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Industrial Ecology for Sustainable Energy Transition: the Role of Carbon Emission Reduction Mechanisms

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Foreword

Disregarding the heat waves that are hitting Europe at the time of writing (mid 2022), when reading about how the International Panel on Climate Change (IPCC) depicts the projections of temperature, sea hights and frequency and intensity of extreme weather events in 2100 it usually looks too far for being a concern for the average man or woman of the third millennium [1–3]. The perspective may change if we think about the lives of the ones we love.

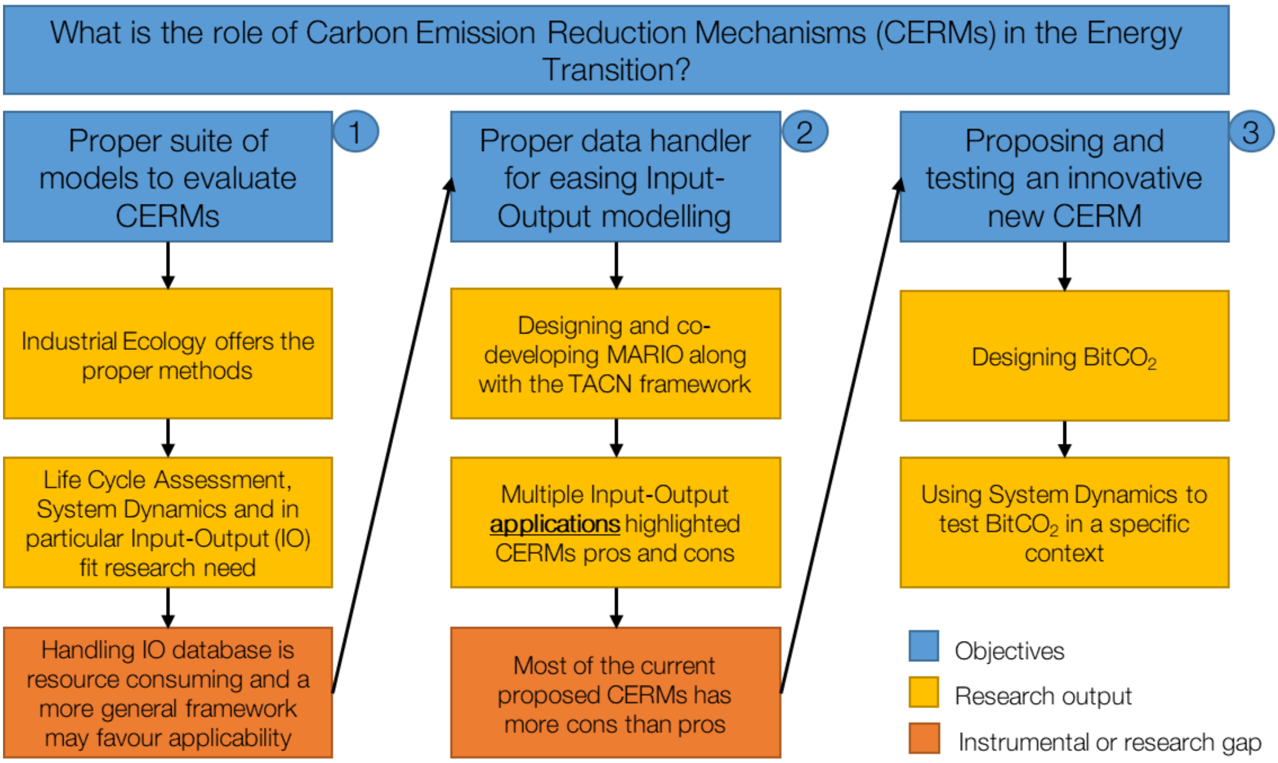
During these 3 and a half years working on the research that has been condensed into this PhD dissertation, I have been so lucky to become an uncle. Noah, my nephew, is now 18 months old and in 2100 he will be slightly older than my grandmom Ada. In Figure 0.1, you can see her falling in love with her grand-grandson.

Figure 0.1 – My grandmom Ada and my nephew Noah.

In the timespan of a few generations, the effects of our today's decisions will very likely make a huge difference for Noah's future possibility. Would he be able to come and spend the hottest weeks of the year in the apartment where I am currently writing, or it will be flooded by the already very closed Adriatic Sea? The answer to this question and other more dramatic ones for millions of newly born people – not only concerning climate change – is highly dependent on the actions we are going to take today and in the next few decades [4]. Furthermore, even if today's decisions are going to address the issue of climate mitigation, what would be the consequences that he may face considering all the dimensions of sustainability?

Energy, **e**mission reduction, and – more broadly – **e**cology problems must be addressed for the future of ours and, more importantly, the **next gen**erations.

Graphical Abstract



Abstract

We live in an increasingly interconnected society, in which the role of energy has always played and will continue to play a fundamental role being one of the main drivers of economic growth and have enabled past industrial revolutions. The use of natural resources is largely represented by the exploitation of fossil energy resources, which over the last century has allowed economic development in many areas of the world, but at the same time has increased emissions of greenhouse gases and polluting gases.

Today, a growing number of countries, predominantly those with high per capita income, are making efforts to significantly reduce CO_2 emissions into the atmosphere. The general objective of this research is to investigate the role of carbon emission reduction mechanisms (CERMs) in the energy transition. In particular, the focus is on the role that carbon pricing policies can play in changing consumption, production, and investment choices within the sustainable energy transition.

An informed decision-making process, supported by multiple modelling approaches, is essential and may be pivotal to supporting the guidance for the needed decarbonisation pathway. Few models explicitly consider the sector-by-sector representation of the meso-economic relations that are physically constraining the dynamic evolution of global economic activities by a clear representation of supply chains. Therefore, as highlighted in the literature, the need for a proper modelling framework arises. The identification of a suite of models aimed at properly assessing the role of carbon emission reduction policies represents the **first specific objective** of this work. Input-Output (IO) analysis, currently experiencing a renaissance driven by increasing improvement in accounting, represents one of the most appropriate methods to capture the complex interconnections within and among economy and ecology. Nevertheless, the applicability and reproducibility of studies may be hampered by data handling, also driven by improvements in databases' detail. Therefore, the **second specific objective** of this thesis is the development of a data management tool to perform transparent and reproducible IO studies. Finally, on the path towards achieving the first two specific objectives, several findings on different CERMs have been collected. The definition and the testing of an innovative and efficient carbon emission reduction mechanism identify the **third** and last **specific objective**.

The IO framework has been proved scientifically robust in providing useful insights on how different carbon emission strategies can impact global emission reduction and on other environmental and socio-economic dimensions.

Different research questions raise the need for the proper set of the proper IO model. Developing a tool capable of easily setting the scope and the detail of an IO model (called MARIO) and extending the classic Supply and Use framework – introducing the accounting of *needs* and *technologies* – simplified enormously the rigorous application of these methodologies.

Applying multiple policy approaches within diverse socio-economic contexts shaped the proposal of innovative CERM called BitCO_2. Having an individual (vs. national), consumption-based (vs. production-based), and incentivizing (vs. coercive) CERMs offer multiple advantages that can justify its practical implementation. This has been tested for a specific carbon-intensive and hard-to-abate sector (i.e. Italian private transportation) adopting a life-cycle methodology and a system dynamics model developed for the purpose.

1. Introduction

The urgency of abating the primal driver behind the increase in temperature that planet Earth has experienced in the latest decades is pushing for the so-called Energy Transition [5]. The Energy Transition consists in rethinking and implementing a new way to supply enough energy in a cost-efficient, socially just, and close-to-zero emission way. According to the recent literature review, analysing more than 600 energy system modelling research, it is technically feasible to run the energy system relying heavily on low-carbon technologies [5–7]. Nevertheless, challenges associated with the impact on social, environmental, and economic dimensions are still under debate.
The first years of the 20s of the third millennium have experienced multiple disruptive events which have required rapid changes concerning precedent years' business as usual. The first waves of the COVID-19 pandemic experienced in 2020 have required unprecedented temporary changes in behaviour [8]. This has impacted a rapidly changing demand pattern that together with the decisions of central banks of supporting financially businesses and consumers after the COVID pandemic has resulted in a level of inflation that has reached the highest levels in 40 years [9,10]. In early 2022 Russian' invasion of Ukraine contributed to further pushing the cost of fossil fuels and other food-related commodities [11]. All of these events are reminding policy-makers how big and interconnected are the challenges of today's complex world.
In the 1980s, the ambiguities already surrounding the concept of economic development became even more present when the Brutland Report was discussed, popularizing the term "sustainable development" [12]. Generally speaking, sustainable development is the development that does not harm the natural world thus without compromising the needs of future generations, but the implicit discretion that is coming with the definition makes it impossible to have unambiguous criteria for judging the degree of success or failure of any specific development effort. Even a wise weighting of indicators cannot free the definition of sustainable development from its subjectivity, being the choice and the adopted weights discretionary [12]. It is possible to start from disaggregation of impacts, identifying multiple levels of analysis: the economic, the social, and the environmental ones.
To support carbon emission mitigation while keeping other fundamental aspects of human life within the levels of dignity identified by the Sustainable Development Goals (SDGs), the Energy Transition should represent a part of a broader concept of a Sustainable Transition.
To estimate the impacts of today's action on the multiple levels of sustainability, a proper Industrial Ecology approach must be embraced. That is the starting point for understanding the role of carbon pricing in internalizing the impacts of carbon emissions on today's decisions. An innovative way to price carbon within today's decision has represented the starting and closing point of this thesis. In fact, this research can also be seen as a journey from a naïve intuition I had in 2016 into something scientifically sound that will hopefully become an actual solution for contributing to carbon emission reduction.
The work is organized as follows. Firstly, this introduction is substantiated by a deepening of the two main directions that this research is considering. On the one hand, evaluating multiple impacts of technology or changes in the economy is discussed. On the other hand, past and future approaches for internalizing the social cost of carbon are introduced. At this point, it is possible to get the relevance of the research questions of this research. After that, a literature review is provided, intended as a guide for introducing all the concepts that have been adopted and expanded during the development of this work. Thirdly, the methodological advancements are presented. Then, several applications of the introduced methodologies are reported to highlight key issues regarding carbon emission reduction mechanisms. This section contains some publications made during these

years. Finally, the chapter on the innovative carbon emission reduction mechanisms is presented with a conclusion, limits, and key findings from applications.

1.1. The multidimensional aspects of sustainable transition

Many pledges all around the world on shifting from high-carbon to low-carbon energy systems, the heart of our society [13]. Consequent social, environmental, and economic issues may arise, impacting the general objective of sustainable development [14–16]. All the aspects of human wellbeing (e.g. food, mobility, housing, education, …) requires resource use. Part of this resource is transformed into energy and employed for producing goods and services.

Today the world is facing two major energy challenges. On the one hand, a transition in the way energy is delivered to households and industries has started [5,17]. On the other hand, 756.6 million people still do not have access to electricity, a key enabler for socio-economic development necessary to keep reducing the number of people in absolute poverty, overcoming the recent inversion of the trend triggered by the COVID-19 pandemic [18,19]. But do we have enough energy to improve living standards in the poorest areas of the world?

Supporting decent living standards for all would require roughly a quarter of the expected energy demand by 2050, making it very unlikely for the risk to pose a threat to the challenge of emission reduction. Furthermore, if equitable fulfilment of basic needs is prioritized over affluence, even less energy demand growth would be necessary [16]. Moreover, a decrease in energy and carbon intensity together with an increase in resource efficiency could further reduce the pressure on climate mitigation efforts while pushing in a beneficial direction also for other crucial development issues [20]. For example, the pathway towards a minimum use of fossil fuels can help drive down the death toll and economic cost associated with particulate matter below 2.5 micrometres (PM2.5) a problem that is costing the world between 6.5 and 10.5 million attributable deaths and between 1.9 to 2.9 billion USD per year [21].

Regional differences among developed and less-developed countries in the world are still relevant, posing different urgency from North America to Sub-Saharan Africa when it comes to SDGs. In Sub-Saharan Africa the level of energy consumption per capita has remained constant, showing a growth in energy demand fully explained by population growth. To close the living standards gap in some of the poorest countries, energy consumption would need to double by 2030 and triple by 2040, posing consequent pressure on resource use. In the same period, according to the Net Zero Scenario by International Energy Agency (IEA), it would be possible to substantially keep the peak global energy supply at 2019 levels, slightly decreasing it also thanks to the efficiency and behavioural change [5]. This is possible by embracing deep electrification of the final consumption of energy, requiring profound changes in technology in electricity, mobility, and heating. This transition would require a considerable investment in the next few decades which is expected to allow for a future reduction in the operational cost of the energy system [6,17]. Nevertheless, further burden, in the form of ancillary balancing activities in the electrical grid, energy storage, and supply of new and currently untapped material is expected to pose a challenge in supply chains [22,23].

In the journey towards a more sustainable society, energy will continue to play a central role. Guarantying the energy supply necessary to trigger socio-economic advancement and to sustain the production of the pivotal technologies for energy transition is crucial. Nevertheless, if the objective of emission reduction is going to keep its relevance, it is important to internalize the cost of each ton of carbon dioxide (CO_2) within investment and consumption choices. That may be done in various ways.

1.2. Internalizing the social cost of carbon

Human activities have always been driven by specific individual goals, exploiting goods and services to achieve them. The sum of the effects of each individual activity results in the social sphere of causation, where human beings interact with each other exchanging value while interacting with the biophysical sphere, thus impacting it to a different degree. In fact, in this process, humans exploit natural resources and release emissions as side products of their activities. The interaction between the two spheres could trigger feedback loops influencing how stocks and flows of materials, goods, and services are allocated between individuals and environments. Society could be seen as the hybrid of these two spheres [24].

In the interaction between human activities and nature, technology has allowed economic development, intended as how the same goods and services can be obtained by exploiting fewer resources. Humans have introduced a measure of the benefit that a good or service brings to an economic agent, which is a person, company, or organization that influences the economy by producing, buying, or selling. This measure is the economic value, which is accounted for in monetary units.

The use of resources and the resulting release of emissions as a co-product of society's economic initiatives, has recently led to a high level of pressure on the environment [25]. Indeed, the release of emissions and overexploitation of resources by an economic agent may have an indirect economic impact on a third party or the society taken as a whole: this economic impact is called externality. If its impact is negative, one way to actively account for it is to endogenize it into the economy by attributing present economic value to potential future damages. There is a great number of mechanisms and methodologies that can be put in place to assign an economic cost to externalities. In theory, the environmentally harmful activity should be surcharged by a cost that equals marginal damage with the marginal cost of mitigating that impact [26]. Nevertheless, when it comes to determining marginal external costs (such as climate change-related issues) uncertainties preclude the determination of an optimal value [27].

According to Intergovernmental Panel on Climate Change (IPCC), anthropogenic greenhouse gasses (GHG) emissions are estimated to have caused about 1°C of global warming above pre-industrial levels with high confidence [28]. Joint efforts at the international level, aimed at limiting carbon emissions, are grounded on the so-called production-based approach (PBA), which means that each of the nations who took part in international agreements, such as the Paris Agreement [29], is responsible for the emissions released within its boundaries. Every country has adopted its strategies for reducing emissions and today 23% of global emissions are regulated by carbon pricing initiatives [30]. Nowadays it is possible to identify mainly two carbon pricing mechanisms: carbon tax and emission trading system (ETS). European Emission Trading System allowance price has been growing consistently after COVID-19, mainly driven by the EU's willingness to enhance an Energy Transition.

Although theoretical and regulatory differences between these two mechanisms exist, they are usually implemented simultaneously in practice. Furthermore, it is observed that the price signal of carbon pricing on investors and consumers' choices is often diluted by other taxes and laws, which are more impactful on economic agent behaviour [31]. Nevertheless, it should be noted that over two decades of international agreements, although these initiatives have achieved significant local results, the first relevant global outcome has been experienced only in very recent time. In particular, energy-related CO_2 emissions have substantially flattened in 2019 [32]. However, it should be noted that this results from the sum between a substantial reduction in advanced economies (i.e. EU, USA, and Japan), which have on average a form of carbon limitation policy, and an equal increase in the rest of the world, where carbon emissions are not regulated yet.

In this context, alternative approaches to PBA have emerged in the scientific [33] and political debate [34] moving toward a consumption-based approach (CBA), which allocates to each country the responsibility for the emission released all over the world to produce what it consumes. In practice, this may take the form of a border carbon adjustment, assigning a price to emissions embodied in imports. CBA emissions have been calculated and investigated through multiregional input-output (MRIO) analysis [35], and its effectiveness in unilateral emission reduction policy has been studied [36] and assessed in comparison with PBA, through optimization models [37,38]. It emerges that, even if CBA seems to be effective in addressing carbon leakage (i.e. increase in overall CO2 emission as a consequence of local emission reduction policy), practical regulatory issues, connected to the need for tracking and verifying emission flows, and sub-optimality of the approach hamper the paradigm shift. Furthermore, it is noted that carbon leakage, usually pointed out when unilateral policies are applied in a net carbon importer country, may occur also in the CBA case when applied to a net carbon exporter country, since there would be no incentive for decarbonizing sectors devoted to export [39]. Finally, even if CBA would require reforming taxation and international trade agreements (e.g. World Trade Organization), efforts in innovating fiscal policies have recently been explored, describing and evaluating the effects of a destination-based cash flow taxation [40].

Carbon pricing initiatives have been advocated as the first-best policy able to optimally fix climate justice [41]. Nevertheless, using the words of the economist Dani Rodrik the world is – most of the time – a second-best issue [42]. In fact, political economy constraints – such as lobbying or low willingness to pay – limits the implementation of such theoretically optimal carbon emission reduction mechanisms. This suggests an innovative pursuit of a mix of second-best policy instruments [41].

To the knowledge of the authors, a market strategy for reducing global GHG emissions which involves consumer participation is to date non-existent or in development. Such a mechanism would lead to allocating a pure market price that reflects the avoided damage that society attributes to GHG emissions. To do so, it is necessary to link the economic agent which is responsible for the emission embodied in the demanded goods and services (i.e. consumer) with the one that is materially paying for climate-related damages (i.e. insurance companies), disregarding the national regulatory framework. In fact, on one hand, the whole metabolism is ultimately driven by the presence of a demanded good or service. By analogy with the CBA approach for nations, the consumer would therefore become responsible for the corresponding footprint. On the other hand, although the costs associated with the growing extreme weather events are indirectly felt by the population as a whole, it is now possible for some people to cover themselves against these damages by taking out an insurance policy. In essence, therefore, insurance companies are becoming the ones who pay directly for climate change damages, which are becoming increasingly important for these companies [43]. So, through the integration between life cycle thinking and industry 4.0 technologies, it becomes possible to close the feedback loop of the entire carbon chain, managing to connect economic agents to the impacts they involve. This is the background behind the idea proposed in this research.

1.3. Thesis Objectives

This chapter is intended as a clear presentation of the general objectives and of the specific objectives to be achieved for its fulfilment.

1.3.1. General Objective

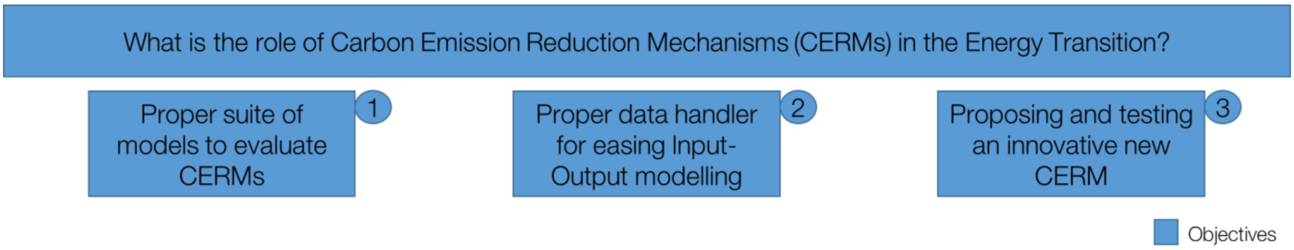
The general objective of this work is to explore the role of carbon pricing initiatives and other carbon emission mitigation strategies and their influence on the energy transition. Indirect measures such

as minimum share of renewable energy consumption targets and specific sectoral regulations can also be considered carbon emission reduction mechanisms (CERMs).
Therefore, the general objective can be resumed with the following question: what is the role of carbon emission reduction mechanisms (CERMs) in the Energy Transition?
To accomplish this general objective, specific objectives must be identified and achieved.

1.3.2. Specific Objectives

In order to study different CERMs, it is necessary to identify the proper suite of models by reviewing different methodologies. The output of the achievement of this first specific objective is identified in chapter 2.
Once the theoretical framework is identified, some operative issues may hamper the implementation of the methodologies. The most appropriate and thus adopted methodology of this research (i.e. input-output analysis) requires the proper modelling framework for implementing case studies. The results of the fulfilment of this objective are resumed in chapter 2.4.3, the one on methodology.
The application of the theoretical methodologies identified within specific objective number 1 and the practical applications allowed by the achievement of specific objective number 2, permits to close of the research with specific objective number 3. In fact, from the insight taken from studying and modelling CERMs, it has been possible to propose an innovative mechanism for incentivizing CO_2 reduction behaviours. The results of the fulfilment of this objective are resumed in the concluding chapter.
The conceptual map of these objectives is presented in Figure 1.1.

Figure 1.1 – Conceptual map of the objectives of the research. The general objective on top is achieved by fulfilling the 3 specific objectives on the bottom.



2. Literature Review

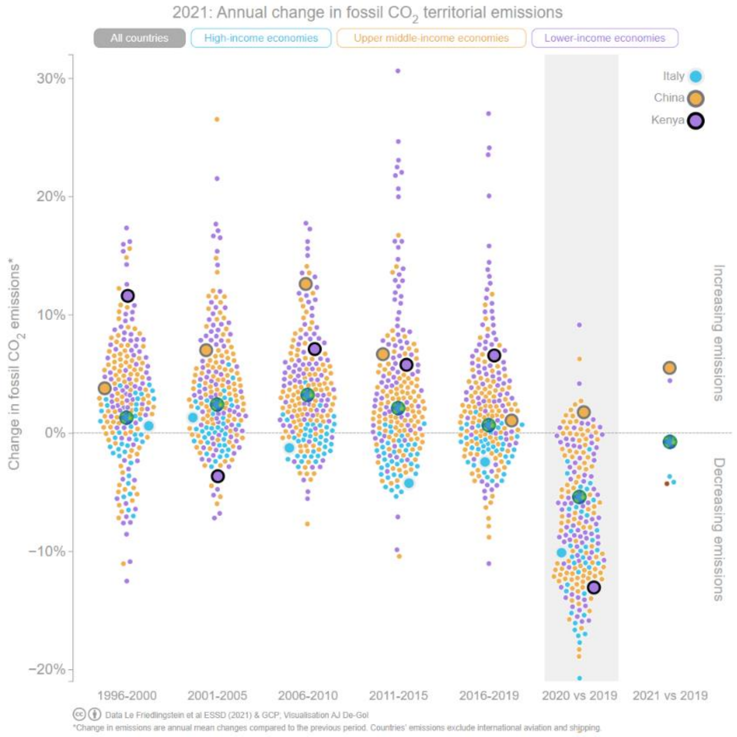
In this chapter, the results of the literature review are presented. It starts from the introduction of the challenge of carbon emission reduction, introducing the different ways to account for the burden of emissions between different agents and their pricing. After that, Energy Modelling is introduced as the first step into an analytical approach to understanding how to reduce emissions starting from its heart (i.e. the energy sector). Soon, the importance of not limiting the observation of the problem to the energy sector is highlighted, expanding the analysis towards all the sectors of the economy. Industrial Ecology is brought as a more comprehensive science for dealing with the multidimensionality of a Sustainable Energy Transition. Then, input-output analysis is introduced as the most suitable framework among the one offered in the literature. Finally, it is shown how this methodology can be integrated with linear programming to expand its applications.

2.1. The problem of greenhouse gas emissions

According to the World Health Organization, during the first waves of the COVID-19 pandemic that hit the world in 2020 over 3 million people lost their lives [44]. In the effort to mitigate this burden and wait for more effective medical treatment and vaccines, non-pharmaceutical interventions such as contact tracing [45] and different levels of limitation of mobility have been introduced [46]. The effects of this temporary confinement impacted final consumption and thus economic activity, contributing to lower than expected global CO_2 emissions during 2020, showing – at their peak, around April 2020 – a year-to-year reduction of 26% [47]. The level of emission reduction rapidly bounced back to pre-pandemic levels, as can be observed by the daily changes estimated through near-real-time data on fuel combustion, power production, and mobility [48].
The aftermath of what was experienced during the first year of the COVID-19 pandemic put the efforts requested for curbing emissions down in a rather challenging shade. In fact, according to Carbon Monitor, the CO_2 emission variation in 2020 over 2019 was about -5.76% [32]. This value is in line with what would be needed according to the UN's Intergovernmental Panel on Climate Change, which identifies this same yearly reduction to reach the 1.5°C goals by 2050 [1]. Nevertheless, comparing 2021 CO_2 emissions and the first half of 2022 with 2019, shows how the reduction driven by the pandemic emergency has not been followed by decisive reductions, being the changes positive: +0.42% and +1.18% respectively [32].
Overall, about 36.4 Gton of CO_2 have been emitted during 2021 [49]. But CO_2 is not the only relevant greenhouse gas (GHG). Methane is the second most important GHG in terms of climate forcing and is estimated that 60% of its slightly uncertain annual emissions are associated with human activities, being responsible for around 23% of the global warming potential (GWP) adjusted GHG contribution [50].
If all GHG are considered it is possible to share the responsibility among different agents (i.e. sectors, products, activities, regions, …) trying to depict trends over the years and hotspots to attention. In particular, moderate decarbonisation of the energy sector in Europe and North America, driven by fuel switching and the increasing penetration of renewables, can already be observed [17,51,52]. Intense demand for materials, energy, housing ground surface, and travel have pushed emissions growth in the manufacturing, buildings, and transport sectors, particularly in Eastern Asia, Southern Asia, and South-East Asia [51]. Furthermore, the recent expansion of agriculture into carbon-dense tropical areas has driven agriculture, forestry, and other land use emissions in Latin America, South-East Asia, and Africa [51].
As can be inferred from the chart in Figure 2.1, economic conditions still influence the rate of change in emissions. High-income economies such as Italy have moved from positive to negative changes

in the last 15 years. Upper-middle income such as China and lower-income economies such as Kenya are still growing their emissions even if some are decreasing the rate of growth.

Figure 2.1 – Change in fossil fuel emissions by county in specific periods. Italy, China, and Kenya are highlighted. The chart is taken from the following online tool developed by the Global Carbon Project: enactivescience.com/gcp2021.



Multiple complex mechanisms are making global emissions substantially flat, experiencing growth of emissions in low-income countries often released to complete the demand of high-income countries. But is the allocation of responsibilities for these emissions straightforward?

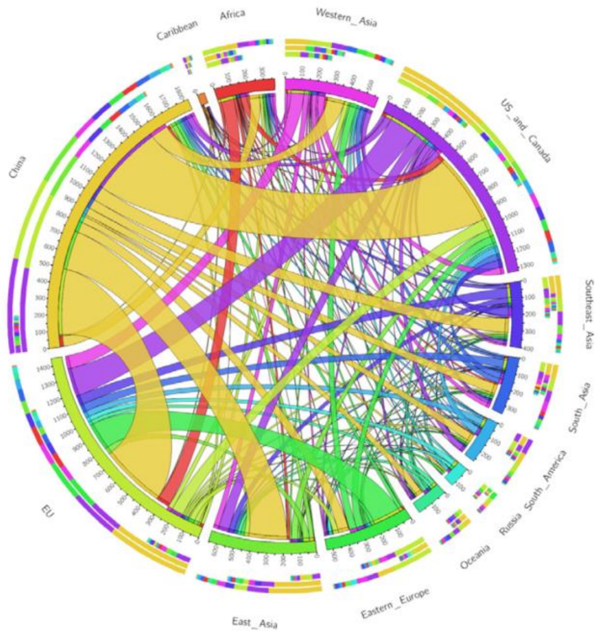
2.1.1. Production Based and Consumption-Based Accounting

Production-based approach (PBA) is currently considered the accounting standard of reference in the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol of 1992 [53]. Virtually all the emission allocation protocols rely on a PBA scheme, thus allocating CO_2 emitted by each country, just considering what has been emitted within its boundaries [31]. However, emissions calculated according to this mechanism provide an incomplete picture of the driving forces behind these releases. In fact, international activities, such as international transportation, pose a problem of allocation, leaving behind the so-called emissions embodied in trade [54,55].

In addition, the PBA can give misleading insights on the mitigation effort within a specific geographical area and poses the issue of carbon leakage. Carbon leakage occurs when an increase in emissions outside of a jurisdiction result from a carbon mitigation policy in that jurisdiction. It can occur when an industry from a regulated country decides to transfer its power plant to another country with lax environmental regulation, thus causing a so-called strong carbon leakage. Otherwise, it can happen when the demand for goods and services starts to be covered by imports from polluting economies thus causing a so-called weak carbon leakage [33]. Thus, a substantial fraction of the GHG growth in some emerging countries is produced to satisfy the demand of consumers in high-income countries. Often, carbon-intensive industries are being sited in developing countries in direct response to climate policy [33].

Debates on the empirical evidence of carbon leakage have animated the scientific debate, due to the technical challenge of properly isolating this phenomenon from other competing drivers of emissions by sector and country [56–58]. In a world that prices carbon more significantly than it has been in the past where low historical implicit disincentives to CO_2 emission were present, research and modelling for avoiding carbon leakage is important for policy-making.
The PBA approach seems to be not adequately comprehensive until a global consensus among world countries is reached. The absence of a carbon price for the whole world may entail significant free-riding risks that could ultimately impair national policy goals and fail to achieve the result of curbing CO_2 emissions on a global scale. The consumption-based approach (CBA) considers imports and exports of goods and services, accounting for the emissions taking place all over the world to satisfy the demand of the target jurisdiction.
The overall problem can be illustrated by the analysis on 2013 China's emissions resumed in Figure 2.2. The result shows the relevance of China's production in other countries' CBA emissions.

Figure 2.2 – Figure 8 of China's Carbon Emissions Report 2015 [59]*: "Emissions embodied in international trade. The flow represents the emissions embodied in trade, the colour represents the original production regions, for example, red flow represents the embodied emission that produced by Africa and exported and consumed by other regions."*



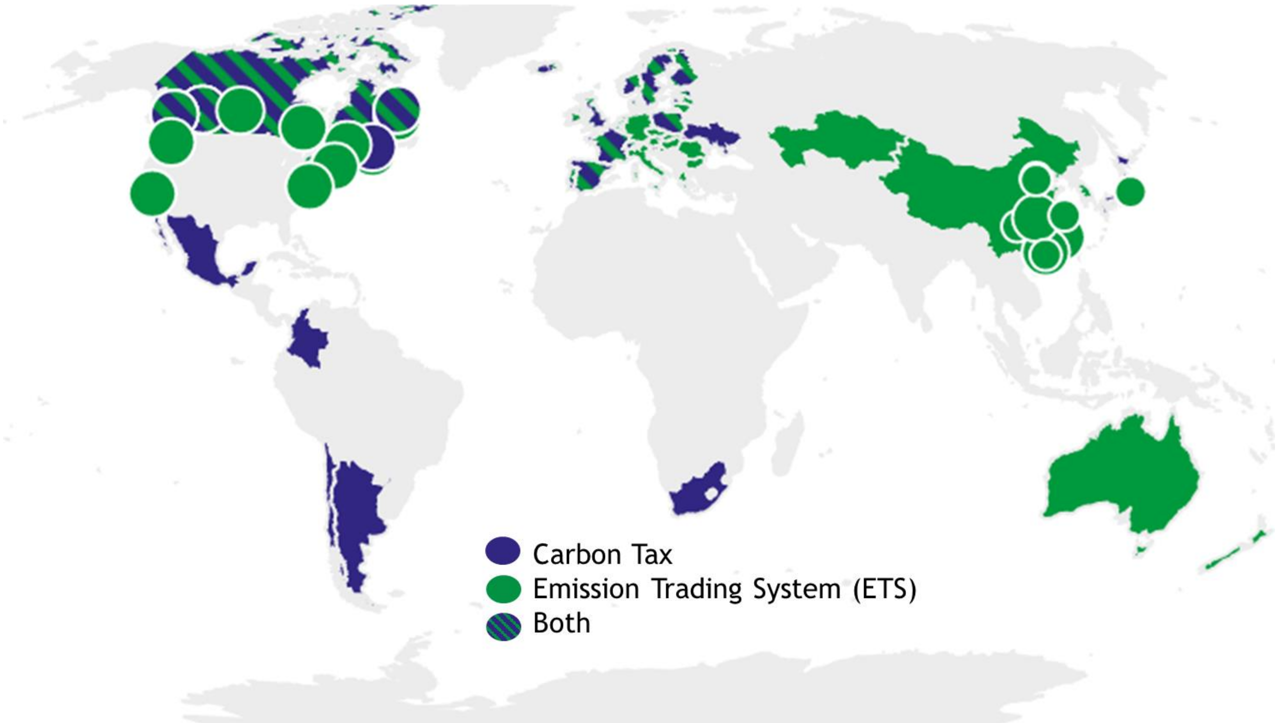
In 2004, 23% - about 6.2 Gton – of global CO_2 emissions, were traded internationally, mainly exported from China and other emerging markets to developed ones [35]. In 2013 the CO_2 embedded in China's exports was greater than the total emissions in the 5th largest CO_2 emitter at the time (i.e. Japan) [59]. In 2015, 8.8 Gton of CO_2 – i.e. 27 % of the world emissions – is linked to international trade [60]. In the same year, among non- Organization for Economic Co-operation and Development (OECD) economies, China is the largest emitter of CO_2, accounting for about 46% of non-OECD emissions [60]. It is estimated that emissions embedded in trade would be even more relevant – by about 11% - if the capital production is considered in the supply chain (e.g. the CO_2 released for producing buildings and machines built to produce exported goods) [61].
CBA allocates emissions to the final consumers of goods and services, no matter where in the world the GHG derived from their production might have been released. In this direction, the European Commission is paving the way for the adoption of the so-called Carbon Border Adjustment Mechanism, which was anticipated by Ursula Von Der Leyen's agenda and expected to extend the current European Union (EU) Emission Trading System (ETS) also on the CO_2 embedded in EU imported products [34,62].

In the academic world, several researchers have introduced the possibility of consumption-based schemes, where the consumer – and not the producer – is made responsible for the GHG emissions [35,37,38,63–65]. Other authors have proposed third ways to allocate the responsibility of emissions between producers and consumers, suggesting measures for assigning credits and penalties or proportional to economic benefits [66,67].
In the next section, the role of pricing, crucial to transforming a theoretical allocation scheme into an actual incentive or disincentive, is introduced.

2.1.2. Carbon pricing

Climate change can be considered one of the biggest market failures in human history [68]. Market failure occurs for two intertwined reasons. The atmosphere is an open-access resource. Thus, any country can release any amount of greenhouse gases when they want. In addition, this leads to consider GHG emissions as a negative externality, because they enter the natural sphere from the social sphere of causation leaving future impacts on the latter not yet accounted for within the economic system [21]. Thus, externalities appear when there is a divergence between social and private costs: environmental externalities can be defined as an unbalance loss in the welfare of a party deriving from the activity performed by another one [22].
The impact of the GHG emission does not fall on those who conduct polluting activities, so those responsible for the emission do not pay the cost and consequently, they impose significant expenditures on other people over time. To cover the cost of future environmental damages by limiting negative externalities, it is necessary to attribute a price to GHG emissions.
One of the most direct and widely used ways to reduce GHG is to introduce a carbon pricing policy [31]. Today, numerous initiatives of this kind are in place. Carbon pricing mechanisms are instruments that attribute a price to GHG emissions expressed as a value per ton of carbon dioxide equivalent. There are many ways to implement carbon pricing initiatives, but most of them are rooted in a carbon tax or market schemes, covering 23% of global carbon emissions (i.e. 12 Gton of CO_2) [30]. They range from the oldest initiative of the EU-ETS, together with some pioneering forms of carbon tax introduced in northern European countries, to the most recent Chinese ETS, launched in February 2021. See Figure 2.3 to have a snapshot of the carbon pricing measures currently under implementation.

Figure 2.3 – Implemented carbon pricing initiatives according to the Carbon Pricing Dashboard at carbonpricingdashboard.worldbank.org/map_data.



Carbon pricing can be implemented using mainly either of two instruments – a carbon tax or an ETS – that may be implemented simultaneously [31].

An emissions trading system (ETS), or market scheme, is a mechanism where emitters can trade emission units to meet their emission targets, targeting the volume of total emissions within the jurisdiction in a certain time. To comply with their emission targets at the least cost, regulated agents can either implement internal abatement measures or acquire emission units in the carbon market, choosing the most cost-efficient options. By creating supply and demand for emissions units, an ETS establishes a market price for GHG emissions. There are two main types of ETSs which are cap-and-trade and baseline-and-credit:

- Cap-and-trade systems: an absolute limit on the emissions within the ETS is fixed and emissions allowances are distributed, partially for free and through auctions, for the amount of emissions equivalent to the cap.
- Baseline-and-credit systems: baseline emissions levels are defined for individual regulated agents and credits are issued to the ones that have reduced their emissions below this level. These credits can be sold to the ones exceeding baseline emission levels.

The EU-ETS is a cap-and-trade system, the oldest ETS ever implemented and it is now entering its fourth phase of implementation. Today the EU-ETS is a rather complex market scheme, importantly regulated by ancillary entities such as Market Stability Reserved (MSR). MSR played a crucial role in the recent downturn of the price of EU-ETS allowances, keeping the price at a pre-pandemic level disregarding the impact that COVID-19 had on production and consumption [69]. Following this period, the price of EU-ETS allowance has only grown, disregarding the consequence of the February 2022 Russian invasion of Ukraine. Now the price is around 80 €/ton, very close to all-time high (i.e. 98 €/ton).

A carbon tax directly sets a price on carbon by defining an explicit tax rate on GHG emissions or—more frequently—on the carbon content of fossil fuels. It is different from an ETS in that the emission volume of a carbon tax is not pre-defined while the carbon price is.

Sweden introduced the first ever carbon pricing initiative at the national level, in 1991 and today is the country that prices carbon at the highest levels (i.e. 140 $/ton) [31]. Virtually all carbon pricing mechanisms are based on a PBA approach, that considers only those emissions produced within the jurisdiction boundaries. In fact, the effective implementation of CBA-based carbon pricing mechanisms represents a difficult technical and socio-political challenge. Nevertheless, Sweden, a climate policy pioneer, has recently proposed the first political initiative in this direction defining for the first time a CBA carbon emissions target, with the country aiming to hit net zero by 2045 [70]. As anticipated the EU is working on the implementation of the Carbon-Boarder Adjustments mechanism, gradually implementing it to properly face multiple technical and political issues. Importers will have to report emissions embedded in their goods without paying a financial adjustment in a transitional phase starting in 2023, giving time to reach full operation in 2026 [62]. Carbon pricing initiatives acting at the national or supranational level can target a large amount of carbon emission. However, their complexity and extension can limit the pace of implementation of mechanism improvements.

