by 2030 with respect to 1990 levels, while the 2050 target is the same as in the 450PPM scenario. In particular, it needs to be highlighted that the reduction to be achieved by 2030 is more stringent in the 450PPM than in EU2030 case.

The abatement targets can be achieved by implementing different policy options that are at the basis of the EU2030 strategy, which is a first focus of this paper.

The first policy option refers to the market-based instrument for emission abatement purpose, as a domestic carbon tax, where every country reduces its own emissions internally, and an international ETS, which allows all countries to trade emissions until an equilibrium price is reached. In order to simplify the analysis, by modelling EU as an aggregate, the two market-based policy options, carbon taxation and EU ETS, result as perfectly equivalent, since the Pigouvian carbon tax in the whole EU corresponds to the minimum cost for achieving the target, which is equivalent to the permits price level reached if EU countries are singled out and the whole economy is involved into emission trading system.

The second policy option implies an increase in energy efficiency, where the target aimed by the EU2030 strategy refers to a 27% improvement in energy efficiency by 2030 with respect to a current policy scenario.

The third policy option here considered refers to the increase in the share of renewable energies in the energy mix. Considering the specific GDynE model features, we have modelled only a part of the EU2030 strategy, namely the increasing share of electricity produced by renewable sources by 2030 (EC, 2014a), without considering other renewable energies used in other sectors.[40]

In terms of the time dimension, we consider a temporal horizon to 2050. However, given the extent of the EU2030 policy, after 2030 there are no additional exogenous shocks to the model, and results are only affected by the cumulative path and dynamics deriving from previous periods. As a standard modelling choice, periods here are shaped as a 5-year temporal structure.

[40] Indeed, the EU2030 policy set a EU target of at least 27% of renewable energy sources, which can be translated in a 45% share of RES in electricity generation (EC, 2014a).

Therefore, the different policy options here considered are:

i. 450PPM: only EU reduces emissions with a market-based policy (carbon tax), respecting the 450PPM target by 2050 developed by IEA;
ii. 450PPM-10%: the same as before but we also apply a 10% levy on the total carbon tax revenue to be detracted from the lump sum and directed to RD activities in energy efficiency and the promotion of electricity from renewable energy sources;
iii. 450PPM-20%: the same as before but we apply a 20% levy on the total carbon tax revenue;
iv. EU2030: only EU reduces emissions with a market-based policy (carbon tax), respecting the 40% reduction by 2030 with respect to 1990 level and the 450PPM target by 2050;
v. EU2030-10%: the same as before, but we also apply a 10% levy on the total carbon tax revenue to be detracted from the lump sum and directed to RD activities in energy efficiency and the promotion of electricity with renewable sources.

Furthermore, we include two policy scenarios as exemplification of global emission reduction strategies opposed to unilateral approaches, hence, can be considered as benchmarks (in both cases the EU emission reduction targets are the same as in the 450PPM path). These scenarios are:

vi. GCTAX: each country or region has an emissions target coherent with the 450PPM path and reduces its own emissions through an domestic carbon tax;
vii. GET: all countries have the same abatement targets as in the GCTAX scenario, but here they can trade allowances in an international (global) ETS such that domestic carbon tax levels are all equalised to the permit price (hence, this is the cost-effective option).

As far as the country and sector coverage is concerned, we consider 20 regions and 20 sectors. With respect to the former, we distinguishing between Annex I (Canada, European Union, Former Soviet Union, Japan, Korea, Norway, United States, and Rest of OECD) and non-Annex I countries. (Brazil, China, India, Indonesia, Mexico, African Energy Exporters, American Energy Exporters, Asian Energy Exporters, Rest of Africa, Rest of America, Rest of Asia and Rest of Europe). The former includes countries in Annex I in the Kyoto Protocol or rich ones with less relevance with respect to efforts to emissions abatements. Among the second aggregate, we consider single countries (the main emerging economies with strong bargaining positions in the negotiations and eligible to emission cut commitment) as well as aggregates. Finally, considering a geographically based rule (Africa, America and Asia) we distinguish both energy exporter countries group and all remaining ones (Rest of) into three groups each. In fact, it is relevant to analyse the impact of abatement policies on economies rich in natural resources but it is also crucial to compare it with the effect on countries in the same area with less or none resource availability, and across macro regions.

Considering the sectoral aggregation, we distinguish 20 industries with special attention to manufacturing industry, in fact 10 out of them are manufacturing sub-sectors (Food, beverages and tobacco; Textile; Wood; Pulp and paper; Chemical and petrochemical; Non-metallic Minerals; Basic metals; Machinery equipment; Transport equipment and Other manufacturing industries). Moreover, other than Agriculture, Transport (also distinguishing Water and Air transport) and Services, energy commodities have also been disaggregated in Coal, Oil, Gas, Oil products and Electricity.

4. Results

4.1 Comparison between policy scenarios with and without RD investment in green technologies

Firstly, we consider the impact of introducing alternative policy measure in addition to a pure ETS, namely RD investment in energy efficiency and renewable energy, as indicated by the EU2030 strategy. Therefore, we compare results from the ETS scenario (450PPM) with those introducing a levy on the carbon tax revenue (450PPM-10% and 20%), taking the two global abatement scenarios (GCTAX and GET) as benchmark.

In Table 1, the unit cost of abating one ton of CO_2 in EU is reported for all the alternative policy scenarios following the 450PPM path. If all countries have abatement targets and implement domestic policies (GCTAX), the cost in terms of Pigouvian carbon tax is extremely high for the EU and it increases over time, as targets become more binding, reaching 582 USD for ton of CO_2 by 2050. By comparing this carbon tax level with the permits price obtained in the GET scenario, it is clear that a scenario where all countries participate to an international emission trading system constitutes a more cost-effective solution. In case of a unilateral EU climate strategy, it is worth mentioning that by relying only on the market-based EU ETS (450PPM) the level of permits price by 2050 is reduced with respect to the former two scenarios. This is due to the dynamic CGE approach adopted, in fact if all countries compete for acquiring inputs on the international markets to substitute fossil fuels, it will become increasingly difficult to reach the climate targets. The increased competition on alternative inputs directly influences the marginal abatement costs by pushing up prices in the international markets for all goods and the permits price in GET become increasingly higher than the price in the 450PPM case. Moreover, as the share of the carbon tax revenue (CTR) used to finance energy efficiency and renewable energies increases (450PPM-10% and 450PPM-20% scenarios), the carbon tax level required to achieve the abatement targets is progressively reduced. Indeed, in 2050 there is a reduction of almost 100 USD per ton in case of the 20% levy with respect to the pure EU ETS case. In this work, the percentage levy applied to the CTR is exogenously given but, whether the interest is to investigate which is the optimal carbon tax level with respect to certain policy objectives, it may be endogenously determined.

Table 1 - Carbon Tax level for EU27 (US Dollars per ton)

	2015	2020	2025	2030	2035	2040	2045	2050
GCTAX	13	26	103	206	269	340	457	582
GET	7	10	45	106	175	232	345	443
450PPM	10	17	71	140	172	208	265	309
450PPM-10%	12	23	69	129	156	182	225	252
450PPM-20%	12	23	68	123	143	161	192	210

Source: our elaboration on GDynE results.

Given that the CTR directly finances RD activities, it is straightforward that as the abatement targets become more stringent and the level of carbon tax increases, then the revenue invested in RD grows as well. A first aspect to notice is that the outcome in terms of overall budget to be invested in RD in the two technological domains (energy efficiency and renewable) could constitute an overall value to be reproduced in more details by models controlling for more specific technological patterns. As an example, in Table 2, it is worth noting that the increasing abatement targets over time produce an increase in carbon tax level, which ensures an increasing value of RD investments up to 2045, where the trend is inverted.

Table 2 - EU Carbon Tax Revenue for EU27 (Mln US Dollars)

	2015	2020	2025	2030	2035	2040	2045	2050
GCTAX	47,693	86,446	294,660	489,313	529,765	546,462	608,885	626,520
GET	25,208	34,048	128,790	249,409	337,482	369,755	447,541	482,846
450PPM	34,912	58,273	200,501	329,515	340,540	344,949	361,182	346,075
450PPM-10%	44,748	77,105	198,130	305,372	308,403	301,453	304,834	280,473
450PPM-20%	44,801	76,842	195,146	291,582	282,155	264,885	259,286	232,701

Source: our elaboration on GDynE results.

The distribution of CTR between energy efficiency and renewable energy technological options is presented in Table 3 together with the 2010[41] IEA registered value for EU countries RD in energy efficiency and renewables. According to the model results, the amount of RD generated is coherent with historical data given that, by adopting a fixed 10% levy on total carbon tax revenue, there is an increase of about 50% in 2015 if compared to the 2010 data, revealing the feasibility of this policy mix strategy. As in the case of the levy applied to the CTR, also the distribution of CTR between the two alternative technological options is here taken as exogenously given, and it is fixed with respect to the current level, hence, these results can be taken as the starting point for a deeper investigation at the

[41] The IEA database on country RD budget are available up to 2013, however series from 2011 include several missing value, thus the 2010 are presented.

technology specific level. Further investigation about how to shape in dynamic terms this distribution should be done in the next future, in order to further explore the optimal distribution with respect to a cost effectiveness criterion or other climate or economic objectives.

Table 3 – Annual flows of public investment in RD activities for EU27 (Mln US Dollars)

		2010	2015	2020	2025	2030	2035	2040	2045	2050
450PPM-10%	Energy Efficiency	*1,936*	2,685	4,626	11,888	18,322	18,504	18,087	18,290	16,828
	Renewable Energy	*1,589*	1,790	3,084	7,925	12,215	12,336	12,058	12,193	11,219
450PPM-20%	Energy Efficiency	*1,936*	5,376	9,221	23,417	34,989	33,858	31,786	31,114	27,924
	Renewable Energy	*1,589*	3,584	6,147	15,612	23,326	22,572	21,191	20,743	18,616

Source: IEA 2010 data; from 2015 to 2050 our elaboration on GDynE results.

The economic gains obtained by fostering green technologies in the energy sector are here presented in terms of the reduction in GDP losses with respect to BAU (Table 4), where investments in the energy sector seem to be most promising in terms of GDP gains. By comparing scenarios representing the global abatement strategies (GCTAX and GET) with those scenarios where the EU adopts a unilateral climate policy (450PPM), EU experience GDP gains in the former cases and GDP losses in the latter. The international economic linkages depicted in GDynE reveal that in the case of a global deal the EU would achieve substantial economic gains by participating in an international climate agreement. This is explained by the expected dynamics of technology development, combined with the relative economic structure and the energy mix of the EU in comparison to the rest of the world. The abatement costs for achieving climate targets for the other countries are larger than for the EU, transforming the climate burden for the EU into an economic growth opportunity. This result might explain the negotiations deadlock due to countries that expect to face the major share of the climate burden. On the other hand, it should also encourage the EU to continue working towards a global agreement, since the unilateral solution is extremely costly and inefficient from an environmental as well as economic perspective. From Table 4 it is also clear that by introducing an increasing levy on carbon tax revenue, the losses in GDP that the EU experiences in case of the pure ETS (450PPM) progressively reduce, up to the 450PPM-20% scenario where efficiency gains are higher than the abatement cost losses and the EU has GDP gains with respect to the BAU.

Considering the corresponding welfare losses, from Table 5 it is also clear that the changes in term of equivalent variations (EV) follow the same dynamics as those of GDP.

Table 4 – GDP losses with respect to BAU for EU27 (%)

	2015	2020	2025	2030	2035	2040	2045	2050
GCTAX	0.10	0.36	0.63	0.99	1.80	2.91	4.23	5.81
GET	0.08	0.37	0.95	1.95	3.20	4.35	5.27	6.12
450PPM	-0.09	-0.27	-0.81	-1.80	-2.89	-3.90	-4.79	-5.51
450PPM-10%	0.01	-0.01	-0.13	-0.41	-0.77	-1.10	-1.41	-1.66
450PPM-20%	0.14	0.33	0.64	0.92	1.08	1.16	1.13	1.07

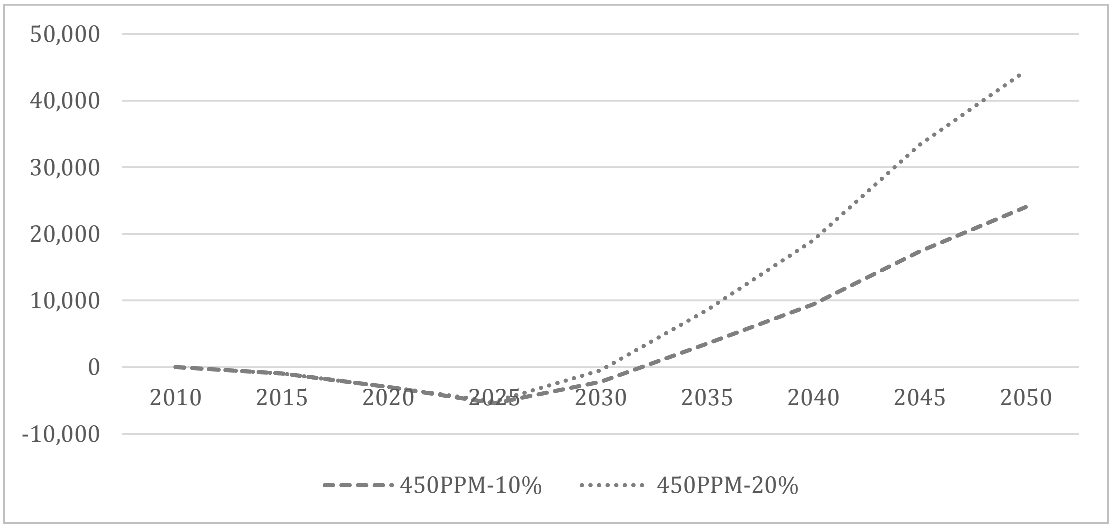
Source: our elaboration on GDynE results.

Table 5 - EV losses with respect to BAU for EU27 (%)

	2015	2020	2025	2030	2035	2040	2045	2050
GCTAX	-0.01	0.45	0.54	1.16	2.59	4.56	6.28	8.48
GET	0.00	0.50	0.84	1.57	2.24	2.99	3.74	5.06
450PPM	-0.08	-0.26	-0.71	-1.60	-2.29	-2.59	-2.60	-2.53
450PPM-10%	0.02	-0.04	-0.20	-0.53	-0.67	-0.59	-0.38	-0.17
450PPM-20%	0.12	0.20	0.34	0.41	0.56	0.79	1.05	1.24

Source: our elaboration on GDynE results.

Figure 1 - Differences in Allocative Efficiency w.r.t. 450PPM for EU27 (Mln US Dollars)



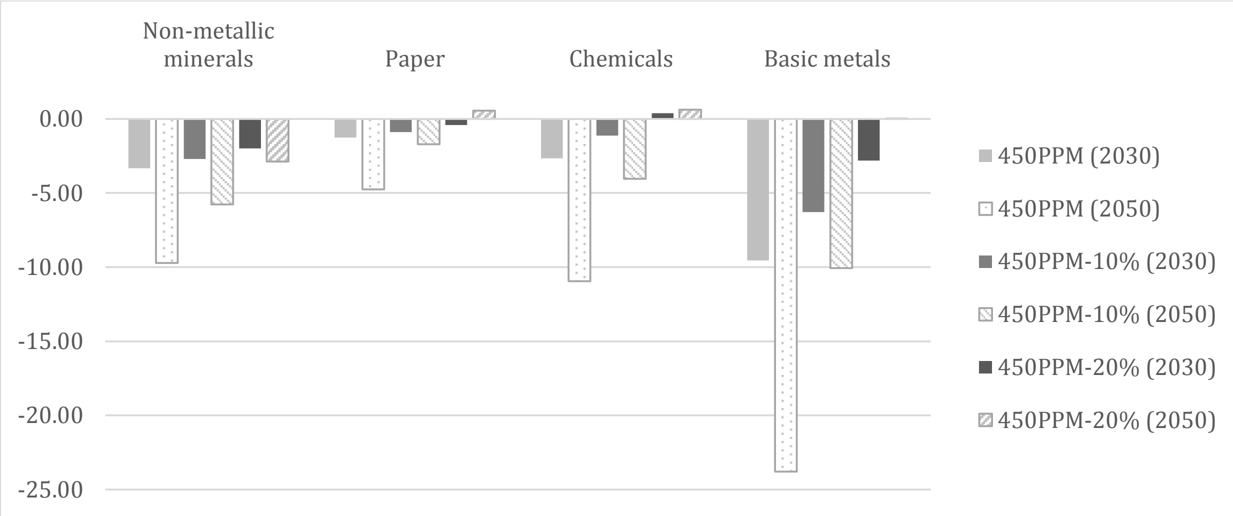
Source: our elaboration on GDynE results.

Moreover, it is worth noting what happens to the contribution of the carbon tax in term of allocative efficiency, which is a part of the total EV. In Figure 1, we compare the two scenarios where RD is financed by the CTR with respect to the 450PPM, where only the EU ETS is in place. Up to 2025, the introduction of a percentage levy on the carbon tax have a negative impact in term of allocative efficiency (which constitutes a part of the EV welfare variation) with respect to the market-based approach. After that year however, the productivity of the investment in RD progressively increases, proportionally to the applied levy, and generates higher contributions to the efficiency and welfare gains.

Additionally, with respect to the gains obtained by fostering clean technologies in the energy sector, by looking at GDynE results it is possible to identify which are the economic sectors benefiting the most from this technology improvement. Hence, when the specific manufacturing sectors are scrutinised, it is worth mentioning that energy-intensive sectors are negatively influenced by emissions reduction if a proper policy mix with RD in clean energy technologies is not implemented (450PPM scenario). Losses in output with respect to BAU are consistently reduced if energy efficiency and renewables are fostered by RD activities and ultimately become sectoral output gains when the percentage applied levy is of 20% (see Table A.7 in Appendix).

Most importantly, we also consider the changes in export flows, in the case of a pure ETS policy and when including a 10% and 20% levy to finance RD, for manufacturing sectors with respect to the baseline scenario (Figure 2; see Table A.8 in Appendix for further details). When looking at the international competitiveness in term of export, if an unilateral EU climate strategy is adopted in the form of an ETS, export flows face a strong reduction with respect to BAU. By contrast, in the 450PPM-10% scenario, when RD efforts in more efficient green technologies and alternative energy sources are exploited, export flow losses decrease with respect to the unilateral ETS strategy. Energy-intensive sectors, in particular, are most adversely affected by emissions reduction achieved by a unilateral 450PPM policy but, turning to the policy mix strategy including green technological support, results are much more encouraging, both in 2030 and 2050 (see Figure 2). In the scenario with 10% levy, the export flow losses for fragile sectors such as Basic metals and Chemicals are reduced reaching in 2050 a maximum of -10.7% (which is still a large loss) for Basic metals and a -4.04% for Chemical, and further reduce or even become export gains with the 20% levy. Moreover, it is also worth noting that in the long-run also the technology-intensive sectors face a reduction in export losses if the 10% or 20% levy is applied, with respect to the ETS case (see Table A.8 in Appendix). This is especially true for the Transport equipment sector, although the beneficial effect in the Machinery and equipment sector is definitely lower. Furthermore, the policy scenarios including RD investment in green technologies also leads to less distortionary changes in the export flows from other regions, here simplified as Rest of the World.[42] This means that combining market-based instruments with policies fostering green innovation can bring significant improvements in international competitiveness of EU industries limiting the harmful effect on those sectors that constitute the core of the industrial growth, but further investigation in this respect are needed.

Figure 2 – Changes in export flows in 450PPM scenarios w.r.t. BAU for EU27 (%)



Source: our elaboration on GDynE results.

Concerning the changes in energy prices, as, among others, Lecuyer and Bibas (2012) claim, the introduction of the measures to support energy efficiency and renewable energy tend to reduce the market price of energy sources, therefore mitigating the impact due to the abatement policy, namely the introduction of a carbon tax or the EU ETS. In our model, this effect is particularly significant when looking at the changes in the EU electricity price (Table 6), in fact the 11% average increase in the 450PPM scenarios is reduced to less than 4% when the levy on CTR is increased to 20%. Hence, by investing in energy efficiency and renewable energies, the internal costs for energy consumption (given by the international market prices for energy and the domestic carbon tax) is reduced with respect to the EU ETS policy option.