The third type of carbon pricing initiative is represented by carbon credits, which are emitted through an offset mechanism. This mechanism defines the GHG emission reductions from the project- or program-based activities, which can be sold either domestically or in other countries. Offset programs issue carbon credits according to an accounting protocol and have their registry. These credits can be used to meet compliance under an international agreement, domestic policies, or corporate citizenship objectives related to GHG mitigation [30]. Through Clean Development Mechanism (CDM), a country with an emission-reduction commitment under the Kyoto Protocol can develop a green project, saving tons of CO_2, in developing countries, that do not sign the treaty. The same mechanism implemented in a country that had signed the Kyoto Protocol is called Joint Implementation (JI). In this way, the signatory party can gain certified emission reduction (CER) credits, equivalent to one tonne of CO_2, that can use to meet its targets with an alternative mechanism. CERs are emitted only if all parties voluntarily agree and if the benefit in decreasing the emission is real, measurable, and additive. Moreover, this mechanism is one of the first cooperation mechanisms, environmental investment, and credit schemes [71].

Until the recent implementation of its fourth phase, CERs could be used within the EU-ETS [72]. Finally, the voluntary carbon market operates outside the compliance markets but in parallel, allowing private companies and individuals to purchase carbon offsets voluntarily, acquiring Verified Emission Reduction (VER) credit. However, not all of these credits have proven solid proof of saved emissions nor tree planting – one of the main types of offsetting projects – can be seen as a silver bullet for reducing CO_2 in the atmosphere [73–75].

Carbon credits in the voluntary market are supposed to be characterized by five core principles, which are additionality, overestimation, permanence, exclusive claim, and the provision of additional co-benefits in line with the UN's SDGs [75]. These principles constitute the basis on which the whole voluntary carbon market is built but may be debatable since they have to be built on a comparative scenario to compare with. This issue represents one of the main concerns that should be addressed for carbon credits' credibility. The second issue is exemplified by a rather difficult question: what is the monetary value of one ton of CO_2 released today?

To answer this question one can rely on the market response (e.g. today’s 80 €/ton of EU-ETS). Nevertheless, volatility of prices, the partiality of market schemes, and subjectivity (e.g. the horizon considered in the evaluation of the asset) in market agents produce rather uncertain and uncomplete responses. An alternative way to price carbon is to estimate the social cost of carbon (SCC). It attributes a monetary cost to climate change damages (or benefit) deriving from the emission of one additional ton of CO_2. Thus, its value considers the advantages of reducing warming against the cost of cutting emissions. SCC has been estimated with country disaggregation, showing high global SCC values (i.e. median, 417 \$/ton CO_2 within a 66% confidence interval) and a country-level SCC that is unequally distributed but often much higher than EU-ETS allowances price. Despite the intrinsic uncertainty in SCC estimations, like unknown future emission, economic growth, damages intensity, and geographical distribution, it has been considered by some governments in economic planning [76].

Non-carbon pricing carbon emission reduction mechanisms

Various other policies can be implemented to facilitate the occurrence of decoupling between economic growth and carbon emissions. Some of these are grounded in placing minimum penetration targets on certain technologies in certain sectors (e.g., low carbon power technologies). Others may directly or indirectly influence the consumption preferences of households. Recently, the recent European Union decided to allow the selling of new cars in Europe in 2035 only if they emit 0 grCO_2/km from their pipeline, pushing in the same direction and trend observed in the past years [77]. A carbon credit market is also present in this industry to allow for a more flexible mechanism.

Political economy constraints – such as lobbying or low willingness to pay – limits the implementation of theoretically optimal carbon emission reduction mechanisms, such as carbon taxes or ETS [41], even when including rebate programs [78]. Moreover, recent evidence from the ex-post analysis has highlighted how the role of carbon pricing may be practically marginal, estimating carbon emission reduction imputable to such policies of around 2% per year, with carbon taxes performing slightly better than ETS [79]. Some political economists see political will as a crucial driver of technology experience drivers and suggest that policy should push system-wide technology development [80], identifying the opposition between owners of climate forcing assets (e.g. fossil fuel fields, beef farms) and climate vulnerable assets (coast properties, tourism facilities) a crucial rapidly changing equilibrium [81]. The pace of reduction of solar photovoltaic, wind, and lithium-ion storage [82], has represented a major case for justifying economic incentives.

Implicit ways of pricing carbon exist such as broader industrial policies which offer advantages and disadvantages making it more difficult to target specific emission reduction, but offering opportunities for addressing other political issues, such as employment and economic sectoral transition [83]. That has been the case with the recent inflation reduction act that introduced low-carbon energy subsidies as one among other strategies to reduce the pressure of increasingly high costs of a primary source, such as fossil fuels [84].

All these carbon emission reduction mechanisms can be implemented and their cost is estimated by multiplying their explicit or implicit carbon price in €/ton by a certain amount of mass of CO_2. For these reasons, precise measurements or at least good estimates of carbon emissions per each economic activity must be provided. A measure or estimate able to consider all the carbon impacts released in the supply chain allows for the computation of carbon footprints of goods and services. In the last few years, some academic studies and projects are currently considering adopting blockchain technologies to ease the tracking of emissions and the exchanges between market agents [85–89]. In all cases, it is crucial to understand what a carbon footprint is and how can be computed.

2.1.3. Carbon footprint

Carbon footprint (CF) can be defined as «the life-cycle GHG emissions caused by the production of goods and services consumed by a geographically defined population or activity, independent of whether the GHG emissions occur inside or outside the geographical borders of the population or activity of interest» [90]. CFs can be calculated considering a Life Cycle perspective using two slightly different methodologies, Environmentally Extended Input-Output Analysis (EEIOA) or process-based Life Cycle Assessment (LCA). These types of assessment have emerged as key approaches to pave the way toward sustainable consumption and production and hybrid approach are possible and more frequently used [91–93].

Typically a sustainability problem is approached by looking at what it takes to produce a good or service and which impacts have to be considered in its production. The product will then be exhausted at the end of its useful life. This approach is linear design thinking of a product. However, what is needed within a sustainable approach, is to be able to consider the whole life cycle of a produced good or service.

Designing a product considering all its stages of life means having a circular approach. Planning what will be the disposal of that product since its design, considering the materials and where they come from allows for moving from a linear towards a circular approach. This is an example of life-cycle thinking. Analysing the life-cycle impacts of a product means performing a life-cycle assessment (or LCA) of that product.

Today LCA is regulated by ISO standard (14040). Nevertheless, it is still complicated to have the same results from two different life-cycle assessment analysts. This is due to the numerous assumptions underlying them. Uncertainty in data gathering and uncertainty in the choice of the proper model to represent a certain product or activity must be considered. Indeed, a certain degree of discretion comes in all the steps that are identified by the ISO standards.

In the first step, the so-called "Goal and Scope definition", the functional unit is identified. This choice becomes particularly crucial when a comparative study is carried out. For example, does a km driven by car fulfill the same need of a km driven by bike? In some cases probably yes, in some others probably not.

Filling the bill of materials is the second step of an ISO-compliant LCA. In this step, the data gathering uncertainty is approached. When a primary source is not available, this piece of information is usually taken from a database that may be up to date or not. Relying on a primary source does not automatically mean having a complete and certain data basis [94].

In the third step, impact assessment, inventoried data are translated into environmental impacts based on indicators. Furthermore, a proper assessment must consider the hypothesis underlying not only in the aggregation that must be performed for certain parameters (which in some cases can be again prone to discretionary choices) but also in the model adopted in impact allocation, especially if multiple products come out of the analysed activity.

Finally, results interpretation is crucial and should consider sensitivities or at least scenario analysis, trying to answer "what if" questions.

Practically speaking, LCA analysis can be performed by adopting two different methodological approaches, which can include all the 4 steps seen before. The first approach follows a process-based approach, taking advantage of pieces of software able to interpret and perturb famous LCA databases such as eco-invent [95]. The second one (i.e. EEIOA), adopts input-output analysis, a methodology diffusely adopted in Economics since Leontief's Nobel prize of 1973, relying on multi-regional global tables such as the ones of EXIOBASE [96,97]. These two methods are grounded on the same mathematical background but practically differ in some aspects leading to good agreement for certain sectors while leaving more than half of the matched products to differ by more than a factor of 2 [98]. The differences can be resumed in the following 3 points:

- Process-based LCA can be usually more detailed in terms of granularity of representation of products
- Nevertheless, EEIOA allows for comprehensive modeling of the whole economy, thus not committing the so-called truncation error, typical of process-based LCA. This happens, because you can say where your diesel comes from, maybe also where the oil used to make your diesel came from. However, it is technically needed to stop at a certain point thus losing potential lower-order impacts with the so-called truncation error.

- Capital goods impacts are not explicitly accounted for in input-output tables because they represent a snapshot of the transactions that have occurred between several sectors and regions of the same economy within one year. In process-based is possible to consider also capital goods flows but is usually not possible to rely on a database that refers to the same year for all the analysed flows, thus making analysis not temporarily coherent.

Consumption and production of goods and services and the relative emissions are strictly interconnected. For this reason, the SDGs of the United Nations address the combination of consumption and production as crucial to limiting environmental degradation (target 4 of SDG 8) and reducing global resource extraction (SDG 12). Strategies that are closer to the consumer, such as embracing sustainable lifestyles, are essential and have been reported to show resource-saving potential [50].

Carbon footprint in LCA studies is usually coming with other kinds of footprints, such as human-ecotoxicity, eutrophication, land use, and water use to name the most explored dimensions of sustainability. Energy modelling for a sustainable energy transition should try to consider the impacts on these dimensions of sustainability. But what is energy modelling?

2.2. Energy transition modelling

An informed decision-making process is essential and may be pivotal to supporting the needed decarbonisation pathways for the energy sector, transport, heavy industry, and building. Decarbonization has a lot of consequences within the energy sector and beyond it, as it was the oil crisis of the 1970s that fuelled the interest for operational research applied in the energy sector, practically starting energy modeling [99]. The advent of the internet made energy modeling more diffuse, scalable, and reproducible paving the way for the golden age of energy modeling that we are currently living [100].

Due to the complexity of energy issues daily faced by academics, firms, and policy-maker, the perfect energy model does not exist and a correct approach is dependent on each problem's specificity. Indeed, there are at least two counteracting urgencies when trying to look for the best toolkit: on one hand, capturing technological characterisations with great details and on the other hand integrating the different levels of complexities. Based on these premises, it is important to create a taxonomy of the available tools which deal with energy modeling, technology-rich, and their chance to be integrated with economy or environmental-wide models.

2.2.1. Energy System Modelling

Energy system modeling is widely used to support energy policy and long-term strategic energy planning decisions with insights generated by models.

Given this, several possible classifications can be found in the literature. Grubb *et al.* categorize the variety of energy models by adopting 6 dimensions, specifically sectoral and geographic extension, level of aggregation, time span, top-down or bottom-up, and optimization or simulation [101]. Houracade *et al.* have tried to condense the complexity of model classification by identifying a 3D space where the axes are technological richness, macro-economic feedback, and micro-economic realism, introducing behavioural complexity of consumers [102]. Hiremath *et al.* further develop the classification by identifying 9 dimensions which further extended the previous ones [103]. The importance covered by the distinguishing between top-down and bottom-up models has brought Herbst *et al.* to introduce a further structuring: energy models are primally distinguished into 2 categories, macro-economic ones and technology-rich ones [99]. The first group (top-down) comprehends input-output, econometric, general equilibrium, and system dynamics models; the second group (bottom-up) contains partial equilibrium, optimization, simulation, and multi-agent models. Model characterization emerged downstream the first Energy Modelling Platform for Europe meeting: a model matrix has been generated on this occasion limiting categories to three (technology richness, scope, and hybridization, geographical focus) for sake of providing policymakers with a synthetic overview. Alongside this proposal, the importance of surveys and personal interaction between researcher groups has been underlined. This process can provide a continuous space for interaction between modellers and for engagement with actors of the energy sector, relying also on online tools [104].

Energy modelling has been used to analyse the dynamic of energy, taking into consideration the role of new technologies in the contest of an exogenous set of macroeconomic data: technologies are described by technical (installed capacity, use of resources, lifespan, efficiency, availability factor…) and economical (cost of investment, O&M costs, other variable costs…). Pfenninger *et al.* delineate 4 possible paradigms for energy modelling which are [100]:

- Optimization-based models: they cover the entire energy system with the primary scope of identifying the scenarios of how an energy system could evolve.
- Simulation-based models: they cover the entire energy system with the primary scope of providing forecasts of how an energy system could evolve.
- Power system and electricity market models: they cover solely the electricity system ranging from optimization to simulation.
- Qualitative and mixed-methods scenarios: they rely on qualitative or mixed methods rather than mathematical models.

Among the optimization models, it is worth mentioning MARKAL, TIMES, MESSAGE, and OSeMOSYS which are the most used tool for this purpose. Nevertheless, identifying optimal power system configurations and decarbonization pathways within an integrated energy system still poses challenges. Primarily, despite the recent developments in energy modelling in terms of spatial and temporal resolution and capacity of multiple energy carriers, some issues still must be addressed (i.e. lack of complementary models for the generation of demand profiles). Secondly, energy modelling frameworks commonly consist of technology-rich bottom-up representations of the energy sector alone, whilst policy interventions on the latter entail economic and environmental consequences on the whole set of productive sectors within a national economy.

Starting from the taxonomy proposed by Hiremath, on which a general agreement persists it is possible to propose 11 dimensions of energy modelling [103]:

- General and specific purposes
- Model structure (internal and external assumptions)
- Analytical approach (top-down or bottom-up)
- Underlying methodology (optimization, simulation)
- Mathematical approach (theoretical structure)
- Geographical extension (global, regional, national, local)
- Sectoral extension (energy technology richness, comprehensiveness of non-energy sector)
- Time horizon (short, medium, and long term)
- Timestep resolution (minimum time slice considered)
- Environmental extension (capability to intercept environmental impacts)
- Data requirements

The relevance of the detailed definition of non-dispatchable renewable energy resources plays a crucial role in modelling energy scenarios and forecasts. Moreover, economic-wide models, which can provide direct and indirect consequences, both in terms of environmental and socio-economic impact, of energy policies are usually based on a one-year timeframe. The growing sensitivity of governments and consumers on pollutants emission and resource utilization may require categorizing energy modelling completeness also from this point of view. Therefore, it is considered that timestep resolution and environmental extension are two further dimensions on which outline and energy model.

The proposed taxonomy can play the role of a compass for policy-makers who should always have in mind that no perfect model exists and the quality of its output must always be driven by the preliminary posed question [105].

Among a large number of great modelling frameworks [6,106], the most ambitious and interesting models that are recently growing academic and policy attention for the European energy transition are PyPSA, Calliope, and the Ember model [7,107,108].

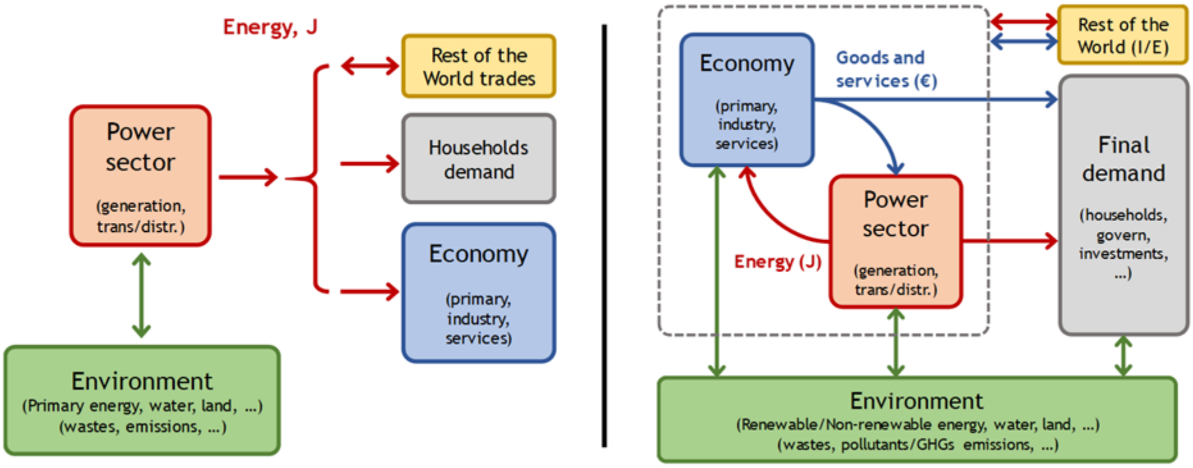
Actually, a growing number of energy system modelling tools – more or less around 50 different models – is pushing for a more scientifically grounded understanding of energy system complexities, and cross-sectoral synergies, with increasingly high time resolution for better characterizing non-dispatchable energy sources such as renewables [109]. Nevertheless, perceived policy relevance, true accessibility, and integrability of tools for better understanding the roles of behaviour and economic dynamics for long-term analysis are still significant challenges [106,109].

2.2.2. Integrations between energy and economic models

Energy system models are widely used tools to evaluate the optimal penetration of technologies or to assess the potential impacts of specific measures. However, different models can answer different questions: model development, which starts from a broad variety of general frameworks, is driven by the intention of the specific purpose of research and calibrated based on its technological, methodological, and geographical scope. While energy system models' approaches are usually based on analytical characterization of the analysed technologies, economic-wide models mostly rely on empirical datasets derived from Environmentally-Extended Input-Output models [110]. Economic-wide models can generally be framed between Input-Output and General Equilibrium models. The first can evaluate, in an endogenous way, the responses of the economic system to different policies and scenarios without taking consumption into account, while the latter describes the relationship between the primary factors (labour, capital, and natural resources such as energy) by using elasticities of substitution.

The recent development of richer input-output tables, enhanced by augmented computational power and interest in environmental themes has been a breeding ground for the expansion of Multiregional Input-Output Tables (MRIO), which potentially allow assessing the interregional and intersectoral impacts of local technological changes. In particular, such MRIO can be used as input data for both Computational General Equilibrium (CGE) and Input-Output models. The GEM-E3, a multi-regional, multi-sectoral, recursive dynamic computable general equilibrium model, provides details on the macro-economy and its interaction with the environment and the energy system, taking into account also the demand behaviour of economic agents. MRIO databases can be provided as input also to the modelling framework of the World Trade Model (WTM) and the World Trade Model with Bilateral Trade (WTMBT), two versions of a constrained optimization model that situates the standard one-region input-output model within the global context, simulating global production and trading arrangement solely driven by the principle of comparative advantage [111–114]. Even if the scope of top-down models is comprehensive, such models are characterised by a high aggregation level: indeed, energy technologies are usually lumped together in one average "energy sector". For such reasons, this approach should be considered complementary to bottom-up models rather than the opposite, and this invites in development of methods for their joint use, usually called "links", which are increasingly proposed in the recent literature [107]. Nevertheless, in the recent literature a new approach, called Rectangular Choice of Technology (RCOT), is emerging. It introduces technological complexity into the input-output framework, allowing different technologies to produce the same industrial output (i.e. electricity), within the sectoral richness of input-output models [115]. Alongside that, energy system dynamics should be represented with high-resolution timesteps which could potentially be modelled throughout dynamic input-output models [110].

Figure 2.4 - Traditional energy modelling of power sector vs power sector integrated into the input-output framework.



However, scientific community research is still in progress to intercept the complexity of the problem of using this tool to represent the electricity production sector, since the needed detailed dynamic and high space and time resolution is still hard to model both in terms of technological description and factor endowment characterization. In this perspective interlinkages between energy and economic models are still widely adopted in form of hard-linking, soft-linking, or integration [116,117].

In the last decade, the widely recognized relevance of cross-sectoral interlinkages among economic sectors has driven research efforts in deepening the issue of joint energy and economic modelling, with a special focus on the integration of bottom-up technology-rich energy models with top-down empirical macroeconomic and econometric models. In particular, several attempts have been made on integrating energy systems optimization models (with a particular focus on MARKAL and TIMES models) with input-output and CGE models, to improve feedback loops between the energy sector and the rest of the economy, hence providing more accurate picture about economic and environmental impacts of different energy scenarios.

Several attempts have been made to link energy and economic models. Some of them are here reported:

- In the assessment of the impact of future energy scenarios in the UK, the TIMES-Macro model has been disaggregated by linking it with the AMOS UK CGE [118].
- Messner *et al.* proposed a soft link between MESSAGE and MACRO models, intending to assess the impact of energy supply costs on the national energy production mix in a general equilibrium framework [119].
- Kober *et al.* linked a macroeconomic model to an energy system model by considering the decreases in consumers' spending due to the introduction of carbon taxes [120].
- Rocco *et al.* propose a novel approach to soft-link bottom-up OSeMOSYS model and top-down Input-Output model and applied it to assess the economic implication of a change in Egyptian energy mix [121].
- Lombardi *et al.* provide a comprehensive soft-linking approach to assess the overall impact of a technological change in the Italian sector of residential cooking through integration between the the bottom-up load curve estimation model, technology-rich optimization model (Calliope), and Multi-Regional Input-Output model [122].

- As part of the EU's current policy modelling suite, the TIMES model has been successfully integrated with the GEM-E3 CGE model for assessing the economic and environmental consequences of a variety of energy policies [123], and similar efforts have been recently made by integrating the TIMES-PanEU model and the NEWAGE CGE model (http://www.reeem.org/).

Some applications of integrated approaches are proposed in chapter 4 and a general framework dealing with various productive models is presented in chapter 2.4.3.

2.3. Industrial Ecology modelling

The science that studies the metabolism of societies is called Industrial Ecology, a field that has its roots in engineering. Within this field of research, several methodologies are configured [124]. In this section, Industrial Ecology principles are introduced and the most relevant methodologies for this research are described.

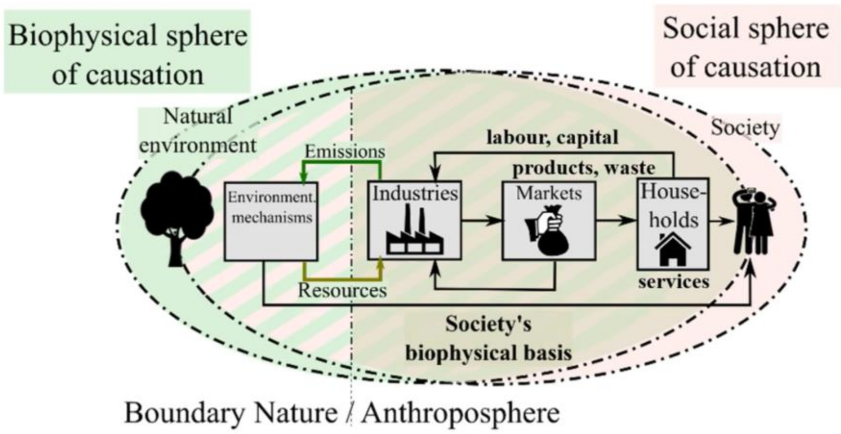
2.3.1. The discipline of Industrial Ecology

The extraction of natural resources for industrial use is closely linked to environmental problems due to the entangled ways in which the modern economy transforms, uses, and disposes of the inputs and outputs of its productive system. Understanding the structure of the economy that regulates the flows through which materials and energy flow between producing industries and consuming households are therefore essential to solving the problems of limited availability and pollution [125].

Industrial ecology is the science that studies the socio-economic metabolism of systems and does so by studying the flows of matter and energy. Robert Ayers introduced the concepts of Industrial Ecology in the late 50s and recently its contribution has been expanded by many scientists all over the world [126].

The concepts of thermodynamics are applied in Industrial Ecology to bring a solid scientific approach to a difficult and sometimes undefined ground of sustainability. Furthermore, Industrial Ecology adopts a life-cycle perspective focusing on system synergies that can be exploited to make a process more resource-efficient. To understand Industrial Ecology, it is useful to refer to the two spheres of causation [127].

Figure 2.5 – The biophysical and the social sphere of causation as depicted in [127].



From one side there is the social sphere of causation where we as humans, try to fulfil our human needs. To do so we act as consumers, looking for goods and services that we can find in markets to satisfy our demand needs. Markets are usually flooded by the outputs of industries that are producing stuff and performing economic activities. To do so, industries require inputs from other industries or resources from the other sphere of causation: the biophysical sphere. Society can be described as a 'hybrid' of both the biophysical and the social sphere of causation [24]. Both spheres are interconnected. Our society needs to organize energy and material flows for their own biophysical and social subsistence (e.g. buying and consuming food taking advantage of the financial conditions allowed by the reproduction of the built-up capital stocks). Basic laws of natural science (e.g. thermodynamics, mass conservation) also apply to social and economic systems and are to be respected [126].

The main focus of industrial ecologists is the frontier between these two spheres where feedback loops may occur. Consider the case of GHG and its impact on the biophysical and social sphere. The increase in the concentration of GHG in the atmosphere is mostly the effect of our society burning fossil fuels, releasing carbon that would have stayed underground for other thousand years otherwise thus increasing the concentration of carbon dioxide in the atmosphere [128]. Its relevant presence in the atmosphere is contributing to having more frequent and/or more intense extreme climate events impacting the social sphere of causation by means – for example – of agricultural damages or heat-wave-induced health issues [1,2,14].

But what are the practical tools offered by Industrial Ecology? Different taxonomies are possible [124,129]. They can be divided into two groups: attributional and consequential approaches [124]. Attributional approaches are limited to allocating the responsibility of the impact associated with the production of a certain product among many different regions and/or sectors. Process-based life-cycle analysis, in which impacts are distributed among the different nodes of the supply chain, is the most frequent application of attributional approaches. However, attributional approaches usually do not include the consequence of the decisions that can be taken on the production or the consumption of the analysed product. That is where a consequential approach is adopted, introducing further assumptions in the model. An example of such a model is a technology choice model approach, which is built on input-output analysis that can also be used to perform attributional life-cycle analysis that is deepened in the next chapters.

2.3.2. Attributional Life-Cycle Assessment

Life cycle assessment (LCA) is a methodological framework for estimating and assessing the environmental impact attributable to the life of a product. Its application is quite recent: its roots date back to the 1960s and 1970s when it was first used in research related to energy requirements and pollution prevention. Since then, its growing importance in the environmental management discipline made possible the development of LCA methodologies and approaches. Although the heterogeneity of methods and techniques, at the end of the 1990s international and draft standards were established to set up the ISO 14000 series, that, net of extensions and updates over the years, are still regulating LCA applications.

Table 2.1 – The ISO 14000 family according to PDCA (Plan-Do-Check-Act) cycle

Plan	Do	Check	Act
Environmental management system implementation	Conduct life cycle assessment and manage environmental aspects	Conduct audits and evaluate environmental performance	Communicate and use environmental declarations and claims
ISO 14050:2009	ISO 14040:2006	ISO 14015:2001	ISO 14020:2000
ISO 14001:2004	ISO 14044:2006	ISO 14031:1999	ISO 14021:1999
ISO 14004:2004	ISO/TR 14047:2003	ISO 19011:2002	ISO 14024:1999
ISO/DIS 14005	ISO/TS 14048:2002		ISO 14025:2006
	ISO/TR 14049:2000		ISO/AWI 14033
	ISO/CD 14051		ISO 14063:2006
	ISO/WS 14045		
Address environmental aspects in products and product standards	Manage GHG	Evaluate GHG performance	
ISO Guide 64:2008	ISO 14064-1:2006	ISO 14064-3:2006	
ISO/CD 14006	ISO 14064-2:2006	ISO 14065:2007	
ISO/TR 14062:2002	ISO/WD 14067-1 ISO/WD 14067-2	ISO/CD 14066	
	ISO/AWI 14069		

The main phases of LCA, based on the UNI EN ISO 14040:2006, include:

- Goal and scope definition of LCA
- Life cycle inventory analysis (LCI)
- Life cycle impact assessment (LCIA)
- Life cycle interpretation (reporting and critical review of LCA, analysis of limitations of LCA, analysis of the relationship between the LCA phases)

The goal and scope definition phase provides information about the product system, its boundaries, and the functional unit that will be considered. In particular, the functional unit is the good or service provided as an output that enables the comparison with other goods or services that perform the same function. It is a quantitative description of the service performance. Giving an example of this, for what concerns lighting systems, "lumens" or "amount of light" does not properly quantify the performance or the service provided: an appropriate functional unit would be "lighting of x m2 with a given amount of lux for one year", where also time and space are defined.

When a unit process provides more than one product or output, the definition of the function unit may need to be revised: ISO standard on LCA suggests 2 options:

- To partition the exchanges "between the products and functions in a way which reflects other (Partitioning)
- To expand the system in order "to include the additional functions" (System Expansion)

relationship between them", for example allocating data between co-products in proportion to an allocation factor, which can be based on mass, energy, or economic relationship.
Interestingly, these methodologies are mathematically equivalent to performing an input-output impact model adopting respectively industry-based technology and commodity-based technology [93]. It should be noted that the current taxonomy here adopted for introducing different life-cycle methodologies may fall short of clearly separating one from the other. In fact, an attributional LCA that adopted system expansion is implicitly assuming a "consequence" on the production of some of the elements of the system. Nevertheless, as is shown in the next section, the meaning of consequential is more prominent and implies further impactful assumptions.
The second phase, related to LCI, is probably the most time-consuming. Databases providing reliable, reproducible, and high-quality data are necessary to ensure strong and verifiable support to the LCA. In the light of this, public and national database initiatives have been funded in several countries, as well as industry database initiatives (i.e. "Life cycle assessment of nickel products" managed by Nickel Development Institute, or "Ecobalances of the European plastic industry" managed by APME).
The third phase, represented by LCIA, provides an evaluation of a product life cycle. Using specified indicators and several categories, it is possible to analyse the product in terms of potential contributions to different impacts on its life. During the LCIA phase, the basic inventory flows, created by the LCI, are used to draw conclusions related to expected impact categories, which are selected, as well as the indicators for each impact category, during the first step of LCIA. The choices must be consistent with the stated goal and scope of the LCA study. Then, inventory results are classified, mainly via the use of software tools, and assigned to different impact categories. The final mandatory procedure that is performed is characterization and it consists of the calculation of impact category indicators using characterization (or equivalency) factors. Normalization, grouping, weighting, and data quality analysis are instead optional elements in LCIA.
The fourth phase, life cycle interpretation, occurs and is interconnected with every stage of the LCA process. It entails the understanding of the results, as well as comparisons across impact categories and "hotspot" detection in the life cycle of the product. It is useful to make conclusions and recommendations, to improve the quality of the study based on quantitative work and analysis. Additionally, in this phase, relevant sensitivity analyses could be displayed.

Implementing attributional LCA

The results produced by an LCA can be applied, theoretically, to any kind of product and by different actors or stakeholders. LCA application should be used by the company or industry to further improve products and processes, support the material and technology choices and explore the potential of win-win solutions where both environmental and economic benefits can be obtained. LCA application provides support to government and environmental policy guidelines as a valuable tool to define strategies and interventions to help reduce the environmental footprint of sectors, services, and products. Thus far, governments have been involved in encouraging the development and implementation of methodologies and capacity building, by sponsoring programs, and new tools, and supporting the creation of databases [125].
For instance, in Japan, several ministries in the early 1990s organized a joint committee of LCA experts leading in 1998 to the start of the national Japanese LCA project, which enabled the development of a national LCIA methodology, along with the implementation of an inventory database and characterization factors for LCIA, indispensable when calculating the impact category indicators. Similarly, US governmental bodies released LCA and impact assessment tools, among which the noteworthy TRACI (Tool for the Reduction and Assessment of Chemical and other environmental Impacts) and the software BEES (Building for Environmental and Economic

Sustainability) for analysing the performance of building products [130,131]. The adoption of life cycle thinking in the policy context has been growing also in Europe in the last decades. In 2003 the EU commission recommended that manufactures shall assess the environmental aspects of a representative EuP (energy-using product) model throughout its lifecycle [132].

Looking up at more recent improvements and projects, one of the last and most ambitious examples of LCA application in environmental policy implementation regards the EU proposal aiming for harmonized approach in specific applications [133]. During the years, several different labels and information reported on products and goods appeared, leading to a dissonance of approaches, though the EU was asking companies making "green claims" to substantiate these against a standard methodology to assess their impact on the environment [EU green deal].

The initiative of the EU, which has been developing PEF (Product Environmental Footprint) and OEF (Organisation Environmental Footprint) methods, is based on standards, procedures, and well-established guidelines: i.e. regarding Product Environmental Footprint, ISO 14040-44 (on principles, scope definition, inventory analysis, and life cycle impact assessment and interpretation), the International Life Cycle Reference Database Handbook (technical guidance documents in line with ISO 14040 and 14044), Ecological Footprint (it provides a measure of the extent to which human activities exceed biocapacity), WRI/WBCSD GHG protocol (Product and Supply Chain Standards Greenhouse Gas Protocol), and national standards, such as PAS 2050 (UK's Product Carbon footprint) and BP X30 (French Environmental Footprint) have been considered. For what concerns the Organisation Environmental Footprint, ISO 14064 (on requirements at the organization level for quantification and reporting of greenhouse gas emissions and removals), WRI GHG Protocol (standards on GHG emissions inventory for companies and organizations), CDP Water Footprint (guidance document of CDP, an independent not-for-profit organization), Global Reporting Initiative (GRI's Reporting Framework sets out principle and performance indicators that organization can use) and again national standards, such as DEFRA guidance on GHG reporting (UK's corporate GHG accounting guide) and ADEME Bilan Carbone (French GHG accounting guidance tool), have been used and implemented. The EU PEF and OEF started with a first road test in 2011, aimed at assessing the validity of the chosen PEF/OEF methods, and it was organized by the Commission in collaboration with several volunteering industries. The deadline for methodology development ended in April 2013. The trial continued and, between 2013 and 2016, a second pilot, the Environmental Footprint (EF) pilot, took place, whose objectives were to test processes for developing product- and sector-specific rules (i.e. Product Environmental Footprint Category Rules PEFCRs and Organisation Environmental Footprint Sectoral Rules OEFSRs), as well as different approaches to verification and communication, means to deliver the information to consumers and companies. From the end of the EF pilot phase (2018) until policy development a transition phase has been established: the main focus will be on the implementation and development of new PEFCRs and OEFSRs, the analysis of initial market uptake, LCIA methods improvements, and draw up guidance documents.

While waiting for the adoption of policies implementing and enforcing the PEF and OEF methods, in France, in the wake of EU recommendations and guidelines, a new environmental label called "Eco-Score" has been established. The indicator, developed by several actors in the food sector and supported by ADEME, aims to represent, in an easy way for the final consumer, the environmental impact of a food product or cooked dishes, taking into consideration LCA, transportation, packaging, and seasonality. By using the "Agribalyse" database, which contains information for several types of food about 14 indicators (climate change, stratospheric ozone depletion, ionizing radiation, photochemical ozone formation, particulate matter, terrestrial and freshwater acidification, terrestrial eutrophication, freshwater eutrophication, marine eutrophication, land use, freshwater ecotoxicity, resource depletion, energetic resource depletion, mineral resources depletion), it is possible to assign an overall score from A (maximum) to E (minimum) that aggregates the data collected [134].

The Eco-score example involves product categories, which are foods and cooked dishes, whose use phase is quite limited: when thinking from cradle to grave, although during conservation and "utilization" or cooking phase energy may be needed (some foods need to be stored at a certain temperature or cooked or heated up), this does not apply to all products, and additionally, the "utilization" phase is limited to just one "use". But nowadays growing consumer needs are satisfied by durable goods, that require substantial amounts of energy during their lifetime, and in particular during their operational phase, adding complexity to how to account for the entire life cycle of the product. Vita *et al.* calculated by using EXIOBASE the environmental footprint (EF) of 200 goods across 44 countries from 1995 to 2011 and found that 68% of the total global household's EF is linked to durable goods. Furthermore, the highest percentage of EF (51%) was related to operational energy, while the production phase embedded just 10% of total EF product related. Regarding the household sectors, transport goods and housing goods show the highest EF, followed by electric appliances and gas stoves and furnaces [135].

Even though the importance of a comprehensive and holistic vision of environmental management is widely recognized, some limitations are still hampering a broad adoption of the LCA approach in the assessment of impacts related to manufactured products and services offered to our society. In this regard, identify two main issues in the current literature are identified. The first one is connected with time-consuming inventory data retrieval and reproducibility, addressable through the implementation of standardized methodologies and industry 4.0 technologies. The second one refers to LCA results in communication and reliability, in which the role of comparativeness is crucial.

2.3.3. Consequential Life-Cycle Assessment

LCA is a methodology that assesses the potential ecological impacts of human activities related to the consumption of goods and services. The life cycle of a product may cover all phases: from "cradle to grave", from the development to its production, consumption, and end-of-life activities. However, it is not granted that the change that occurred from a specific intervention is not impacting multiple agents of the system. Specifically, given the specificity of cases Consequential LCA (CLCA), is adopted to describe how environmentally relevant physical flows change as a consequence of possible action carried out in the product system. To understand the environmental response to certain decisions, several methods could be applied. The main CLCA modelling approaches take advantage of economic equilibrium, system dynamics, technology choice, and agent-based models. The most suitable model for a specific analysis must be carefully chosen following its purpose. The economic equilibrium approach aims at determining market fundamental attributes of price and quantity by the interaction between the "supply-side" and "demand-side". The former acts accordingly to maximize industries' profit, the latter is constituted by consumers, which are seeking to maximize their utility function. Technology choice models optimize technology choices in multiple markets, and it is based on an economic input-output model. Both technology choice and equilibrium model frameworks are appropriate to investigate macro-scale changes but do not generally include the time variable, a necessary feature for simulating a policy and analysing its effects over time. Agent-based models and system dynamics, instead, embody the basic requirements, but the former approach specifically fits complex systems characterized by micro-level interaction between a multitude of autonomous, individually different agents [124]. The scope of the mechanism that needs to be modelled, though, does not require a full interpretation of the microscopic stakeholders' behaviour. Therefore, it is sufficient to simulate an aggregated class of stakeholders with the set of modelling instruments proper to the System Dynamics theoretical framework.

Agent-based models

Agent-based models (ABMs) were developed to allow for modelling a more complex system. When modelling an economic market some non-realistic notions are often assumed, like the concepts of a perfect market, homogeneous agents, and long-run equilibrium.

This approach consists of autonomous, interacting agents. Applications range from modelling agent behaviour in the stock market, supply chains, and consumer markets, to predicting the spread of epidemics [136]. Agents are discrete units that behave according to a set of pre-programmed rules. Different types of agents exist, each one has its goal function and requires some assumptions. The zero-intelligent agent represents the most basic type of agent. It is also called a randomly behaving agent since it makes random decisions. It interacts with other agents and emulates their behaviour with some probability. Human programmed agents instead interact accordingly to a set of rules, given individually by a human programmer. This type of agent roots in games such as the prisoner's dilemma where algorithms determine how each agent should act. However, their behaviour just attains to the programmed rules as they are unable to learn autonomously. Autonomous agents instead are initialized by humans but afterward, they have the capability to learn without human intervention [136].

ABMs can include into CLCA the interaction between agents and the effects of their behaviour, which is very useful in technology adoption models. Each model could deal with hundreds or thousands of rule-setting data, and different types of agents have different goals. For this reason, the model could be perceived as not transparent. Generally, ABM is suitable for approaching localized questions and representing the micro-level [124].

System Dynamics Modelling in Industrial Ecology

System Dynamics (SD) approach is used for investigating, understanding, modeling, and tackling well-defined endogenous problems concerning physical or conceptual systems that are suitable to be formulated as casual relationships. This is the case of complex issues that consist of feedback mechanisms, delays, and quantitative causal relations between variables. SD was firstly introduced by Prof. J.W. Forrester in the 1950s and then deepened by J. Sterman who formalized the SD approach defining its theoretical roots in his book *Business dynamics: System thinking and simulated for a complex world* [137]. According to this theory, a real-world problem can be addressed by a first conceptual dynamic hypothesis based on the formulation of Causal Loop Diagrams. This conceptualization is at the basis of the subsequent mathematical formulation of the simulation model. A specific feature of SD simulation models is the characterization of variables as stocks, flows, and auxiliaries. Stocks represent the integration of a rate variable (flow) over time, while auxiliary variables are needed for an algebraic connection between different stock and flow structures to define multiple feedback loops.

This approach has been widely adopted in the existing literature about innovation diffusion phenomena, in a particularly large variety of studies on new transportation mode adoption, especially BEV adoption, based on SD models. This is the case of the work done by Ercan *et al.* [138] who used an SD approach to propose possible public transportation policies to be adopted by policymakers or urban planners. Their model is aimed to simulate the most realistic and practical CO_2 mitigation scenarios for U.S. cities by the adoption of public transportation. Another example is provided by the study done by Fong *et al.* [139] who demonstrated the capability of SD to serve as a decision-making tool in Malaysia's urban planning process while considering future CO_2 emission trends. Deepen's focus on the use of SD theory to model discrete choices for what concerns private transportation modes is presented in the PhD dissertation of David Ross Keith [140] who developed a model to simulate innovation diffusion mechanisms that include production capacity and dealer inventory in the market of hybrid vehicles. A more sophisticated analysis in the same field is performed by Feng *et al.* [141] who incorporate fuzzy logic in an SD model to replicate the comparative process that consumers use to decide among alternatives in a more realistic process. Their work is aimed to evaluate how feedback and interactions generated by the introduction of social commerce into EVs can influence consumers' choices. The same approach has been exploited also in numerous policy assessment studies both on a national and regional scale. This is the case of BenDor and Ford [142] who performed a study to assess the feasibility of a combination of fees and rebates to promote the sale of cleaner new vehicles using an SD-based simulation model. Another example is provided by the work done by Shepherd *et al.* [143] who have studied the impact of national subsidies for the electric vehicles take-up in the UK market. Their results suggested that subsidies are impactful only if combined with a dedicated marketing strategy.

Input-output and Technology Choice Models

The technology Choice Model (TCM) represents another operational framework for CLCA. It optimizes technology choices in multiple markets while being subjected to parameter uncertainties, suboptimal decisions, and factor constraints. TCM allows for a high level of detail in modelling both market effects and environmental impacts [124].

TCM's basic structure is the same as the Rectangular Choice of Technology (RCOT) model, which is an economic input/output model that takes into account multiple technology choices [115]. The technology matrix of a traditional input/output assessment is squared, where rows and columns represent the various sectors of the economy. In RCOT the technology matrix is rectangular instead, due to an extension in the number of columns to characterize more than one technology.

The TCM is the integration of RCOT into the matrix formulation of LCA. It is achieved by introducing a scaling vector s for the activity levels of the sectors in the economy, needed to obtain the functional unit of the LCA

To fully characterize the model the rectangular environmental matrix is required. It defines the elementary flows of the unit process according to ISO standards of LCA. It contains the direct flows to and from the environment from each process. In the elementary flow matrix, elementary flows are represented by rows, while the columns represent the same processes as in the technology matrix.

An important advantage of using TCM is the fact that the model determines the optimal mix of technologies under given constraints, to reach the proposed environmental and economic objectives. The RCOT model applied to CLCA recalls many limitations though. The first one is not accounting for the potential technology learning curve or the non-linearity of technology factors with the volume level. Other limitations might regard the scarcity of data, sometimes even outdated, needed to determine the factor endowments or the use of static factor prices.

This methodology is grounded on a more general framework which is worth deepening in a dedicated sub-chapter.

2.4. Input-output analysis within Industrial Ecology

Industrial ecology is the science that studies socioeconomic metabolism, bringing a scientific approach to tackle the challenges regarding human development within the natural environment [125,127]. Material flow analysis, process-based life cycle assessment, input-output (IO) analysis, integrated assessment models, and computable general equilibrium models represent the families of industrial ecology methodologies that have been expanded and combined to overcome their limitations. Practically speaking, the economy-wide comprehensiveness required for having an industrial ecology approach finds its root in a specific field of economics called Structural economics.

Structural economics is a field of science related to changes in technology, lifestyles, and the environment introduced by Leontief and formalized by Duchin, representing an overlapping area of competencies and interests between engineering and economics [12].

2.4.1. From Leontief to 2022 and beyond

Historical roots

The philosophical origins of economic IO analysis can be traced back to the Physiocrats in France, at the time of Louis XV in the late eighteenth century. At that time, Francois Quesnay produced a "Tableau Economique", showing the physical flows between different sectors of the local economy [110,144]. The technique as it is now known was developed by Leontief during the 1930s and 1940s and has since been considerably extended [145,146]. The term "interindustry analysis" or "structural economics" is also used, since the fundamental purpose of the input-output framework is to analyse the interdependence of industries in an economy [12,110]. Nowadays, the basic concepts set forth by Leontief are key components of many types of economic analysis and, indeed, input-output analysis is one of the most widely applied methods in economics [110].

Input-output has been also extended to be part of an integrated framework of employment and social accounting metrics associated with industrial production and other economic activity, allowing for the international and interregional flows of products and services or accounting for energy consumption and environmental pollution associated with an interindustry activity.

For a substantial economic data model, it is necessary to accept some limitations. IO data architecture commonly requires an economy to be disaggregated into several sectors, each producing a particular type of output, with an output structure that is assumed to be fixed and without substitutions occurring between the outputs of different sectors. It is also assumed that the inputs of each sector are simple proportions of the output level of that sector and that the total effect of output in different sectors is the sum of the separate effects, i.e., that no external economies and diseconomies operate. IO analysis is thus a strictly linear technique, a limiting fact for its applicability in some circumstances.

An input-output table is built up from surveys of transactions among the sectors of an economy in a year. Therefore, it characterizes the economy (in the form of an "economic snapshot") at a particular stage of development, in a form that identifies and measures the physical processes of production, exchange, and consumption of goods and services.[147]. Although goods and services traded are tangible, the monetary value (e.g., in dollars) of an industry's units of production is used to represent it. The fact that the underlying processes are physical makes it significant for energy analysts and also provides a means to link practitioners in the physical and biological sciences with economists when addressing issues of common interest [147].

The widespread availability of computational high-speed computers has made Leontief's input-output analysis a widely applied and useful tool for economic analysis at many geographical levels: local, regional, national, and even international. Before the emergence of modern computers, the computational requirements of input-output models made their implementation very difficult and even impractical.

In its most basic form, an input-output model consists of a system of linear equations, each of which describes the distribution of an industry's output in the economy. Most extensions to the basic input-output model are introduced to incorporate additional details of economic activity, such as in time or space, to address limitations in available data, or to link input-output models to other types of economic analysis tools.

By the late 1960s and 1970s, the U.S. economy was becoming increasingly dependent on imported sources of oil and was being forced to deal with supply shortages as a result of embargoes imposed in the early 1970s by the mainly Arab countries organized in a cartel known as the Organization of Petroleum Exporting Countries (OPEC). Concern was also growing at the same time among the public about the environmental impact associated with increased energy consumption, focusing in particular on the air pollution related to coal burning. Since energy was a critical factor of production for many industries in many regions of the country, researchers and government policymakers began to focus on the role of energy in the economy. The basic input-output framework focused on energy use has been expanded to account for inter-industry energy flows, particularly broadened in the late 1970s and early 1980s in the wake of the Arab oil embargoes and their effects on the U.S. economy. The mathematical structure of all these extensions reflects almost perfectly Leontief's classical model [110].

The most straightforward extension of the Leontief framework is to explicitly account for energy use by simply adding a set of linear energy coefficients that define energy use by production dollars of industrial sectors. This approach has some methodological and practical limitations, but it continues to be used frequently today, particularly because it is often difficult to acquire the additional data needed to address the key weaknesses of ensuring internal consistency in accounting for energy supply and use across the economy [110].

This is particularly true and relevant for environmental applications where it is important to account for interindustry flows in physical units, tracking life-cycle impacts thorough-out all the steps of the supply chain that are usually taking place in multiple regions, thus requiring global multiregional IO (MRIO) analysis. National statistical offices, take multiple pieces of information and put them together in their national table which is then resumed in global tables. Multiple entities are now providing their version of a global input-output representation of the world economy: GTAP, EXIOBASE, WIOD, EORA, and recently, FIGARO, are the most profound efforts have made so far but each of them adopted a slightly different approach and consequently, assumptions [97,148–152].

Basic framework

The basic Leontief IO model is generally constructed from observed economic data for a specific geographic region (nation, state, county, etc.). One is concerned with the activity of a group of industries that both produce goods or services (outputs) and consume goods or services from other industries (inputs) in the process of producing each industry's output. In practice, the number of industries considered may vary from only a few to hundreds or even thousands. For instance, an industrial sector title might read "manufactured products," or that same sector might be broken down into many different specific products.

The fundamental information used in IO analysis concerns the flows of products from each industrial sector, considered as a producer, to each of the sectors, itself and others, considered as consumers. This basic information from which an input-output model is developed is contained in an interindustry transactions table. The rows of such a table describe the distribution of a producer's output throughout the economy. The columns describe the composition of inputs required by a particular industry to produce its output.

The economic activity must be able to be separated into several segments or producing sectors. These may be industries in the usual sense (e.g., steel) or they may be much smaller categories (e.g., steel nails and spikes) or much larger ones (e.g., manufacturing). The necessary data are the flows of products from each of the sectors (as a producer/seller) to each of the sectors (as a purchaser/buyer). These interindustry flows or transactions are measured for a particular time period (usually a year) and in monetary terms – for example, the dollar value of steel sold to automobile manufacturers last year [110].

Leontief's original IO framework conceived of industry production functions as measured in physical units, such as specifying the technical coefficients in tons of coal or bushels of wheat, as inputs, required per dollars' worth of an industry's output or per ton of steel output. However, the data collection requirements and many other constraints rendered implementation of the framework in physical units too unwieldy, certainly at the time and even today to a lesser extent. Hence, the basic methodology for IO analysis evolved, in both theory and application, through measuring all quantities in value terms with implicit fixed prices.

The contributions of many researchers have extended the IO framework incrementally in the direction of employing physical units and, in the process, have helped lay the groundwork for new research areas such as industrial ecology and ecological economics. In addition, there have been substantial developments in related areas where public policy concerns have encouraged such development and data have been collected to help implement the framework.

IO analysis provides a useful framework for tracing energy use and other related characteristics such as environmental pollution or flows of physical materials associated with the interindustry activity. The generalization of IO analysis techniques to a much broader conceptual level began with simpler attempts to link IO models and other national income accounting techniques with many measurable quantities associated with inter-industry activity, such as energy use, environmental pollution, and employment. These generalized models are introduced in their most rudimentary form as a logical extension to the basic formulation that evolved to handle energy and environmental factors. Endogenous resource matrices may contain primary non-renewable energy consumption so as carbon dioxide emission from combustion.

Moreover, hybrid tables can be used for explicitly accounting for physical quantities when possible. One big advantage is the access to coherent data integration between multiple sources not requiring assumptions on the price of commodities that may vary year-over-year or region-by-region [153]. Nevertheless, specific care must be taken for hybrid model building. Multiple sectoral outputs must be measured in the same units of measure. Importantly, to catch this complexity the distinction between economic activity and its output must be explicitly represented in the so-called supply and use framework.

The supply and use framework

Input-output analysis has served economists and industrial ecologists in estimating the economic, environmental, and social impact associated with variation in industries' interconnections for decades [124,154]. Adoption of a multi-regional supply and use input-output tables (SUTs) allows for distinguishing commodities from the economic activities that produce them, leading to more accurate and detailed results [155].

SUTs are a powerful accounting tool that aims to show a comprehensive picture of the inner workings of an economy and look at establishing a relationship between goods, services, and industries. To do so, SUTs give detailed information on production processes, inter-dependencies in production, use of goods and services, and the generation of income by production [156].

The Supply and Use Tables (SUTs) are an integral part of the System of National Accounts (SNA) [157] forming the central framework for the compilation of a single and coherent estimate of gross domestic product integrating all the components of production, income and expenditure approaches as well as providing key links to other parts of SNA framework. In their simplest form, the SUTs describe how products (goods and services) are brought into an economy (either as a result of domestic production or imports from other countries) and recorded in the supply table and how those same products are used (as intermediate consumption, household final consumption, non-profit institutions serving households, general government final consumption, gross capital formation, and exports) and recorded in the use table [156].

A SUT provides the link between components of gross value added, industry inputs, and industry outputs. Although typically shown only by the industry dimensions, SUTs can also be formulated to show the role of different institutional sectors. As a consequence, SUTs do not just provide a framework to ensure the best quality estimates of the economy, they are also an important analytical resource for many important different analyses like Computable General Equilibrium (CGE) models and Input-Output models. This concept finds a more consistent representation in the Social Accounting Matrix (SAM), which links together the macro-statistics of national accounts with the micro-statistics of labour market, household income, consumption, and other social statistics [158]. SUTs are an integral part of the SAM and, although they do not include social notations important to correctly describe the income flow, they provide a macroscopic representation of a circular flow, where everything stays within the economy. This is an underlying assumption in the SUTs framework, every commodity that has been produced by all the activities needs to be consumed by other activities or by final demanders.

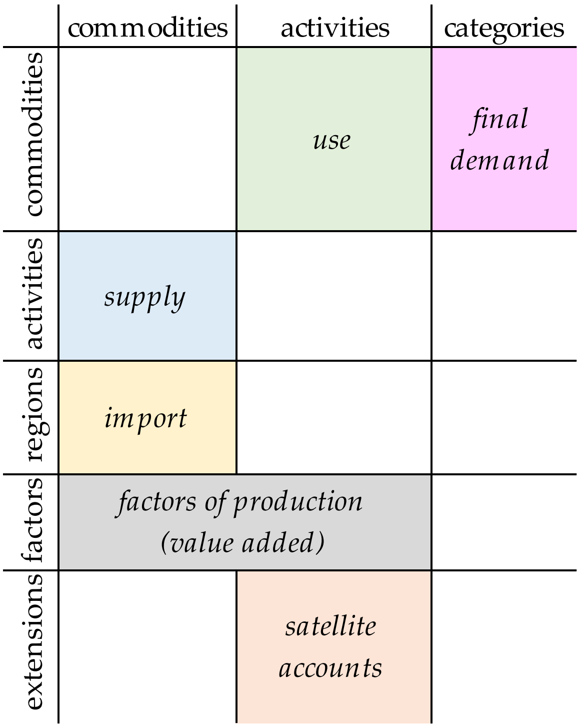
All these transactions are recorded in the extended SUTs which provide the answer to 4 key questions:

- Who **supplies** a certain commodity
- Who **uses** a certain commodity as an intermediate activity or as a **final demander**
- How much **value added** is generated in the process
- What are the impacts on the considered **satellite accounts**

The transactions are schematized in matrices that are described in for a single region table that also used **imports** that may be accounted in different ways depending on whether Isard accounting rules are employed or not [110].

Disregarding its physically grounded principles and information richness, this framework is currently adopted by a few researchers [155]. For further investigation of this topic, the reader is invited to consult Eurostat's Supply and Use Manual [156].

Figure 2.6 – The Supply and Use framework.



The future of input-output analysis

In 2013, Dietzenbacher, Lenzen, Suh, and other eminent researchers in the field speculated on the future of the next 25 years [159]. Dietzenbacher sees a growing trend in demand and supply of more detailed, statistically more robust physical multiregional tables while expecting new approaches for dealing with the increasingly concerning issues of the global supply chain. Lenzen ironically foresees a future in which the increasingly high computational power allows for the implementation of real-time hyperdetailed input-output tables are possible, allowing for near-to-perfection computation of footprints. Also Suh envisages a growth of the IO field driven by data and information technology advancement, but he also underlines how in the past great changes (such as the commodity and activity distinctions) came from new regulations of international entities. In the same way, future advancements may be accelerated by a combination of political will and consumer pressures driven by the need for better accounting for environmental impacts.

Today efforts concerning the input-output analysis community are mainly focused on identifying a modelling framework capable of representing with greater detail and realism the dynamics governing production processes [160]. To do this, in addition to working on increasingly higher resolution tables of activities, commodities, regions, etc., numerous efforts are also focused on better accounting for and modelling the dynamics of infrastructure investments and capital goods [61,161,162]. Among the various remarkable works, the recent researches of Södersten and colleagues represent the most advanced effort of extending the classical framework making information for capital expansion explicit proposing methodologies for disaggregating yearly consumption of fixed capital and gross fixed capital formation [61,161]. Vita *et al.* adopted IO to investigate the impact associated with the fulfilment of fundamental human needs, as defined by Max-Neef framework [163].

Information on requirements for capital expansion and needs satisfaction would be useful not only for improving accounting principles but also for coupling input-output with other methodologies.

2.4.2. The comparative advantage: coupling input-output and linear programming

One of the main strengths of the input-output approach is that it considers many complexities of a real economy such as the interdependency among all the producing sectors within an economy. However, the classic IO approach is characterized by the fact that the level of all the final demands – including investment – is endogenously fixed. Thus it may be necessary to couple the input-output framework with some other modelling approaches.

Among the possible modeling approaches which could be adopted for sustainability issues, the World Trade Model (WTM) represents a unique framework for expanding the opportunities offered by MRIO analysis [114]. This framework represents a generalized interpretation of the theory of comparative advantage, which could be exploited for evaluating infrastructure systems and policy implementation alternatives [160]. The economy's ability to produce a particular commodity at a lower opportunity cost than its trading pairs is a general definition of comparative advantages which regulates modelling choice every time two or more production alternatives are available.

Duchin *et al.* proposed two extensions of the traditional environmentally extended IO model, namely the Rectangular Choice of Technology (RCOT) model [164] and the World Trade Model (WTM) [111]. A combination of these two models has been employed for analysing possible scenarios and implications of satisfying 2050 food requirements [165]. As formalized by Strømman and Duchin, the WTM can be extended by taking into account the costs of international trade within the so-called World Trade Model with Bilateral Trade (WTMBT) [166]. The same authors, together with Hertwich, have also employed the WTMBT to investigate costs and changes in the geographic distribution of production driven by the minimization of global carbon emissions [167]. These modelling approaches can be defined as Input-Output based optimization models grounded on the comparative advantage principle, respectively adopted to assess the production alternative or the international trade patterns that minimize the global use of economic factors given a set of economic and environmental binding constraints. Duchin and Levine have recently further explained WTMBT conceptual framework, mathematical formalization, and integration with MRIO in two papers

[113,114]. Many applications of these modeling approaches can be found in the literature. As an example, López-Morales and Duchin study the role of natural resource availability on the Mexican economy, assessing regional water endowments' resilience to consumption and related sustainability-oriented policies [168].

Dynamic input-output models

Dealing with the energy transition, which is likely to occupy at least the next decade, may not be appropriate to limit the approach to evaluating policies as if they were happening "overnight". To overcome this limitation, it may be necessary to rely on a dynamic model.

Dynamic IO modeling extends properties that are missed in the static model to include the determination of the sectoral production and accumulation of capital goods through a multi-sector capacity expansion. The amount and the structure of each sector's commodity demand for capital goods per unit increases of its total production are identified with a new coefficient matrix usually named capital coefficient matrix. The advantage of the dynamic input-output formulation is its intertemporal consistency for all sectors between the specific capital items produced and delivered in one period and increments of output that in subsequent periods will be available for use.

Moreover, within this framework, the dynamics of the consumption of capital which is the amount of investment for replacing depreciated equipment industry can be elaborated. In a static model, replacement capital is only considered as a category of final demand (i.e. gross fixed capital formation) and value-added (i.e. consumption of fixed capital) needed for the production and the composition of such consumption by sector in terms of different commodities cannot be identified.

Last but not least, one of the limitations of I-O models is that the capacity is not an endogenous property of the model which make the model a weak tool for capacity expansion scenario analysis.

For the first time, the dynamic input-output model was proposed and formulated by Leontief [169]. In his formulation investment is considered as the rate of change in required capital stock, with a vector differential equation considering the increase of the total output in a time step and the matrix of capital coefficients representing the composition of the investment in terms of different commodities for an industry. In his formulation, the possibility of structural change in the economy is also considered.

One of the main issues of the dynamic model proposed by Leontief was the existence of an economically meaningful solution for the problem. It means that the vector of output for different periods should be nonnegative. Szyld et. al. discussed in detail the cases that such a problem could emerge in a dynamic input-output model [170]. The fact that negative outputs will typically be presented comes from that the fact the entire physical productive capacity is utilized (i.e., full capacity utilization), which involves both perfect foresight of future stock requirements and the reversibility of the capital. To address this issue by assuring the irreversibility of capital already in place, a multi-phase process was proposed by Leontief according to which capital stocks are increased only when output growth [169]. Uzawa proposed to replace introduce a maximum function, avoiding negative investment thus guaranteeing the existence under certain conditions of solutions to the Leontief dynamic input-output model [171]. In fact, the introduction of this non-linearity amounted to allowing for unused capacity when output is falling. While the Uzawa approach emerged promising, Dorfman et. al. showed some concerns about contradictions in switching between this regime when output is falling and the full capacity utilization required when output is rising [172]. This potential problem is not encountered if one abandons the requirement of full capacity utilization even when output is growing. If output and capacity are not defined to be identical, then the model must provide not only the sectoral output but also, sectoral pattern of capacity utilization.

To solve these issues Duchin et. al. introduced the notion of an investment plan for expansion in each sector, through the introduction of a new non-linear system of equations for the Leontief dynamic input-output model [173]. In this study, it is assumed that the effective expansion of a sector's capacity may require several periods, in which case expansion plans must be formulated, and their implementation begins this amount of time in advance. The amount of planned expansion depends upon future sectoral production as anticipated when the plan is formulated. Once in place, the plan is adhered to even if the sector's circumstances change. If adequate capacity is already in place, no expansion is implemented.

While many discussions have been done on the development of a dynamic IO model for different purposes, realistic closure of the model is unfortunately not achieved due to the fact the data related to the capital formation of different industries are not well available. Furthermore, it is not always easy to reproduce and automatize the models presented in such a study. Overcoming this issue could represent a unique opportunity for improving and validating the efforts presented in the literature. Furthermore, it is not always possible to work with openly available databases. This could represent an important limitation for the spread of new studies.

2.4.3. A taxonomy for input-output models

The input-output analysis represents a suitable and comprehensive industrial ecology methodology for evaluating a structural change in a determined supply chain while considering the implications on the complex network of interlinkages among different economic sectors [125]. IO analysis refers to the macroeconomic analysis approach based on the study of the sectoral interrelations of an economy and requires the use of input-output tables, and economic-wide databases able to capture the flows of monetary value between different sectors [174]. Some features can distinguish traditional input-output models, depending on the following main parameters:

- Table characteristics:
  - *Geographical scope and scale*: single-regional or multi-regional IO (respectively SRIO and MRIO) analysis can include one or multiple economies within the same table. Being this research focus on assessing the role of emission reduction mechanisms for mitigating a global issue such as climate change, limiting the regional scope to an SRIO model may hamper IO implicit comprehensiveness.
  - *Table type*: IO analysis has been mostly performed by adopting squared tables (called IO tables). Nevertheless, as has been shown by Lenzen, the framework offered by Supply and Use tables (SUT) can be adopted to directly perform impact analysis [155,161]. The SUT structure allows for a more physically sound representation of economic flows, distinguishing activities and their physical products. That represents an advantage when describing energy systems within the IO framework.
  - *Table units*: the vast majority of IO tables display sectoral interdependency by tracking flows in monetary units. Being able of detecting physical flows such as energy in the proper unit of measure (e.g. Electricity in GWh) within an economy-wide representation of sectoral interconnections represents an important advantage for energy analysis using industrial ecology methods. Currently, few tables are represented in this way (i.e. hybrid unit tables).
- Model characteristic:
  - *Time scope and scale*: virtually all IO tables are a snapshot of one year. Multiple years can be represented in series, without a model explicit link between each time step. To explicitly introduce the concept of dynamic expansion of the economy, additional matrices must be included. Being emission reduction characterized but multiple

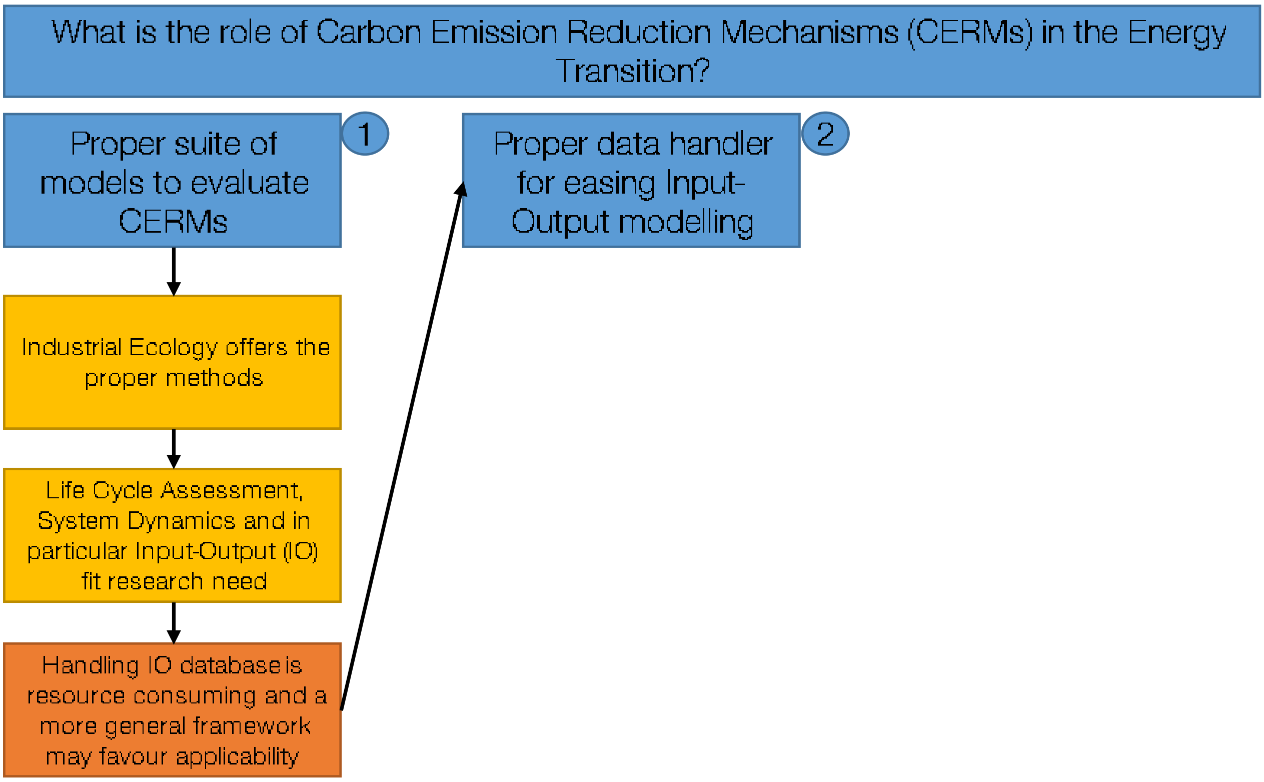
different pathways, having a coherent description of year evolution seems more appropriate. Nevertheless, useful insights can be grasped even by adopting a so-called comparative statics approach, in which changes occur "overnight".

- *Linear-programming coupling*: traditional models are grounded on Leontief's pioneering equations or slight variations. However, traditional IO's model structure can be expanded by introducing linear optimization programs aimed at stylized economic agent utility functions or resource limitations.

A combination of table and model characteristics can be selected within the IO framework, modelling different carbon emission reduction mechanisms with the most case-suited configuration. This same taxonomy is used to introduce the applications adopted in chapter 4, the one reporting the applications.

As shown in Figure 2.7, an updated version of Figure 1.1, the first specific objective is achieved and it is now possible to move to specific objective number 2. In fact, from the literature review, it has emerged how IO analysis can offer the most suitable framework for analysing carbon emissions reduction strategies. However, practical issues and conceptual differences in modelling applications must be properly addressed in chapter 3.

Figure 2.7 – Partial map of the study.



3. Materials and methods

In this chapter, the materials and methods developed in this research are explained. In particular, the most adopted framework used in this research, which is input-output (IO), is explained
In the previous chapter, the most relevant pieces of information for setting this research have been presented. The scientific field of Industrial Ecology allowed for the identification of IO as the most suitable framework for studying carbon emission reduction mechanisms. IO has been introduced from its inception to the most complex evolution of the framework. The literature review has also identified the most crucial aspects of carbon emission computation and accounting.
This chapter is intended as a way to reshape, rename and expand the IO framework to allow for a coherent formalization of the practical contribution in the field. That is why the chapter starts with a sub-chapter on nomenclature and definitions that clarify the use of some of the most frequent keywords already introduced and crucially adopted in the rest of this dissertation. Then, a chapter on the role of openness of code – intended as a methodological need – is presented to highlight the relevance of sharing, reproducing, and improving tools and analysis. Sub-chapter 3.3 and 3.4 represent the two main contributions of this research on the IO framework, proposing a tool to ease and standardize IO and the generalization and expansion of the supply and use framework that has been employed for the IO applications presented in chapter 4.

3.1. Nomenclature and definitions

Industrial Ecology is a maturing scientific discipline [175]. Some researchers have tried to apply a visual and intuitive graph approach to display the system structure of the different models and of Industrial Ecology [176]. IO analysis, today widely practised by industrial ecologists, is older than the formalizations of the concepts of Industrial Ecology and it has been studied and applied in a number of different applications in the field of Economics. Each of these applications has been formalized with a rather different nomenclature.
For sake of transparency and clarity, here the definitions of the most used terminology in this research are explicated, starting with the most general terms already adopted in the previous chapters. For each definition an example is provided:

- *Scientific branch*: the study of a phenomenon that starts from the definition of peculiar common elements and scopes (e.g. Industrial Ecology, the study of industrial systems that operate more like natural ecosystems, defines the scope of the research – the socio-economic metabolism – and some common elements, such as the need to trace flows between agents).
- *Framework*: a family of methodologies pertaining to the same scientific branch or group of branches, i.e. field (e.g. the input-output framework represents all the group of methodologies that shares its basic principles, parameters, and or equations).
- *Methodology*: a specific group of activities necessary to pursue the answer to a specific research question (e.g. the preparation and implementation of the World Trade Model identify a different methodology with respect to the classic IO analysis even if they are sharing some of the needed information and equation).
- *Approach*: here is generally intended as a synonym of methodology. May sometimes be specifically used as a synonym for model.
- *Model*: the specific set of equations that are depicting one or more phenomena that are included in the analysis. It is a specific set of a methodology that was derived from or integrated into a framework (e.g. a World Trade Model with Bilateral Trade considering the cost of international transport, such implying slightly different inequation).

- *Application*: the specific adoption of a model having as input a specific set of data thus resulting in a specific manifestation of the expected results (e.g. the World Trade Model applied with a specific regional and sectoral aggregation and specific set of constraints with few differences between scenarios generating the spectrum of results of the application).

Having introduced these general definitions, it is possible to deepen the nomenclature and symbology adopted in the proposed framework. Most of it is a synthesis of various sources, ranging from technical reports to scientific papers [129,156,158].

Any input-output framework requires clear definitions of who are the agents, and what they do represent. This formalization has been crucial also for the development of the proposed innovative carbon emission reduction mechanism. Thus, the definition of agents represents the starting point for comprehending the proposed advancement brought by this research:

- *Agent*: a person, company, or organization that influences the economy by producing, buying, or selling.
- *Technology*: it identifies one or more means that are needed to pursue one or more *activities*. This term is widely adopted in modelling. A *technology* can be installed or not and, in case it is installed, available or not (e.g. 5 units of 300 W solar panels can be installed but they are not available during night hours).
- *Activity*: it identifies every action or group of actions carried out through a *technology* to produce a *commodity*. This term is derived from the input-output framework when supply and use tables are adopted (i.e. supply and use framework), thus having a macro-economic meaning. Actually, in this research its sense is broader, allowing for the modelling of micro-activities such as driving an electric vehicle, which represents the *technology* adopted in that case. When a classic supply and use framework is adopted, the *technology* and its *activities* collapse in one unique way of producing any kind of output, representing the group of industries of the same business category.
- *Commodity*: it identifies any good or service that can be provided within the pursuit of one *activity*. This term is derived from the supply and use framework, thus having a macro-economic meaning. Actually, in this research its sense is broader, allowing for the modelling of micro-commodities such as the private-transportation service, which fulfil the *need* for private transport in that case. When a classic supply and use framework is adopted, each *commodity* and the *needs* it can fulfil collapse in one unique product, representing the group of goods and services of the same demanded product categories.
- *Need*: it identifies the demanded necessity that can be addressed by one or more *commodities*. This term is adopted also in modelling and cooperation. When a technology choice model is adopted the demand-side of the matrices "consumes *needs*" the output of more than one sector is covering the same demand (e.g. the *need* for electricity can be fulfilled by electricity from solar panel or by electricity from gas turbine).
- *Sector*: when an input-output framework is adopted or a supply and use table is transformed into an input-output framework *activities* and *commodities* are overlapped (a transformation model must have been adopted, thus implicitly introducing assumptions about the relation between *commodities* and *activities*). The result of this overlapping is simply a *sector*.

Italic is used in this manuscript when these nouns are used to assume the meaning intended in the definitions reported above.

The definitions of these terms allowed for the representation and the symbols for all the matrices and parameters adopted within the generalized supply and use framework here presented, which I

called the Technology-Activity-Commodity-Need (TACN) framework. The notational is derived from my engineering background and in particular from thermodynamics. Every time a capital letter identifies a matrix it contains absolute values (i.e. flows between agents). If the same letter is represented in lower-case, it is the same kind of information but in a coefficient form, thus specific with respect to some other absolute value, usually output by *activity* or *commodity* volume.
In Table 3.1, a partial representation of the matrices adopted in the TACN framework is reported. Together with the elements defined above, matrices and their indices (such as the ones for regions, time, demand categories, factors of production, …) are represented. As an example, *X_* is reported to show how any matrix can be expanded in the dimension of time identifying, for example, the production of commodities and the output of each activity in every time step considered in a dynamic model.

Table 3.1 – Table of parameters. AKA columns stand for "Also Known As" and it is reported to ease readers' understanding by linking familiar alternative names in similar research. Some indices or matrices may not be present in the IOT, SUT, or TACN version.

Symbol	AKA	Name	Dimensions IOT	Dimensions SUT	Dimensions TACN	Type
r		Region [*e.g. Italy*]	TRUE	TRUE	TRUE	index
a	Industry (i)	Activity [*e.g. Production of electricity by gas*]	FALSE	TRUE	TRUE	index
c	Product (p)	Commodity [*e.g. Electricity from gas*]	FALSE	TRUE	TRUE	index
s		Sector [*e.g. Gas power*]	TRUE	FALSE	FALSE	index
f		Factor of production [*e.g. Wages*]	TRUE	TRUE	TRUE	index
k		Satellite account [*e.g. Carbon dioxide*]	TRUE	TRUE	TRUE	index
d		Demand category [*e.g. Households demand*]	TRUE	TRUE	TRUE	index
n		Need [*e.g. Electricity*]	TRUE	TRUE	TRUE	index
t		Technology [*e.g. Combined cycle power plant*]	TRUE	TRUE	TRUE	index
q		Timestep [*e.g. 1 year*]	TRUE	TRUE	TRUE	index
Z	*Z, T*	Intersectoral transaction flows matrix	r*s x r*s	r*(c+a) x r*(c+a)	r*(c+a) x r*(c+a)	matrix
Y	*Y, f*	Final demand	r*s x 1	r*c x 1	r*n x 1	matrix
X	*x*	Production	r*s x 1	r*(c+a) x 1	r*c x 1 = r*a x 1	matrix
*X_*	*x*	Dynamic production	r*s x q	r*(c+a) x q	r*c x q = r*a x q	matrix
V	*R, F, W, VA, K*	Value added transaction flows matrix	f x r*s	f x r*a	f x r*a	matrix
EY	*F_hh, F_y*	Satellite transaction flows matrix for final us	k x 1	k x 1	k x 1	matrix
z	*A*	Endogenous transaction coefficients matrix	r*s x r*s	r*(c+a) x r*(c+a)	r*(c+a) x r*(c+a)	matrix
w	*L, B*	Leontief coefficients matrix	r*s x r*s	r*(c+a) x r*(c+a)	r*(c+a) x r*(c+a)	matrix
y		Final demand mix share	r*s x 1	r*c x 1	r*n x 1	matrix
v	*B, S, F*	Value added transaction coefficients matrix	f x r*s	f x r*a	f x r*a	matrix
e	*B, S, F*	Satellite transaction coefficients matrix	k x r*s	k x r*s	k x r*s	matrix
f		Footprint coefficients matrix	k x r*s	k x r*(a+c)	k x r*(a+c)	matrix
F	*E*	Footprint matrix	k x r*s	k x r*(a+c)	k x r*(a+c)	matrix
U	*U*	Use transaction flows matrix	FALSE	r*c x r*a	r*c x r*a	matrix
S	*V, M'*	Supply transaction flows matrix	FALSE	r*a x r*c	r*a x r*c	matrix
u	*B*	Use transaction coefficients matrix	FALSE	r*c x r*a	r*c x r*a	matrix
s	*D*	Supply transaction coefficients matrix	FALSE	r*a x r*c	r*a x r*c	matrix
g		Technology to activity matrix	FALSE	FALSE	r*t x r*a	transformation matrix
j		Commodity to need matrix	FALSE	FALSE	r *n x r*c	transformation matrix
K		Investment cost	FALSE	FALSE	1 x r*t	matrix
k		Specific investment cost	FALSE	FALSE	1 x r*t	matrix
D		Deployed capacity of technology	FALSE	FALSE	1 x r*t	matrix
WY		Why matrix	FALSE	FALSE	r*c x r*d*n	matrix
KY		Capital investment matrix	FALSE	FALSE	r*c x r*t*n	matrix
D		Deployed capacity of technology	FALSE	FALSE	1 x r*t	matrix

Some variables can assume matrix or vector shape. Having exploited the capital-small letter distinction to represent absolute and coefficient pieces of information, the number of underlines below every variable identifies its algebraic dimension. Thus, in formulas single-underlined variables are vectors and double-underlined are matrices.