Table 6 – Changes in electricity prices in EU27 (%)

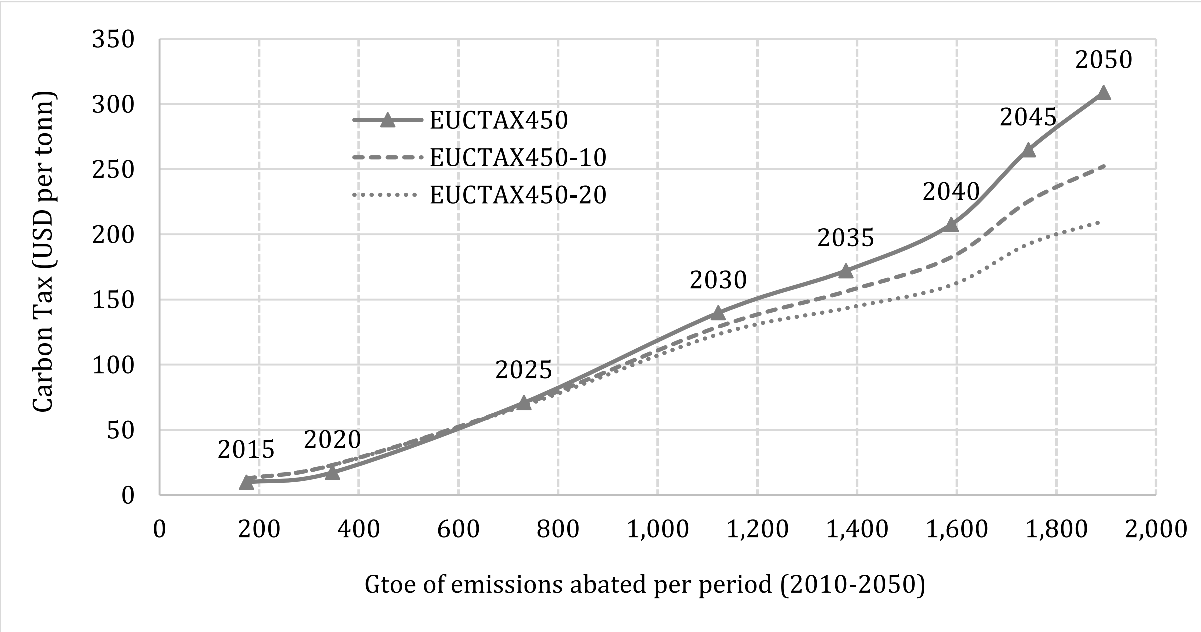
	2015	2020	2025	2030	2035	2040	2045	2050	*Average*
450PPM	8.27	12.22	11.54	11.43	12.16	12.96	10.26	9.61	*11.06*
450PPM-10%	7.84	10.91	7.66	5.44	5.89	6.69	4.23	4.20	*6.61*
450PPM-20%	7.06	9.48	4.24	0.51	1.22	2.53	0.66	1.37	*3.38*

Note: % change w.r.t. previous period. Source: our elaboration on GDynE results.

[42] This is valid for the 450PPM-10% case with respect to the 450PPM policy (Figure A.1 and A.2 in Appendix). This effect is even more relevant if compared to the global emission trading case, where although also ROW regions have reduction targets (Figure A.3 in Appendix).

A further advantage of using the CTR for financing green technologies is given by the gains in term of efficiency and cost effectiveness, as shown by the curves of Marginal Abatement Costs (MAC) reported in Figure 3. From the comparison among the three unilateral EU abatement strategies, results show how marginal costs of achieving a certain emission target are progressively reduced if energy efficiency and renewable energy are fostered, with respect to the unique ETS instrument.

Figure 3 - Marginal Abatement Cost curves for EU27



Source: our elaboration on GDynE results.

Finally, the broad energy intensity level compatible with the EU2030 target, which implies reaching an increase of at least 27% of energy efficiency by 2030 with respect to a BAU case, is 60.16 toe of energy consumption for each million USD of GDP at the EU level. This corresponds to the application of the 27% target to the BAU energy intensity indicator in 2030, which equals to 82.41 (Table 7). The energy intensity level obtained by the pure ETS strategy reaches the value of 62.31 in 2030, which is higher than the EU2030 target. By imposing the 10% levy on carbon tax revenue in EU, the energy intensity level (61.45 toe/Mln USD) is lower than in the 450PPM scenario; when the levy increases to 20%, the corresponding energy intensity indicator is further reduced (60.76) and the EU2030 target is almost reached.

Table 7 - Energy Intensity for EU27 (Toe/ Mln US Dollars)

	2015	2020	2025	2030	2035	2040	2045	2050
BAU	124.48	104.88	91.81	82.41	74.01	66.98	60.67	56.19
GCTAX	121.43	98.62	77.81	60.44	47.43	37.59	29.76	24.17
GET	122.66	101.73	84.63	69.57	55.57	44.18	34.63	27.82
450PPM	121.13	98.50	78.44	62.31	50.26	40.82	33.45	28.12
450PPM-10%	121.02	98.25	77.90	61.45	49.19	39.66	32.30	27.02
450PPM-20%	120.89	97.94	77.31	60.76	48.60	39.14	31.97	26.73

Source: our elaboration on GDynE results.

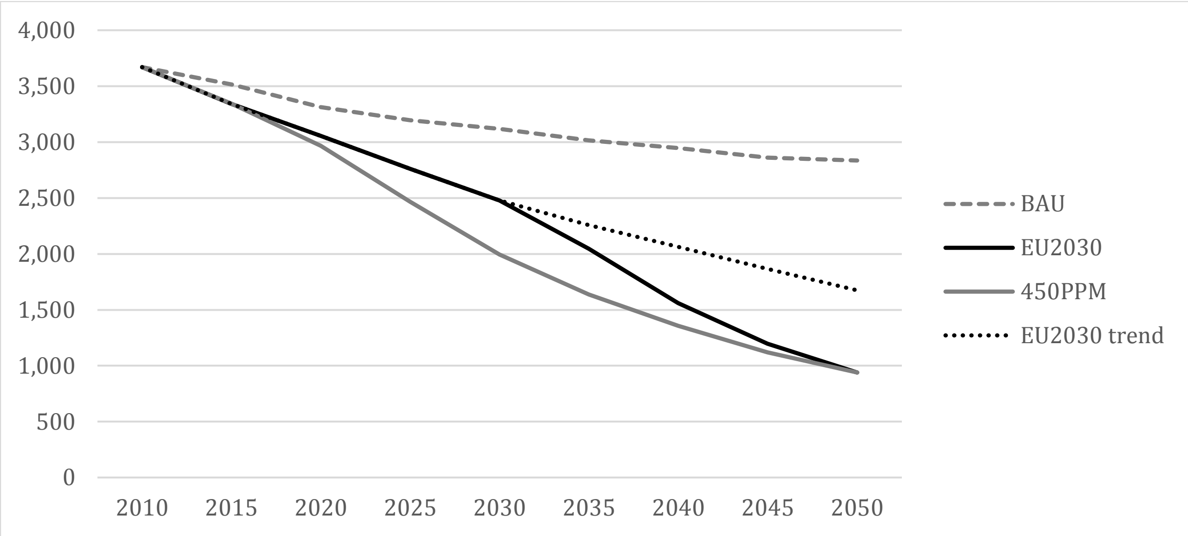
4.2 Comparison between alternative timing of emission reduction targets

In the previous section, we analysed the impacts of alternative policy mix to achieve the reduction targets coherent with the 450PPM scenario and results suggest that there are significant potential benefits of financing RD activities in green energy technologies in addition to the EU ETS. However, since the European Commission's announcement of the EU2030 strategy in October 2014, a further and relevant issue is arising in term of timing of the abatement target. The questions are in fact related to whether or not the European strategy is adequate in term of stringency and ambition and if EU2030 targets will allow the EU to be on track with respect to the long-run 2050 objectives.

In view of that, Figure 4 reports the different CO_2 emissions paths for EU according to the alternative mitigation strategies. In both 450PPM and EU2030 scenarios, the 2050 abatement target implies a reduction of almost 80% in GHG emissions with respect to 1990 level, which corresponds to a 67% reduction in 2050 if compared to the model baseline. However, if we look at the 2030 percentage reduction with respect to BAU, the EU2030 target of 40% is lower than the 450PPM case, whose corresponding target implies a 52% reduction. Therefore, while in the 450PPM strategy we assume a constant rate of emissions reduction through the entire time horizon, with the EU2030 strategy, to achieve both the 2030 and the 2050 targets, the abatement rate should increase after 2030. In fact, if we extend the CO_2 trend of EU2030 scenario from 2010-2030 to 2050 (EU2030 trend in Figure 4), the feasible reduction in 2050 is lower than in 450PPM and limited to 41% of BAU emissions. Therefore, in what follows, we are investigating the trade-off between anticipating or postponing the more stringent abatement targets, also with respect to the alternative measures in the EU climate policy mix (ETS, energy efficiency and renewable energy).

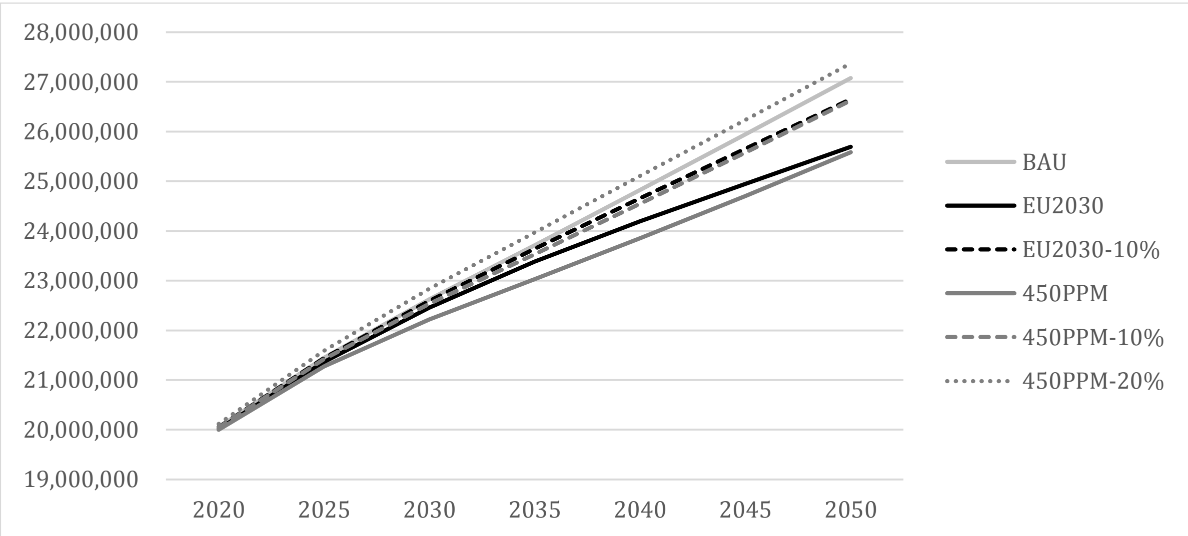
Besides the differences in term of emissions reduction, questions arise about which path should be preferable in term of abatement costs, efficiency or security of mitigation strategy. Therefore, a first aspect to consider is the impact on the GDP level (see Figure 5).

Figure 4 - CO_2 emission paths for EU27 (Mtoe)



Source: our elaboration on GDynE results.