3.2. The relevance of open-science

Modelling is becoming more and more relevant in addressing modern society's complex problems: epidemiological models have been fundamental in addressing the COVID-19 pandemic during 2020 [177]. Furthermore, European funds are allocated for studying energy transition through modelling approaches able to capture the multi-levelled complexity of the sustainable development challenge

[104]. Moreover, open data allows scientists to be able to reproduce, overcome and expand previously presented work: as Pfenninger and colleagues stated in 2017, «models and their associated data must be openly available to facilitate higher quality science, greater productivity through less duplicated effort, and a more effective science-policy boundary» [178].

Transparency and accessibility are among the key principles of Oxford Policy Management, endorsed by a number of the most important institutions in this field of research [179]. This principle is fundamental to «promote open access to and review of planning inputs (data, model design and assumptions) and encourage the accessibility of planning outputs to key stakeholders, subject to government restrictions and commercial confidentiality constraints» [179].

Great efforts have been put in place in the international input-output community for "opening science" in the field of Industrial Ecology. Nevertheless, analysing global environmentally extended multi-regional input-output (MRIO) tables is becoming more challenging: increasing interest in describing intersectoral linkages with a high level of detail is making spreadsheets less practical to use due to multiple sectors and regions resulting in thousands of rows and columns. In particular, the work done by the EXIOBASE team for collecting global monetary and physical flows in one unique and freely available MRIO table is exceptionally relevant [97]. *Pymrio*, an open-source tool for MRIO analysis, is now available in its 0.4.2 version [180]. The tool, openly available at https://github.com/konstantinstadler/pymrio, allows to automatically download the most recognized environmentally extended MRIO tables (e.g. EXIOBASE, WIOD, and EORA26), calculating matrices of coefficients and having access to various visualization methods.

Pauliuk *et al.* underline how adopting general principles for the development of good scientific software can be beneficial for the whole scientific field, having access to productive pieces of code that can save industrial ecologists time and efforts and permitting collaboration to improve the research tools [175]. This has been the case for the studies conducted within this research. GitHub pages are available for practically every model application, embracing the invite of the Industrial Ecology community.

The reason why this chapter appears in the *Materials and methods* section is that openness importantly impacts the way modelling is performed. The industrial ecology tool that has been developed in my research group during the years of my PhD, embraces this philosophy not only to allow reproducibility of model applications but also for making the analysis behind the implementation of the innovative carbon emission reduction mechanisms transparent.

Any modeler who aims to calculate any kind of footprint of a good or service needs a model of industrial interconnections that epistemologically requires numerous assumptions. This represents a standard aspect of modelling, but it must be made explicit to anyone, expert or novice, who approaches understanding the footprint value reported in any footprinting study. Making these assumptions transparent, clear, and accessible is, therefore, the first characterizing aspect of the carbon reduction mechanism proposed in this study.

3.3. MARIO: Multifunctional Analysis for Regions through Input-Output

Within the current open-modelling community, a tool for easily and quickly handling any kind of IO tables is not available. A couple of recent efforts have been undertaken [180–182], but no tool exists that can comprehensively process all the different types of IO tables and provide a toolkit to implement transparent, automatic, and easily reproducible shock and footprinting analysis. For this reason, Multifunctional Analysis of Regions through Input-Output (MARIO) has been developed and published openly on GitHub, accompanied by a detailed web guide [183].

MARIO is a Python package for handling input-output tables and models which aims at providing a simple & intuitive API for common IO tasks without needing in-depth programming knowledge.

MARIO takes advantage of its automatically generated Excel spreadsheet interface, estimating the specific energy, economic, and environmental burdens expected for each scenario that an industrial ecologist may want to study. MARIO supports automatic parsing of different structured tables such as EXIOBASE [97], EORA [151], EUROSTAT [156], and ad-hoc built tables in different formats such as single regional input-output (SRIO) and MRIO tables in monetary or hybrid units. Supply and Use tables are also supported and can be transformed into IO tables employing a built-in function, implementing the transformation models extensively described and adopted in the literature [110,156]. Furthermore, MARIO allows for smooth handling of database aggregation, modification, and extensions. Finally, productivity and balance tests together with backward-forward linkages analysis [174] and production or consumption-based visualization of results in different scenarios provide IO analysts with basic coding skills with a wide set of instruments.

When a database is parsed, all the IO matrices will be stored as pandas DataFrame (https://pandas.pydata.org) in a nested Python dictionary where all the matrices are stored for every specific scenario under analysis. MARIO consists of three main objects:

- *CoreModel* class working as the highest-level object for handling the matrices and basic IO mathematical calculations.
- *Database* class which contains methods and properties for shock analysis and modification of the database.
- *marioMetaData* class which tracks all the modifications on the database and generates metadata reports in different formats such as json or txt files.

Some of the most useful functionalities of MARIO are here listed:

- *Database Parsing*: MARIO can parse a series of differently structured databases which are open sources such as EXIOBASE, pyrmio library database (github.com/konstantinstadler/pymrio), and EORA. Where a database is not structured, pandas DataFrames, Excel files, or text files could be used to create a MARIO Database.
- *Database Aggregation*: IOTs and SUTs are mostly published with highly disaggregated data. MARIO could aggregate the data by passing an excel file or pandas DataFrame which defines the aggregation.
- *Mathematical Calculations*: MARIO calculates all the matrices and their dependencies automatically when they are requested to avoid overusing the memory.
- *Database Modification*: a MARIO database could be modified by adding new environmental data or economic data through excel files or pandas DataFrame.
- *Database Balance Check*: a monetary IOT or SUT should respect an economic balance that can be checked by MARIO and imbalanced sectors could be identified.
- *Shock Implementation*: MARIO provides methods to implement a change in the database to assess the impact of a specific scenario and analyse the results.
- *Exporting Database*: the modified database, as well as the implemented scenarios, can be saved in different formats such as excel or csv files along with the metadata.
- *Visualization*: MARIO relies on plotly library (plotly.com) for its visualization routines. The outcome of scenarios could be compared for different parameters such as impacts embodied in international trades, environmental footprints of different sectors, production and consumption of different economic agents, and more.

Complete documentation of how MARIO works and how it can be installed on any computer is provided at mario-suite.readthedocs.io.

During the PhD research, MARIO has been adopted for several traditional IO analyses. Moreover, it has been of fundamental support to ease the development of more sophisticated IO-based models allowing for a trial and error process which maximises resource saving. Some of these models have generated some interesting insights for supporting the general objective of this thesis and are therefore described in the following *Applications* chapter.

3.4. Towards a Dynamic Supply and Use Global Model

The Technology-Industries-Commodity-Need (TACN) framework defined in sub-chapter 3.1 can be used to generalize the development of a wide range of models, from the classic Leontief approach, passing through small-scale energy models to the dynamic supply and use global model.
The applications presented in chapter 4 have been formalized by adopting the TACN framework. In the next sections – after the presentation of the two-step approach – the framework is formalized and then – in the one following – a theoretical meso-economic demonstration using real-world data is provided.

3.4.1. The two-step approach: investment and operation

Transformations such as the Sustainable Transition, require the introduction of new types of machinery, interventions, or generically innovation in the way inputs are transformed into output (i.e. *technology*). Such *technologies* are usually introduced to fulfil a certain necessity – usually already satisfied by a present solution – with the promise of reducing operational impacts. The classic Leontief input-output approach can serve this purpose, allowing for impact assessment.
The *technology* impact assessment is separated into two steps that help in distinguishing between the economic, environmental and social impact associated with the introduction of the *technology* (i.e. investment step) and its operation (i.e. operation step). In particular, the following aspects are considered for each step:

- Investment step (*i*): it includes all the costs associated with producing the components, and moving them to the installation site, implying consequent direct and indirect effects on suppliers' production. By default, it does not include research and development spending or activities that will take place after the end-life of the plant. This step is modelled by perturbing the matrix of final demand, disaggregated coherently within the needed commodities.
- Operation step (*o*): it includes all the consumption of intermediate services, goods, and factor of production, comprising the amortization of the capital expenditures associated with the introduced technology or intervention. This step is modelled through a perturbation of the technological coefficients matrix.

The impacts resulting in every year are therefore disaggregated into these two steps, allowing for a better understanding of the source of variation within the domestic and global economy.
In the supply and use framework, it is possible to assume a change in a specific interrelation between two economic activities of a supply chain by intervening on a specific coefficient. Since the objective of this work is to evaluate the impact of a technological change related to both implementation and use, it is required to distinguish every intervention in those two steps. In both cases, there is an impact on socio-economic factors (linked with production through the matrix of monetary exogenous coefficients f) and environmental extensions (linked with production through the matrix of physical exogenous coefficients e), respectively F and E. The investment step will be handled, as shown in equation 3.1, with the current *technology* assessment (no subscript identifies baseline data, while subscript i identifies investment data). The structural change in operation influences, as shown in equation 3.1, how the baseline final demand is delivered (subscript o identifies data after implementation of the intervention).

$$\underline{\underline{\Delta F_i}} = \underline{\underline{f}}\ [\overbrace{(\underline{\underline{I}} - \underline{\underline{z}})^{-1}\ \underline{Y_i}}^{x_i}] - \underline{\underline{f}}\ [\overbrace{(\underline{\underline{I}} - \underline{\underline{z}})^{-1}\ \underline{Y}}^{x}]$$
$$\underline{\underline{\Delta E_i}} = \underline{\underline{e}}\ [(\underline{\underline{I}} - \underline{\underline{z}})^{-1}\underline{Y_i}] - \underline{\underline{e}}\ [(\underline{\underline{I}} - \underline{\underline{z}})^{-1}\ \underline{Y}] \tag{3.1}$$

$$\underline{\underline{\Delta F_o}} = \underline{\underline{f_o}}\ [\overbrace{(\underline{\underline{I}} - \underline{\underline{z_o}})^{-1}\ \underline{Y}}^{x_o}] - \underline{\underline{f}}\ [\overbrace{(\underline{\underline{I}} - \underline{\underline{z}})^{-1}\ \underline{Y}}^{x}]$$
$$\underline{\underline{\Delta E_o}} = \underline{\underline{e_o}}\ [(\underline{\underline{I}} - \underline{\underline{z_o}})^{-1}\underline{Y}] - \underline{\underline{e}}\ [(\underline{\underline{I}} - \underline{\underline{z}})^{-1}\ \underline{Y}] \tag{3.2}$$

**Reminder! A variable with one underline identifies a vector, while one with a double underline identifies a matrix. A variable in capital letters has absolute units (e.g. M$ or ton), while one in small letters has output-specific units (e.g. M$/M$ or ton/M$).*

Where X and Y represent the total production of commodities and industrial activities and the final demand of commodities, respectively; z symbolizes the supply and use representation of the technological structure of the economy; I is the identity matrix of the same dimensions of z.
Changes may be translated in the model by updating the market share matrix (v, the make side of matrix z). In particular, a specific variation of a v coefficient represents how much of each activity is required every time a certain commodity is demanded. Therefore, a change in the v matrix could be used to model the change in the productivity of a specific *activity* (e.g. the market share of electricity produced by wave energy is increased according to the expected productivity of the plant).
As it is going to be presented in chapter 4, this approach can serve those research objectives that do not require a dynamic representation of the system, being exhaustively depicted by a model representation capable of considering one snapshot before and one after the introduction of the intervention.

3.4.2. Expanding the supply and use framework: from technologies to needs

The objective of the TACN framework is to allow the representation of a wide range of models within the accountability principles clearly defined by supply and use tables. The level of *technologies* and the level of *needs* are introduced to overcome the lack of representation of two crucial aspects of modelling.
From the *technology* side, the concept of installed capacity is usually not present in supply and use tables. In fact, the level of *activity* is usually registered without considering the maximum level of output theoretically possible from each of them. Considering this in meso-economic models would allow for the accounting of unexploited capacity. Let's consider the example of chip production or lithium extraction: they are both constrained by the lack of productive capacity (i.e. installed capacity of these specific *activities* in modelling terms) [184,185]. Knowing the capacity rate of each industrial activity could provide valuable information for better-facing supply chain disruptions. Furthermore, the custom building of a production optimization model would ease the representation of the interconnections that regulate – for example – micro-scale modelling (e.g. how many units of battery storage *technology* are necessary to optimally serve specific electricity *needs* of a household knowing the availability of electricity production of one unit of solar photovoltaic *technology*?).
From the *need* side, the concept of necessities that can be fulfilled by different *commodities* allows for competitiveness between *activities*. It can be seen as the functional unit demanded. From the meso-economic perspective, it would be possible to introduce a new level of an account that consider, not only "what" is consumed, but "why" it is consumed, thus expanding the attributional information of final consumption (e.g. 90% of Italians' final consumption of methane is attributed to heating and 10% to hot sanitary water). Let's consider the example of energy *needs*: every year in our homes we demand heating in winter, disregarding if that heating is coming from heat pumps, which consume

the electricity *commodity*, or gas boilers, which consume methane *commodity*. A reason to choose between one alternative or the other must be formalized in the model. Therefore, the level of *needs* can have a consequential relevance only when optimization of some kind is implemented. Every time a meso-economic model such as the ones built starting from an input-output framework is regulated by an optimization model, the principle of comparative advantage determines production levels.

The TACN framework for national accounting tables

In order to correctly map *technologies* – and their *activities* – and *needs* – and the *commodities* that can fulfil them – dedicated matrices are introduced. These matrices are here called *g* and *j* and they can be formulated by adopting different approaches. The following proposed formulation of *g* and *j* can support an expansion of the classic supply and use framework while offering additional useful data for policy-makers and modellers.

Matrix *g* is a matrix of supply of *activities* by *technologies*. It is useful to understand what are the relations between technology – which may be used for multiple activities – and their *activities*. If a meso-economic perspective is adopted, a perfectly mapped one *activity* to one *technology* can allow for the accounting of crucial information, which is the installed capacity of *activities*. In Table 3.2, the specific matrix *g* is mapping one *activity* with one *technology*. Consider illustrative values reported in the following tables as if they were measured in some monetary units (e.g. euros). In general, it is possible to build the *g* matrix adopting different assumptions regulating "how many" and "how much" of each *activity* is provided by each *technology*, just like it is possible when transforming SUTs [156]. See application 4.2.2 for an example of a TACN framework adopted to build a model that is considering multiple *activities* for some *technologies* (e.g. driving a battery electric vehicle *technology* or using it to provide electricity to the home, i.e. vehicle to home or V2H).

Table 3.2 – On the left-hand side, the g matrix, mapping technologies, and activities. On the right-hand side, is the C matrix, which stores the maximum theoretical output that each technology can provide within the considered time step.

g [t x a]	**activity 1**	**activity 2**	**activity 3**
technology 1	1	0	0
technology 2	0	1	0
technology 3	0	0	1

C [t x 1]	**Installed capacity**
technology 1	200
technology 2	300
technology 3	99999

Introducing the *technology* level allows for the definition of the matrix *C* of installed capacity that is fixing the maximum theoretical total *activities* output that each *technology* can provide (a kind of technically constrained factor endowment). The same unit of measure if multiple *activities* are performed by one *technology* is needed to keep the framework coherent. Note that if no information can be collected for one or more *technology* a large number can be used to identify the lack of information without binding the model that can be shaped on this data.

On the *need* side, it is important to know "why" a *commodity* has been consumed. Various reasons can lay behind the flat information usually reported by the final consumption matrix of input-output and supply and use tables, the *Y* matrix. Knowing what are the *commodities* that are consumed by each final demand category, and distinguishing between household consumption and investment, provides non-exhaustive information for understanding and modelling possible alternatives. That is why, the Why matrix *WY*, Capital investment matrix *KY* and the Deployed capacity vector *D* are introduced within the TACN framework, expanding the classic *Y* matrix. *WY* can be seen as disaggregation of all the usual demand categories presented in *Y*, excluding the investment category which is treated in *KY*.

The *WY* matrix is answering the question "why a certain commodity is consumed?". As an example, methane could be consumed to fulfilling a *need* for private mobility. Nevertheless, also the *commodities* electricity, diesel, gasoline, and hydrogen could be demanded to satisfy the same *need*.
The *KY* matrix and the *D* vector can answer another crucial question when it comes to understanding the dynamic evolution of industrial interconnections, which is "what is needed to expand capacity by one unit in each sector?". The *KY* matrix allows for the accounting of the process of capacity expansion or decommissioning by recording which *commodities* were needed for a change in the capacity of each technology. As an example, the *need* for transportation of the blades of wind turbine *technology* (i.e. the *technology* that produces the outputs of the production of electricity from wind *activity*) could be provided by the *commodity* land transport services. A separated vector, *D*, completes the information by recording how many units of additional capacity were recorded in the considered time step.
In Table 3.3, an example of the expended *Y* matrix proposed within the TACN framework is given.

Table 3.3 – The WY matrix, the KY matrix, and the D matrix. In this example commodities, 1 to 4 are consumed fulfilling needs 1 to 3 satisfying final demand and the investment demand to deploy the new capacity described by D within the considered time step.

WY [c x d*n]	**demand category 1**			**demand category 2**			**demand category 3**		
	need 1	**need 2**	**need 3**	**need 1**	**need 2**	**need 3**	**need 1**	**need 2**	**need 3**
commodity 1	20	0	0	15	0	0	33	0	0
commodity 2	0	30	0	0	32	0	0	45	0
commodity 3	0	0	25	0	0	4	0	0	8
commodity 4	0	0	5	0	0	12	0	0	1

KY [c x t*n]	**technology 1**			**technology 2**			**technology 3**		
	need 1	**need 2**	**need 3**	**need 1**	**need 2**	**need 3**	**need 1**	**need 2**	**need 3**
commodity 1	5	0	0	1	0	0	4	0	0
commodity 2	0	2	0	0	0.5	0	0	6	0
commodity 3	0	0	1	0	0	4	0	0	0
commodity 4	0	0	0.5	0	0	0.5	0	0	3

D [1 x t]	**technology 1**	**technology 2**	**technology 3**
Deployed capacity	5	1	2

With the information provided by the expanded *Y* matrix, it is possible to easily get the specific investment cost matrix *k*, crucial information for capacity expansion modelling. See the equation in Table 3.4.

Table 3.4 – The investment matrix K, an aggregated and reshaped version of the capital investment matrix KY. It can be made specific by multiplying for the inverse of the diagonalized vector of deployed capacity D.

K [n x t]	technology 1	technology 2	technology 3
need 1	5	2	1.5
need 2	1	0.5	4.5
need 3	4	6	3

$$\underline{\underline{k}} = \underline{\underline{K}}\,\hat{\underline{D}}^{-1}$$

k [n x t]	technology 1	technology 2	technology 3
need 1	1	2	0.75
need 2	0.2	0.5	2.25
need 3	0.8	6	1.5

The intermediate demand of *commodities* is added to the final demand in every input-output methodology. Running an optimization model means introducing degrees of freedom. The level of the *needs* is offering the model different ways to satisfy the demand while respecting all the other constraints. The j matrix is introduced for mapping each *need* with the *commodity* that can fulfil it, defining the categories sensitive to comparative advantage if an optimization model is set. See a simple example in Table 3.5.

Table 3.5 – The j matrix, mapping needs, and commodities. In this example, commodity 3 and 4 both fulfil the same need (i.e. need 3).

j [n x c]	commodity 1	commodity 2	commodity 3	commodity 4
need 1	1	0	0	0
need 2	0	1	0	0
need 3	0	0	1	1

In essence, that is what is also happening in a World Trade Model or in a Rectangular Choice of Technology model, in which the *need* for a specific product is modelled. If the dimension of time is explicitly considered in the model, the TACN framework can serve to build a dynamic industrial ecology model. The methodology is intended as a way to move in the direction suggested by professor Faye Duchin, thus to "situate a model of the world economy based on comparative advantage within a dynamic framework, which in addition is conceptually extended to permit a more realistic representation of infrastructure than has been previously attempted" [160].

3.4.3. A Dynamic World Trade Model adopting Rectangular Choice of Technology

Carbon emission reduction policies have the potential of changing consumption, production, and trade patterns. The modelling of such complexity requires a multiregional representation of the economy and/or the interchangeability between two different *commodities* which can fulfil the same *need* (es. the electricity *need* of an Italian company can be satisfied by imported electricity produced by Swiss hydro or by local gas-powered plants).
The model could be formulated as follows:

$$Min\ \alpha = \sum_r \underline{\underline{p}}_r^T \underline{\underline{f}}_r \underline{X}_r$$

$$s.t. \begin{cases} \underline{X}_r + \sum_{r \neq c} \underline{EX}_{cr} \geq \underline{\underline{z}}_r \underline{X}_r + \underline{Y}_r + \sum_{r \neq c} \underline{EX}_{rc} + \sum_{r \neq c} \underline{\underline{t}}_{cr} \underline{EX}_{cr} \quad \forall r \\ \underline{\underline{f}}_r \underline{X}_r \leq \underline{B}_r \quad \forall r \\ \underline{X}_r \geq 0 \quad \forall r \end{cases} \tag{3.3}$$

It minimizes global factors cost (α) endogenously returning production (X) and exports (EX) by each sector. The global factors, considered as costs from the model perspective, are primary inputs characterized by factor prices (p). This minimization is subjected to three sets of constraints. The first one secures that total domestic supply, which is represented by the sum of output and imports, covers the domestic final uses, expressed in turn by the sum of internal demand, final demand, exports, and international transportation of imports, characterized by the specific cost of transportation (t) between one region (r) and the other (c). Notice that t, the matrix of international transport coefficients, depends on each regional sector and distances between regions.
The second constraint defines that all the invoked production factors are less or equal to regional factors endowments (B). The last constraint establishes that the production in every regional sector cannot be less than zero.
Additional constraints can be imposed, such as limiting the total emissions of CO_2 within a PBA or CBA perspective.

Introducing the dimension of time

Dealing with the energy transition, which is likely to occupy at least the next decade, may not be appropriate to limit the approach to evaluating policies as if they were happening "overnight". To overcome this limitation, it may be necessary to rely on a dynamic model. The choices of the model are determined by the availability of information on the capital requirements for capacity expansion of the economic activities described, usually very hard to be determined. Some techniques to overcome the absence of this information are described in the recent literature [61].
Multiple ways to implement dynamic IO models exist, but no global model with energy-source detail is present in the literature. Moreover, assumptions on the evolution of the cost of capacity expansion per energy technology are requested. The formulation of the dynamic global IO model based on a TACN framework is here formulated.

$$Min\ \alpha = \sum_{q=0}^{end} \frac{\underline{\underline{f}}\,\underline{X}_q}{(1-\delta)^q}$$
$$s.t. \begin{cases} \underline{\underline{i}} * \underline{X}_q \geq \underline{Y}_q + \underline{\underline{z}} * \underline{X}_q + \underline{\underline{k}}_q\,\underline{D}_q & \forall q \\ \underline{\underline{f}}_q \underline{X}_q \leq \underline{D}_0 + \sum_{q=0}^{q} \underline{D}_q & \forall q \\ \underline{X}_q \geq 0 & \forall q \end{cases} \qquad 3.4$$

Future costs occurring from the beginning (0) to the end (*end*) of the period are discounted considering a fixed discount rate (δ) for the whole economy. In every year (q), the supply of commodities that serves the same need ($i*X$) has to satisfy the final, intermediate demand ($z*X$), and the additional capacity deployed (D) costs (k, exogenously change year by year). Furthermore, it is not possible to overcome the cumulative installed capacity (second constraint).
This model allows for the simultaneous assessment of all carbon impacts associated with both production and plant operations. In this way, it is possible to evaluate the different choices of the model with the respect to further constraints for example linked to the respect of a regional carbon budget for a given number of years.
This model has been tested taking advantage of MARIO for aggregating EXIOBASE v3 to 2 regions, 3 *technologies*, 3 *activities*, 3 *commodities*, 2 *needs*, 1 factor of production, 1 satellite account, 4 years TACN model. Its testing has been successful thus a more complex case study has been conducted on a smaller scale to show how this framework can serve also for engineering-scale problems (see section 4.2.2 of the Application chapter).

4. Applications

In this chapter, the framework presented in chapter 3 is being implemented to model carbon emission reduction mechanisms (CERMs). Depending on the mechanism that is investigated, it is applied by being scaled to a classical input-output approach fully managed by the toolkit MARIO or integrated into other modelling approaches, implemented through the comparative principle up to a dynamic application that takes advantage of all the peculiarities of the technology-activity-commodity-need (TACN) framework.
Every application is introduced by a template scheme that is clarifying key characteristics of the CERM, the model, and the database adopted as explained in 2.4.3.

4.1. Classic input-output approach

Some CERMs can be assessed by adopting the classic IO Leontief model. Using the approach explained in 3.4.1 can ease the analysis of the implementation of new interventions.

4.1.1. Assessing the impact of new renewable technology: wave energy

As is shown in the introductory chapters, it is possible to trigger carbon emission reduction by imposing or nudging the economy with a target on the penetration of low-carbon sources. Nevertheless, even if the operational phase of renewable energy sources is usually practically zero-emission attention should be paid to the impact associated with the investment step that may offset benefits. In this application, the deployment of a specific wave energy technology is planned and its impact estimated.

- CERM characteristics: implicit carbon pricing measure – a minimum target for low-carbon energy technology
- Table characteristics: SUT-EXIOBASE v3.8.2 – year 2019
  - *Geographical scope and scale*: Multi-regional – aggregation to Italy and a few other crucial partners
  - *Table type*: Supply and Use
  - *Table units*: Monetary – EUR 2019
- Model characteristic: Supply and Use Leontief model through MARIO add sector and shock functions
  - *Time scope and scale*: multiple snapshots of the same economy are simulated trying to depict the expected learning curve in device production and installation year over year.
  - *Linear-programming coupling*: classic input-output – no integration with linear programming.

Introduction

The current challenge of climate change requires a gradual shift towards renewable technologies and a more efficient energy production system. The potential of renewable and solar power alone, although far greater than anticipated, may not be sufficient to cover all electricity demand, which is expected to grow significantly in the future [52]. Electrification and energy transition, therefore, require a wide portfolio of technologies capable of producing electricity from renewable sources as continuously as possible. In particular, Europe expects to capture a major competitive advantage from offshore renewable technologies [186]. Many technologies are being considered to exploit the potential offered by offshore sites [187]. Most of this potential is identified in the offshore wind farm. However, many other resources can be exploited today. Developed countries and in particular European economies are well-positioned to promote offshore renewable energy progress worldwide

[186]. G20 members control the vast majority of global economic activity and trade and are home to more than three-quarters of the total installed capacity of renewables [187]. In 2020, 99.3% of total offshore wind capacity and almost all installed ocean energy capacity globally was deployed in G20 countries [187]. Energy from the sea alone could meet twice the electricity demand of the entire world population [188]. Furthermore, the technology was demonstrated to be consistently more available and persistent on an hourly level through an entire year of operation concerning wind and solar [189]. The European Union has fostered its renewable energy plan with its *Fit for 55* strategy, implying a further development of all renewable sources [190]. The possibility of installing many megawatts of this technology would guarantee Europe the maintenance and construction of the technological know-how necessary to be a leader in this technology.

Italy in particular, driven by the investments of the Recovery and Resilience Plan, could benefit from incentives coming from the European Union in the future to consolidate and concretize the know-how of offshore technologies [191]. Great uncertainties, however, are associated with this technology [192]. In particular, the realization of these plants is now based on large investment costs that do not always guarantee economic profitability for companies that install this technology.

The objective of this work is to evaluate the social, economic, and environmental impact associated with the deployment of installed capacity of rotating mass sea-wave (RMSW) technology to assess the conditions and the sectoral implications of the introduction of its supply chain in the Italian context.

Brief literature review

A good number of studies investigate the socio-economic or environmental impact of some low-carbon electricity technologies. In

Table 4.1 some studies which investigate the profitability, sustainability, and competitiveness of marine energy conversion devices are reported.

Some studies focus on physical and environmental impact assessment. This is the case of *Douglas et al.* who perform an analysis evaluating the energy and CO_2 emission payback times of a turbine used to exploit the tidal effect in the UK [193]. The results are comparable to those of a wind turbine, with an energy payback time of around one year, showing how marine currents are currently more easily exploitable than wave currents for the conversion of marine energy into electricity [193]. In 2020, about 98% of the total 534.7 MW installed capacity of marine energy power technologies was represented by tidal barrage [187]. The technology is remarkably mature also thanks to its great similarities with hydroelectric power, the oldest renewable technology among those currently used. Wave energy devices are less mature as a power technology and their profitability is crucially linked with the productivity of the site (i.e. capacity factor). Dunnet and Wallace use the Marine Environmental Data Service of Canada to estimate the minimum cost of electricity to return on investment in 10 years by screening sites off the Canadian coast that provide more than 20% uptime for the technology [194]. The relevance of site characteristics is also shown by multiple levelized cost of electricity (LCOE) studies on Pelamis and Wave Dragon devices [195]. The authors of the most recent study on these technologies find a competitive LCOE of around 85-140 $/MWh, outperforming by up to a factor of 10 the same technology assessed in various sites around the globe in studies published from 2010 to 2019. Steel-intensive wave energy converters such as buoy-rope-drum prototypes may present uncertain environmental impacts, mainly associated with needed steel, concrete, and electricity used for production [196]. In the study, uncertainties are assessed through a rigorous Montecarlo simulation on a life cycle assessment (LCA) intended to assess the degree of uncertainty in computing midpoint and endpoint life-cycle results. Researchers from Ocean Energy System (OES), a technology program in collaboration with the International Energy Agency, investigated the costs associated with various ocean energy technologies, presenting a consistent and practical guide to computer LCOE for these renewable devices [188]. Similarly, Têtu and Chozas developed a comprehensive methodology for evaluating wave energy converter projects at the early development stage [197].

De Roeck coordinated an OES project to validate an input-output analysis (IOA) to assess the job implied by the ocean energy sector. They estimated about 58 thousand direct, indirect, and induced employment, mainly in the manufacturing sector, for reaching 53 MW of ocean energy capacity in 2050 in France [198].

Hybrid approaches that link life-cycle assessment and input-output analysis have been used for evaluating the environmental impact of new technologies, such as carbon capture and storage [199].

Table 4.1. – Brief literature review of similar studies by topic or methodology.

Ref	Authors	Year	Assessed technology	Investigated impact	Methodology
[194]	Dunnet *et al.*	2009	Wave energy	Economic	Life cycle costing
[193]	Douglas *et al.*	2008	Tidal energy	Energy, CO_2	Life cycle assessment (LCA)
[195]	De Oliveira *et al.*	2021	Wave energy (Pelamis and Dragon)	Economic	Levelized cost of electricity (LCOE)
[196]	Zhai *et al.*	2021	Wave energy (buoy-rope-drum)	Environmental	LCA
[188]	OES	2015	Tidal, wave energy	Economic	LCOE
[197]	Têtu and Chozas	2021	Wave energy	Economic	LCOE
[198]	OES	2021	Tidal, wave energy	Employment	Input-output analysis (IOA)
[199]	Singh *et al.*	2011	Carbon capture and storage	Environmental	Hybrid LCA and IOA

Numerous studies have tried to evaluate innovative low-carbon technologies by adopting mainly LCA, IOA, or LCOE approaches. Each study focuses on either economic or environmental dimensions. To the knowledge of the authors, there are no studies that try to evaluate a project based on the production of electrical energy from wave devices by exploring the impact that the introduction of a supply chain dedicated to it would have on the economic, social, and environmental dimensions.

Methodology

Input-output analysis has served economists and industrial ecologists in estimating the economic, environmental, and social impact associated with variation in industries' interconnections for decades [124,154]. Adoption of a multi-regional supply and use input-output tables allows for distinguishing commodities from the economic activities that produce them, leading to more accurate and detailed results [155].

In the present analysis, the adoption of RMSW technology is modelled, simulating an early adoption within a few Italian islands followed by a scale-up of the technology taking place mainly in Norther-sea sites. The simulated installation assumes a deployment strategy taking place from 2023 to 2040, assuming a *ceteris paribus* approach, i.e. no other changes take place within the world economy. To do so, one economic activity, contributing to the production of electricity, is added for every RSMW power plant introduced. This is necessary to distinguish among different economic structures taking place at different times and places. Finally, the additional production of electricity by the RMSW technologies displaces an equal amount of electricity from other power technologies, keeping total demand constant.

Case study

A capacity expansion plan of an Italian energy company has been used for assessing the supply-chain impact of new RMSW-based technology. The company expected to increase the performance and reduce the cost of the technology so that the levelized cost of electricity (LCOE) can reach 1/5 of today's version of the pilot plant (see Figure 4.1A). The first generation of RMSW plants planned to operate in Italian islands up to 4.1 MW of total installed capacity, is expected to be installed for more than 7 k€/kW specific capital expenditure (CAPEX). Costs are expected to decrease significantly with the second-generation plants. This is expected to be possible due to a development plant that reaches a global installed capacity of 51.7 MW in 2035 and 132.1 MW in 2040, mainly in the Northern Sea sites.

CAPEX is impacted by learning curves following, like many technologies, a generalized version of Moore's law [200]. CAPEX reduction represents the most challenging obstacle to commercial-scale penetration of wave energy technologies. Data provided by the developer company suggest a learning curve that would allow a ~12% CAPEX reduction for every doubling of capacity (see Figure 4.1B).

To perform the methodology described in the previous chapter, an input-output representation of the economic network in which the technology will develop is needed. For this case study, Exiobase version 3.8.2, a supply and use representation of international flows between 49 countries has been adopted [97,201]. The 2019 version of the database has been aggregated to represent the main regions involved in the planned capacity expansion and a closing *Rest of the World* region.

The capacity factor, a technologically crucial parameter for the success of wave energy technology, link the micro-data with the input-output model. In fact, knowing the expected capacity factor, which is exogenously provided by the developer company based on the installation site, together with plant size, availability factor, and assumed insular electricity price (400 €/MWh) is possible to estimate the annual production of electricity. The substitution hypothesis can largely influence industrial ecology models [202], and in this case, all the produced electricity is expected to overtake electricity produced by diesel generators. The reasoning behind this hypothesis is that RMSW is expected to be installed in islands where most of the electricity is provided by diesel generators, the marginally most costly power source, without impacting grid balancing.

Figure 4.1 – Fig 1A: Evolution of installed capacity and LCOE of RMSW technology from today to 2040 as expected by technology developer. The area in sky-blue, which represents the expected range for wave energy capacity in the EU by 2030 according to Ocean Energy Europe [203]*, provides a scale of the possible penetration of RMSW technology; Fig 1B: Assessing CAPEX evolution with increasing cumulative installed capacity for RMSW. The area in green shows the most pessimistic and most optimistic trend of CAPEX to cumulative installed capacity. The sky-blue area identifies IEA's range of commercial-scale project costs for similar technologies* [188].

Fig 1A

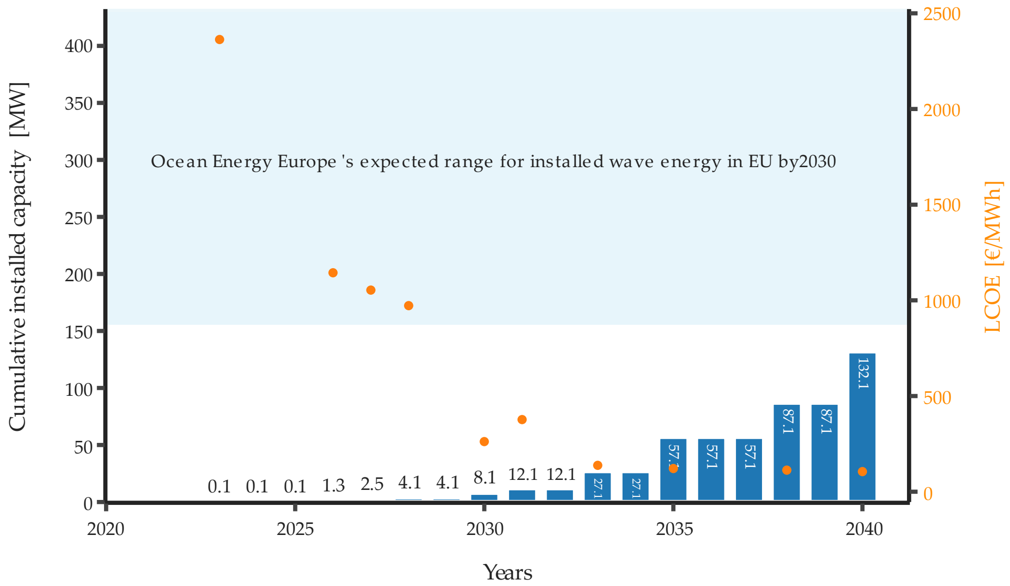
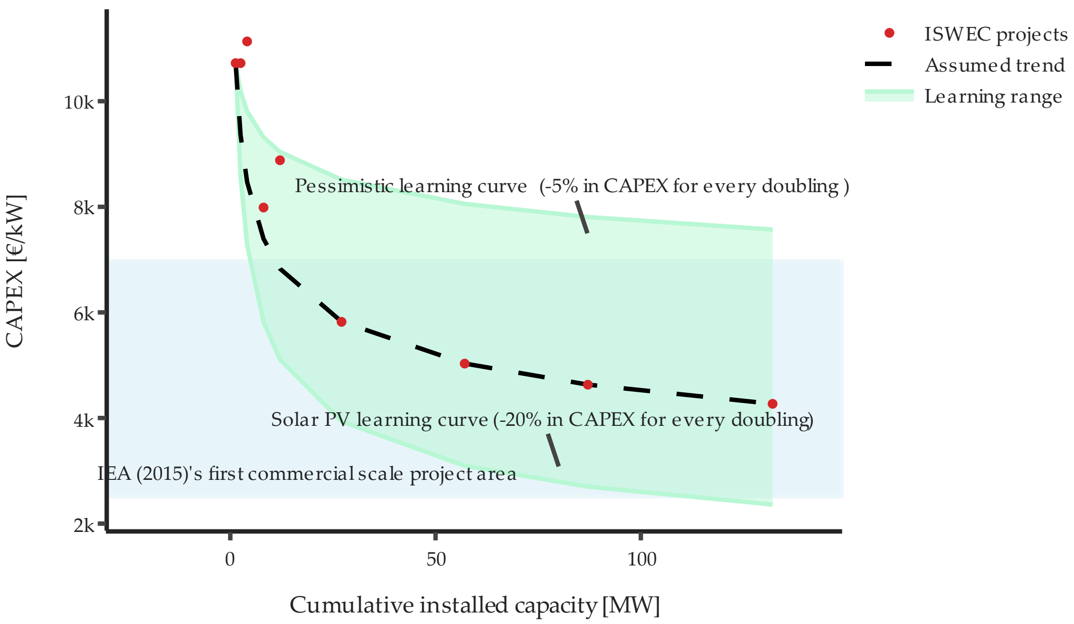


Fig 1B



Results

Capacity expansion results

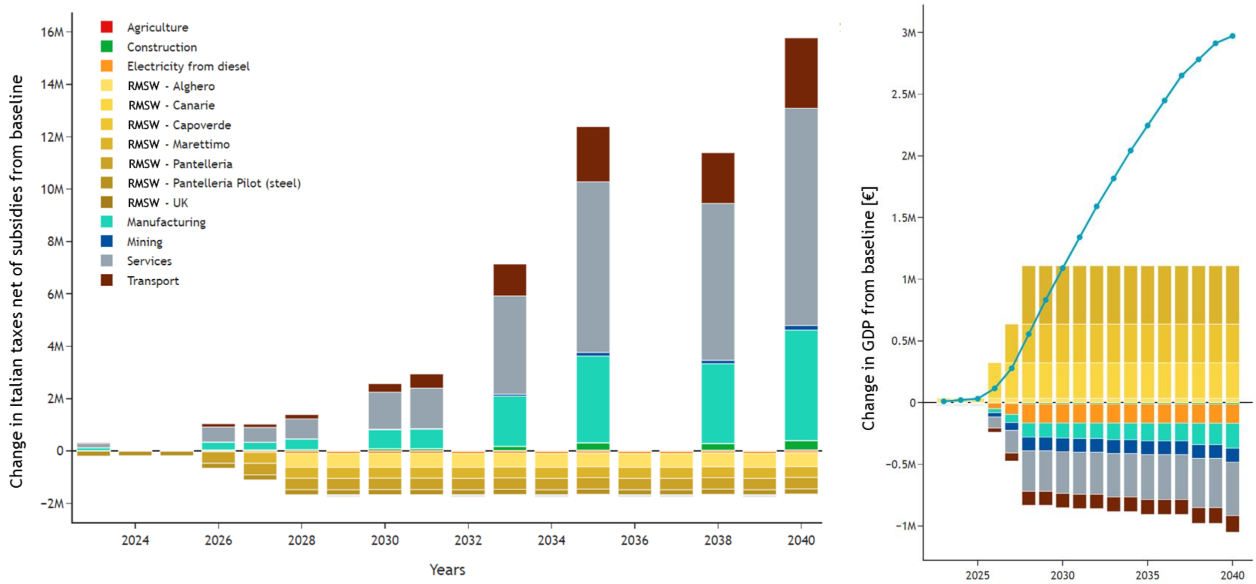
The production of electricity from RMSW sources allows displacing the production of electricity from diesel generators impacting domestic and non-domestic supply chains. This impact can be broken down into three main dimensions: economic, social, and environmental. The most relevant indicator has been identified for each of these dimensions. In particular, the economic dimension will be explored by measuring the impact, by sector and region, in terms of their gross domestic product (GDP); the social dimension has been measured by assessing changes in employment in the country where the supply chain is expected to be developed and the first plants are expected to be delivered, i.e. Italy; the environmental dimension will be considered by assessing the main indicator for which RMSW is primarily considered, i.e. global greenhouse gas (GHG) emissions. Thus, in the next sections, the results will be presented considering those 3 main indicators.

Impact on local gross domestic product

For the first 4.1 MW of installed capacity, as can be seen from the high investment costs and, consequently, LCOE, the plant fails to pay for itself. According to the planning, these plants are expected to operate in the Italian islands. The hypothesis underlying this first stage of development of RMSW is that part of the cost structure is covered by national funds in the form of fiscal adjustments. For the case of these plants, the expected amount of money flowing from state to plant owner is around 1.6 M€/year, reaching at the end of the period of analysis (i.e. 2040) 23 M€ in national subsidies.

Nevertheless, as it can be observed in Figure 4.2a, the development of the new supply chain, taking place mainly in local territories, is expected to increase total revenues from taxation, making the balance positive by around 32 M€ for the government.

Figure 4.2 – Fig 2A: Tax revenues associated with investments in RMSW, assuming the planned capacity expansion; Fig 2B: Impact of operating RMSW plants on the Italian GDP.



The overall investment generates additional 700 M€ of gross domestic product (GDP) with respect to a baseline case (i.e. no intervention). Most of them (560 M€) contribute to generating GDP within the Italian economy. The cost structure assumed by the used input-output table together with the assumption of producing the technology within the Italian economy, implies the generation of local GDP, in particular concerning the manufacturing sector.

Operating RMSW implies, by assumption, not producing electricity from diesel generators. This impact positively on the local economy, taking advantage of the value added by the new plants and displacing imported intermediate commodities mostly related to the extraction, refinery, processing, and transportation of the fossil fuel. The most important reduction of economic activity associated with electricity production from diesel takes place mostly out of Italy, resulting, overall in a positive impact on *post-operam* local GDP variation (see Figure 4.2b).

Impact on local occupation

The analysis of the domestic impact on occupation provides a similar picture to the local GDP variation. In this research, workers are assessed from the satellite extension in the adopted input-output database. In particular, differences are recorded based on the number of annual employees by sector, which can be interpreted in the observed period as the number of additional annual contracts in light of RMSW projects. From Figure 4.3, it is possible to observe the evolution of net employment by sector and by employed skill level.

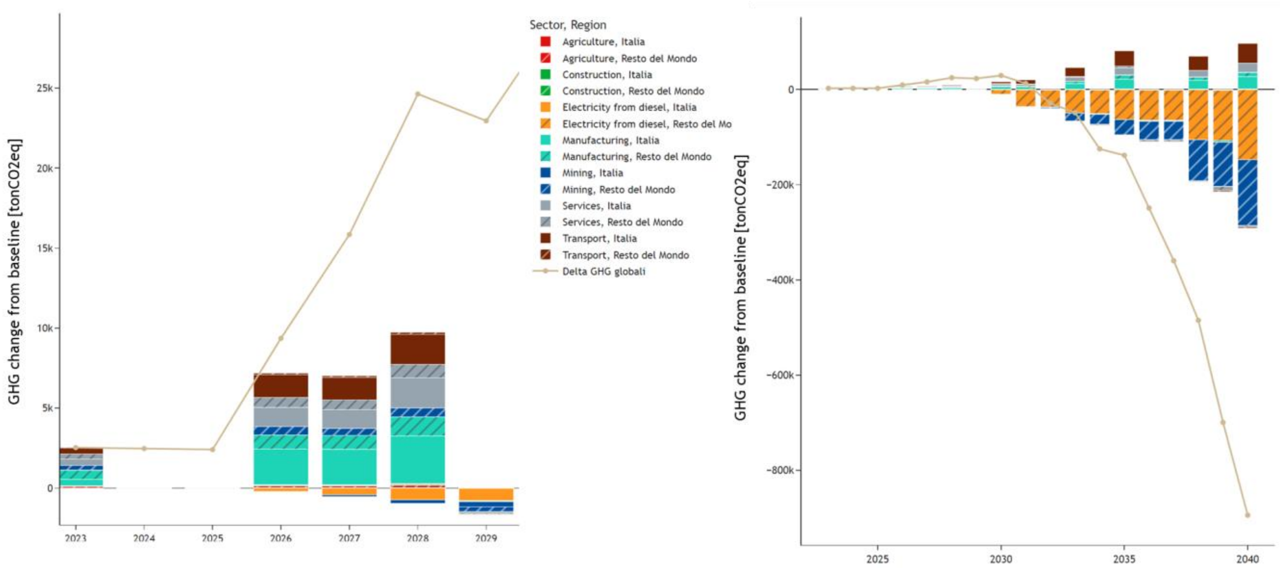
Figure 4.3 – A net variation of annual contracts by year, skill level, and sector relative to baseline throughout the observed period. Crossed-out contributions relate to the operational step, while filled contributions relate to the investment step.

Most of the positive spillovers involve high and medium-skill-level workers. Services and manufacturing represent the two sectors with the highest net employment, followed by transportation and construction for the medium level. The occupational impact of RMSW operation translates, by hypothesis, to a positive contribution in high-skill workers. Over the analyzed period the involvement of approximately 480 more full-period workers, reflecting an increase in net annual contracts of 2’700, 4’000, and 500 respectively for high, medium, and low-skilled workers.

Impact on global green-house gases emissions

The development and adoption of RMSW technologies imply a change in GHG emissions that, can be slightly positive or, as the technology produces electricity in place of diesel generators, largely negative. These contributions can be investigated considering different periods, regions, or sectors.

Figure 4.4 – Fig 4a: Variation of global GHG by sector and time in the early stage of technology deployment; Fig 2b: Long-term impact of the RMSW plants on global GHG.



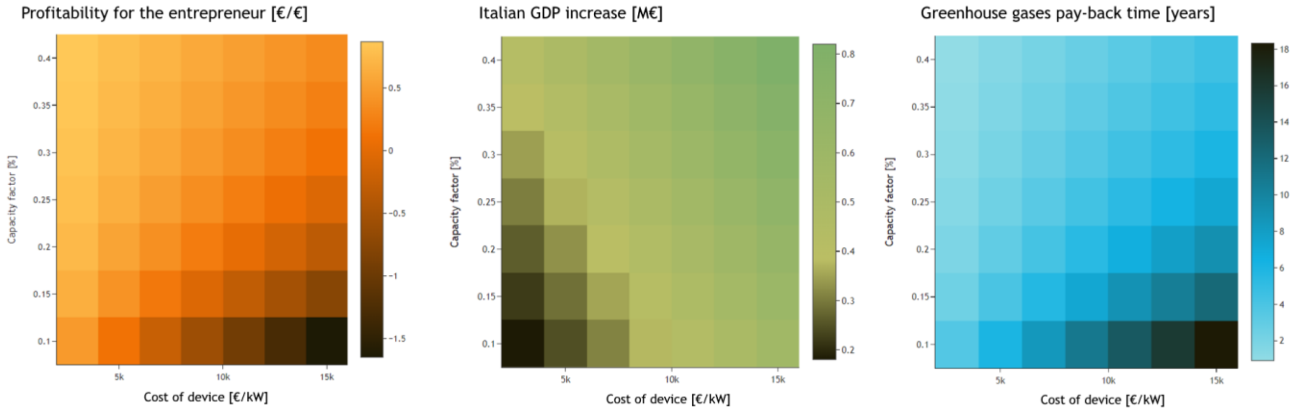
In the early stage of technology development, a net increase in GHG emissions is recorded, mainly due to the need to produce the devices, which are built with a considerable amount of steel, accounted for in Manufacturing in Figure 4.4a. Increasing quantities of emissions associated with the extraction, refining, transportation, and combustion of diesel are, of course, avoided as more and more RMSW power capacity is brought online. However, the low capacity factor of the early RMSW plants, would not guarantee off-setting the emissions required to build and install the plants.

The increasing contribution of emissions no longer generated by the diesel plants of the non-Italian islands, where the technology is exploiting higher capacity factor sites, is expected to save up to 0.9 Mton CO_2eq by 2040. This result is achieved despite the GHG released by the transport sector, services, and manufacturing also due to the reduction of the carbon footprint of fossil fuels (blue contribution in Figure 4.4b).

Technology assessment results

Given the high uncertainty associated with plant productivity (i.e. capacity factor) and the specific cost of installing the technology (i.e. CAPEX), a range of possible values was assumed. Plant owner profitability, government returns, and environmental impact can importantly influence the success of the development and deployment of a low-carbon power source. Evaluating the adoption of 1 MW of this technology allowed for different levels of uncertainty that may affect the two most important technical parameters of RMSW and their impacts on its 3 most relevant dimensions. For each combination of these values, different effects on plant owner profitability, socio-economic spillovers on GDP, and efficacy in reducing GHG emissions are observed as represented in Figure 4.5.

Figure 4.5 – Sensitivity analysis. The first block represents the net profit (positive values) or loss (negative values) that an entrepreneur would face for every set of capacity factors and CAPEX. The second block represents, for the same changing variables, the impact on Italian GDP, while the last one displays the number of years required to offset the emission released to produce and install 1 MW (i.e. GHG payback time).



The analysis is carried out keeping constant all the other micro (e.g. the economic value of the MWh of electricity produced) and macroeconomic conditions (i.e. sector interconnections, described by the adopted input-output table). Due to low capacity factors and high CAPEX costs, it is increasingly difficult for the entrepreneur to create a profitable plant. As the CAPEX increases, the added value retained in the main economy that produces the device (i.e. Italy) increases. The GDP is positively impacted even if the capacity factor increases because this would imply, starting from the assumptions at the base of the model, to displace an increasing amount of electricity production from diesel which, as seen, marginally affects the Italian economy. One of the main reasons a technology like RMSW's could be evaluated is its ability to reduce greenhouse gas emissions. As seen, the production of the plant results in a considerable release of GHGs. How quickly the plant manages to save a number of emissions equal to that required for its production and installation is the GHG pay-back time, graphed in the last box of Figure 4.5. Increasing CAPEX negatively impacts this value. The hypothesis underlying this behaviour is that a higher price is associated with greater use of economic and environmental resources. On the other hand, a high capacity factor allows for faster avoidance of GHG emissions. However, even in the most favourable configuration, at least two years of operation are required to make the operation carbon negative.

Conclusions

The methodology, adopting an approach that does not allow for the adoption of inventories with a high level of granularity such as those usually available for processed-based LCA analyses, can help to simply assess the potential of a decarbonization intervention. In addition, because of its characteristics, it allows to jointly assess the magnitude of the impact on socio-economic and environmental indicators that may be of interest to all stakeholders impacted by the intervention. Further detail on these metrics can facilitate investigating the effects on specific sectors or categories of workers that may interest the policy-maker or other interested stakeholders.

The technology evaluated in this application of the model shows weaknesses and strengths. The employment potential that can be unlocked by the marine power generation sector is very relevant for Europe. Thousands of jobs can be created with similar skills to those sectors that could see a restriction of employment demand such as offshore oil and gas extraction. However, the technology is still far from being economically viable and support from national or European subsidies is needed. A more in-depth cost-benefit analysis with up-to-date data could attempt to compare the benefits associated with the employment generated by the new production chain and the extra investment expenditure that needs to be incurred. As recommended by the recent IRENA report, providing public support through feed-in tariffs, premiums or infrastructure investments (grid connection via submarine cable network) and other measures can give the private sector the most elements necessary to plan investment strategies, facilitating the research and development of these renewable technologies [187].

However, the opportunity to finance this specific technology may be lost due to the high carbon content of the RMSW device. Despite technological developments that have allowed the transition from concrete to a steel hull, the carbon footprint is still high. GHG pay-back time is quite higher than other renewable technologies (i.e. solar and wind) and could represent an obstacle to the high-scale financing of this technology.

4.1.2. Assessing the role of behavioural change: meat-based diet adoption in Africa

The role of consumer choice may be very relevant in curbing carbon emissions [204]. A very relevant difference in the carbon footprint of vegetarian over-average diets can be attributed to the low intake of meat. In this application, the impact of the future volume of meat consumed in developing sub-Saharan Africa is assessed. Insights on the possible role of a shift in diet preferences on carbon emission are obtained.

- CERM characteristics: non-carbon pricing measure – nudging consumer habits proposing explicit alternatives to meat consumption
- Table characteristics: Hybrid EXIOBASE v3.3.18 – year 2011
    - *Geographical scope and scale*: Multi-regional – aggregation to sub-Saharan Africa and a few other crucial partners
    - *Table type*: Input-Output
    - *Table units*: Hybrid
- Model characteristic: Hybrid Input-Output Leontief model through MARIO shock function
    - *Time scope and scale*: multiple snapshots of the same economy are simulated trying to depict the expected evolution in sub-Saharan Africa's efficiencies and demanded volumes.
    - *Linear-programming coupling*: classic input-output – no integration with linear programming.

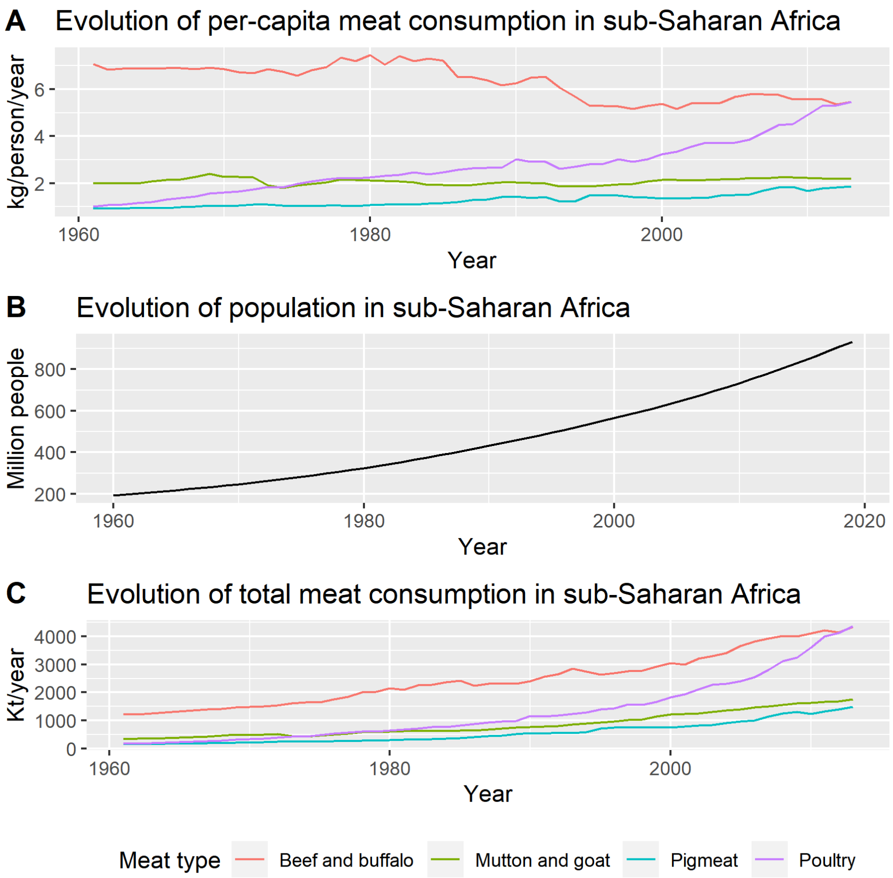
Introduction

Food, diets, and nutrition – together with a steeply growing human population – are determining the escalation of several grand environmental challenges [205–207]. In response to these growing issues, numerous global assessments of the future of food systems and the sectoral environmental footprint have been carried out [165,208], including initiatives such as the EAT-Lancet Commission [206]. Among all agri-food segments, the meat and dairy industry has the highest resource and energy intensities [209,210]. The livestock supply chain occupies 83% of total farmland and it results in 60% of global greenhouse gas (GHGs) emissions from the agricultural sector– i.e. 14.5% of the total GHGs emissions [209].

The agri-food sector is also responsible for other major environmental impacts [211,212], including land use change and degradation [213], biodiversity loss, and water consumption and contamination [214]. In addition, farming and grazing-related activities require a significant input of energy throughout their supply chains [215]. The projected increase in the global food demand coupled with a growing share of animal-based products [216] might put the global ecosystem equilibrium under pressure, and its related impact must be carefully accounted for. Indeed, it poses a significant challenge to the achievement of several Sustainable Development Goals (and primarily SDGs 2, 3, 6, 7, 13, 14, and 15).

While trends have been heterogeneous across regions, in most countries meat consumption has grown steadily together with economic development. During the twentieth century, the global demand for all meat types has in fact grown from 28.5 kg/capita/year in 1961 to 51 kg/capita/year in 2013, the latest year available in FAOSTAT statistics [217].

Figure 4.6 - Historical evolution of meat consumption in sub-Saharan Africa. (A) Per-capita meat consumption, by meat type; (B) Population; (C) Total meat consumption, by meat type.



Yet, when restricting the analysis to sub-Saharan Africa (excluding the Republic of South Africa; from now on SSA throughout the paper), it can be observed in Figure 4.6 - Historical evolution of meat consumption in sub-Saharan Africa. (A) Per-capita meat consumption, by meat type; (B) Population; (C) Total meat consumption, by meat type. that consumption of all meat types in the region stood at an average of 11.5 kg/capita in 2013 with little change from the 9.5 kg/capita in 1960. A stronger growth rate has characterized the region in the first decade of the twenty-first century, mostly driven by demand for poultry. Irrespective of low meat consumption levels, SSA is the first region in the world by grazeland and cropland areas [218], with 24% and 16% of the global total, respectively.

Brief literature review

Previous studies have evaluated the historical relationship between the demand for meat and socio-economic and cultural factors on both a global scale [219–221] and in developing countries [222,223]. Researchers estimated long-run income elasticities of demand for meat [224,225] and showed that, historically, economic development has been largely associated with an increased demand for meat, albeit with meat-type and regional heterogeneity. The current and projected sustained economic and demographic growth in SSA could therefore significantly boost the demand for meat [226].

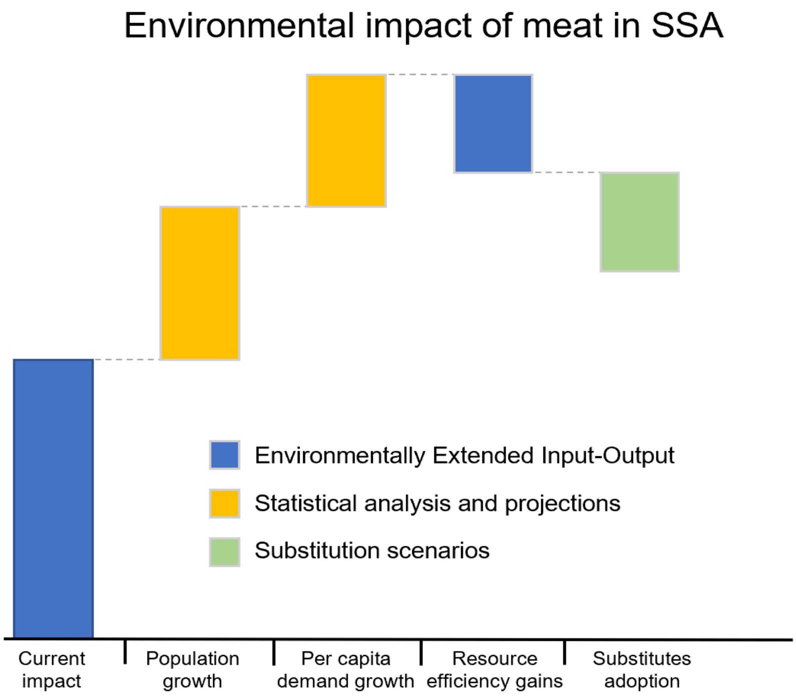
A rigorous, meat-focused analysis of the future of meat in SSA based on explicit modelling of future demand under different scenarios encompassing economic, demographic, and socio-cultural dimensions is thus missing in the existing literature. Moreover, also an analysis of the potential local and global environmental impacts of a such growing appetite for meat in SSA cannot be found in the existing literature. This is irrespective of MRIO EEIO (Multi-Regional Environmentally-Extended Input-Output Analysis) having been used extensively in large-scale life cycle assessments (LCA) of the environmental footprint of food, diets, and nutrition [227–231]. Other relevant aspects not found in published studies include an evaluation of the potential role of meat substitutes. Such a comprehensive picture (future demand; environmental impact; substitutes adoption) is however crucial for understanding the role that transformations in SSA could affect global environmental flows.

In this paper, the question of the expected magnitude of the growth in the regional demand for different meat types by 2050 is addressed. This allows us to quantify both the related impacts on the regional environment and energy system and the implications for global environmental change. The analysis is supplemented by an assessment of different scenarios over the adoption of several meat substitutes and the relative change in the total environmental impact.

Methodology

The scenarios shed light on the role of these different factors in determining the meat demand and the relevant environmental pressure. The analysis consists of multiple steps (as schematically represented in the cascade diagram of Figure 4.7) which altogether – starting from today's environmental impacts of meat consumption in SSA – aim to estimate the future impacts for an array of scenarios to 2050.

Figure 4.7. Schematic cascade representation of the analysis carried out in this paper.



The demand modelling evaluates how socio-economic and cultural factors can be crucial determinants of the meat demand pathway followed by SSA. This is an important step forward in understanding the role of different demand drivers and their interactions in the context of SSA. Then, the EEIO analysis exploits a table of technical coefficients and environmental extensions with schematic assumptions over the future changes in productive efficiency to evaluate the ranges of potential environmental impacts from the increased meat consumption.

The main purpose of the paper is therefore to support the framing of policies targeting food security and sustainable environmental resources management. It must be remarked that the demand modelling and EEIO analysis carried out are however not meant to deterministically predict future trends, as the uncertainty in the transformation that will occur remains broad.

For sake of brevity, demand drivers modelling and projection of future consumption pathways for SSA have been omitted from the present version of this study. See [232] for further detail.

MRIO EEIO analysis and SSA's resource efficiency evolution

Multiregional input-output analysis methodologies have been recently employed in literature for evaluating consequential impacts associated with different diets [228,233–235]. Here, in order to evaluate the environmental impact associated with future meat demand pathways in SSA, we adopt a Leontief impact model (Eq. 4) exploiting the hybrid version of EXIOBASE, a multi-regional environmentally extended input-output table (version 3.3.18 hsut 2011). The database offers a physical – when possible – and monetary representation of the economy, describing the interactions among 164 sectors of 48 regions and the environment. SSA is here modelled on the African "Rest of the World" region. The analysis is run using an in-house under-development Python module which expands the capabilities offered by pymrio. Beef, poultry, and pork demand in physical dry units are allocated to the Products of meat cattle, Products of meat poultry, and Products of meat pigs sectors, respectively (mutton and goat are not considered due to the absence of an explicit corresponding sector in the adopted database). Impacts are estimated throughout the entire supply chain (all sectors) and globally (including import/export flows). The analysis is run in four time steps: 2020, 2030, 2040, and 2050.

$$Impact = E_s[(I-A)^{-1}y_s] - E_s[(I-A)^{-1}y_0] \quad 4.1$$

Where:

- E_s identifies the matrix of environmental extensions coefficients (i.e. matrix of resource efficiencies) in scenario s;
- y_s is the vector of final demand (subscript s refers to the specific scenario while 0 refers to the baseline);
- I the identity matrix with the same dimension of A which is the matrix of intermediate transaction coefficients (i.e. matrix of technology coefficients).

Every scenario is identified by each combination of pathways and time steps which results in impacts that are strongly related to the production technology and yield. Indeed, in evaluating the environmental impacts of future demand for meat products, changes in economic-wide efficiencies play a role. Here no explicit change in sectoral interactions, nor change in international trade patterns, are assumed (i.e. the same matrix of intermediate transaction coefficient is adopted in every scenario – see Eq. 4). Nevertheless, several resources efficiency variants, representing a set of potential pathways of use of environmental resources change over time in the livestock supply chain of SSA, are introduced. These pathways of production techniques changes assume dynamic resource efficiency gains, whereby regional efficiency gradually converges towards the efficiency of different countries worldwide as expressed by the current impact coefficients of the EXIOBASE 3 hybrid tables. The dynamic transition is operated at a ten-year time-steps, from 2020 to 2050.

Resource efficiency scenarios mirror a gradual convergence towards the median efficiency in the reference regions selected when generating the meat consumption scenarios: Central Europe, East Asia, Central Latin American, and MENA. For each scenario, in the 2020s the resource efficiency is assumed to reflect 90% of today's SSA's efficiency a 10% of the reference region median efficiency; in the 2030s the ratio shifts to 80% and 20%, respectively; in the 2040s to 65% and 35% each; and in year 2050s it reaches levels of 50% for both today's SSA coefficients and the reference regions coefficients.

Environmental impact assessment for SSA

Every year environmental impacts are assessed starting from the technological description of national and international interlinkages described in the global input-output table adopted, by means of final demand, intermediate transactions (i.e. technology), and environmental extensions (i.e. environmental resource efficiency) coefficients. In every time step, a demand shock is performed updating the level of final meat demand accordingly to the future consumption pathways projection together with a change of SSA's environmental extension coefficients in both baseline and specific scenario matrices. In this way, the impact is evaluated by computing the difference between two scenarios which differ only in terms of meat consumption levels.

In each time step t, environmental extension coefficients are used to evaluate midpoint life cycle impact assessment indicators. Greenhouse gases emissions are expressed in CO_2equiv units as the weighted sum of CO_2, CH_4, and N_2O (i) by their emission factors (EF):

$$CO_2^{equiv}{}_t = \sum GHG_{it} \times EF_i \qquad 4.2$$

The eutrophication potential is estimated using the methodology adopted in recent seminal studies [233]:

$$EP_i = \frac{v_i/M_i}{v_{ref}/\ M\_ref} \qquad 4.3$$

Where v_i and v_{ref} are the potential contributions to eutrophication of one mole of substance *i* and *ref* (i.e. PO_4^{3-} equivalents), respectively, M_i and M_ref (kg\ mol^{-1}) are the mass of *i* and *ref*.

Bluewater consumption is considered the key indicator of the water footprint of meat products. Bluewater refers to water sourced from surface or groundwater resources and is either evaporated or incorporated into a product. The concept of blue water footprint thus refers to the physical resource depletion as opposed to green water footprint, which describes direct use of water recharge, i.e. water from precipitation. Moreover, we refer to water consumption (i.e. the amount of water removed for use and not returned to its source) as opposed to water withdrawal (total water removed from a water source such as a lake or river, a portion of which is returned to the source and is available to be used again).

To estimate the land footprint of the meat supply chain, the total land requirements for agriculture, pastures, forestry, and woodfuel are considered by summing them up.

EXIOBASE 3 hybrid tables report energy consumption as resource use (i.e. fossil fuels such as coal, oil, and natural gas) or as an economic sector (i.e. electricity production). To translate these units into a comprehensive figure of primary energy demand, physical units of fossil fuels (FF_{it}) are transformed into primary energy by multiplying them by average energy contents (EC_i) as reported in the International Energy Agency unit converter tool:

$$PED_t^{FF} = \sum FF_{it} \times EC_i \qquad 4.4$$

These estimated energy requirements are only in part directly driven by the energy-economic sector such as electricity production. A significant share of these requirements reflects embodied energy into machinery and services consumed throughout the supply chain.

Meat substitutes adoption in SSA and relative environmental benefits

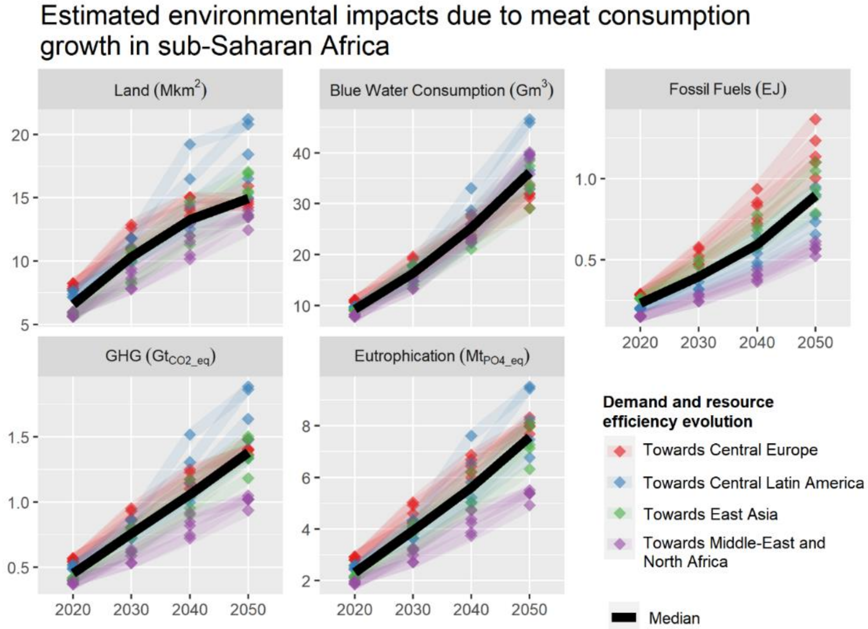
Plant-based, protein-rich meat alternatives such as tempeh and soy-based products are already cheaper than animal meat and widespread in many developing countries. On the other hand, high-tech meat substitutes such as lactose-based products and in-vitro beef are generally more expensive.

Yet, production costs are rapidly declining and social perceptions are also shifting, which might make such products highly competitive over the next decades.
For each of the meat types considered, scenarios of different degrees of meat substitutes adoption are designed. Each alternative is identified as a substitute for a specific meat type depending on texture, characteristics, and consumer perception. The LCA estimates collection aims at capturing the same dimensions of environmental impact examined in this study for animal meat.
Meat substitution dynamics on the median meat demand scenario for each resources efficiency variant, simulating 10%, 25%, and 50% of animal product consumption substitution by 2050 is implemented. In this assessment, each meat type is evenly substituted by those shares. Where multiple substitutes are identified for one single meat type, an equal mix of those substitutes is simulated (gluten, leguminous, insect, and lab-based products for beef; dairy-based products for poultry; soy-based products for pork), hence adopting the mean value of each environmental impact category.

Results

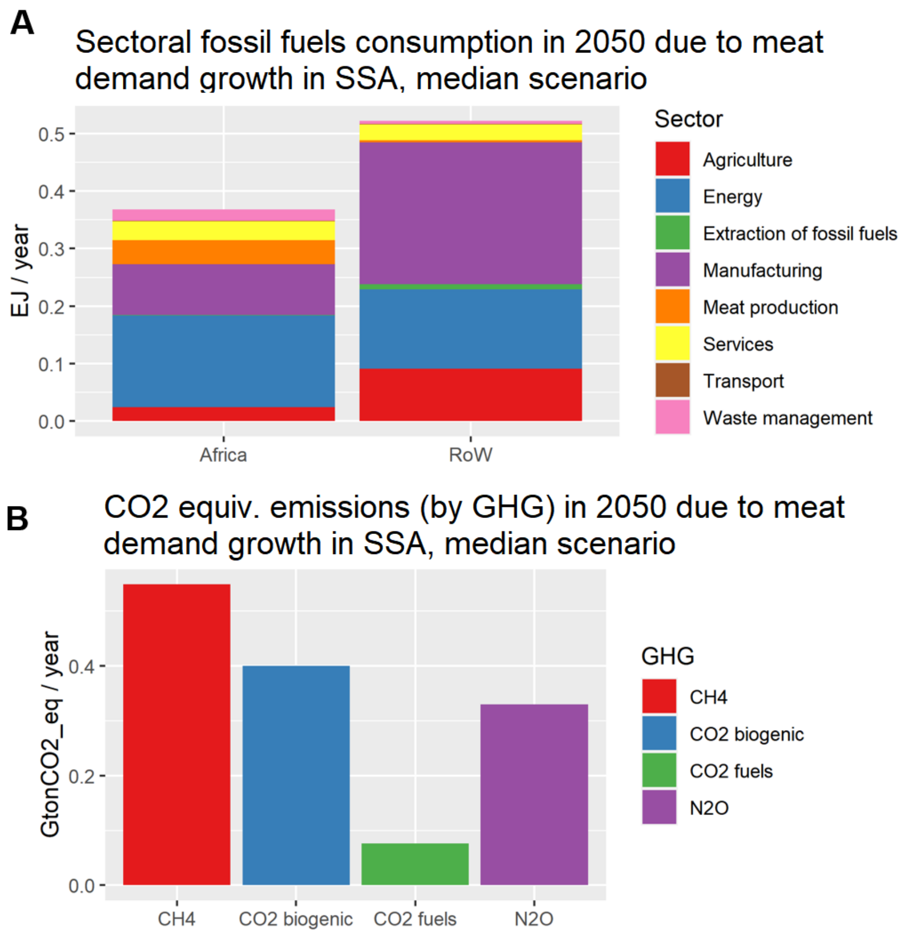
For sake of brevity, Meat consumption projections in SSA to 2050 have been omitted from the present version of this study. See [232] for further detail.
It is found that by 2050 – depending on the interplay of resources efficiency and demand growth – globally greenhouse gases emissions could grow by 1.4 [0.9-1.9] Gt CO_2e/yr (~175% of today's regional agriculture-related emissions), cropping and grazing-related land may cover additional 15 [12.5-21] · 106 km^2 (one quarter of today's global agricultural land), blue water consumption would rise by 36 [29-47] Gm^3/yr (nearly doubling the current regional agricultural consumption), the eutrophication potential would grow by 7.6 [4.9-9.5] t PO_4e/yr, and additional 0.9 [0.5-1.4] EJ/yr of fossil fuels and 49 [32-73] TWh/yr of electricity would be consumed. These results are inclusive of the different meat types considered in our analysis. Meat type-specific results suggest that in relative terms beef meat is responsible for greater environmental impact than the other meat types, and mainly when it comes to its land, GHG, and eutrophication potential footprints, which are all at least ten times larger than those of pork and poultry. Bluewater consumption is more evenly spread among meat types, but pork is the main consumer. Finally, energy consumption shows similar values across the meat types.

Figure 4.8. Distribution of the estimated additional local environmental impacts across scenarios 2050 from meat consumption growth in sub-Saharan Africa. Distribution of additional (i.e. on top of today's levels) impacts across the five categories analysed for 2020, 2030, 2040, and 2050 by consumption and resources efficiency scenarios for sub-Saharan Africa.



As previously detailed, the environmental impacts relative to each consumption pathway are estimated with hybrid-units EEIO tables. Environmental impacts of the supply chain of meat depend on the production of the total quantities required, and the resource efficiency of the adopted production processes (i.e. natural resource and emissions intensities). To represent the role of resource efficiency in the economic system with respect to environmental dimensions, five resource efficiency variants – responsible for linking production with environmental impacts – are designed. These pathways of resource efficiency change assume dynamic efficiency gains, whereby regional resource intensities gradually converge towards resource efficiencies of different reference economies worldwide, as expressed by the coefficients of the EXIOBASE 3 dataset. Each coefficient represents the marginal sectoral impact or resource consumption per additional physical unit produced in each region. The dynamic transition is operated at a ten-year time-steps, from 2020 to 2050.