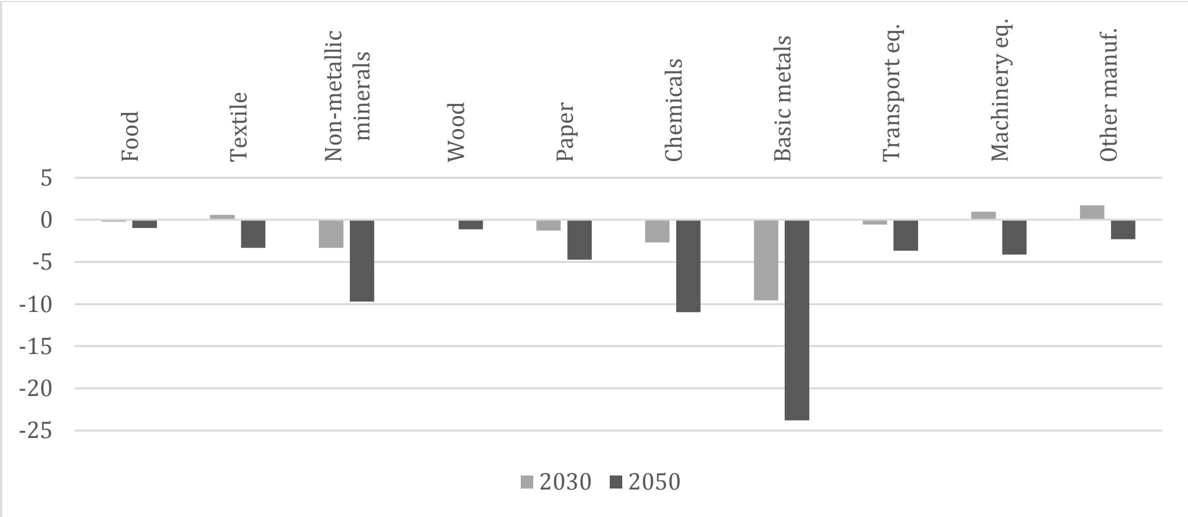
Figure 5 – GDP level for EU27 (Mln US Dollar)



Source: our elaboration on GDynE results.

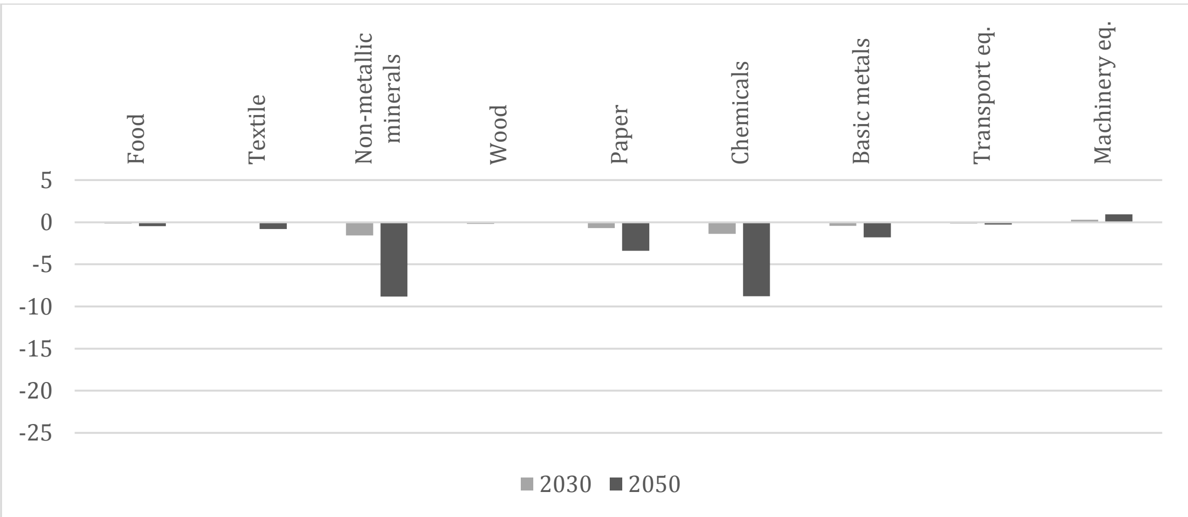
Limiting the attention to the EU2030 and 450PPM scenarios, it is an incontrovertible evidence that setting the CO_2 abatement to 40% in 2030 will limit the GDP losses with respect to BAU (especially between 2035 and 2040, while in 2050 GDP levels are quite similar). This is not surprising given that, in case of unilateral mitigation policy, delaying more stringent target to the future would imply exploiting further technological advantages and the corresponding lower abatement costs. Indeed, also considering the sectoral results, Figure 6 and 7 show the differences in the export performances with respect to the BAU case and suggest that the EU2030 policy implies a significant reduction in the competitiveness losses for all industrial activities, both in 2030 and 2050. Further arguments in support of this result are the level of cumulated variations in term of GDP and welfare (EV), which are reported in Table 8. In both cases, the cumulated losses are higher in the 450PPM scenario, in 2030 as expected, but in 2050 as well.

Figure 6 – Changes in export flows in 450PPM w.r.t. BAU for EU27 (%)



Source: our elaboration on GDynE results.

Figure 7 – Changes in export flows in EU2030 w.r.t. BAU for EU27 (%)



Source: our elaboration on GDynE results.

Nonetheless, a preference toward the EU2030 scenario instead of the 450PPM it is not so straightforward according to additional indicators (see Table 8). First, the GDP growth rate in 2030 is higher in case of EU2030, due to the lower abatement target, but the relation is inverted in the long run and in 2050 the 450PPM strategy ensure a higher GDP rate.[43] Accordingly, in 2030 the 450PPM strategy determines a higher price for carbon taxation than the EU2030, but in 2050 the opposite relation holds (Table 8). Therefore, there is a threshold point also considering the carbon tax level

[43]If the 450PPM scenario is implemented, from 2040 the GDP growth rate become higher than in the EU2030 scenarios (see Table A.9 in Appendix for further details).

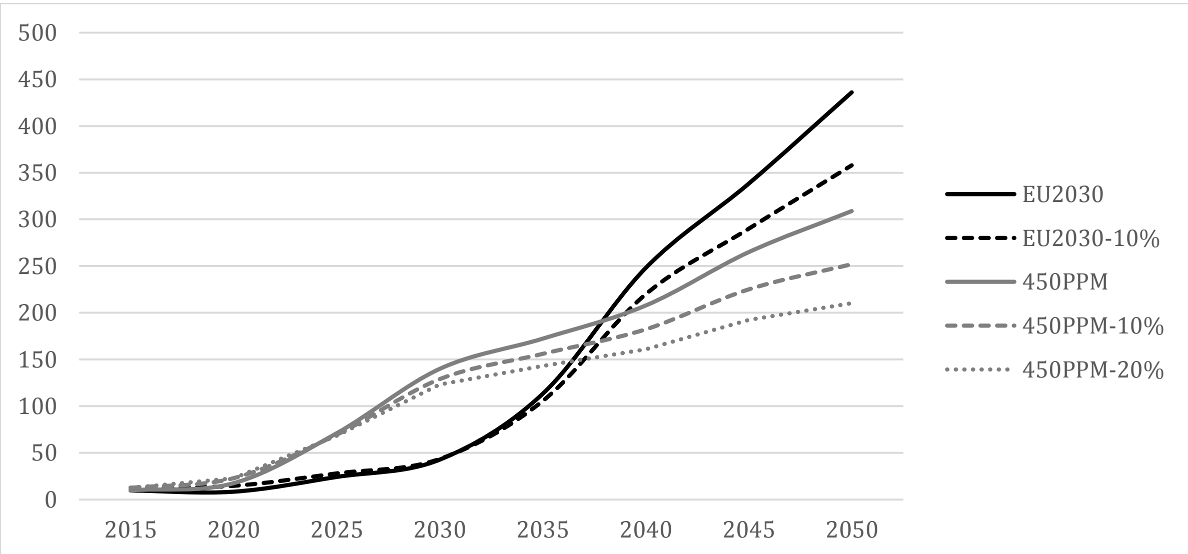
given that the timing of EU2030 targets involves a very steep increase in carbon price between 2030 and 2040 (Figure 8).

Table 8 – Comparison between EU2030 and 450PPM scenarios

	Year	EU2030	450PPM
CO_2 reduction w.r.t. 1990 level (%)	2030	40%	52%
	2050	77%	77%
Carbon tax level (USD per ton)	2030	43	140
	2050	436	309
GDP cumulated losses w.r.t. BAU (Mln USD)	2030	-310,985	-649,060
	2050	-3,653,781	-5,038,157
GDP growth rate (%)	2030	1.03	0.89
	2050	0.60	0.72
EV cumulated losses w.r.t. BAU (Mln USD)	2030	-266,954	-587,694
	2050	-2,748,704	-3,301,992
Energy consumption - Reduction w.r.t. BAU (%)	2030	-13.6	-25.7
	2050	-52.4	-52.7
Energy import-to-GDP ratio (Toe/Mln USD)	2030	2.13	1.76
	2050	0.64	0.64
Energy intensity (Mln USD/Toe)	2030	71.72	62.31
	2050	28.21	28.12

Source: our elaboration on GDynE results.

Figure 8 - Carbon Tax level for EU27 (US Dollars per ton)

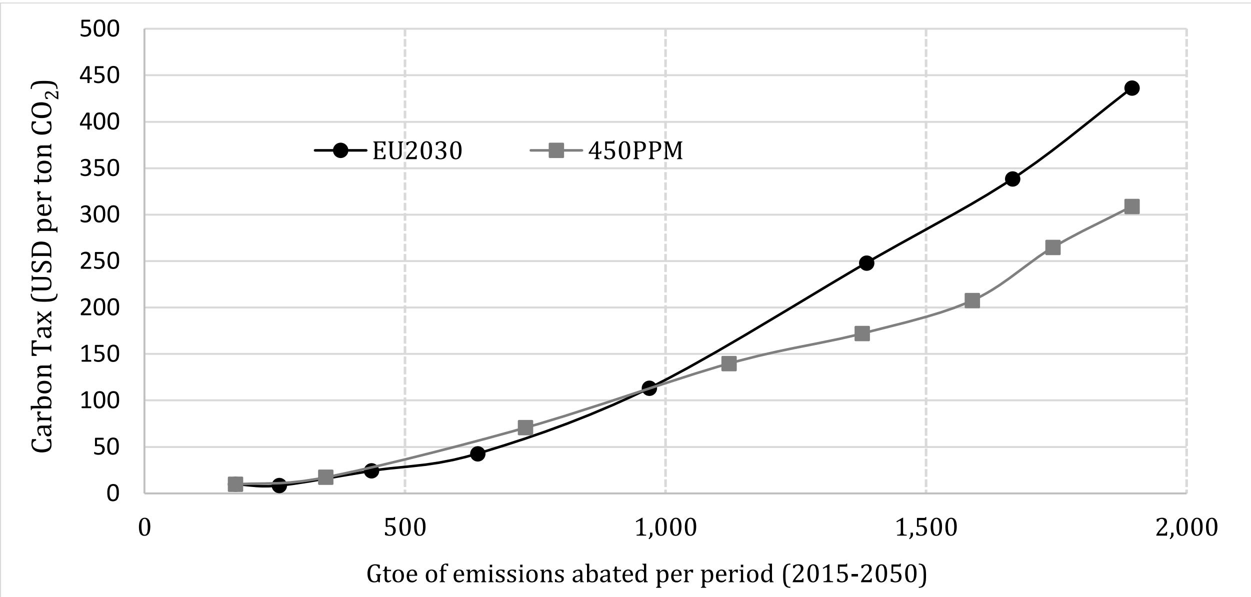


Source: our elaboration on GDynE results.