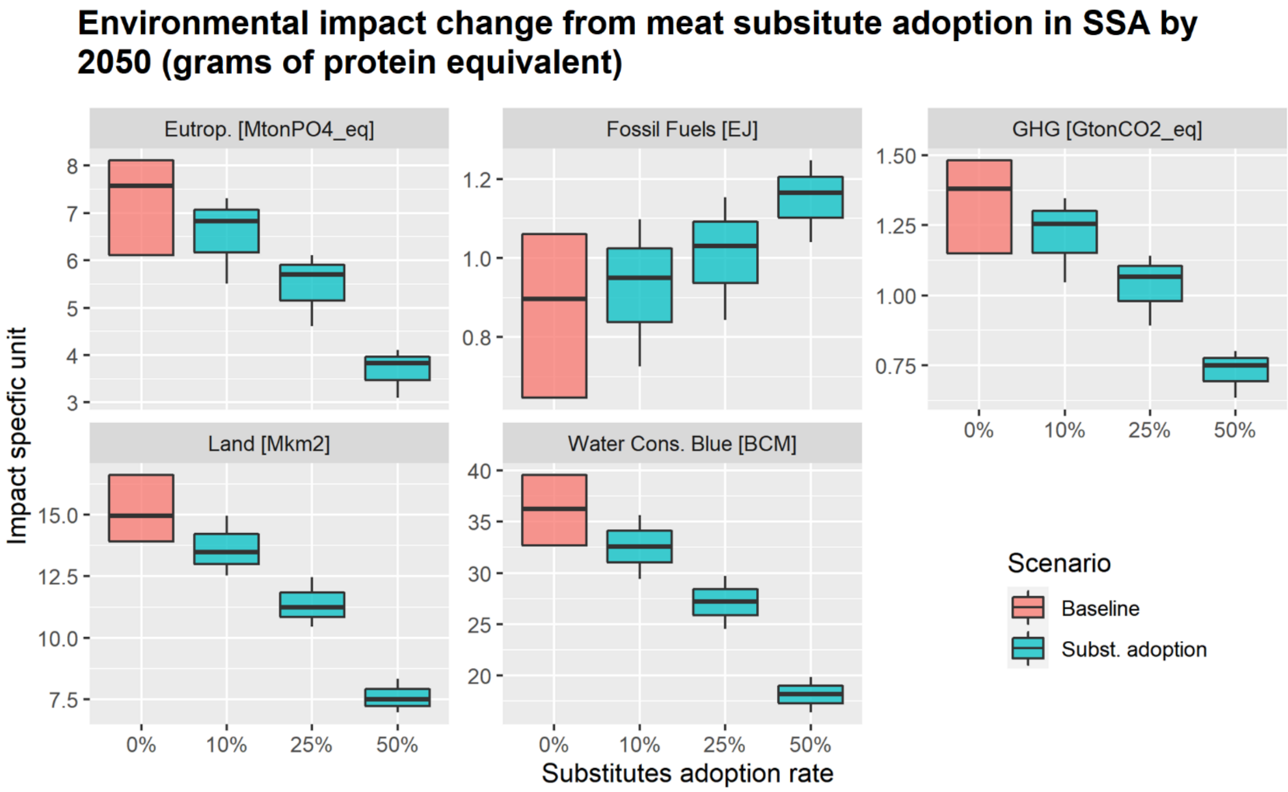
Figure 4.9. (A) Distribution of fossil fuels consumption across world regions for a set of aggregated final use sectors. (B) Distribution of LCA greenhouse gas emissions for the four GHGs considered: CO2 (biogenic and fossil fuels), N2O, and CH4.



Scenarios mirror a convergence towards the median resource efficiency in the reference regions selected when generating the meat consumption scenarios: Central Europe, East Asia, Central Latin America, and MENA. Moreover, the evolution in resource efficiency over time is associated with socio-cultural convergence: meat demand scenarios where the impact of economic development is mediated by a given regional preference are later evaluated in the EEIO environmental impact analysis assuming resource efficiency convergence towards the same region.
Overall, our results show that while the demand-side has a prominent role in defining the expected environmental outcome, there is also a very large room for resource efficiency and technology to mediate these impacts.

Environmental benefits of meat substitutes adoption in SSA

Figure 4.10. Change in the environmental impact of different levels of penetration of plant-based meat alternatives relative to baseline meat consumption scenarios. Facets distinguish the impact categories; fill colours identify the baseline vs. the substitutes adoption scenarios.



To evaluate the role that different levels of adoption of meat substitutes could play in reducing the regional environmental footprint of diets, we simulate future substitution dynamics. For each of the meat types considered, we simulate scenarios of gradual adoption of most diffused meat alternatives (where 10%, 25%, and 50% of animal product consumption by 2050 is substituted). In particular, the absolute quantity of meat substitutes per kg of meat substituted in each adoption scenario is such that it provides the same amount (grams) of proteins that would be provided by one kg of each meat type.

Figure 4.10 shows the change in environmental impact for each impact category relative to the baseline of 25th, 50th, and 75th percentiles of consumption and resources efficiency scenarios. The analysis shows that across all environmental impact categories but fossil fuels consumption, adoption of meat substitutes implies significant reductions in the 2050 environmental impact. In response to a 25% substitution, most (median) impacts show nearly linear reductions, with -24.9% for land and Bluewater, -22.8% for greenhouse gas emissions, and -24.7% for eutrophication at the 50th percentile of the impact distribution. Conversely, fossil energy consumption grows by 15% as – according to the compiled LCA database – the production of some of the substitutes is more energy-intensive than animal meat.

As previously highlighted, CO_2 emissions from fossil fuel combustion play a marginal role in the final GHG impact of meat. Conversely, the final GHG emissions are strongly reduced because of the substantial decrease in the emission of other greenhouse gases in the meat supply chain (and chiefly CH_4), which more than offset the larger fossil energy consumption. A decarbonization of the regional energy systems could also reduce the environmental impact of energy consumption for the production of meat substitutes.

Conclusions

The results suggest that – in the absence of drastic resource efficiency or technological improvements – meat demand in SSA is bound to become a major reason for concern if environmental flows are to be preserved at a sustainable level. A significant role will be played by the quality and pace of global growth of plant-based meat substitutes (which generally have a significantly lower environmental impact than meat) or in-vitro cultured meat breakthroughs. The analysis of the adoption of these alternatives shows that at high levels of substitutes adoption there is nearly a linear reduction between the substitutes adoption rate and the reduction in the environmental impact of most impact categories (chiefly land use, blue water consumption, and eutrophication potential). Conversely, the substitution implies a significant growth in fossil fuel energy consumption, but such an increase remains very marginal in terms of its GHG emission potential when compared to the reductions due to lower CH_4, and N_2O emissions.

Another relevant dimension to consider relates to the household energy requirements for cooking. This energy use is also very inefficient. Thus, the cooking energy pathways and the dietary choices will thus play a major role in determining the cooking energy and environmental requirements.

As all other scenario-based forecasting assessments, the analysis carried out in this paper is characterized by multiple sources of uncertainty that can be mitigated but not completely eliminated.

Relatedly, resource efficiency trends are tidily linked with environmental impact, and the possibility that new technologies can disrupt existing paradigms and boost efficiency cannot be ruled out. In response to this source of uncertainty, our analysis includes different "target" efficiency levels to evaluate a broad range of efficiency outcomes.

Finally, also the meat substitutes assessment is affected by technological uncertainty: research and development in innovative and low-impact food solutions are growing robustly, and ground-breaking technologies such as lab-cultured meat could become pervasive if costs fall sufficiently. Similarly, cultural attitudes and perceptions of these alternatives could also shift rapidly from the current situation, thus improving the environmental footprint of food just by shifting consumer preferences.

4.2. Coupling input-output and linear programming

Some sustainability problems are better modelled through optimization problems. In fact, sometimes the structure of the economy cannot be assumed to be unchanged before and after a significant change in behaviour, policy, or cost of new technology.

4.2.1. Assessing the effects of carbon policies: production vs. consumption-based approach in Europe

The debate around the opportunity to avoid carbon leakage by introducing a tax on an imported product proportional to its embodied carbon emissions represents the first practical implementation in the direction of a consumption-based policy. In this study, published already 2 years ago, the role of a consumption-based policy for Europe has been compared with the current production-based accounting carbon pricing principle [38].

- CERM characteristics: carbon pricing measure – modelling European Union Emission Trading Scheme considering production and consumption-based accounting principles
- Table characteristics: EXIOBASE v2 – year 2007
    - *Geographical scope and scale*: Global table
    - *Table type*: Environmentally Extended Input-Output
    - *Table units*: Monetary – EUR 2007

- Model characteristic: World Trade Model with Bilateral Trades based on an input-output framework
    - *Time scope and scale*: overnight shock – every run represented a different level of carbon emission reduction.
    - *Linear-programming coupling*: World Trade Model with Bilateral Trades regulated by comparative advantage – demand by sector is fulfilled by the lowest-cost region including transport costs.

Introduction

The presence of greenhouse gases (GHG) in the atmosphere has been argued to have a significant impact on the radiative balance of the atmosphere, leading to changes in climatic patterns [236]. Over the last 150 years, the concentration of carbon dioxide (CO_2) in the atmosphere, which accounts for the largest share of anthropogenic GHG emissions, has significantly increased mainly due to the combustion of fossil fuels [237]. Even if most of the GHG emissions have been historically produced within developed countries' borders, the weight of developing countries in total global emissions is becoming increasingly relevant. At the same time, important efforts have been made by developed countries to reduce the carbon emission generated within their borders: considering in EU28, while the population has grown by 7% from 1990 to 2015, CO_2 emissions have dropped by a factor of 21% [237]. Recently, the International Energy Agency has estimated a substantial flattening of global energy-related emissions for 2019, an algebraic sum between 400 Mton CO_2 less in developed countries and the same amount more in developing countries [238].

Brief literature review

This sub-section provides a brief overview of the recent literature focused on modelling carbon emissions reduction policies and on the assessment of their effects on international trades.

A widespread modelling approach in economics relies on Computable General Equilibrium models (CGE). Wang *et al.* [239] study the effect on China's growth of a gradually strengthen energy cap to limit Chinese rapid growth in energy consumption and GHG emissions, finding that the energy cap policy will not disadvantage the economic development or harm the consumption in the residential sector. The different roles and impacts of upstream and downstream subsidies have been investigated through the market equilibrium model by Fischer *et. al* [240], finding that downstream subsidies technology policy may expose global abatement technology price to an undesirable increase while upstream grants reduce it. Other researchers analyze the impact of a multi-regional ETS through a CGE model, showing how extending participation, and integrating the scheme to a composite set of countries, may represent a more economically effective measure to tackle emission reduction than separate sets of single region ETS [241].

Other modelling approaches slightly different than CGE models belong to the family of Environmentally Extended Input-Output models (EE-IO). An example of this approach is represented by the work of Liu *et al.* who developed an EE-IO model to assess the most appropriate mitigation strategy between PBA and CBA for each type of industrial activity. Their work, applied in a provincial context in Canada, shows that it tends to be more effective to apply PBA for primary sectors and CBA for sectors at the bottom of the industrial chain [242]. Static and linear EE-IO models are also used to perform a different kinds of footprinting and LCA analyses. In particular, Ivanova *et al.* plumb the deep interaction between different world sectors and countries to analyze the environmental impact of household consumption in terms of material, water, land use, and GHG emission, computing households' carbon footprint (CF) [231]. Wood et. al introduce a method to evaluate the impact of consumer-oriented policy overall productive system, detecting rebound effects, change in domestic and international production mix, and reduction in carbon intensity [243]. Lenzen *et al.* face the problem of carbon emissions double counting demonstrating and discussing a non-arbitrary method of consistently delineating supply chains of goods and services. In this way, a mutually exclusive and collectively exhaustive share of responsibility for all actors in an economy is provided [244]. Vita et. al. have recently studied the impact on water use, land use, toxicity, and carbon footprint of a wide range of scenarios of reduction or shift in consumption and technological patterns using the *Exiobase v.2* databases [204]. Zhu *et al.* propose an alternative paradigm with respect to CBA and PBA, developing an algorithm able to summarize a fair share of responsibility [245]. Choi *et al.* study and assess the impacts of an emission mitigation policy in 2 steps, taxing diesel in the first time period and encouraging the use of renewables in the second time period, through a sequential input-output framework [246]. In the report of the *CarbonCAP* project, the evaluation of the environmental and socio-economic impacts of several consumption-based emission reduction options are provided based on three different models (E3ME, EXIOMOD and FIDELIO) [26].

Two recent contributions try to fill the research gap identified in the literature, by comparing the effects of PBA and CBA carbon mitigation policies on the environmental and socio-economic context. Both these studies adopt a combined use of Input-Output and CGE models. Sommer and Kratena evaluate the two approaches in the way of a revenue-neutral carbon tax through a Dynamic New Keynesian model, finding no significant advantages in switching from PBA to CBA even if negative carbon leakage is observed [37]. Nabernegg *et al.* investigate the impact of a set of policies in the Austrian national context, for 3 sectors with a high carbon footprint (building, public health, and transport), identifying effective solutions for reducing consumption-based emissions [247].

While recent studies included in the literature review provide in-depth theoretical assessments of PBA CBA-based policies, based on the Authors' knowledge fewer empirical analyses focused on the prospected effects and comparison of PBA and CBA carbon policies at global level have been published so far. For this reason, the general objective of this study consists in assessing the effectiveness of production- and consumption-based paradigms in the application of carbon emissions taxation at the EU level, quantifying their economic and environmental performance as a consequence of a gradual reduction in the EU carbon emissions budgets. The empirical test is accompanied by a theoretical and legislative comparison of both the paradigms, identifying their advantages and drawbacks. Special attention is devoted to the identification of the practical implementation barriers to the consumption-based paradigm.

The empirical analysis is performed according to the *World Trade Model with Bilateral Trades* (WTMBT), assuming the *Exiobase v.2* database as the reference database for macroeconomic empirical data (referred to year 2007). The WTMBT optimizes the global international trade patterns within a given set of constraints by considering the comparative advantage as the only production and trade mechanism. Therefore, specific country agreements, other policies implementation, or any social phenomenon that may affect international trade have been neglected. Since the only degree of freedom of the model resides in the shape and arrangement of international trades, the application of alternative carbon emissions policies will generate different production and consumption patterns among countries, resulting in different global consumption of factors of production, resources, and CO_2 emissions. Any change in trade patterns is assumed to occur overnight (i.e. comparative statics), without considering any structural dynamics of the countries, and by considering constant production technologies. Notably, compared to the current literature on the topic, this study introduces for the first time an empirical comparison of PBA and CBA emissions policies at the global level.

Methodology

This section introduces the adopted model, conceptualized in the framework of Input-Output analysis, and the way production- and consumption-based emission policies are implemented.

The World Trade Model with Bilateral Trades

The *World Trade Model with Bilateral Trades* [113] (WTMBT in the following) is a meso-economic linear optimization model based on the *comparative advantage principle*. Considering *m* world regions with *n* industries each, the WTMBT enables to endogenously determine the production yields and trades patterns required to satisfy an exogenously specified final demand yield in each region, minimizing the use of factors of production (labor and capital) by complying with regional factors endowments (e.g. availability of natural resources, land, workforce, etc.). The choice of developing the study on the version of the World Trade Model which includes the cost of bilateral trades (i.e. WTMBT), is driven by the relevance of transport in determining the arrangement of production and trades and by its non-negligible impact on carbon emissions. The economic and environmental implications of national and international transport of products are included in the model and weighed depending on transport distances. With respect to General Equilibrium Models (CGE), the WTMBT requires less exogenous data since it considers households and government final demand as constant and perfectly rigid with respect to endogenous change in prices of goods and services. Therefore, instead of maximizing social utility, the WTMBT establishes that the highest-cost producers set the product prices, and each region chooses to produce or import by minimizing the overall costs by complying with their own production factors availability (i.e. factor endowments). In the WTMBT, production technologies, factors use coefficients and final demand for each country are derived from Multi-Regional Input-Output tables (MRIO). Other exogenous inputs like factor endowments, weights of transported goods, and regional distances are derived from other databases (e.g. World Bank, International Energy Agency), depending on the scope of the adopted MRIO and on the type of analysis to be carried out.

Assumptions of WTMBT are simple and grounded on widely recognized economic principles. However, the results of the model are affected by sources of uncertainty: process characterization allows each sector to produce only one output, technological coefficients and demand are fixed and sectoral aggregation may lead to detail loss. Furthermore, factor endowments represent crucial parameters, since they practically limit regional production, and are hard to rigorously be determined. Therefore, it cannot be expected that such limitations and hypotheses could intercept even more complex market mechanisms, resulting in a perfect representation of reality.

Table 4.2. – Exogenous and endogenous parameters of the WTMBT.

Category	Symbol	Dimensions	Description
Indices	m		Number of regions
	n		Number of sectors
	k		Number of factors of production
	i, j		Indices for regions $i, j = 1 \dots m$
Exogenous variables	$\mathbf{A}_i$	$(n \times n)$	Matrix of technical coefficients in region i
	$\mathbf{F}_i$	$(k \times n)$	Matrix of factor input in region i
	$\mathbf{D}$	$(m \times m)$	Matrix of interregional distances
	$\mathbf{T}_{ij}$	$(n \times n)$	Matrix of transport supplies from i to j
	$\mathbf{y}_i$	$(n \times 1)$	Vector of final demand in region i
	$\boldsymbol{\pi}_i$	$(k \times 1)$	Vector of factor prices in region i
	$\mathbf{f}_i$	$(k \times 1)$	Vector of factor endowments in region i
Endogenous variables	$\mathbf{x}_i$	$(n \times 1)$	Vector of output in region i
	$\mathbf{ex}_{ij}$	$(n \times 1)$	Vector of goods exported from i to j
	$\mathbf{p}_i$	$(n \times 1)$	Vector of goods price index in region i
	$\mathbf{r}_i$	$(k \times 1)$	Vector of factor scarcity rents in region i

Two different mathematical formulations of the WTMBT can be adopted, depending on the adopted endogenous/exogenous parameters summarized in Table 4.2, but they return the same result, that is, the arrangement of international trades that leads to the minimization of global factors use. In particular:

- *Quantity Model* (also referred as the *Primal Model*), expressed by the system of equations 4.7. It minimizes global factors cost (Z) endogenously returning production and exports by each sector. The global factors, considered as costs from the model perspective, are primary inputs, value added in the form of compensation of employees, taxes and subsidies, net operating surplus and consumption of fixed capital. This minimization is subjected to three sets of constraints. The first one secures that total domestic supply, which is represented by the sum of output and imports, covers the domestic final uses, expressed in turn by the sum of internal demand, final demand, exports and international transportation of imports. The second constraint defines that all the invoked production factors are less or equal to regional factors endowments. The last constraint establishes that the production in every regional sector cannot be less than zero. Notice that $\mathbf{T}_{ji}(n \times n)$ is the matrix of international transport coefficients and it represents the specific cost of importing products from j to i: these values depend on each regional technology and on distances between regions (further explained later). Moreover, $\mathbf{y}_i(n \times 1)$ represents the regional final demand, denoting all the quantity of output requested by final users of region i, independently from where this good or service is produced.

$$
\begin{aligned}
&Min \quad Z = \sum_i \boldsymbol{\pi}^T{}_i \mathbf{F}_i \mathbf{x}_i \\
&s.t. \quad \begin{cases}
\mathbf{x}_i + \sum_{j \neq i} \mathbf{ex}_{ji} \geq \mathbf{A}_i \mathbf{x}_i + \mathbf{y}_i + \sum_{j \neq i} \mathbf{ex}_{ij} + \sum_{j \neq i} \mathbf{T}_{ji} \mathbf{ex}_{ji} & \forall i \\
\mathbf{F}_i \mathbf{x}_i \leq \mathbf{f}_i & \forall i \\
\mathbf{x}_i \geq 0 & \forall i
\end{cases}
\end{aligned}
\tag{4.7}
$$

- *Price Model* (also referred as the *Dual Model*), expressed by the system of equations 4.8. It targets the maximization of the total values of final demand net of scarcity rents (W), endogenously returning price indices and scarcity rents for each sector, subjected to three sets of constraints: the first and second ones ensure that prices of goods do not exceed costs for endogenous and traded products; the last constraint ensures the non-negativity of prices indices.

$$
\begin{aligned}
& Max \quad W = \sum_i \mathbf{y}_i^T \mathbf{p}_i - \sum_i \mathbf{f}_i^T \mathbf{r}_i \\
& s.t. \quad \begin{cases} \mathbf{p}_i - \mathbf{A}_i^T \mathbf{p}_i \le \mathbf{F}_i^T (\boldsymbol{\pi}_i + \mathbf{r}_i) & \forall i \\ \mathbf{p}_i - \mathbf{T}_{ji}^T \mathbf{p}_i \le \mathbf{p}_j & \forall i \\ \mathbf{p}_i \ge 0 & \forall i \end{cases}
\end{aligned} \qquad 4.8
$$

A region makes an endogenous choice between potential regional sources for imports by including the related transport costs into account. In the original Dunchin's formulation of the WTMBT [113], transport technologies were modelled by explicitly considering the weights of transported products: to overcome the lack of such sectoral detailed data, an alternative approach has been assumed here, by hypothesizing that regional specific cost for each transport technology increase proportionally with the travelled transport distance. This has been made by defining the international transport coefficients matrix $\mathbf{T}_{ij}(n \times n)$ (in monetary units) calculated by equation 4.9: technical coefficients related to transport activities in each region $\mathbf{M}_j(n \times n)$ (in monetary units) are weighted based on the ratio between the average transport distances among countries i and j (d_{ij}, in km), and the average transport distance covered by the exporting country for its own endogenous transport (CD_j, in km).

$$\mathbf{T}_{ji} = \frac{d_{ji}\mathbf{M}_j}{CD_j} \qquad 4.9$$

Most of the parameters exogenously required by the model (see Table 4.2) can be obtained from Multi-Regional Monetary Input-Output (MRIO) databases, providing technical coefficients, final demand, and factor inputs. Notably, factor input $\mathbf{F}_i$ may collect both the value-added components (with prices π_i different than zero) and the environmental transactions (with prices π_i equal to zero), including CO_2 emissions, energy use, land use, and so on. Several MRIO can be adopted for this purpose, and the main ones are: Eora [248], WIOD [149], GTAP [148], and EXIOBASE [249]. The selection of the appropriate database depends on the purpose and scope of the analysis; a comprehensive comparison among them can be found in the recent literature [150].

Noteworthy, technical coefficients and final demand for each region provided by MRIO databases reflect one specific arrangement of international trades in one given year. However, since the arrangement of international trades is provided endogenously by the WTMBT, data provided by the MRIO must be properly processed before being used in the model. In particular, technical coefficients for each region should represent the total inputs required by a sector to produce its outputs, independently of where outputs are produced, hence deriving total direct technical coefficients per unit of each output for the jth region: $\sum_i \mathbf{A}_{ij} = \mathbf{A}_j \ \forall j$. The same can be done for the final demand matrix, deriving the total amount of product invoked by one region independent of the country which delivers it $\sum_i \mathbf{y}_{ij} = \mathbf{y}_j \ \forall j$. According to this procedure, technical coefficients and final demand matrices are populated only in their diagonal blocks, which characterize the overall input and final demand structures of each region.

Definition and application of CO_2 emissions policies

Once the WTMBT is fully characterized, carbon emissions reduction commitments (named *carbon budgets* in the following) are respectively defined and imposed on one or more regions as additional constraints to the model. In compliance with this new set of constraints, the *Primal Model* returns the new arrangement of international trades that enable to satisfy the final demand of all the regions by minimizing global economic factor use, while the *Dual Model* returns the related price indices and scarcity rents of products. Notably, the scarcity rents endogenously returned by the model result

from the exogenously imposed carbon budget constraint, and these rents can be assimilated to the corresponding carbon tax yields. In other words, to achieve the change in overall carbon emissions initially imposed on the model, these carbon tax yields need to be set and imposed on industries.
Figure 4.11 provides a general sketched overview of the modelling process, identifying model results based on the overall factor cost (Z) and on the overall regional CO_2 emissions. *Case 00* represents the trades, costs, and emissions derived from the adopted MRIO database. The arrangement of international trades in the *Case 0* (assumed as the baseline scenario) will be different from the original arrangement of the MRIO model, because production and trades are only governed by the comparative advantage principle, assumed as an approximation of the complex dynamics governing real production systems. Once carbon budgets are defined and applied through a PBA or a CBA approach, the WTMBT returns new arrangements of international trades (*Case n*), implying different values of costs and emissions compared to the baseline.
Application of CO_2 emissions policy on a given region based on a *Production-Based Accounting (PBA)* paradigm can be performed by imposing to the *i*th region a maximum amount of allowed *direct* CO_2 emissions as a new constrained factor endowment for the group of regions subjected to limitation (e.g. EU) $f_{EU,CO2}^{PBA}$, defined by equation 4.10 as a fraction ρ (%) of the baseline CO_2 emissions for the same region (i.e. the matrix product of the CO_2 emissions coefficients $\mathbf{F}_{i,CO2}(1 \times n)$ and the total production $\mathbf{x}_i^0(n \times 1)$).

$$f_{EU,CO2}^{PBA} = \rho \cdot \sum_{i \in EU} \left(\mathbf{F}_{i,CO2} \cdot \mathbf{x}_i^0 \right) \qquad 4.10$$

In the same vein, the implementation of the *Consumption-Based Accounting (CBA)* paradigm is performed by imposing to the *i*th region a maximum amount of allowed CO_2 emissions *embedded into its final demand* as a new constrained factor endowment $f_{EU,CO2}^{CBA}$, defined by equation 4.11 as a fraction ρ (%) of the baseline CO_2 emissions embedded in the final demand of the same region. The latter term is calculated as the sum of the direct emissions caused by region i to produce its final demand (first term in rhs of 4.11) plus the emissions caused by all the other regions to produce exports supplied to the *i*th region (second term in rhs of 4.11).

$$f_{EU,CO2}^{CBA} = \rho \cdot \sum_{i \in EU} \left[\mathbf{F}_{i,CO2} \left(\mathbf{x}_i^0 - \sum_{j \neq i} \mathbf{ex}_{ij}^0 \right) + \sum_{j \neq i}^{m} \left(\mathbf{F}_{j,CO2} \cdot \mathbf{ex}_{ji}^0 \right) \right] \qquad 4.11$$

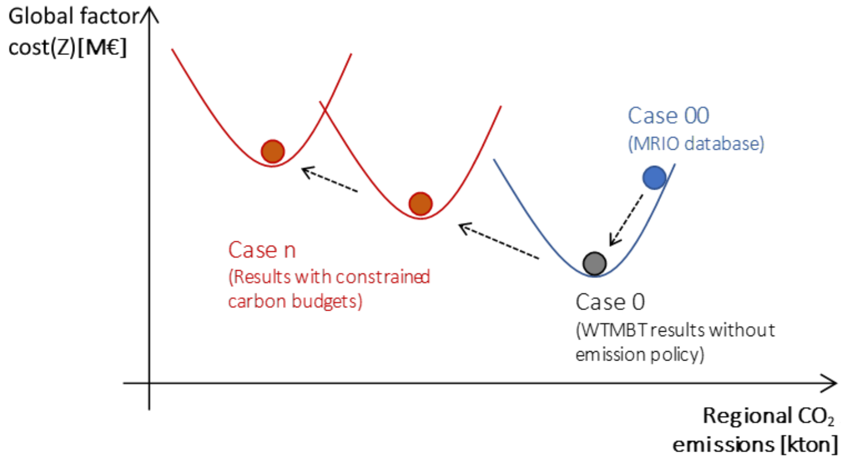
According to the CBA paradigm, every country is responsible for the emissions caused by the production of its own imported products: therefore, the model will try to re-import and re-export products through low emissions countries to numerically satisfy constraint 4.12. To avoid such a phenomenon, constraint 4.12 is formulated by imposing the exports of each country equal at most to its overall production.

$$\sum_{j \neq i} \mathbf{ex}_{ij} \leq \mathbf{x}_i \qquad 4.12$$

It is worth noticing that while the interpretation of the results of the *Primal Model* is straightforward (i.e. the quantities of products traded among regions), the interpretation of the results of the *Dual Model* is less immediate. Beside the price indices of sectors' outputs, the scarcity rents $\mathbf{r}_i$ endogenously returned by the model can be interpreted as the contribution of the carbon emissions policy in increasing the price of products, that is, the CO_2 emissions price endogenously determined by an emissions trading market.
A final methodology remark is in order to justify the adopted approach. The modelling approach proposed in this study can be defined as a *comparative statics* analysis: the adopted WTMBT is capable to capture the prospective economic and environmental effects caused by an exogenously imposed shock (i.e. a carbon tax scheme) as if it appears *overnight*, assuming that industries are ruled by the comparative advantage principle, and disregarding other policy mechanisms and regulatory frameworks already in place. Notably, this approach is widely accepted in economic theory and

currently adopted by analysts in economics and industrial ecology fields. Therefore, policy frameworks for carbon emissions reduction already in place are not included in the analysis: this is justified and fully consistent with our objective, since we are interested in the comparative assessment of the effects of pure PBA and CBA schemes.

Figure 4.11. *Schematic representation of the modelling process. The blue curve represents the range of possible model solutions corresponding to different global factor uses and carbon emissions in case no carbon policies are imposed. Other curves represent the same outputs but considering scenarios with different carbon budgets.*



Main data and assumptions

The *Exiobase v.2* (http://www.exiobase.eu/) [250] has been selected as the reference Multi-Regional Environmentally Extended Input-Output database. The database includes data related to 48 countries and 5 rest of the world regions (see electronic supplementary material), with a resolution of 163 sectors each, it provides interindustry transactions, 7 final demand categories, 7 value added categories, and a multiplicity of environmental transactions (namely resources consumption and emissions, including CO_2 emissions from combustion covered by the analyzed emissions policies). With reference to *Table 4.2*, the MRIO database provides technical and input coefficients $\mathbf{A}_i$and $\mathbf{F}_i$, and final demand $\mathbf{y}_i$. To reducing computational efforts due to the WTMBT, EXIOBASE sectors have been aggregated moving from 163 to 57 sectors (refer to electronic supplementary material for the detailed list of sectors): logic underlying sectoral aggregation choices has been driven by the attempt of keeping carbon intensive sector fully disaggregated, in order to detect and analyze potential changes in world technology mix. Transport distances matrix $\mathbf{D}$ has been derived as the distances between countries' capitals. Finally, factor endowments $\mathbf{f}_i$ have been estimated starting from the factor use in the baseline year available from the adopted MRIO model.
European Union (EU27) has selected the application of the carbon emissions policies, assuming 2007 as the reference year for defining the baseline case (*Case 0*). While the selection of the time frame is mainly due to the MRIO data availability, the choice of the EU as the country scope for the application of the carbon emissions policies is motivated by the need to better understand the reasons behind the undesirable effect of carbon leakage occurred with the EU Emissions Trading System (EU ETS), and which countermeasures could be taken to mitigate this effect.
Since we rely on an Input-Output database with 2007 as the reference year, the issue of adequacy of outdated input-output datasets for providing insights on current policy measures may arise. However, it should be observed that relying on outdated IOTs is a common practice in economic and environmental analyses, since the structure of national supply chains does not exhibit disruptive changes over time, as empirically demonstrated by the authoritative studies of Miller and Blair [174], Wood [251] and Dietzenbacher and Hoen [252].

Scenarios definition

With reference to *Figure 4.11*, starting from MRIO data (Case 00), the baseline scenario (Case 0) has been determined by running the WTMBT without any emissions policy implemented, and it will be subsequently adopted as the reference case for comparing the effects of PBA and CBA emissions policies.

With respect to *Case 00*, global factors use in *Case 0* (i.e. gross value added) is overestimated by +5.2%. The shares of macro-regions factor use do not change significantly: Canada (+14.8%) and the Middle East (-2.5%) respectively results as the most over- and under-estimated regions. Overall, EU27 results in a +9.3% overestimation of factor use. From an environmental point of view, global CO_2 emission from fossil fuel combustion results in line with 2007 IEA data (approximately 29 Gton). Overall, observed differences between *Case 0* and *Case 00* have been considered acceptable.

From a practical viewpoint, the only differences between PBA and CBA reside in the definition of the carbon budget constraints, respectively determined through relations 4.10 and 4.11. Both the scenarios are performed by imposing a progressive reduction of the EU27 carbon budget of 1%, 5%, 10%, 20%, 30%, and 40%, hence simulating the imposition of policy commitments. Notably, such carbon budgets are applied to the whole EU27 region: this choice is in line with the current EU ETS, which established a CO_2 emissions allowances market at the European level, stimulating cooperative behaviour between its countries. Table 4.3 summarizes the cases investigated in this analysis.

Finally, due to the crucial role played by exogenously determined national factors endowments, a sensitivity analysis has been carried out by testing different sets of them in order to assess the robustness of the obtained results.

Table 4.3. Summary of the modelled scenarios. The economic and environmental impact of the prospected policies is performed by considering the difference between the PBA x% or the CBA x% with the Case 0 (assumed as the baseline).

Policy case name	*Description*
Case 00	*Production and consumption pathways for the global economy, derived from the EXIOBASE v.2 MRIO database.*
Case 0	*Result of the WTMBT optimization model with constraints on factor endowments (economic and environmental resources) but without any constraint on carbon emissions. This case is set as the baseline for assessing the impact of carbon emissions policies.*
PBA x%	*Result of the WTMBT subjected to an additional constraint on EU27's PBA carbon emissions, equal to the PBA carbon budget in the Case 0 reduced by x%.*
CBA x%	*Result of the WTMBT subjected to an additional constraint on EU27's CBA carbon emissions, equal to the CBA carbon budget in the Case 0 reduced by x%.*

Results

Starting from output of the *Case 0*, assumed as the baseline, results PBA and CBA policies implementation have been derived. Among the multiplicity of results returned by the WTMBT, this section examines the change in global CO_2 emissions and factor use.

Figure 4.12 and Figure 4.13 respectively reports the changes in global CO_2 emissions and the change in factor use that result from the imposition of PBA and CBA carbon policies. Results are expressed in terms of change in emissions and factor use with respect to the baseline scenario, grouped by region, by sector, and as total net values (black diamonds). Arrangement of production and trades among sectors and regions resulting from PBA and CBA policies influences the direct carbon emissions and factor use of each region, which ultimately results in a net change in global CO_2 emissions and global factor use. If an increase in overall CO_2 emissions occurs, it reveals that the carbon leakage effect is predominant compared to the desired CO_2 emissions reduction eventually induced by the implemented policy. On the other hand, global factor use will always increase

compared to the baseline to comply with the new carbon budget constraint: this may be interpreted as the increase in total costs due internalization (or monetization) of an environmental externality or, equivalently, the overall cost induced by implementation of the prospected policy intervention.
with PBA EU countries find more convenient to import products from abroad. For carbon budgets reduction greater than 5%, the CBA policy becomes effective in reducing global emissions, while PBA policy appears to cause carbon leakage, increasing global emissions. As previously mentioned, both schemes result in an increase in global factor use, that results greater for CBA than PBA: this is motivated by the fact that while a decrease in PBA carbon budget allows EU countries to rely on less expensive and higher carbon intensive imports, the same is not allowed for an equal reduction in CBA carbon budget, which forces EU countries to rely on more expensive technologies with lower carbon intensities. It can be concluded that, for high values of carbon budget reductions and within the adopted modelling framework, the PBA scheme fails in reducing global carbon emissions while implying additional global costs; conversely, the CBA policy succeeds in reducing global carbon emissions. As an example, with reference to a carbon budget of 40%, the PBA scheme causes a global increase of 0.8 Gton with an increase of 12.5 B€; conversely, the CBA scheme causes a global reduction of -1.2 Gton by means of 25.5 B€ of increase in factor use.
With a carbon budget reduction ranging from 1% up to 20%, the implementation of CBA results in global CO_2 emissions reduction accompanied by cost increase for the EU and a corresponding cost decrease in other regions: EU regions are thus relying on more expensive endogenous technologies by reducing imports from foreign carbon-intensive industries (from the USA in particular). However, after a 20% of carbon budget reduction, a reduction in cost for the EU region reveals that a portion of the EU's final demand is satisfied by imports from a balanced mix of foreign industries. On the other hand, with reference to PBA, the carbon leakage effect becomes increasingly important with the increase in carbon budgets reductions: after 20%, the direct emissions in foreign countries (rest of Europe, Russia and Canada in particular) become increasingly relevant, becoming greater than avoided CO_2 emissions in EU. Notably, even if the EU emissions get lower, the overall cost of the policy and the overall emissions increase, thus resulting in an overall inefficient and undesirable plot.
With reference to Figure 4.12 and Figure 4.13, the following comments can be made.
For carbon budget reductions within 5%, both PBA and CBA provide comparable environmental effectiveness and costs, reducing global carbon emissions. However, while the application of CBA stimulates the cooperation between EU countries and the adoption of their own cleaner technologies,
The sectors whose exhibit greater changes in carbon emissions with respect to the base case are, not surprisingly, the more carbon-intensive ones. Indeed, the weight of the imposed policies (both PBA and CBA) are proportional to the carbon emission yields, and the model attempts to satisfy the imposed carbon budget constraints starting from those sectors. Power generation is mostly affected by the PBA and CBA carbon policies: from Figure 4.12, it is evident that in a PBA approach, production of goods and services shifts from EU to foreign countries not subjected to carbon policy constraints, and the electricity required by the products supply chain follows this shift. This ultimately results in higher global emissions due to high carbon intensity of electricity production by extra-EU countries. Likewise, with reference to Figure 4.13, the increase in global factor use is mostly due to electricity generation shift from EU region to Asia and Middle East regions. The application of CBA affects again power generation, but in a radically different manner compared to PBA: indeed, the reduction in carbon emissions by the EU region is not the result of a leakage, but it results from a shift from high to low carbon-intensive power generation technologies mostly occurring within the EU region.

Figure 4.12. EU27 carbon budget reduction (%) vs regional and global change in CO_2 emissions (Mton). Upper side: results grouped by macro-region; Lower side: results grouped by industries. Left side: results of production-based policy; Right side: results of consumption-based policy.

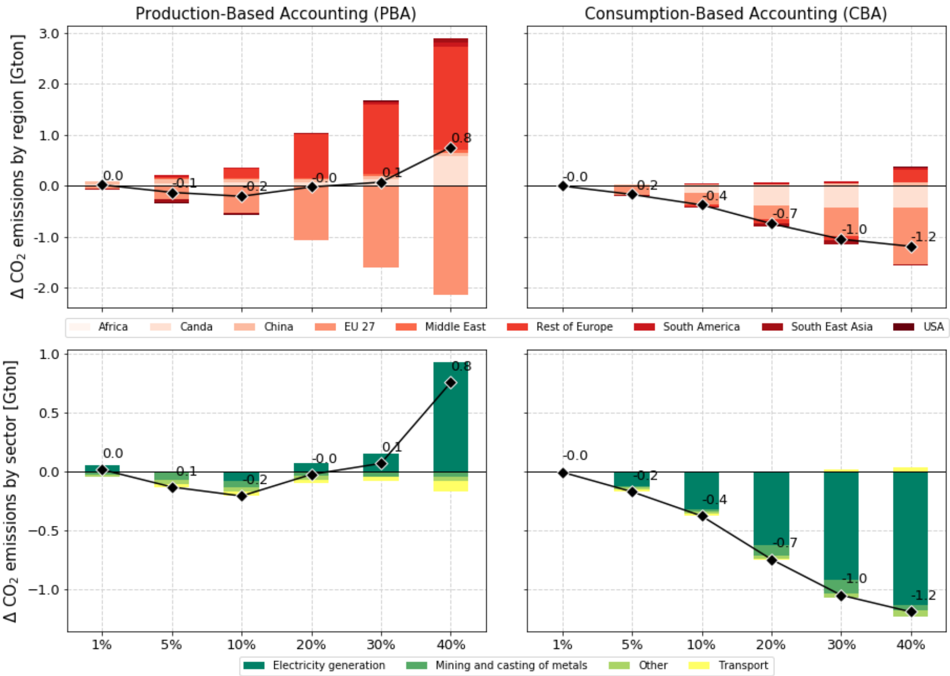
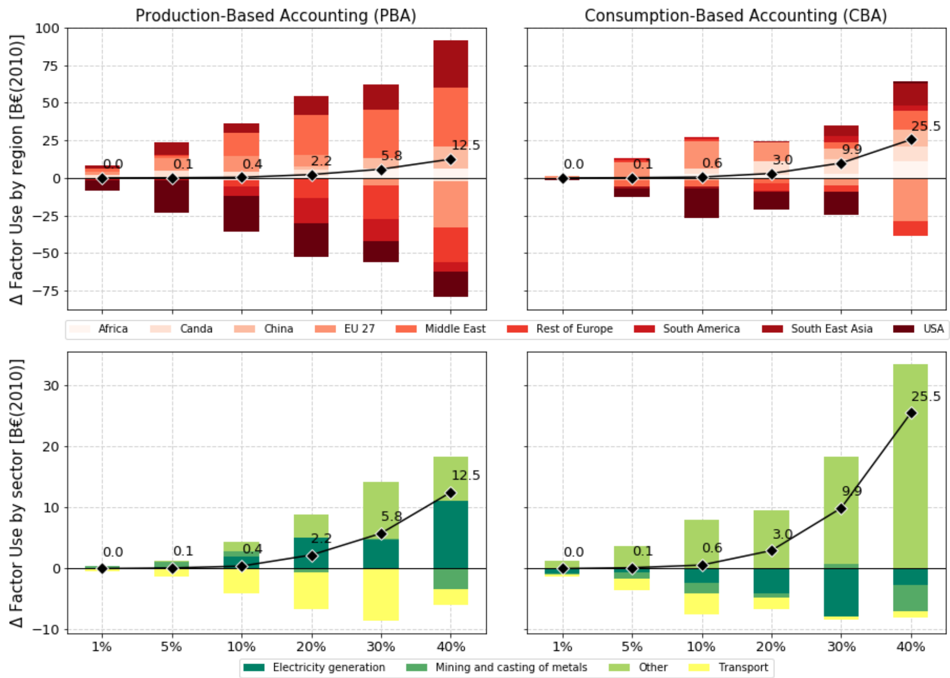


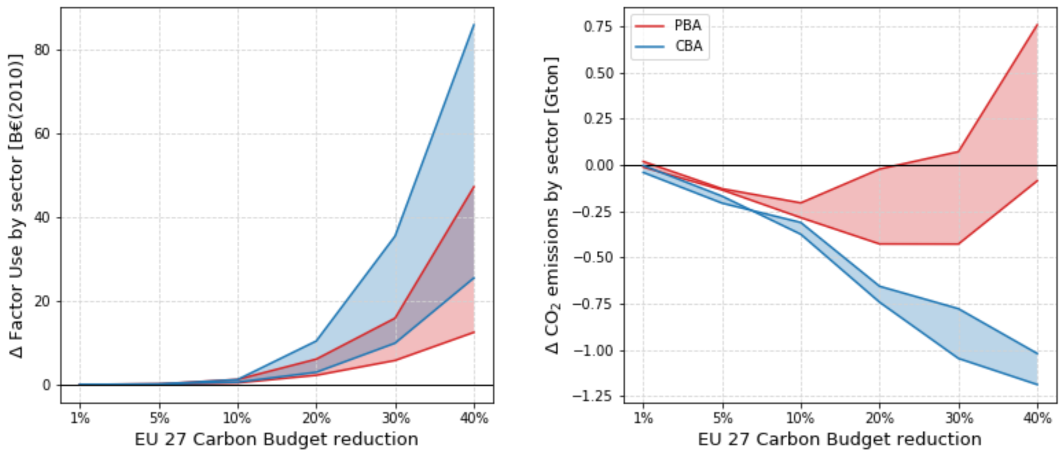
Figure 4.13. EU27 carbon budget reduction (%) vs global change in factor use (primal problem objective function, in B€2010). Upper side: results grouped by macro-region; Lower side: results grouped by industries. Left side: results of production-based policy; Right side: results of consumption-based policy.



A closer look at the results may give further insights related to the carbon policy mechanisms. As an example, looking at the CBA case with a 20% of carbon budget reduction, it appears that Canada makes greater use of economic factors, which is matched by a significant cut in CO_2 emissions. By looking at the sectoral contributions of this country, it is observed how metal production increases

(also exported to European countries such as Spain), gas extraction activities decrease, and the electricity mix changes from gas to nuclear power generation. Therefore, the effectiveness of CBA in terms of CO_2 emissions reduction appears also outside the countries where this policy is applied. In other words, the countries trading in the area where the CBA policy is applied will be those most able to meet the additional demand for carbon-intensive products with the cleanest infrastructure. Another example of this behaviour is provided by Italy, that becomes a producer of electricity from cleaner energy sources in the CBA 20% case, managing to meet the demand of neighbouring countries through a relatively cleaner infrastructure; however, this implies an increase in the use of economic factors in the electricity transmission sector in the same region.
Results of the sensitivity analysis on factors endowments of all the national economies are reported in Figure 4.14, where a reduction in the available amount of national workforce, land and primary energy has been tested. As suggested by the figure, CO_2 emissions and factor use are strongly sensitive to changes in factor endowments, and this sensibility increases with the increase in carbon budgets reductions. The economic cost of CBA policy still appears to be higher compared to PBA. The robustness of the model results is demonstrated by the sensibility of CO_2 emissions, which keep the same trends for PBA and CBA: overall, policies based on PBA always result in affected by carbon leakage, while CBA policies always provide a net emissions reduction.

Figure 4.14. *Results of the sensitivity analysis on global factor endowments. Left side: change in global factor cost (B€2010); Right side: change in global CO_2 emissions (Mton).*



Conclusion

This paper provides a formalization and a first comparative application of two opposite paradigms for allocating responsibility for CO_2 emissions. In particular, the research provides a global empirical application of a CO_2 emissions policy based on a consumption-based approach and compares the obtained results with the widely adopted production-based approach. The study adopted the World Trade Model with Bilateral Trades applied to background macroeconomic data supplied by the *Exiobase v.2* global Multi-Regional Input-Output database. This approach makes it possible to evaluate the introduction of the policy net of market mechanisms that intervene and that are included in more complex models (e.g. Computable General Equilibrium models) requiring further assumptions. In this sense, the analysis conducted here can be defined as a study on the supply side only, useful to evaluate the interactions that would occur if these policies were implemented overnight.
The results of this study are useful to understand the potential of international trades in reducing overall carbon emissions given a set of constant technological alternatives available to produce the

same products. The obtained results suggest that defining CO_2 emissions policies based on a consumption-based paradigm seems to be the most effective way to reduce global carbon emissions, avoiding the carbon leakage phenomenon caused by current production-based policies. Indeed, an imposed reduction in CO_2 emissions embedded in the European Union's final demand through a Consumption-Based Approach policy would result in a global CO_2 emissions reduction up to almost 1.2 Gton. On the other hand, an imposed reduction in direct European Union CO_2 emissions according to a PBA approach would result in an overall increase in global carbon emissions up to almost 0.8 Gton. The analysis conducted here shows how a paradigm shift from a Production-Based Approach towards a Consumption-Based Approach can lead to an actual improvement in the effectiveness of mitigation policies on what should be the ultimate target of these (i.e. global emissions). This may not represent the most adequate strategy for the achievement of the CO_2 emission cuts targets, but it can be taken into consideration by policy-maker as a more effective alternative that, net of the possible legislative hurdles, would represent an intermediate solution as long as more efficient strategies are hampered by political constraint.

In order to improve the quality and reliability of the obtained results, several aspects of the adopted modelling framework deserve to be developed in future studies. Given the crucial role of factor endowments in determining production and trade patterns, many efforts should be devoted in their conceptual and numerical definition (e.g. availability of renewable energy sources, water, others...). Secondly, the definition of transport modes deserves further analysis: an improved technology-dependent definition of transport distances among regions needs to be made, and all the unrealistic transport solutions should be numerically constrained by the model. Then, introducing Rectangular Choice of Technology (RCOT) will make the model flexible and capable to select among alternative technology options for providing the same product, hence giving the opportunity to investigate multiple technology options. Finally, besides the improvements related to the modelling approach, one very crucial aspect that deserves a thorough discussion is concerned with the practical and legislative barriers that may arise in the implementation of an environmental policy based on the Consumption-Based paradigm. Alongside this, multiple different scenarios may be conducted to explore which is the best policy paradigm to be adopted depending on the economic and technological structures of the analysed region.

4.2.2. Assessing the changes in endowment and consumer preferences: COVID-19 impact on the Italian energy system

The COVID-19 pandemic hit not only the sanitary system but also the energy system. In fact, changes in behaviour of consumers, induced by the necessity to limit mobility, impacted the energy system, in particular in the transportation sector. Most of these changes have been in place just for a few months but some others may have triggered an acceleration in trends such as smart working, which may be considered to limit the emissions associated with commuting and business travels. Furthermore, in light of the expansive policy steps put in place by the European Commission, countries like Italy which have been dramatically hit by the pandemic may recover by investing importantly in green technologies.

- CERM characteristics: non-carbon pricing measure – assessing the impact of short-term reduced mobility and medium-term green investments
- Table characteristics: Eurostat Supply and Use table of Italy – year 2010
  - *Geographical scope and scale*: Single Region Italy
  - *Table type*: Environmentally Extended Supply and Use
  - *Table units*: Monetary – EUR 2010
- Model characteristic: Leontief-Kantorovic Supply and Use optimization model

- *Time scope and scale*: multiple runs of the same economy are simulated trying to depict the expected evolution in Italian gross domestic product and consumption patterns.
- *Linear-programming coupling*: Leontief-Kantorovic assumption – the "shape" of the final demand and total gross domestic product levels have been exogenously set so that the model can find its optimal mix of sectoral production.

Introduction

The effects of the COVID-19 pandemic on the global energy sector in 2020 have caused unprecedented variations in both energy demand and supply. Recent estimates by the International Energy Agency (IEA) quantify this disruption in a 5% reduction in world energy demand from 2019, a decrease of 7% in energy-related CO_2 emissions, and an 18% drop in investments in energy [253]. The single strongest driver of those figures is the mandatory shut-downs of several activities due to lockdowns and other measures to prevent the virus diffusion of the virus, with the most notable effects on energy consumption in transport and industry. Different research studies have evaluated the impact of the pandemic on energy systems worldwide, considering different phases of the energy supply chain, final sectors, and geographical levels.

A direct impact is observed in the transport sector. Daily commuting habits have been strongly affected, with stronger effects observed in international travel, specifically in aviation [254]. Modal shares in urban transportation during the pandemic have been strongly influenced [255,256], with a huge decrease in public transport and a shift towards private cars and active modes, i.e. biking and walking. While the direct effects in 2020 have been widely acknowledged, also thanks to a number of measurements and estimations [257,258], future trends are much less clear.

Considering the buildings sector, the effect on the energy consumption of households is mostly limited to the lockdown phase [259], although some effects may last longer if people opt for remote working. However, those effects, including higher energy consumption for heating and appliances, need to be compared to the corresponding savings in offices for the same activities. Some research works have also focused on the direct energy and environmental effects of fighting the COVID-19 pandemic [260], highlighting that sustainability is not often a priority.

Additional energy impacts are related to the ongoing economic crisis due to the effect of the pandemic on the global economic system.

Brief literature review

A comprehensive study of the environmental and socio-economic impacts of the pandemic response is provided by the work done by Mofijur et al, in which pollution mitigation, increase in oil prices, unemployment, and poverty rates are included in the analysis [261]. Furthermore, economic conditions influence behaviour and future perspectives, also manifesting psychological issues connected with economic vulnerability induced by the response to COVID-19 spread [262].

Meso-economic modelling frameworks are adopted for determining the short-term impacts on environmental and economic indicators for distinguishing amongst highly disaggregated economic sectors. Lenzen and colleagues [263,264] estimated an annual reduction of gross domestic product (GDP) and greenhouse gases (GHG) on a global basis of about 4.2% and 4.5% respectively through a global input-output model using disaster impact analysis. Pichler *et al.* analysed the economics and the epidemiology of reopening the UK's commercial and educational activities, capturing the complexity of supply and demand shocks on production networks through a purpose-built input-output model, investigating the trade-off between containing the spread of the virus and limiting the economic downturn [265]. Furthermore, Deloitte estimated sectoral output downturns during the early stage of the pandemic describing the relation between expected logistic behaviour of COVID-19 spread and the sector-specific response of Italian regulators [266].

Sectoral economic data usually require years of data gathering and analysis, especially in the developing world, therefore past research has developed other methodologies for producing the needed information for impact assessment. Electricity consumption and night-time light intensity can proxy economic activity and can say something about the economic loss faced by countries, and that is how Beyer and colleagues estimated almost real-time gross value added changes in Indian districts during government restriction, showing how relaxing measures without effectively reducing risks of a COVID-19 infection may not guarantee a full economic recovery [267]. Surveys are used for exploring short-term and medium-term perceptions of citizens, both in developing countries [268] and developed countries [262], highlighting differences in regional, gender, and age response to the adopted restrictive measures.

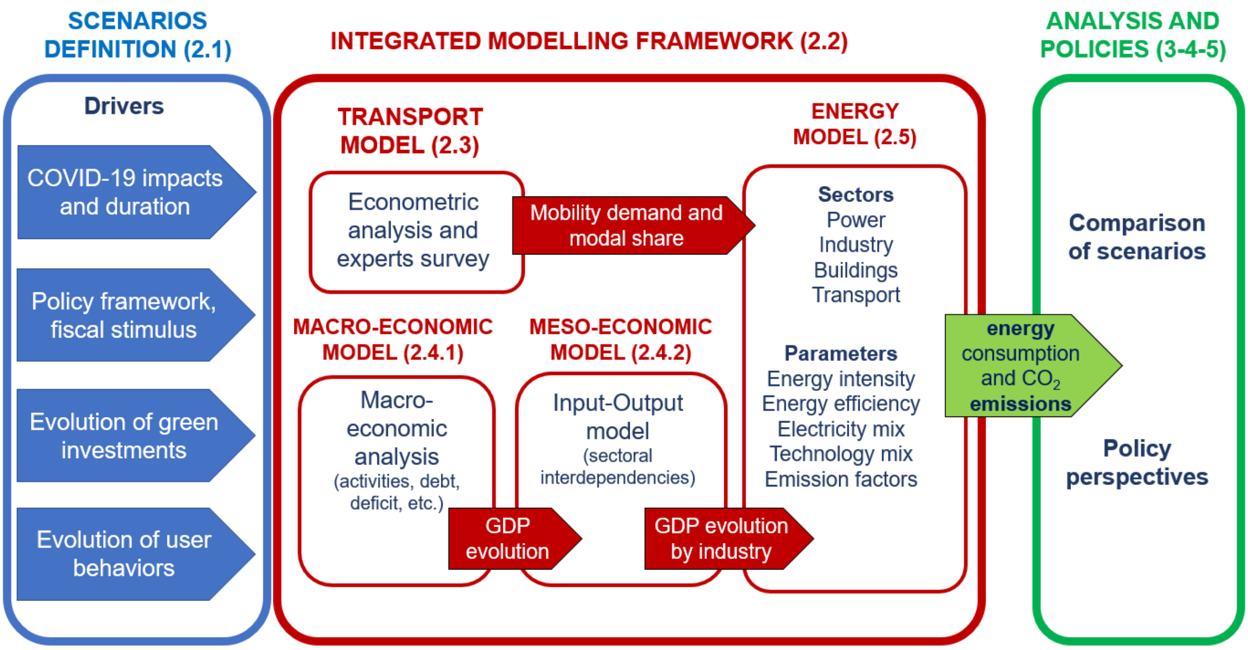
However, the largest part of previous studies has been focused on the effects during the pandemic or the short-term consequences related to the recovery. Few studies have tried to evaluate the impacts with a medium- to long-term perspective. Malliet and colleagues investigate the short-term impact of the pandemic crisis in France, also providing a long-term assessment of the impact of carbon pricing on speeding up the economic recovery through a computational general equilibrium (CGE) model [269]. Studies on the long-term environmental and economic impact induced by COVID-19 are lacking in the current literature, and none have been completed for Italy.

This work aims at filling this research gap, by generating and comparing alternative future scenarios in the case of Italy, relying on a multi-disciplinary approach that can be replicated for other countries. The choice of combining multiple models allows adopting a properly-designed methodology for each step of the process of estimating sectoral impact, including economic dimension, energy requirements, and consequent environmental impacts. Based on the quantitative scenario results, policy insights and perspectives are then derived and discussed.

Methodology

The modelling framework of this project is developed in a multi-disciplinary perspective, to account for different drivers related to the COVID-19 pandemic, including the impact and duration of the COVID-19 emergency, the policy framework, and the fiscal stimulus, the evolution of the green investments and the user behaviours. Thus, different models have been used to estimate the final effects in terms of energy consumption and CO_2 emissions, as represented in the chart in Figure 4.15.

Figure 4.15 – Research project workflow and organization of the paper. The numbers refer to the paragraphs of the full paper [270].



Scenarios definition

The modelling framework has been applied to three different scenarios, a “best-case”, a “medium-case” and a “worst-case”. Each scenario assumes a different duration of the “active” phase of the COVID-19 pandemic: we define an end-point of the pandemic when a treatment or a vaccine reduces the stress for the Italian health care system to pre-COVID-19 levels. For all scenarios, we assume that before this end-point is met, COVID-19 remains one of the most critical issues for the health care system and significant resources are required to keep the quality of treatment at an acceptable level. After the end-point, the situation in the health care system returns to its pre-COVID-19 situation. All these scenarios have been compared against a pre-pandemic trend, defined as “baseline”, that estimated the future energy consumption and emissions if COVID-19 had never happened.

Each of these three COVID scenarios represents a shock (with a different length) to a baseline scenario which refers to the expected pre-COVID economy and energy pathway in Italy to 2030 as it was forecast by the official Italian Energy and Climate Plan of January 2020.

The main drivers of impacts for each scenario relate to the intensity of the economic downturn and its recovery (V-, W-, L- shaped), which are a function of many parameters including for instance company bankruptcies representing both a supply but also a demand shock to the economy. It is also driven by the policy framework and in particular the fiscal and macroeconomic stimulus (both national and from the European Recovery Fund), the conditionality of these stimuli on green investments, and finally the short-term as well as the long-term change of behaviour (e.g. increased home office, fewer business travels, etc).

For sake of brevity, the methodological details of the other models employed in this research and shown in Figure 4.15, have not been reported. See the full paper and its supplementary information for more details [270].

Economic and energy modelling

The future evolution of the Italian Gross Domestic Product (GDP) has been forecasted considering the projections from the main international institutions (e.g. International Monetary Fund, European Commission, OECD, Bank of Italy) aiming to reduce the level of uncertainty in the analysis. The time series of the developed economic scenarios cover the period 2016-2030 and can be divided into

two subsamples: the period 2016-2019 which accounts for historical data, and the GDP forecast for the period 2020-2030.
Apart from the three COVID-19 scenarios, the evolution of the GDP has been projected for a fourth counterfactual scenario. This baseline scenario has been developed using the long-term growth projections available until November 2019, the pre-COVID-19 forecast. Data of the real GDP long-term forecast from the OECD [271].
The role of the meso-economic model is to provide a sectoral disaggregation of the GDP pathways derived by the economic model: this constitutes an essential step and an input to the Energy model which requires sector-specific activity levels for every scenario. The Input-Output model adopted for this purpose can be defined as a single-region, multi-sectoral, linear optimal resource allocation model grounded on empirical data in the form of Input-Output tables (Eurostat national accounts). The model represents the transactions of goods and services across all national industries and final consumers in one given time frame (1 year). In particular, the model assumes the structure of all industries in the economy as fixed and not influenced by the level of production of each sector (this is usually mentioned as the *Leontief technology assumption*), while the production must serve an exogenously fixed product distribution of final demand (sometimes referred to as the *Kantorovich assumption*) [272]. Final demand yield is bound by the availability of factors of production at the aggregated national level, which is determined by the macro-economic model (section 0). Notably, the industrial structure of production and the composition of the consumers' consumption basket is determined exogenously in order to be coherent with the assumed scenario narrative. This approach has been recently adopted for assessing future development scenarios in [273,274]. The so-called Leontief-Kantorovich model is formalized by the linear optimization problem 1, working for each of the *j* cases resulting from the combination of years and scenarios.

$$\begin{aligned} &max \quad Y_j = \mathbf{y}_j{}^T \cdot \mathbf{i} \\ &s.t. \\ &\qquad (\mathbf{I} - \mathbf{A}_j) \cdot \mathbf{x}_j \geq \mathbf{s}_j \cdot Y_j \\ &\qquad (\mathbf{B}_j \cdot \mathbf{x}_j)^T \cdot \mathbf{i} \leq GDP_j \\ &\qquad \mathbf{x}_j \geq \mathbf{0} \end{aligned} \qquad (1)$$

In particular, the model determines the vectors of output (**x**) and absolute demand (**y**) of both products and economic activities, as well as the resulting maximized scalar value of aggregated final consumption (Y). This is done while:

- guaranteeing the satisfaction of both final demand, which is distributed as described by the consumer preferences (**s**), and intermediate demand, determined by the supply and use representation of the technological structure of the economy (**A**);
- respecting the exogenous constraint of not exceeding the overall scalar level of gross domestic product (*GDP*), represented by sum (being **i** a sum vector) on each activity product between the representation of the input factor (labour and capital) structure of each economy activity (**B**) and its output;
- providing positive values of product and activity output.

In order to perform this analysis, a dataset of supply and use input-output tables (SUT), economic-wide databases able to capture the flows of monetary value between different sectors, was used. Eurostat's data explorer tool allows for the extraction of Italian supply and use tables from 2010 to 2016 [275]. The dataset, which presents a high level of detail resulting in 65 products, 65 activities, and 5 factors of production, serves two purposes:

- offering the Italian supply and use structure of products, activities, imports, and factors of production for the years 2014, 2015, and 2016 which is adopted also for representing years from 2017 to 2030, being the most updated input-output database available;

- projecting linearly future preferences of product consumption on the basis of past values (from 2010 to 2016) of vector $\mathbf{s}_j = \mathbf{y}_j \cdot (\mathbf{y}_j^T \cdot \mathbf{i})^{-1}$.

The approach assumes that past trends properly fit changes in consumer preferences: some products are becoming less relevant in final demand share (e.g. printing and recording services) while some others weigh more and more (e.g. electricity, gas, steam, and air conditioning services). It should be mentioned, that even if a final product would be no longer demanded, its production is not necessarily going to 0 since indirect demand of intermediate industries may be necessary.

For the sake of simplicity of case definition as well as result analysis and comparison, the same annual share of final demand is adopted in every scenario. This approach may seem simplistic but we think that more complex yet speculative approaches, still to be supported by the literature, are not necessarily superior in modelling future changes in consumer preferences. The level of sectoral GDP is therefore solely determined by the optimal solution of production for maximizing final demand while respecting the shares of the basket of products consumed and constraining economic activities' overall output to the level of national GDP provided by the economic model. This assumption implies the continuation of relative trends in production by activity and, consequently, sectorial energy demand, in each scenario.

The resulting sectoral GDP is delivered to the energy model for every combination of year and scenario.

The analysis focuses on transport and industry, which are the sectors that are most strongly affected by the effects of the pandemic. A precise estimation of the effects of COVID-19 on buildings is beyond the scope of this work since there are no evident drivers to analyze clear phenomena in buildings. The potential increase in households' energy consumption due to teleworking, as suggested by some research studies, may be offset by a comparable decrease in the energy consumption in offices, with little effect on the total buildings' consumption. Thus, an historical trend has been considered to incorporate this sector in the final results, which reflects the continuous increase in both energy efficiency and electricity penetration in the sector. Other sectors, including agriculture, forestry, and fishing have not been considered due to their very low impact on final energy consumption (they represent together 2.5% of the total consumption).

The energy consumption of the industrial sector has been calculated by considering the historical trend of the energy intensity, measured as energy consumed per unit of GDP. This trend has been calculated for the main energy carriers used in the industrial sector, by considering seven industry sub-sectors that represent more than 90% of the energy consumption in the Italian industry (cement, chemicals, food manufacturing, machinery, metals, paper, and printing, textiles). Electricity and natural gas are the main energy carriers across all the activities, while specific industries use also heat (produced by external plants), coke oven coke, and petroleum coke, in addition to a marginal share of other fuels.

Results

Economic conditions

Under modelling assumptions, the three COVID-19 scenarios projection points to contracting by 8% in 2020. After this sharp fall, in the best-case scenario, the GDP growth rate exhibits a rebound, thanks to the expansionary measures, converging to the long-term rate of growth by 2025. Considering the medium-case scenario, the reduction becomes significant both in the medium and long-term. Even if the economy will register a positive growth rate (+3% in 2023) when the COVID-19 could fade, this growth will be weaker than in the best scenario because the extended pandemic will have depleted the economic system for more periods. The worst scenario exhibits the same evolution of the variables but with a higher magnitude. In all the three COVID-19 cases, the implementation of restrictive fiscal policies (I.e. new or higher taxes) reduces the restoring capability of the Italian economy reducing the growth rate. Compared to the twin alternative, this decrease in the GDP level is equal to 0.75%, 0.83%, and 0.94% for the "Best", "Medium", and "Worst" scenarios, respectively. Hence, a trade-off between economic growth and public finance sustainability arises.

Figure 4.16 – Evolution of the GDP growth rate in the four scenarios, percentage.

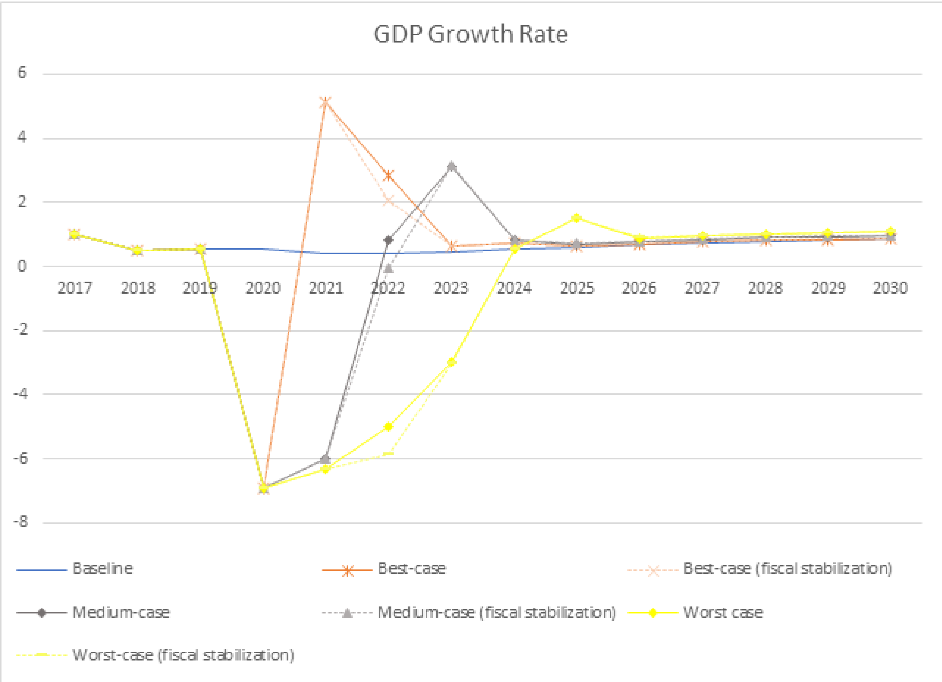
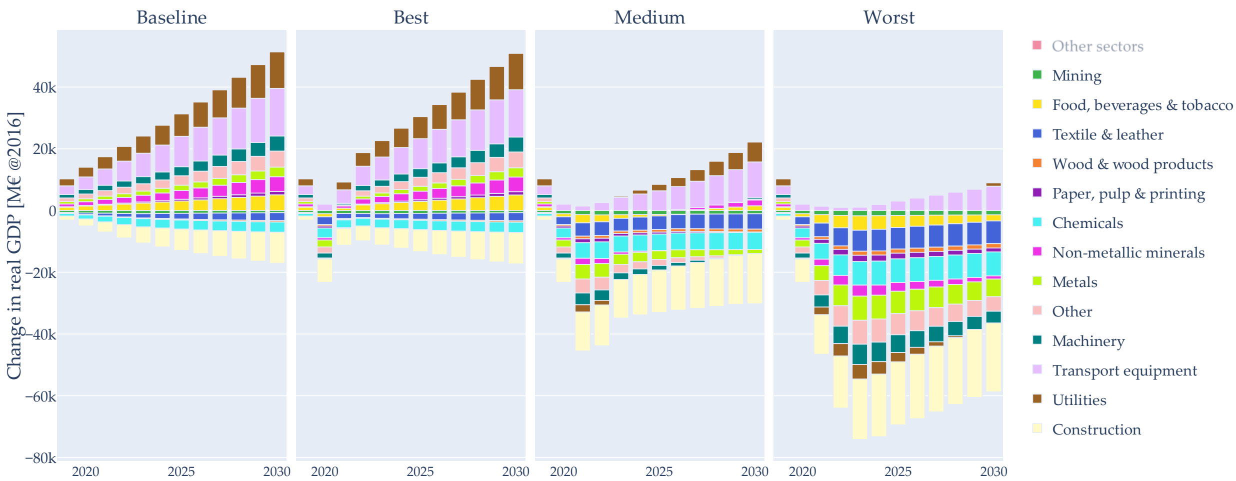


Figure 4.17 – Change in real GDP by industrial sectors from 2019 to 2030 in different scenarios with respect to the 2016 baseline in million euros at 2016 prices.



The presented evolution of GDP by year and scenarios is then distributed among industrial sectors based on the input-output model described above.

Figure 4.17 provides the change in GDP by industrial sector, expressed as the difference with respect to the values observed for the reference year 2016, for all the analysed scenarios.

In the "Baseline" scenario, the national GDP was expected to grow as the sum of different opposing contributions, obtained by projecting the historical national consumption trends of recent years (2010-2016). Among others, Utilities, Transport equipment, Machinery, and Food industries were expected to steadily increase their contribution to national GDP growth, increasing by about 37 B€

between 2016 and 2030 (representing an increase of 2% compared to the 2016 GDP). Some other industries on the other hand, in particular Construction and Chemicals, were expected to see in the baseline scenario a continuation of their downward trends.

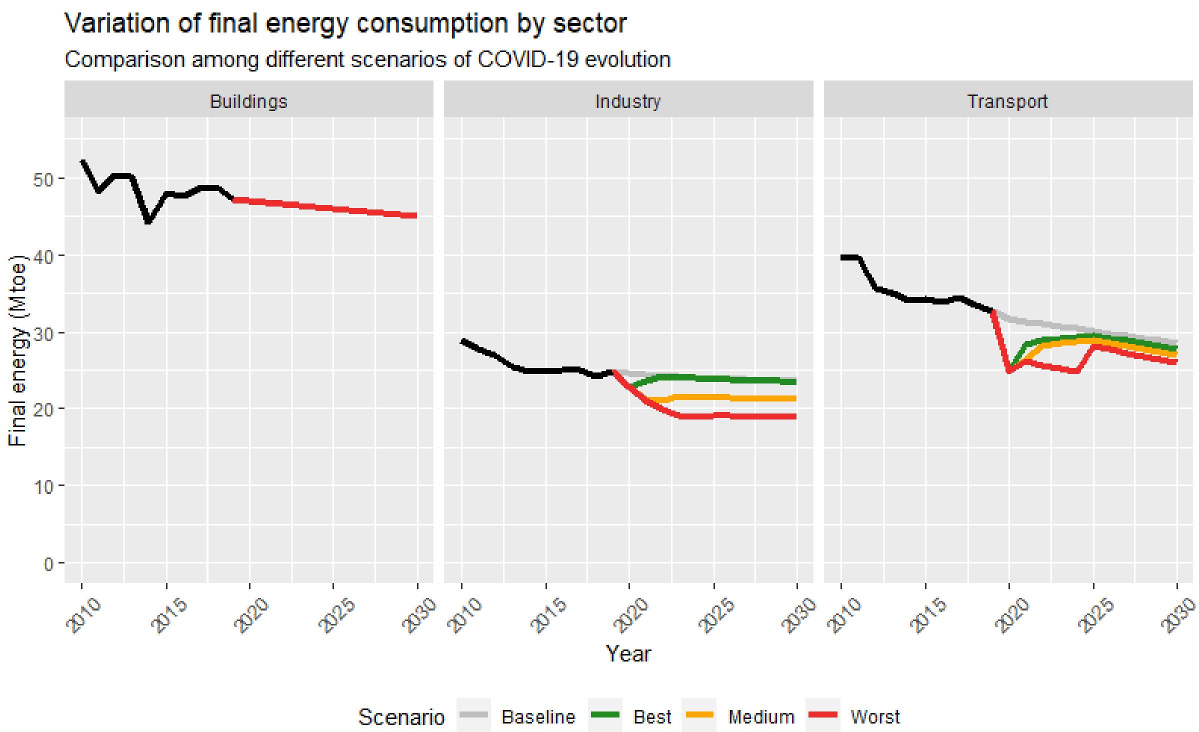
The "Best" scenario differs only slightly from the "Baseline": after the 2020 shock, which causes a short-term sharp GDP reduction across all national industries, the overall and sectoral GDP values are expected to recover quickly (already by 2022) coming almost back in line with the projections of the "Baseline" scenario.

In the "Medium" and the "Worst" scenarios, on the other hand, almost all the industries are experiencing a much more sustained and stronger downturn in the short term (in the "Medium" scenario up to 2022, in the "Worst" scenario an even more brutal downturn lasting until 2023) before a slight recovery starts but which will never allow overall and sectoral GDP levels to reach pre-COVID levels within the analysed time horizon. In these scenarios, only the Utilities and Transport equipment industries show positive contributions to GDP, overall contributing by +1% ("Medium" scenario) and +0.5% ("Worst" scenario) by 2030 with respect to the total 2016 GDP. All the other industries are expected to reduce their GDPs. More specifically, in the "Medium" and "Worst" scenarios, the downturn of the Textile & leather, Chemicals, and Construction industries are expected to experience a reduction in sectoral GDP ranging from -21% up to -30% in 2030.

Energy consumption and emissions

The medium-term effects of COVID-19 in terms of energy consumption have been estimated for each scenario. In comparison with the baseline (i.e. a world without the COVID pandemic), the "Best" scenario shows a 1% reduction, and the "Worst" scenario a 9% reduction in 2030. Considering the sectorial energy consumption, the negative effect on industry appears stronger, with a 23% reduction of energy consumption by 2030 in the "Worst" scenario in comparison to the baseline.

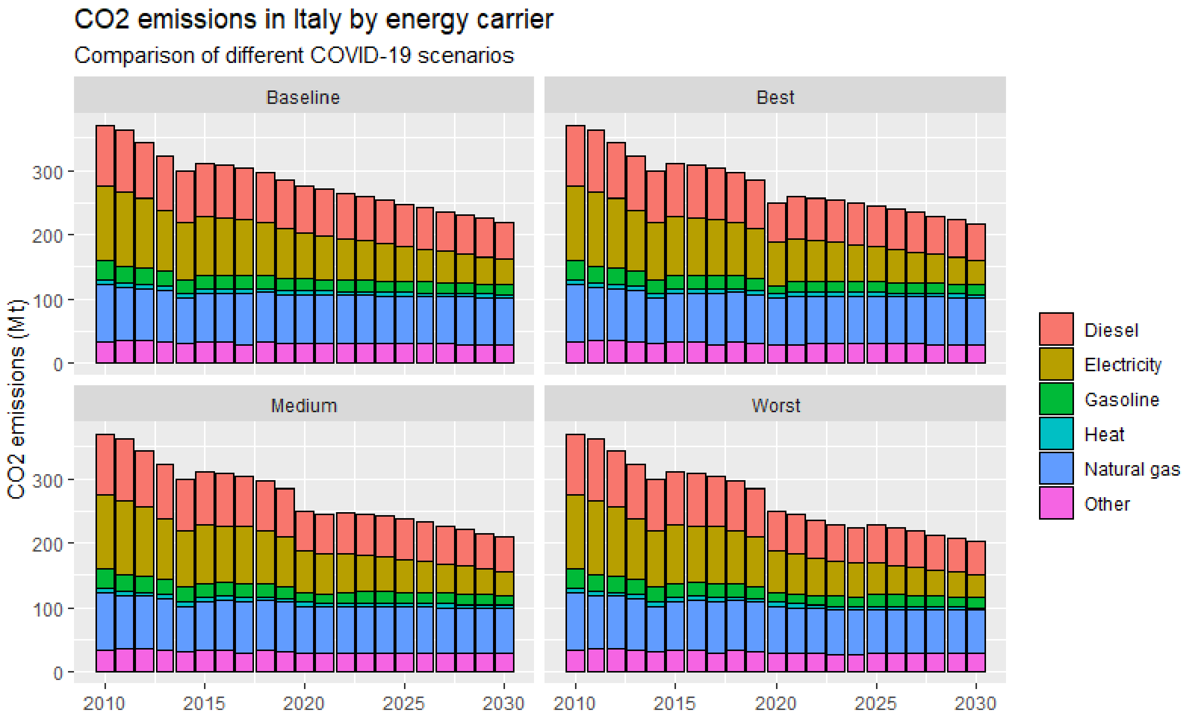
Figure 4.18 – Future final energy consumption in Italy by scenario and by sector.