We also consider the energy security issue and look at several indicators, as the reduction in energy consumption, the ratio between energy import and GDP and the level of energy intensity (Table 8). According to all these indicators, the 450PPM strategy seems preferable over the EU2030, both in the medium (2030) and in the long term (2050).

As a further remark, we present in Figure 9 the MAC curves relative to the 450PPM and the EU2030 strategies. For an amount of emissions abated lower than 1,000 Gtoe the two reduction paths generate similar marginal costs, however, above this level, the EU2030 strategy allow achieving the same long run target but the cost of each further reduction if much higher than in the 450PPM scenario. Thus, as we have already noticed, from one side the more stringent target in 2030 according to this latter scenario determine higher GDP losses, nevertheless, on the other hand, it is also more cost effective in the long run, given the lower costs for additional emissions abated.

Figure 9 - Marginal abatement cost curves for EU27



Source: our elaboration on GDynE results.

Noticeably, the impact of the timing of the abatement targets is also linked to the effectiveness of the two policy measures related to energy efficiency and renewable energy. In fact, the more stringent the CO_2 objectives, the higher will be the required carbon tax level and the RD flow available to finance the RD in green technologies. Given that the core of the EU climate policy is the ETS, the introduction of additional goals or measures in term of energy efficiency and renewable energy should be designed considering the overall increase in term of effectiveness.

Hence, in this light of reasoning, we present in Table 9 a comparison among the three scenarios EU2030-10%, 450PPM-10% and 450PPM-20%. Given the same long run abatement targets, the GHG percentage reductions in 2030, coherently with the previous cases, are 40% in case of EU2030-10% and 52% in the two alternatives of the 450PPM scenario.

When first comparing the two scenarios with a 10% levy, we find similar results in term of carbon tax level and GDP growth rates as in Table 8. In fact, also in this case there is a threshold point above which the carbon tax in EU2030-10% scenario become much higher than the 450PPM-10% (see also Figure 8) and the GDP growth rate lower (see also Table A.9 in Appendix). Coherently, the 450PPM-20% scenario ensures lower carbon tax price and higher growth rate than the respective 10% case.

The interesting result is that in term of GDP, the 450PPM-10% scenario ensures to reach almost the same level as in the EU2030-10%, despite the fact that in the pure ETS cases without the levy on the carbon tax revenue the GDP level was sensibly higher if the EU2030 strategy applied (see Figure 5). Consistently, the cumulated GDP and welfare (EV) gains with respect to the pure ETS cases are much higher in the 450PPM cases (Table 9), suggesting that the more challenging the CO_2 abatement targets are, and higher will be the effectiveness of the RD investment in energy efficiency and renewable energies. Indeed, despite the different abatement targets, the reachable GDP level is the nearly same in both cases. Clearly, a higher percentage levy (450PPM-20%) ensures greater GDP and EV gains with respect to the pure ETS and 10% levy, both in the medium and long term horizon, and the absolute GDP level is also greater than in the BAU case (Figure 5), suggesting that such climate policy, beyond the positive mitigation benefits, can also deliver net economic benefits.

Finally, anticipating the timing of the emissions reduction seems also to be preferable in term of energy security given that the 27% increase in the energy efficiency level in 2030 is not reached following the EU2030-10% scenario, while both the 450PPM options ensure much more closer results.

Table 9 – Comparison between EU2030-10%, 450PPM-10% and 450PPM-20% scenarios

		EU2030-10%	450PPM-10%	450PPM-20%
CO_2 reduction w.r.t. 1990 level (%)	2030	40%	52%	52%
	2050	77%	77%	77%
Carbon tax level (USD)	2030	43	129	123
	2050	358	252	210
GDP cumulated gains w.r.t. ETS (Mln USD)	2030	266,779	526,023	1,086,425
	2050	2,658,602	3,645,444	6,602,011
GDP growth rate (%)	2030	1.08	1.04	1.15
	2050	0.78	0.82	0.86
EV cumulated gains w.r.t. ETS (Mln USD)	2030	1,208,450	2,102,250	4,139,200
	2050	10,975,380	13,323,580	22,761,570
Energy intensity (Mln USD/Toe)	2030	71.17	61.45	60.76
	2050	27.00	27.02	26.73

Source: our elaboration on GDynE results.

5. Conclusions

The aim of this work was to analyse the interactions among the different mitigation measures within the European climate strategy and their differences in term of cost effectiveness due to alternative timing of abatement targets. The analysis was based on the energy version of the GTAP model, namely GDynE, a dynamic CGE model with specific economic and energy data that also includes sector-specific and econometrically estimated values for the elasticity of substitution between capital and energy and between fuels. Additionally, we introduced a mechanism that, through a levy on the total carbon tax revenue, directly finances RD investment in energy efficiency and renewable sources in the electricity sector.

We consider several policy scenarios, which differ in term of mitigation measures and timing of the abatement targets. With respect to the former dimension, we distinguish between a pure market-based mechanism (ETS) from a policy mix including also specific support to energy efficiency and renewable energy enhancement through RD investment. Moreover, when accounting for the timing of CO_2 targets we consider a first scenario (named 450PPM) where the abatement rate is homogeneous in the whole period and ensures to reach the long run 2050 objective. On the other hand, the second policy scenario, coherent with the EU2030 framework, sets a lower short-term emissions reduction and the same 2050 target as in the 450PPM case. Hence, following this difference, we focused on the suitability of the newly approved European agenda to 2030 to allow EU to stay on track with respect to the 2050 long-term strategy.

Firstly, we compare policy scenarios sharing the same timing in abatement targets, a market-based mechanism including or not RD investment in green technologies. The increasing abatement targets over time produce an increase in carbon tax level, which ensures an increasing amount of RD investments. Therefore, by financing RD in green technologies through the introduction of an higher levy on the carbon tax revenue, the losses in term of GDP and welfare with respect to the baseline case reduce up to the point where efficiency gains are higher than losses due to the abatement costs (ultimately, applying a 20% levy ensures economic gains with respect to the baseline case).

When focusing on the sectoral differences, the results show that manufacturing sectors in general and energy-intensive activities in particular are negatively influenced by emissions reduction in ETS scenario. However, if a proper policy mix with RD in clean energy technologies is implemented (with the 10% or 20% levy), losses in output and export flows are consistently reduced. Indeed, combining the three mitigation measures increases the cost effectiveness of the policy mix, as suggested also by the profile of the Marginal Abatement Cost curves.

Additionally, the introduction of measures to foster energy efficiency and renewable energy technologies have also positive effect reducing the electricity price and the energy intensiveness of economic activities.

Furthermore, when considering the comparison among policy scenarios with different timing in abatement targets, a first evidence is that the choice on whether preferring or not to delay more stringent targets in the future, also depend on the selected mitigation options (*e.g.*, ETS alone or the three-measure policy). Indeed, when only the ETS is in place, postponing the achievement of more stringent CO_2 reduction seems preferable, however when introducing energy efficiency and renewable energy support the relative suitability of anticipating more challenging abatement targets seems to increase. Therefore, the time path of these emissions reductions influences the effectiveness of the RD investment in green technologies. Certainly, this is also due to the specific modelling strategy we used, where greater the emissions reduction are, higher will be the carbon tax level, together with the carbon tax revenue and the flow of public investment in RD activities. However, considering a policy maker perspective, this seems reasonable in term of the actual feasibility to propose strategies to finance RD investment in green technologies.

From a methodological perspective, several improvements can be pursed. In order to introduce a better representation of specific alternative technologies, which would better ensure the achievement of mitigation and technology innovation targets, further improvements may involve the linking with technology-specific models that distinguish between innovation and diffusion phases. Additionally, different assumptions about the percentage levy to be applied and the distribution of the RD flow between alternative green technologies can be analysied; they can also be endogenously determined when defining an optimal level to achieve a specific policy objective.

To conclude, while unilateral mitigation policy remains a second-best option to climate change, the introduction of additional measure with respect to a pure market-based mechanism can improve the economic efficiency of the overall policy mix. The threat of negative overlapping regulation can be avoided together with the risks of, *e.g*., rebound effect due to increasing energy efficiency or carbon leakage. However, an essential condition is the well-functioning of the market for carbon allowances, where no overallocation can occur and therefore an appropriate reduction to the maximum permitted emissions should be set, paying particular attention to energy-intensive and trade exposed economic activities. In this regard, if the measures proposed in the EU2030 framework to reduce the maximum number of allowances and the market stability reserve mechanism act properly, the introduction of energy efficiency and renewable energies support generate positive economic effects. The increased abatement efforts for the most polluting activities can help supporting the transition to a decarbonisation path, participating in RD financing in green technologies or reducing other distortive taxation. Hence, in this case, the introduction of further abatement measures in the aim of fostering technological change as energy efficiency and renewable energy may reduce the overall compliance costs and stimulate innovation.

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Appendix

Table A.1 - List of GDYnE countries

GTAP code	Code	Country	GTAP code	Code	Country	GTAP code	Code	Country
BRA	bra	Brazil	EU27	mlt	Malta	RAM	gtm	Guatemala
CAN	can	Canada	EU27	nld	Netherlands	RAM	hnd	Honduras
CHN	chn	China	EU27	pol	Poland	RAM	nic	Nicaragua
CHN	hkg	Hong Kong	EU27	prt	Portugal	RAM	pan	Panama
EExAf	xcf	Central Africa	EU27	rou	Romania	RAM	pry	Paraguay
EExAf	egy	Egypt	EU27	svk	Slovakia	RAM	per	Peru
EExAf	nga	Nigeria	EU27	svn	Slovenia	RAM	xca	Rest of Central America
EExAf	xnf	Rest of North Africa	EU27	esp	Spain	RAM	xna	Rest of North America
EExAf	zaf	South Africa	EU27	swe	Sweden	RAM	xsm	Rest of South America
EExAf	xac	South Central Africa	EU27	gbr	United Kingdom	RAM	ury	Uruguay
EExAm	arg	Argentina	FSU	blr	Belarus	RAS	arm	Armenia
EExAm	bol	Bolivia	FSU	rus	Russian Federation	RAS	bgd	Bangladesh
EExAm	col	Colombia	IDN	idn	Indonesia	RAS	bhr	Bharain
EExAm	ecu	Ecuador	IND	ind	India	RAS	khm	Cambodia
EExAm	ven	Venezuela	JPN	jpn	Japan	RAS	kgz	Kyrgyztan
EExAs	aze	Azerbaijan	KOR	kor	Korea	RAS	lao	Lao People's Democr. Rep.
EExAs	irn	Iran Islamic Republic	MEX	mex	Mexico	RAS	mng	Mongolia
EExAs	kaz	Kazakhstan	NOR	nor	Norway	RAS	npl	Nepal
EExAs	kwt	Kuwait	RAF	bwa	Botswana	RAS	xea	Rest of East Asia
EExAs	mys	Malaysia	RAF	cmr	Cameroon	RAS	xoc	Rest of Oceania
EExAs	omn	Oman	RAF	civ	Cote d'Ivoire	RAS	xsa	Rest of South Asia
EExAs	qat	Qatar	RAF	eth	Ethiopia	RAS	xse	Rest of Southeast Asia
EExAs	xsu	Rest of Former Soviet Union	RAF	gha	Ghana	RAS	sgp	Singapore
EExAs	xws	Rest of Western Asia	RAF	ken	Kenya	RAS	lka	Sri Lanka
EExAs	sau	Saudi Arabia	RAF	mdg	Madagascar	RAS	twn	Taiwan
EExAs	are	United Arab Emirates	RAF	mwi	Malawi	RAS	pak	Pakistan
EU27	aut	Austria	RAF	mus	Mauritius	RAS	phl	Philippines
EU27	bel	Belgium	RAF	moz	Mozambique	RAS	tha	Thailand
EU27	bgr	Bulgaria	RAF	nam	Namibia	RAS	vnm	Vietnam
EU27	cyp	Cyprus	RAF	xec	Rest of Eastern Africa	REU	alb	Albania
EU27	cze	Czech Republic	RAF	xsc	Rest of South African Custom	REU	hrv	Croatia
EU27	dnk	Denmark	RAF	xwf	Rest of Western Africa	REU	geo	Georgia
EU27	est	Estonia	RAF	sen	Senegal	REU	xee	Rest of Eastern Europe
EU27	fin	Finland	RAF	tza	Tanzania	REU	xef	Rest of EFTA
EU27	fra	France	RAF	uga	Uganda	REU	xer	Rest of Europe
EU27	deu	Germany	RAF	zmb	Zambia	REU	xtw	Rest of the World
EU27	grc	Greece	RAF	zwe	Zimbabwe	REU	tur	Turkey
EU27	hun	Hungary	RAF	mar	Morocco	REU	ukr	Ukraine
EU27	irl	Ireland	RAF	tun	Tunisia	ROECD	aus	Australia
EU27	ita	Italy	RAM	xcb	Caribbean	ROECD	isr	Israel
EU27	lva	Latvia	RAM	chl	Chile	ROECD	nzl	New Zealand
EU27	ltu	Lithuania	RAM	cri	Costa Rica	ROECD	che	Switzerland
EU27	lux	Luxembourg	RAM	slv	El Salvador	USA	usa	United States of America

Table A.2 - List of GDYnE commodities and aggregates

Sector	Code	Products	Sector	Code	Products
agri	pdr	paddy rice	wood	lum	wood products
agri	wht	wheat	paper	ppp	paper products, publishing
agri	gro	cereal grains nec	oil_pcts	p_c	petroleum, coal products
agri	v_f	vegetables, fruit, nuts	chem	crp	chemical, rubber, plastic products
agri	osd	oil seeds	nometal	nmm	mineral products nec
agri	c_b	sugar cane, sugar beet	basicmet	i_s	ferrous metals
agri	pfb	plant-based fibers	basicmet	nfm	metals nec
agri	ocr	crops nec	basicmet	fmp	metal products
agri	ctl	bovine cattle, sheep and goats, horses	transeqp	mvh	motor vehicles and parts
agri	oap	animal products nec	transeqp	otn	transport equipment nec
agri	rmk	raw milk	macheqp	ele	electronic equipment
agri	wol	wool, silk-worm cocoons	macheqp	ome	machinery and equipment nec
agri	frs	forestry	oth_man_ind	omf	manufactures nec
agri	fsh	fishing	electricity	ely	electricity
Coal	coa	coal	gas	gdt	gas manufacture, distribution
Oil	oil	oil	services	wtr	water
Gas	gas	gas	services	cns	construction
nometal	omn	minerals nec	services	trd	trade
food	cmt	bovine cattle, sheep and goat meat products	transport	otp	transport nec
food	omt	meat products	wat_transp	wtp	water transport
food	vol	vegetable oils and fats	air_transp	atp	air transport
food	mil	dairy products	services	cmn	communication
food	pcr	processed rice	services	ofi	financial Oth_Ind_serices nec
food	sgr	sugar	services	isr	insurance
oth_man_ind	ofd	Oth_Ind_ser products nec	services	obs	business and other services nec
food	b_t	beverages and tobacco products	services	ros	recreational and other services
textile	tex	textiles	services	osg	public admin. and defence, education, health
textile	wap	wearing apparel	services	dwe	ownership of dwellings
textile	lea	leather products			

Table A.3 - List of GDYnE Regions

GTAP code	Description
CAN	Canada
EU27	European Union
FSU	Former Soviet Union
JPN	Japan
KOR	Korea
NOR	Norway
USA	United States
ROECD	Rest of OECD
BRA	Brazil
CHN	China
IND	India
IDN	Indonesia
MEX	Mexico
EExAf	African Energy Exporters
EExAm	American Energy Exporters
EExAs	Asian Energy Exporters
RAF	Rest of Africa
RAM	Rest of America
RAS	Rest of Asia
REU	Rest of Europe

Table A.4 - List of GDYnE aggregates

Sector	Description
agri	Agriculture
food	Food
coal	Coal
oil	Oil
gas	Gas
oil_pcts	Petroleum, coal products
electricity	Electricity
text	Textile
nometal	Non-metallic mineral products
wood	Wood
paper	Pulp and paper
chem	Chemical and petrochemical
basicmet	Basic metal
transeqp	Transport equipment
macheqp	Machinery and equipment
oth_man_ind	Other manufacturing industries
transport	Transport
wat_transp	Water Transport
air_transp	Air Transport
services	Services

Table A.5 - Baseline GDP Projections to 2050 (Bln constant USD)

	2010	2015	2020	2025	2030	2035	2040	2045	2050	Growth p.a.
CAN	1,424	1,668	1,893	2,092	2,286	2,493	2,707	2,924	3,145	2.1%
EU27	16,489	18,302	20,051	21,451	22,627	23,714	24,823	25,943	27,080	1.3%
FSU	1,344	1,589	1,858	2,105	2,346	2,580	2,782	2,937	3,065	2.2%
JPN	4,186	4,575	4,895	5,173	5,379	5,500	5,546	5,592	5,641	0.8%
KOR	1,100	1,316	1,474	1,595	1,686	1,759	1,817	1,863	1,896	1.4%
NOR	393	427	472	522	572	621	672	728	786	1.8%
USA	13,947	15,868	17,779	19,633	21,548	23,565	25,656	27,799	29,986	2.0%
ROECD	1,646	1,861	2,071	2,267	2,459	2,660	2,872	3,099	3,330	1.8%
BRA	1,474	1,753	2,077	2,421	2,775	3,137	3,500	3,863	4,223	2.8%
CHN	4,687	7,157	10,602	15,128	20,630	26,893	33,517	40,130	46,321	6.8%
IND	1,482	2,091	2,925	4,068	5,591	7,558	9,996	12,872	16,119	7.0%
IDN	498	648	848	1,104	1,421	1,802	2,250	2,769	3,361	5.4%
MEX	995	1,233	1,478	1,733	1,985	2,219	2,432	2,636	2,830	2.8%
EExAf	889	1,117	1,408	1,785	2,273	2,902	3,702	4,722	6,039	5.4%
EExAm	801	942	1,126	1,326	1,542	1,772	2,014	2,266	2,525	3.1%
EExAs	1,723	2,092	2,529	3,026	3,559	4,125	4,708	5,297	5,898	3.3%
RAF	571	733	953	1239	1627	2102	2692	3400	4271	5.7%
RAM	753	912	1,087	1,278	1,489	1,750	2,049	2,380	2,746	3.5%
RAS	1528	1932	2457	3112	3924	4927	6151	7631	9394	5.1%
REU	962	1,152	1,379	1,612	1,842	2,063	2,269	2,459	2,638	2.7%
World	56,893	67,366	79,362	92,669	107,560	124,142	142,154	161,311	181,294	3.1%
Developing	16,364	21,760	28,869	37,832	48,658	61,250	75,279	90,427	106,366	5.3%
Developed	40,529	45,606	50,493	54,836	58,902	62,892	66,875	70,884	74,928	1.6%

Source: our elaboration on GDynE results.

Table A.6 - Baseline CO_2 Projections to 2050 (Gt CO_2)

	2010	2015	2020	2025	2030	2035	2040	2045	2050	% Change 2010-2050
CAN	0.53	0.58	0.65	0.66	0.66	0.66	0.67	0.68	0.70	30.2%
EU27	3.67	3.52	3.31	3.20	3.12	3.01	2.95	2.86	2.83	-22.7%
FSU	1.62	1.70	1.75	1.84	1.89	1.96	2.05	2.06	2.09	28.9%
JPN	1.11	1.11	1.10	1.09	1.08	1.05	1.04	1.02	1.01	-8.7%
KOR	0.48	0.51	0.56	0.57	0.56	0.53	0.51	0.50	0.50	4.1%
NOR	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.07	8.4%
USA	5.36	5.33	5.31	5.29	5.29	5.27	5.27	5.22	5.19	-3.3%
ROECD	0.51	0.54	0.62	0.61	0.59	0.57	0.55	0.53	0.53	2.9%
BRA	0.35	0.39	0.47	0.52	0.56	0.61	0.65	0.71	0.81	130.9%
CHN	7.19	9.42	11.58	12.80	13.76	14.33	14.42	14.51	14.78	105.6%
IND	1.59	1.93	2.37	3.03	3.62	4.21	4.77	5.28	5.75	261.7%
IDN	0.41	0.48	0.54	0.60	0.69	0.75	0.79	0.86	0.95	133.4%
MEX	0.41	0.41	0.45	0.45	0.45	0.46	0.46	0.47	0.47	15.9%
EExAf	0.70	0.84	1.04	1.18	1.27	1.39	1.50	1.61	1.76	151.0%
EExAm	0.41	0.49	0.59	0.67	0.75	0.82	0.88	0.93	0.99	139.9%
EExAs	2.06	2.49	3.07	3.49	3.82	4.13	4.43	4.82	5.28	156.5%
RAF	0.19	0.20	0.25	0.30	0.36	0.41	0.49	0.58	0.75	300.3%
RAM	0.29	0.31	0.38	0.44	0.50	0.50	0.48	0.49	0.52	80.8%
RAS	1.14	1.45	1.92	2.23	2.49	2.72	3.06	3.44	3.88	240.1%
REU	0.63	0.70	0.82	0.87	0.89	0.92	0.96	1.01	1.09	74.0%
World	28.71	32.48	36.84	39.90	42.39	44.38	46.00	47.67	49.95	74.0%
Developing	15.36	19.13	23.47	26.56	29.14	31.24	32.90	34.72	37.04	141.1%
Developed	13.35	13.35	13.37	13.34	13.25	13.14	13.10	12.95	12.91	-3.3%

Source: our elaboration on GDynE results.

Table A.7 - Changes in output value from BAU for EU27 (%)

	2015	2020	2025	2030	2035	2040	2045	2050
				450PPM				
Non-metallic minerals	0.03	-0.01	-0.06	-0.22	-0.58	-1.09	-1.63	-2.10
Chemical	0.02	-0.13	-0.37	-0.96	-2.02	-3.53	-5.28	-6.80
Basic metals	0.01	-0.41	-1.22	-3.30	-6.35	-9.76	-12.87	-15.02
Pulp and Paper	0.03	-0.04	-0.11	-0.37	-0.80	-1.26	-1.71	-2.11
Transport eqp.	0.02	-0.08	-0.24	-0.66	-1.37	-2.27	-3.13	-3.76
Machinery eqp.	0.03	-0.01	-0.11	-0.25	-0.78	-2.09	-3.53	-4.38
				450PPM-10%				
Non-metallic minerals	0.05	0.04	0.05	0.00	-0.11	-0.24	-0.36	-0.44
Chemical	0.04	-0.01	-0.09	-0.39	-0.83	-1.37	-1.93	-2.40
Basic metals	0.03	-0.39	-1.04	-2.60	-4.36	-5.81	-6.77	-6.99
Pulp and Paper	0.03	0.04	0.08	0.08	0.02	-0.05	-0.13	-0.18
Transport eqp.	0.02	-0.05	-0.15	-0.42	-0.81	-1.20	-1.50	-1.59
Machinery eqp.	0.06	-0.05	-0.23	-0.68	-1.33	-2.10	-2.65	-2.69
				450PPM-20%				
Non-metallic minerals	0.05	0.07	0.14	0.22	0.33	0.45	0.60	0.73
Chemical	0.04	0.09	0.18	0.24	0.34	0.48	0.67	0.74
Basic metals	0.03	-0.33	-0.71	-1.59	-2.16	-2.16	-1.70	-0.84
Pulp and Paper	0.03	0.13	0.28	0.52	0.75	0.93	1.07	1.19
Transport eqp.	0.02	0.01	0.00	-0.10	-0.20	-0.22	-0.16	0.04
Machinery eqp.	0.06	-0.12	-0.36	-0.91	-1.50	-1.78	-1.71	-1.26

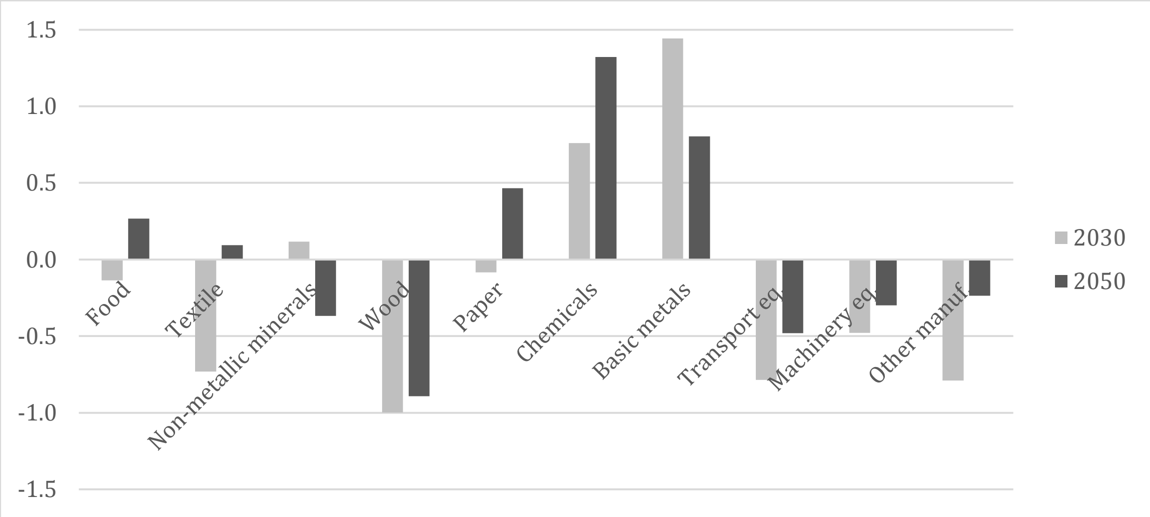
Source: our elaboration on GDynE results.

Table A.8 - Changes in export value from BAU for EU27 (%)

	2015	2020	2025	2030	2035	2040	2045	2050
				450PPM				
Non-metallic minerals	-0.20	-0.55	-1.62	-3.33	-5.18	-7.03	-8.50	-9.71
Chemical	-0.18	-0.49	-1.27	-2.67	-4.69	-7.08	-9.12	-10.95
Basic metals	-0.65	-1.83	-4.98	-9.55	-14.37	-18.79	-21.69	-23.80
Pulp and Paper	-0.08	-0.24	-0.64	-1.27	-2.15	-3.18	-4.06	-4.75
Transport eqp.	0.00	-0.11	-0.23	-0.54	-1.37	-2.40	-3.20	-3.69
Machinery eqp.	0.16	0.19	0.69	0.97	-0.30	-2.22	-3.51	-4.12
				450PPM-10%				
Non-metallic minerals	-0.19	-0.53	-1.45	-2.71	-3.84	-4.78	-5.36	-5.76
Chemical	-0.01	-0.13	-0.52	-1.14	-1.92	-2.76	-3.47	-4.04
Basic metals	-0.59	-1.51	-3.73	-6.28	-8.36	-9.80	-10.16	-10.07
Pulp and Paper	-0.04	-0.15	-0.49	-0.90	-1.27	-1.59	-1.72	-1.70
Transport eqp.	-0.01	-0.14	-0.49	-0.95	-1.53	-2.06	-2.27	-2.22
Machinery eqp.	0.05	-0.17	-0.70	-1.56	-2.82	-3.99	-4.35	-4.15
				450PPM-20%				
Non-metallic minerals	-0.17	-0.42	-1.14	-2.00	-2.57	-2.86	-2.92	-2.87
Chemical	0.12	0.23	0.30	0.39	0.47	0.62	0.60	0.62
Basic metals	-0.46	-0.93	-2.07	-2.82	-2.84	-2.27	-1.19	0.02
Pulp and Paper	-0.02	-0.07	-0.27	-0.41	-0.36	-0.18	0.15	0.57
Transport eqp.	-0.06	-0.21	-0.61	-1.07	-1.37	-1.50	-1.30	-0.91
Machinery eqp.	-0.21	-0.69	-1.83	-3.16	-4.13	-4.59	-4.22	-3.46

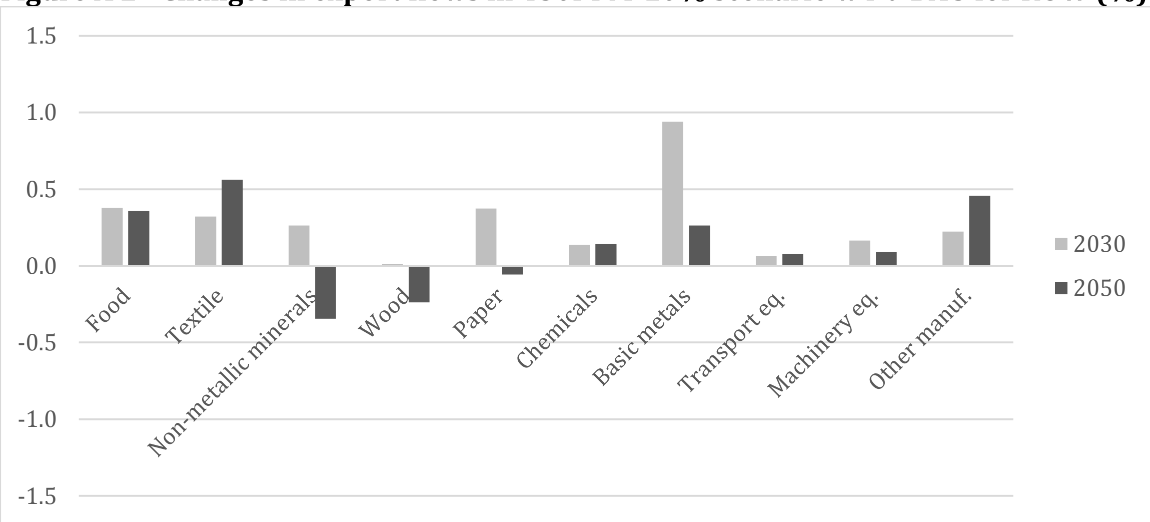
Source: our elaboration on GDynE results.

Figure A.1 - Changes in export flows in 450PPM scenario w.r.t. BAU for ROW (%)



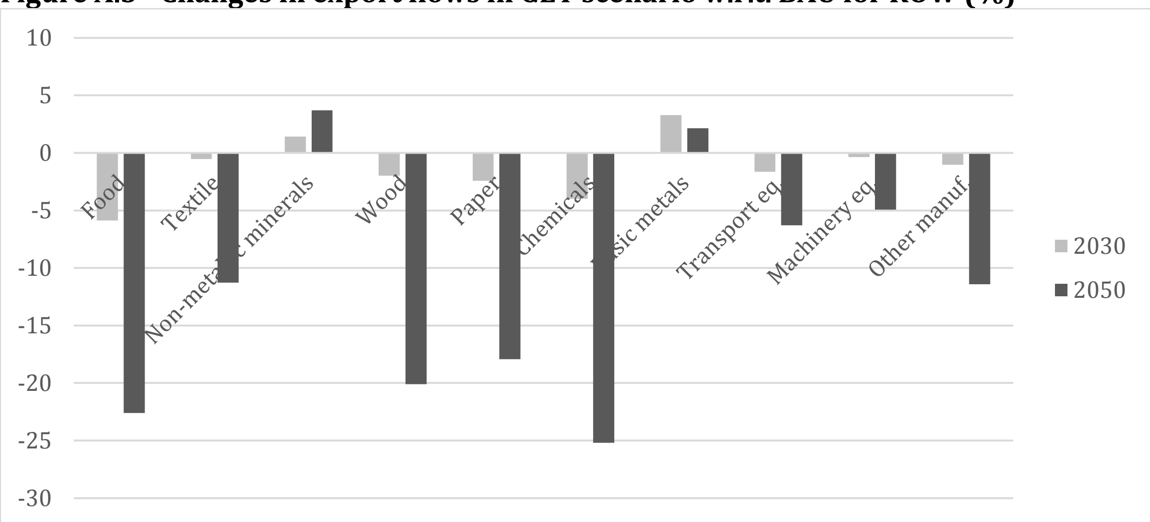
Source: our elaboration on GDynE results.

Figure A.2 - Changes in export flows in 450PPM-10% scenario w.r.t. BAU for ROW (%)



Source: our elaboration on GDynE results.

Figure A.3 - Changes in export flows in GET scenario w.r.t. BAU for ROW (%)



Source: our elaboration on GDynE results.

Table A.9 - GDP growth rate (%)

	2015	2020	2025	2030	2035	2040	2045	2050
EU2030	2.18	1.89	1.35	1.03	0.82	0.69	0.62	0.60
EU2030-10%	2.20	1.91	1.39	1.08	0.93	0.86	0.80	0.78
450PPM	2.18	1.87	1.28	0.89	0.73	0.72	0.71	0.72
450PPM-10%	2.20	1.91	1.37	1.04	0.89	0.87	0.84	0.82
450PPM-20%	2.23	1.95	1.46	1.15	0.99	0.95	0.90	0.86

Source: our elaboration on GDynE results.

Conclusion

Energy policies play a crucial role in climate change mitigation given that, through the reduction of fossil fuels consumption and the diffusion of low carbon technologies, promote the abatement of greenhouse gases and the transition to a decarbonisation of the global economic system. Moreover, although the relevance of the climate change problem is now widely accepted and several international initiatives attempt to take coordinated actions, a truly global regime to emissions reduction and mitigation is still missing. The deadlock in the international negotiation demonstrates this, and among the main reasons, there are the alternative positions of Annex I and Non-Annex parties, as well as those between the biggest emerging economies and least developed countries. As a result, several Nations and regions, as the European Union, have committed themselves to adopt binding emissions reduction targets and started to implement unilateral measures. The impacts of those policies with respect to the environmental, economic and social dimensions depend on the specific measures adopted but also on the internal economic structure. In fact, as the International Energy Agency highlighted, "[changes] in relative energy costs across countries not only affects industrial and energy competitiveness but also economic competitiveness. The extent to which an increase, relative to other economies, in the pre-tax price of energy undermines economic competitiveness depends largely on the extent to which a given country relies on energy-intensive manufacturing, as well as the scope for higher prices to be offset by economically viable investments towards greater energy efficiency" (World Energy Outlook, IEA 2013, p.293).

In this context, the aim of the present work was to analyse the current European energy and climate change agenda, its potential impacts in term of economic and energy competitiveness, and their distribution with respect to alternative sectoral activities. A further investigated aspect is the complementarity among different mitigation measures also with respect to the timing of the abatement targets. In doing so, the study relied on an applied dynamic climate-economy, on which, validation and robustness checks have previously been conducted.

Summing up, the research objectives are threefold. First, the Capital-Energy elasticity of substitution at the sector level in manufacturing industries have been econometrically estimated from a panel of 21 OECD countries (1990-2008). Then, a sensitivity analysis of the dynamic energy CGE model GDynE has been conducted together with the evaluation of the environmental and economic impacts of energy and CO_2 policies given the technological differences across manufacturing sectors. Finally, the last part of the work includes an assessment of EU2030 climate strategy, considering the complex policy mix in term of effectiveness of alternative policy measures, overlapping regulation and relevance of the timing of abatement targets.

Results from the elasticity estimations show that the energy long-run elasticity values for specific manufacturing sectors are highly heterogeneous with respect to the elasticity value computed on the aggregate manufacturing sector. Consequently, energy intensive sectors may require specific complementary energy conservation policies in order to be compliant with emission targets. This heterogeneity in the energy relationships for distinguished manufacturing sectors suggests that when energy applied models are used, a distinction in behavioural parameters for sectors that behave differently in term of energy stringency target is necessary in order to obtain reliable policy evaluations.

The heterogeneity in the values of the elasticity of substitution between energy and capital, which represents the energy-related technological flexibility, shows that the distinction between energy-intensive and non-energy-intensive sectors behaviour is less clear. Therefore, switching to a low-carbon technological path may generate high economic costs if this degree of technological flexibility, which directly affects the costs of achieving emission targets, is not considered.

Then, when analysing the sensitivity of the dynamic CGE GDynE model, we accounted for the impacts of changes in substitution elasticities on abatement costs, the distribution of the effects among countries and sectors and the cost effectiveness of the different policy measures. In particular, we focused on two classes of behavioural parameters: the elasticity of substitution between energy and capital and between different types of energy sources (inter-fuel substitution). Both types of parameters are responsible for the variation in results and the different distribution of impacts and, as general remark, a reduction in the flexibility of energy substitution possibilities makes abatement efforts more expensive. In fact, as the differences at the aggregate level in GDP, carbon tax level and Marginal Abatement Costs show, the restrictions in the substitution possibilities in the energy nests generate changes in the magnitude and distribution of the abatement costs.

In particular, a higher (lower) technological flexibility determines, on average, a decrease (increase) in carbon intensity at the world level. However, at lower regional level, an increase in substitutability is not necessarily linked with a reduction in carbon intensity and a different distribution of the abatement costs occurs. Hence, restrictions in substitution possibilities in the energy nests generate changes in the distribution of costs associated with the abatement efforts with regard to the two regional groups considered. Therefore, changes in flexibility in energy use generate different regional impacts, where the internal economic structure can intensify the differences induced by the sectoral parameters. Furthermore, changes in parameters value have large impacts in terms of distributive effects, given that there are significant differences also considering the value of production across sectors and regions.

In the third part of the work, the interactions among the several mitigation measures within the European strategy to 2030 and the differences in term of cost effectiveness due to alternative timing of abatement targets have been considered. Given that the increasing abatement targets over time generate an increase in carbon tax level, financing RD in green technologies through a levy on the carbon tax revenue can reduce the losses in term of GDP and welfare and eventually ensures gains with respect to the baseline case.

Considering the differences among economic activities, manufacturing sectors in general and energy-intensive activities in particular are negatively influenced by emissions reduction through a pure market-based mechanism. However, as the Marginal Abatement Cost curves show, if a proper policy mix with RD in clean energy technologies is implemented, losses in output are consistently reduced.

Furthermore, when considering the alternative timing in abatement targets, if only the ETS is implemented, postponing the achievement of more stringent CO_2 reduction seem preferable, however when introducing energy efficiency and renewable energy support, the relative suitability of anticipating more challenging target seems to increase.

Two main types of implications follow from this analysis. Firstly, from a methodological perspective, although applied energy and climate models, as CGE, are widely used in supporting climate change and energy policies analysis, they need to be improved with more detailed technological information. Economic sectors are highly differentiated in term of energy intensity, dependence on energy sources and technological flexibility. Indeed, as the sensitivity analysis shows, there is high variability in the model results with respect to economic costs of mitigation policies and distribution across regions. Because this is due to different behavioural parameters, econometric validation of the sectoral heterogeneity is needed and further improvements to this type of models are highly recommended in order to increase the reliability of policy simulation results. In particular, given the regional differences in reacting to common sector-specific elasticity values, there is a need to empirically estimate energy-related behavioural parameters for specific country or region, at the highest disaggregation level compatible with available data.

Additionally, in order to introduce a better representation of alternative technologies that would favour the achievement of mitigation and technology innovation targets, a further improvement may be the linking of macro models (as CGE) with technology-specific models that consider, for example, specific abatement potentials of alternative technologies, also distinguishing between innovation and diffusion phases. This would allow a more detailed representation of the impacts of primary extraction of energy resources, processing and conversion of energy services, delivery to consumers and, above all, the innovation and diffusion of clean technologies. Moreover, linking macro CGE models with bottom-up energy models can also provide more realistic representations of the relation between public RD investment and sectoral gains in term of energy efficiency or the reactivity of the electricity sector to renewable energy development. Additionally, different assumptions about the percentage levy applied and the distribution of the RD flow between alternative green technologies can be analysied; they can also be endogenously determined when defining the optimal level necessary to achieve a particular policy objective. Further investigation should also be carried about how to shape in dynamic terms the optimal distribution among alternative green technologies (here simplified between energy efficiency and renewable energy sources), with respect to a cost effectiveness principle or other policy objectives.

Secondly, in term of policy implication, when considering the allocation of abatement targets between different sectors and the specific measures to reach them, the sector-specific degree of flexibility in energy use, together with the regional economic structure, contributes in determining the country's effectiveness to reach the climate goals. Heterogeneity in the technological flexibilities should be taken into consideration when defining distribution of abatement targets and the policy mix. This is also coherent with the argument made by the EC in the communication of the EU2030 agenda when, highlighting the crucial role of the EU ETS and the energy efficiency measures, suggests that priority sectors will be proposed considering where major energy efficiency gains can be achieved.

Finally, while unilateral mitigation policy remains a second-best option to climate change, the introduction of additional measure with respect to a pure market-based mechanism as the EU ETS can improve the economic efficiency of the overall policy mix and reduce the threat of negative impacts of overlapping regulation. Recycling the revenue gathered from carbon taxation or from the auctioning of ETS allowances to finance the introduction of further abatement measures, fostering green technologies, may reduce the compliance costs and stimulate innovation. Alternatively, it can help reducing the burden of other distortive taxes, *e.g.*, those on labour, as the double dividend hypothesis suggests, or provide helpful resources to those sectors or to the most efficient installations subject to the risk of carbon leakage due to increasing carbon costs (as remarked by the EC in the EU2030 communication). However, for all of this to work, as the increasing reduction to the maximum permitted emissions and the market stability reserve suggest, a necessary condition is the well-functioning of the ET ETS, where no overallocation can occur allowing the market price to properly sustain the transition to a decarbonised economy in the short but also in the long run.