The future trends of direct CO_2 emissions are reported in Figure 4.19, divided by energy carrier. Their evolution across scenarios follows the one represented above for the final energy consumption, but there is a strong decrease in the electricity-related emissions, thanks to a rise in the share of renewable sources in power generation, in accordance with national targets. In the Medium

scenario, CO_2 emissions in 2030 sum up to 210 Mt, representing 5% less than the baseline and a 33% decrease from 2015 emissions. In the "Best" scenario, 2030 emissions reach 218 Mt, 1% lower than the baseline, while in the Worst scenario they sum up to 202 Mt (8% less than the baseline).
In the medium scenario, and considering the sectors addressed in this study, industry shows a 10% decrease with respect to the baseline, while transport reaches a 6% decrease (emissions totalling 46 Mt and 80 Mt respectively). When compared with 2015 values, sectoral emissions show a 42% decrease for industry and a 27% decrease for transport.

Figure 4.19 – Future CO_2 direct emissions in Italy by energy carrier (million tonnes).



Considering the different industrial sub-sectors in Italy, the ones with the highest emissions before the pandemic were Cement, Metals, Machinery, and Chemistry. These industries were accounting together for almost two-thirds of the total industrial emissions. The sector with the highest emission decrease from pre-pandemic levels (i.e. 2019) to 2030 is the chemical industry, ranging from -39% (Best scenario) to – 51% (Worst scenario). The other major emitters showed slightly lower decreases, with figures for the ranges 30%-44% for cement, 25%-40% for machinery, and 27%-41% for metals. However, a large contribution to these emission reductions comes from the historical improvement of the energy efficiency in industries, with the CO_2 savings in the *Best scenario* that are almost in line with the Baseline scenario. The effect of the pandemic may further contribute to the decrease in industrial emissions in Italy.

Conclusions

The integrated approach developed for this study allows for defining the main drivers of energy consumption in the different final sectors, which are the economic activity, industry, and mobility demand of citizens. These drivers have been estimated with separate models which are able to address the peculiarities of each of these aspects by defining the relevant parameters and methodologies, based on the common assumptions defined for each future scenario. These models are based on data that are continuously in evolution, and the results can be further updated in the future to reflect the most recent trends.
The results confirm the differences across the scenarios, and the decrease of energy consumption related to a reduced industrial activity as well as a lower mobility demand, which are both lower

under COVID-19 than in a baseline scenario where COVID-19 did not happen. The effects are stronger in the industry sector, in which the economic crisis causes a persistent decreased energy consumption. In transport, especially for the passenger segment, there is a partial recovery of the demand in the long term. The econometric model and expert interviews suggest a shift away from public motorized transport in favour of private motorized transportation modes but at the same time a modest decrease in overall Italian motorized transport demand until 2030. This likely reflects increased work-from-home practices and increased use of active modes in the post-COVID future.

The effects of the different scenarios on the CO_2 emissions are in line with those observed for energy consumption. Some slight differences from one sector to another are related to the different energy mixes of the final energy consumption. However, throughout our scenarios, the pandemic is causing emission reductions in addition to a decreasing trend that is noticeable already in the Baseline scenario. Such trend is mostly related to energy efficiency measures in both industry and transport, and to an expected increase in electrification of final uses.

The results of this study are affected by some limitations, mostly because it is not an ex-post study but that it is carried out in the middle of the ongoing pandemic with a constantly evolving epidemiological situation but also the political and economic reaction to it. Another limitation is the unavailability of updated data. In some cases, energy consumption trends and parameters are assumed from historical time series, which do not account for the most recent realities of the pandemic. While in most cases those parameters should not be affected by reduced demand, some structural changes may lead to unforeseen variations in the future. Possible examples include the need for alternative business models to sustain public transport modes in the case of a persistent reduction of demand, modified urban patterns and population distribution after the pandemic (including the role of remote working), and accelerated trends of digitalization in specific sectors.

The future evolution of sectoral GDP will be affected by not only transformation in consumer habits, but also by a structural change that may occur at intermediate levels of demand. For example, digitalization of work as a favoured response to the pandemic may boost the adoption of software and hardware by firms, while discouraging paper and printing services. Furthermore, an increase in electrification and decarbonization rates, in line with national and European efficiency and carbon reduction objectives and strictly linked to economic priorities, may importantly affect results.

The results of this work show the range of impacts that different COVID-19 scenarios can have on future energy consumption in Italy, considering a 2030 perspective. Some aspects of the pandemic crisis may result in persistent effects, including non-recovered economic losses and new mobility habits.

The COVID-19 pandemic has had dramatic effects on the economic trajectory of many countries. It is important that the huge resources devoted to recovery from the current economic crisis are used in the most effective way. Such resources should support innovative technologies, solutions, and industries to build a new economic and energy system that is less vulnerable to potential disruptions and which prepares for being competitive in the future decarbonized and more digital world. Focusing investments on actions that reinforce existing unsustainable economic, industrial, transport, and energy models involves significant risks and would represent a missed opportunity to develop a sustainable, resilient and competitive society in the long run.

Finally, considering urban transport, results show that the COVID-19 pandemic may lead to a persistent, modest increase in demand for private transport modes and a more substantial decrease in public transport use. This trend may result in a negative impact on congestion as well as on energy consumption and emissions. Therefore, strong targeted policies are needed to provide the citizens with viable alternatives that allow for a more sustainable transportation system and lower environmental impacts while guaranteeing equality in access to transport modes. Good practices supporting active transport modes are already being supported in different European cities, and it is important to avoid losing this positive momentum.

4.2.3. Validating the Dynamic Supply and Use Model at the micro-scale: dynamic input-output modelling meets energy modelling for household renovations

In Italy, a considerable number of emissions could be saved by retrofitting existing high-consuming residential buildings [51]. Nevertheless, the effectiveness of a system of incentives that is regulating the residential requalification market is questionable. In this study, a dynamic technology-activity-commodity-need (TACN) model is adopted to assess how current incentives can be impactful in carbon emission reduction mechanisms. An estimate of the implicit carbon pricing associated with such measures is also provided.

- CERM characteristics: Implicit carbon pricing measure – modelling the impact of current Italian incentive in the residential requalification market
- Table characteristics: User-built database considering user *needs* and *technology* characteristics
    - *Geographical scope and scale*: Single node energy system
    - *Table type*: Full-TACN framework
    - *Table units*: Hybrid
- Model characteristic: MARIO U – an ad-hoc built energy model representing a beta version of a fully TACN integrated version of MARIO, currently under development
    - *Time scope and scale*: dynamic model with 1 hour resolution for a seasonally-weighted month and extended towards a 10 year time horizon considered in the investment decision.
    - *Linear-programming coupling*: optimization model minimizing the total actualized cost of the system (considering both operation and investment) or total emissions.

Introduction

In addressing the pledged goal of carbon neutrality by 2050, announced through the European Green Deal [276], the European Union (EU) has identified renewable energy sources, energy efficiency, and reduction of greenhouse gas (GHG) as its three pillars [277]. In the context of the Recovery and Resilience Facility, put in place to respond to the current economic downturn caused by the still ongoing pandemic emergency, Italy is expected to receive 191.5 B€ from the EU in form of grants and loans [278]. This budget, further supplemented by other European and national resources, will be invested to a large extent (i.e. around 40%) in the energy transition. In particular, most of this approximately 60 B€ will be invested in the energy efficiency of buildings [279]. According to the recently published National Recovery and Resilience Plan, 13.8 B€ will be invested in energy and seismic renovation of public and private housing [191]. Specifically, this investment will be largely implemented in the form of credits accrued to the state by private households that will carry out energy upgrading in compliance with the limits imposed by the Italian regulator. The rationale behind the measure is, on the one hand, to broaden the target group of people who would like to renovate the energy efficiency of their homes but are not in the financial position to bear the high initial intervention costs. On the other hand, to benefit from the consequent impact on GHG emissions, which are expected to decrease considerably compared to a baseline scenario in which the private housing stock is not renovated. Therefore, in this historical moment, households are faced with the once-in-a-lifetime individual opportunity to benefit from this measure. However, the presence of external incentives that can make the intervention near-zero cost, can lead to sub-optimal implementation from the energy point of view, with relevant consequences on the expected impact on energy savings that drives the policy. The objective of this work is twofold. On the one hand, to provide a tool to assess the economic and environmental benefits, considering Life Cycle Assessment (LCA) impacts, of home and car renovation at an individual level. On the other hand, to calculate the implicit carbon price of existing incentive measures, such as those envisaged by the National Recovery and Resilience Plan.

Brief literature review

Energy system modelling is a methodology that can mathematically translate the considerations put in place when deciding how to cover future energy needs [280]. Given the multidimensional nature of optimisation problems faced in finding the solution that minimises the operational and investment costs associated with one's specific needs, while incorporating personal needs and preferences, it is necessary to adopt a model with the following characteristics:

- Multi-need: must consider different needs (e.g. transport, electricity, ...);
- Multi-technology: must consider multiple technologies that are able to meet one or more needs (e.g. an electric car could fulfil transport and electricity needs);
- Multi-dimension: must describe technologies and indicate the economic and environmental consequences associated with the choice of a given technology and its use (e.g. photovoltaics modules produce zero-emission electricity but imply emissions embedded in their production);
- Multi-year: must consider the dismantling of old technologies and installation of new ones through time;
- Fine temporal resolution: must model with a fine temporal resolution to have a more accurate representation of variable energy resources.

A recent literature review article has summarised the state of the art of several energy models [109]. A growing number of these try to expand the description of non-energy sectors, are increasingly focused on open access, and give more and more role to detailed characterisation of energy demand with high temporal resolution. Nevertheless, to the best of the authors' knowledge, there are no models in the literature that are able to explicitly manage the planning and production of commodities in a way that can be tailored to the multiple needs of individual users (e.g. need for electricity and transport service), while considering direct and indirect economic and environmental costs.

Methodology

The proposed methodology intrinsically relies on traditional frameworks adopted within Input-Output analysis (IOA). IOA is a widely diffused cost accounting technique, generally adopted for the analysis of national economies as well as for assessing environmental footprints of products along supply chains [174], and constitutes the computational structure of LCA [124]. This work develops a household-based energy model, allowing for optimal multi-carrier technologies and related dispatch strategy selections. While its structure is shaped upon a traditional supply-and-use input-output framework [156], the model consists of a first-attempt of rearranging such structure for a micro-scale application, in order to properly capture the complexities of the residential sector. In order to provide realistic solutions in terms of the installed capacity of technologies, which is of utmost importance to drive the choice of the final user, a mixed-integer linear programming approach has been adopted. This framework allows to expand the interactions between the energy system under analysis and the rest of the economic sectors, allowing to account for direct and indirect life cycle environmental impacts (e.g. CO_2 embedded in the production of technologies and due to their use). The next sections describe the technological scope as well as the mathematical structure of the model proposed. Please refer to Table 4.4.4 and Table 4.4.5 for nomenclature.

Table 4.4.4. Indices

Indices	Symbol
Energy needs	n
Energy commodities	c
Activities	a
Technologies	t
Storage technologies	s

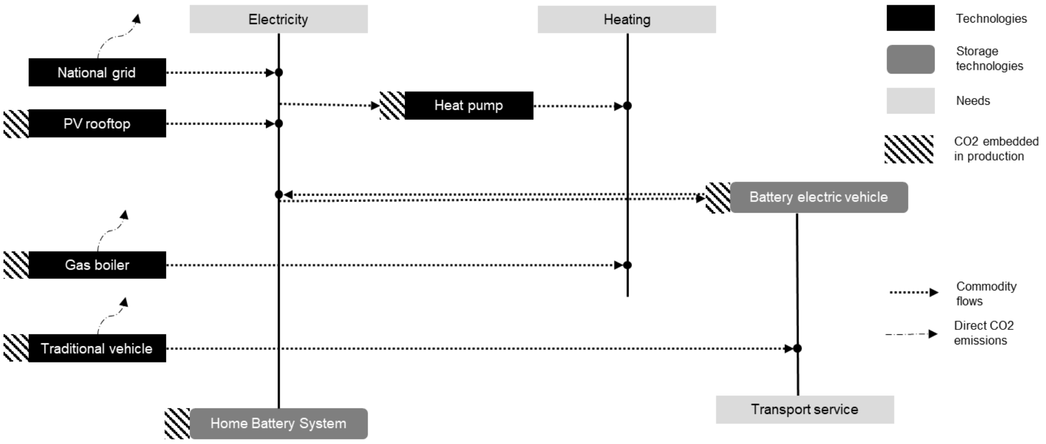
Table 4.4.5. Parameters

Exogenous parameters	Symbol	Size
Final demand	Y	$n \times h$
Specific production matrix	m	$a \times c$
Specific intermediate consumption matrix	u	$c \times a$
Specific operational costs	o	$a \times h$
Specific investment costs	k	$t \times 1$
Specific CO_2 emissions related to operation	e	$a \times h$
Specific embedded CO_2 emissions within technologies	f	$t \times 1$
Availability of technology	A	$t \times h$
Discount rate	r	1×1
Carbon price	cp	1×1
Special identity matrix - use side	i	$n \times c$
Special identity matrix - supply side	j	$t \times a$
Endogenous parameters	**Symbol**	**Size**
Total demand (intermediate and final)	R	$(n+t) \times h$
Deployed capacity (at the beginning)	D	$t \times 1$
Operating capacity (along time)	C	$t \times h$
Storage state of charge	SoC	$s \times h$
Production of commodities / Production by activities	X_c / X_a	$c / a \times h$
Production of needs / Production by technologies	S_n / S_t	$n / t \times h$

Sets and technological scope

A selected set of t multi-carrier technologies, along with s storage technologies, are exploited to enable a number a of activities. In turn, activities are responsible for the supply of a range of c energy commodities: the production of commodities by the activities is described within the specific production matrix m. Furthermore, commodities may be consumed by activities themselves (i.e. consumption of the commodity "electricity by national grid" by means of the activity "heating production by heat pumps") and by the final user; while the former transactions are described in the specific intermediate consumption matrix u, the latter are included within the final demand matrix Y. The full graphical representation of the reference energy system considered within the boundaries of the model is displayed in Figure 4.20.

Figure 4.20. Reference energy system; N.B: multiple technologies (including storage ones) compete for the production of the same need



Mathematical formulation

The model consists of a MILP optimization algorithm that allows for the computation of the least-cost technology selection, arranging the production of energy commodities X_c and the deployed capacity of technologies D_t (*variables*) while respecting a set of constraints. Following the concepts underlying the rectangular choice of technology (RCOT) method, explored by Duchin and Levine [164], more than one commodity, each provided by one activity, may be alternatively exploited to satisfy a single energy need, while, at the same time, more than one activity can be provided with every single technology. Therefore, two *special identity matrices* have been defined:

- *i*, defining, for each energy need *n*, which commodities *c* may fulfil it;
- *j*, defining which activities *a* could be provided by each technology *t*.

The appropriate adoption of *i* and *j*, allows to collapse the production (equation 4.13) and consumption (equation 4.14) matrices expressed by commodities and activities, deriving production and consumption expressed by needs and/or technologies:

$$S_t = j \times X_a \qquad S_n = i \times X_c \tag{4.13}$$

$$R_n = i \times (u \times (s \times X_a)) + Y_n \tag{4.14}$$

In order to respect the energy production-consumption balance, the last two contributions are constrained to be equal.

$$S_n = R_n \tag{4.15}$$

The production of commodities by each activities X_a (directly linked to the production of commodities X_c via the specific production matrix *m*) is also constrained to be lower than the available operating capacity of such activities C_a in every time step.

$$X_a \leq C_a \tag{4.16}$$

In turn, C_a is not only dependent on the deployed capacity of the corresponding technology D_t, but also on the availability A_a of each activity in a specific time-step *h*, as described in equation 4.17,

$$C = diag(j' \times D) \times A \tag{4.17}$$

As previously mentioned, the objective function (equation 4.18) of the model is the minimization of costs, including both investments, operation costs and *carbon cost*, over a time horizon of *y* years.

$$\text{Obj} = \min\left((\text{cp}\cdot f_t + k_t)D_t + \sum_y \frac{\left(\sum_h (\text{cp}\cdot e_a + o_a)X_a\right)}{(1+\text{r})^y} \right) \quad 4.18$$

In the previous equation, the total investment cost of the capacity deployed at the beginning of the project is represented by the term k_tD_t, where k_t represents a vector of specific investment cost per unit of installed capacity of technology *t*; moreover, the specific CO_2 emissions footprint of the deployed capacity *f* are multiplied by a carbon price cp and multiplied again by the deployed capacity itself, to be accounted within the total costs to be minimized. The specific operation costs of activities o_a are multiplied by the related activities production X_a, then summed over the time-steps *h* and annualized according to a discount rate r. The same occurs for the specific environmental impact related to the activities operation *e* multiplied, again, by cp. It is worth noticing that k_t, o_a and cp may be used as leverages to model incentives on specific technologies, as will be described in the next section.

Results

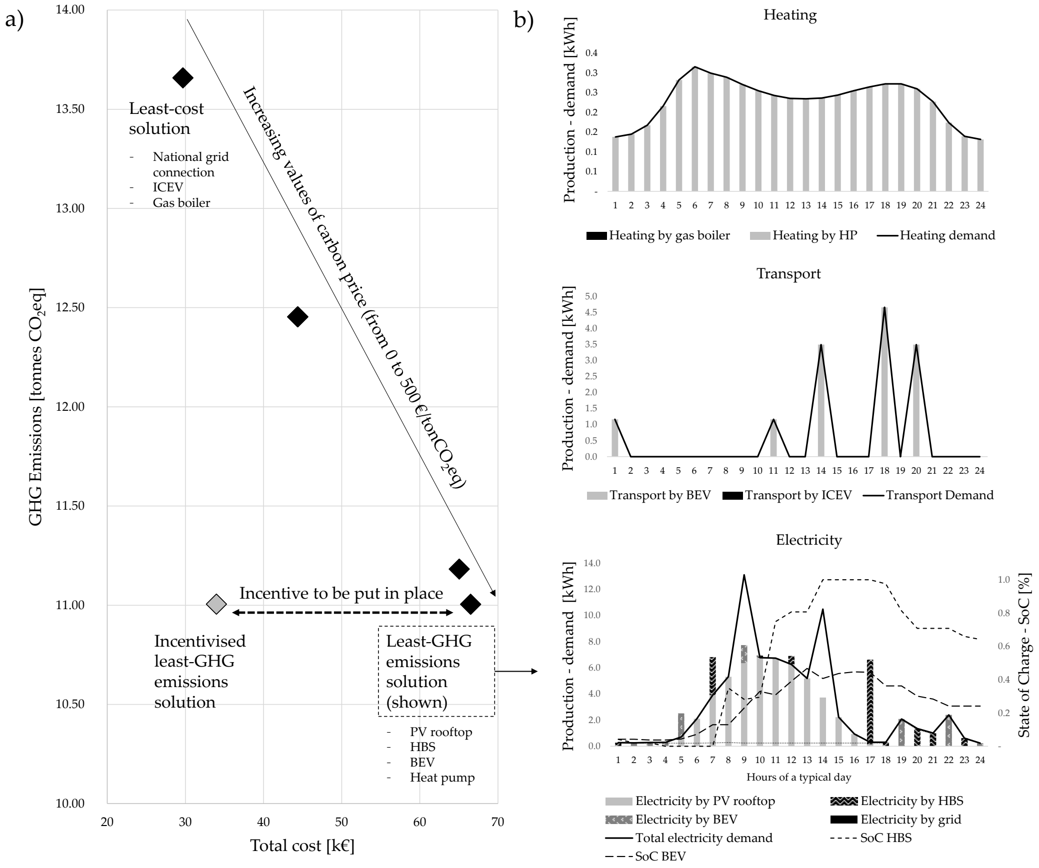
To analyse the potential of the framework suggested in this research, a simplified illustrative case study is presented. In this case study, a single household is modelled and, as represented in Figure 4.20, three main energy needs have been considered. The case study simulates three consecutive days of one year as a typical three days, assuming that the whole year can be characterized with these archetypal days. The final needs are estimated by the authors according to the consumption of an archetypal household in Italy: the shapes of the consumption of the electricity and transport services during a day have been derived by a suite of demand simulation models [281,282] and for the heat profiles, When2Heat dataset has been utilized [283]. The availability of sunlight for photovoltaic (PV) panels is taken from Renewables Ninja database [284]. Table 4.4.6 represents a set of plausible hypothetical cost and emission characteristics of the technologies considered in the optimization problem to meet the needs [285–287]. A 10-year lifetime and a yearly discount rate of 1% is considered for the project.

Table 4.4.6. Case study parameters

Technology	Investment Cost [€/unit]	Exogenous Variable Cost [€/kWh]	Embedded Emission [$kgCO_2eq$/unit]	Direct Emission [$kgCO_2eq$/kWh]
National grid	-	0.23	-	0.470
PV rooftop	1’550	-	-	-
HBS	8’000	-	975	-
BEV	40’000	-	10’000	-
ICEV	26’000	0.212	8’000	0.222
Gas boiler	1’500	0.078	33	0.650
Heat pump	3’000	-	30	-

With reference to the data, the baseline configuration has been determined without any specific incentive and implicit carbon price. In this case, electricity, transport, and heat productions are based on the least cost optimum solution in exploiting the national grid, Internal Combustion Engine Vehicle (ICEV) and natural gas boiler as the production technologies. With respect to the baseline, a sensitivity analysis on the cost of CO_2 is performed to see its effect on the decision of a household based on the least cost solution. In this way, different levels of implicit carbon prices will be determined and compared with the solution in which the subsidy is explicitly accounted in the investment costs. In this case study, any implicit carbon price lower than 200 €/tonCO_2eq does not impact the solution of the model. Approaching 325 €/ tonCO_2eq, the carbon price forces the model to switch to less carbon-intensive and more capital-intensive technologies. At very high CO_2 costs, PV panels and storage, Heat Pump and Battery Electric Vehicle (BEV) are the preferred technologies. The left-hand side of Figure 4.21 shows how different implicit carbon prices influence the relation between the total investment and operational cost of the system and its total emission. In particular, assuming an 85% discount on the capital cost of PV panels, Home Battery System (HBS), Heat pumps and 10’000 € discount on BEV leads to the same solution of a very high carbon price, of around 500€/ tonCO_2eq, in which no electricity from the grid is consumed. The right-hand side of Figure 4.21 represents the dispatch of heating, transport, and electricity production with the State of Charge (SoC) of the two storages as the solution of the incentive scenario. With the new configuration, the total direct emission of the household would be zero. While the heating and transport needs are met by single technologies, the electricity production dispatch is more diverse due to variability of the PV as the main source of production. The presence of storages system is necessary to provide the opportunity of being independent of the grid. In this case, besides the HBS, BEV can give the possibility of using the electricity stored in the battery for electricity needs. As it can be seen from the figure that HBS and BEV are increasing the SoC making the HBS able to cover the electricity needs in the hours without the availability of sunlight and BEV to cover the transport needs and a part of electricity needs when the cars are not riding.

Figure 4.21. a) the relation between the cost of the intervention and associated GHG emissions in different implicit carbon prices. b) the model choices of heating, transport, and electricity dispatch during a typical day in the least-GHG emissions case.



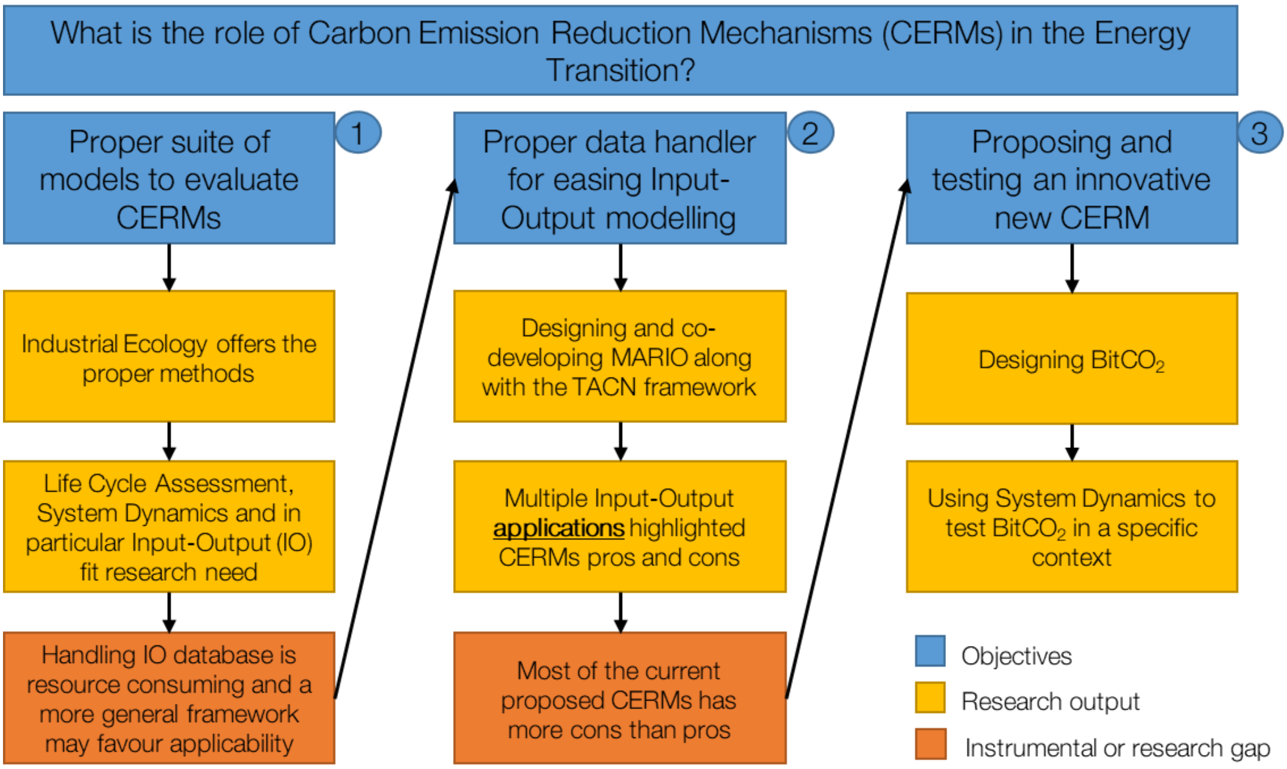
Conclusions

Energy subsidies are one of the main policies to reduce CO_2 emissions at the national level. The calibration of the appropriate incentive level to influence investors' and citizens' choices in facing the necessary expenses to upgrade the national energy system is the object of numerous analyses, often having to consider economic and non-economic aspects. The framework presented in this paper allows providing an assessment, based on cost minimisation over a set time horizon, of the best implementation strategy for an illustrative household renovation. Consideration of the LCA impacts associated with the production of the technologies required to upgrade the residential energy sector allows for an evaluation of the intervention in its entirety. These impacts can be endogenized in valuation choices, making it possible to identify different levels of implicit carbon pricing, which can be compared with scenarios in which the price of certain technologies is directly reduced, in accordance with the plans outlined by the regulator. In this case study, it emerges that the assumed subsidies are more than sufficient to incentive the modelled household to make housing renovation convenient, while drastically abating residential carbon emissions. These initiatives imply high implicit carbon prices, up to more than 10 times higher than the current allowances costs of the European emission trading system (i.e. 50 €/tonCO2eq), but in line with the ones reported in the literature for Italy [288]. The research shows the potential of an approach that could be easily expanded to consider cooking requirements and any number of other technologies to fulfil the needs of households.

5. Towards a novel carbon emissions reduction mechanism

This final chapter shows the process that brought to an innovative carbon emission reduction mechanism – called $BitCO_2$ – that has emerged from the literature review and, more importantly, from the research on this topic adopting the input-output (IO) framework.
In fact, the first sub-chapter puts together the lessons learnt from the application of the technology-activity-commodity-need (TACN) framework introduced in chapter 3. After that, a literature review related to innovative approaches to Life-Cycle assessment (LCA) is presented. Finally, two modelling applications of $BitCO_2$ for a specific sector, are reported: firstly, the theory behind the proposed innovative carbon emission reduction mechanism and the background LCA computation in the analysed specific sector is explained; secondly, a System Dynamics (SD) of the presented individual market-based carbon emission reduction mechanism is implemented for the same sector. This completes the logical process behind this study (see Figure 5.1).

Figure 5.1 – Definitive version of the map of this study,



5.1. Lesson learnt from the applications

Expanding the Supply and Use framework into the so-called TACN framework has allowed an easier implementation of IO models thus improving the applicability of Life-cycle Thinking studies. Coherently and comprehensively characterizing *needs* at the scale of macro-economic surveys is a rather complex task. However, the advantages of this level of information could greatly improve the information that national accounts could provide to modellers and policy-makers.
The IO framework has been proved scientifically robust in providing useful insights on how different carbon emission strategies can impact global emission reduction and on other environmental and socio-economic dimensions. Different research questions raise the need for the proper set of the proper IO model. Having a tool capable of easily setting the scope and the detail of an IO model (i.e. MARIO) simplified enormously the rigorous application of these methodologies.

The information collected in multiple, reproducible applications, permitted the identification of the proper characteristics of the most appropriate model for evaluating the impact of different carbon emission reduction mechanisms. In Table 5.1 a resume of lessons learnt from applications.

Table 5.1 – Resume of lessons learnt from applications

Reference	Application type	Field	CERM type	CERM	Main advantage	Main drawback
Section 4.1.1.	Assessing the impact of new renewable technology	Wave energy	Implicit carbon pricing measure	Minimum penetration target for low-carbon energy technology	Impacting of one of the most relevant sectors to be decarbonized ↑	Ignoring GHG embedded in production may lead to no net climate benefits ↓↓
Section 4.1.2.	Assessing the role of behavioural change	Meat-based diet adoption in Africa	Non-carbon pricing measure	Nudging consumer habits proposing explicit alternatives to meat consumption	Considering consumer choices can have a big impact on future total emissions ↑	Centrally imposing consumption choices is very hard to implement ↓↓↓
Section 4.2.1.	Assessing the effects of carbon policies	Production vs. consumption-based approach in EU	Carbon pricing measure	EU-ETS considering production and consumption-based accounting principles	PBA policies can lead to carbon-leakage. CBA can prevent it in net carbon importers like EU ↑↑	Today virtually all carbon pricing policies are based on PBA. Technical and political obstacles may limit CBA applicability ↓↓
Section 4.2.2.	Assessing the changes in endowment and consumer preferences	COVID-19 impact on the Italian energy system	Non-carbon pricing measure	Short-term reduced mobility and medium-term green investments	Considering consumer choices can have a big impact on future total emissions ↑	Centrally imposing consumption choices is very hard to implement ↓↓↓
Section 4.2.3.	Energy model validation for optimal investment and dispatch	Household renovations in Italy	Implicit carbon pricing measure	Italian incentive in the residential requalification market	Impacting of one of the most relevant sectors to be decarbonized ↑	No direct link between energy incentives and avoided emission makes mechanism inefficient ↓↓

The application presented in section 4.1.1 demonstrated how adopting a footprint approach can avoid pushing on technologies that may have not sufficiently low emissions embedded in production, even if their operation is nearly carbon-free. Including emissions embedded in production may not be necessary for mature renewable power technologies such as photovoltaics and wind power as they are characterised by increasingly lower energy pay-back times [289] and, consequently – as carbon intensity is decreasing globally – emission pay-back times.
The advantages of a consumption-based approach are clearly demonstrated at the national level by application 4.2.1. However, as mentioned in chapter 2, most of the mechanisms in place to date are production-based. The debate is still open about the actual benefits in terms of emission reduction compared to the technical and political difficulties that a consumption-based policy managed on a national scale would imply. However, the current socio-political context may suggest a coming major effort to decarbonise the economic system that would make carbon-leakage increasingly hazardous.
The centrality of individual consumption choices is suggested by both applications 4.1.2 and 4.2.2. The role of the consumer is essential and the real driver behind production. Meeting human needs while minimising the impact on the environment requires large-scale changes in consumption habits that may require investments of time and money. Moreover, comparing impact among different consumption behaviour targeting the same need may represent a trigger towards more sustainable consumption. This is also supported by literature findings highlighting in particular the effectiveness of social information in inducing energy savings [290].
However, in order to compare a generic baseline with a specific consumption choice, consistent alternatives should be modelled making assumptions explicit. Application 4.2.2 showed how costly incentives for emission reduction can be if the target is not explicitly set.
These considerations are limited by the inherent limitations of the modelling approach adopted and the uncertainty related to the data as discussed in the previous chapters. However, the current scientific debate complements and reinforces the considerations emerging from this picture. A Life Cycle Thinking approach suggests that it is preferable to endogenize all cradle-to-grave aspects

associated with the impact of a product or activity. This can be declined in many ways, some simple but with marginal impact (e.g. labelling) others implementable on a large scale but very complex (e.g. carbon boarder adjustments). Scalability and life cycle approach can be implemented simultaneously if one shifts the point of view from the producer to the driver of consumption: we, the consumers. There is a large number of people around the world who could be actively involved in driving the global production system. To do so, public resistance to carbon taxes should be overcome improving communication, reinvesting mechanisms' revenue or adopting new carbon emission reduction mechanisms [291].

Nonetheless, the characteristics of an innovative CERM start to emerge: the path for an individual, consumption-based, comparative approach should be explored. Nevertheless, technical issues associated with competitiveness and technology limitations may rise.

5.2. The future of life cycle assessment and the role of comparativeness

The theme of comparativeness

One of the major issues related to the adoption of LCA regards the communication and reliability of results, which enable consumers and other agents to benchmark and compare different product choices.

Galindro *et al.* have recently developed a deepened literature review investigating the problems regarding LCA results communication and possible improvements [292]. They identify four main issues: diversity of methodologies, absence of positioning of products among its peers, lack of external reference values for comparison and understanding of multiple indicators. Uncertainty level of the employed data and methodological choices influence results consistently. In this sense, the introduction of Environmental Product Declaration (EPDs) represents an important mean for providing quantified and objective information on the environmental burdens of products with similar function. This comparison is possible thanks to the definition of rules for product categories (PCR) with the involvement of different stakeholders such as industry, society, and academia. Coherently, the European Commission highlighted the importance of enabling competition based on environmental performance. Therefore, the absence of clear communication of results, also resulting from the number of indicators presented in the analyses, suggests the need to establish a synergy between LCA and benchmarking practice. Today it is difficult for consumers and market actors to relate to many environmental labels and reporting initiatives: more than 450 environmental labels are active worldwide, for which different methodologies are used, some of which are more reliable than others. Thus, there is a need for harmonization and it is necessary to establish a common methodological approach in order to compare, verify and provide relevant and consistent environmental claims that enable to display and benchmark of the environmental performance of products based on a single and comprehensive assessment. Verifiable or transparent information is crucial also to reduce the risk of "green washing": when making "green claims" companies should substantiate these against a standard methodology to assess their environmental impact. Furthermore, these puzzling circumstances generate a lack of trustworthy information and hinder consumers' contribution to the green transition (44% of consumers do not trust environmental information [293]). Customers have to face too many, and sometimes misleading, environmental claims. In the light of overcoming this obstacle, efforts in this direction have resulted in initiatives such as the EU pilot project Product Environmental Footprint (PEF) and Organization Environmental Footprint (OEF) (2011-2018). Among the several foci of the pilot project, it was investigated which was the best solution to deliver information to buyers and the analysis reported that simple information. In particular the single score is understood and perceived as the most effective way to convey data and to guide choice towards more environmentally friendly alternatives. Nevertheless, a deep analysis of the pilot phase of PEF initiative points out several issues undermining the warranty of fair comparability such as product performance definition, category classification, and modelling of electricity [294].

Other benchmarking techniques are highlighted in the literature. For example, Data Envelopment Analysis (DEA), a methodology based on linear programming, is used to assess relative efficiency between homogeneous product units (i.e. decision-making units). Due to the fact that this technique depends on data that have been assessed under the same methodological framework, it has been employed more for organizational-oriented rather than product-oriented studies. It emerges that the most urgent issue is the need to integrate the benchmarking of LCA results with other classification procedures, such as PCRs since they would facilitate the definition of homogeneous shared methodologies for evaluating production processes [292].

Tracking footprint with modern technologies

For complex and geographically distributed systems such as current global supply chains, LCA studies often fail to account for all possible inputs of a product system [295]. Real-time and dynamic data are required but difficult to be collected from enterprises that are frequently unable to grasp the environmental impact data in the entire life cycle of the products. Furthermore, assessment and evaluation systems and tools (such as Gabi, SimaPro, eBalance) are independent and not directly integrated with the existing enterprise information systems (such as CAPP, ERP, PDM, etc.).

New opportunities can result from technological progress. The application of LCA has been developed and integrated with other technologies to support highly detailed and real-time analysis of inventory data. In this perspective, Tao *et al.* provided a multi-layered structure to compute energy savings and emission reduction by integrating LCA with the internet of things (IoT) and bills of materials (BOM) [296]. The “perception access” layer is in charge of collecting the energy consumption and environmental impact data, the “data” layer primarily provides data support such as BOM data; the “service” layer provides the evaluation services for the “application” layer, which practically provides to the final user (enterprise, government, third-party) the evaluation data. Van Capelleveen *et al.* present the so-called “Footprint of things”, a hybrid architecture able to take advantage of a radiofrequency identification (RFID) regulated IoT infrastructure to collect real-time, process-specific inventory data as opposed to the current averages approach. By combining a distributed system, where products are the data carrier, with a central repository. Life cycle inventory data can be collected and analysed automatically benefitting from the use of IoT to improve the accuracy and quality of data and to overcome cross-supply chain challenges [94]. Mishra and Singh propose a framework to allow automated LCA using the above-mentioned technologies in order to evaluate all the CO_2 emissions of each life cycle step with the aim to offset them by planting trees. By doing so, they propose a set of equations able to point out all the needed information for a generic manufacturing product embodied carbon assessment [297]. Zhang et al. propose an implementation framework regulated by blockchain technology able to orchestrate the data flow collected by IoT technologies across the various steps of the supply chain. Moreover, it provides a rough estimate of the proposed system if implemented by a Chinese manufacturing producer, noting that the vast majority of the cost lies in the development and maintenance of the software [87]. The application of blockchain technology in LCA is able to guarantee transparency and traceability, by using RFID, providing real-time and accurate data. The structure suggested, which relies on the interaction between blockchain technology, IoT, and big data analytics, is composed of four layers: the “infrastructure” layer, formed by hardware and software, is the base for collecting and transmitting data received from smart sensors to the upper layers; the “blockchain” service mainly records and processes stored data of input and output; the “applications” layer provides four key applications related to environmental aspects and two additional applications (i.e. "product information management" and "uncertainty treatment management") to serve generic purposes; the final layer is the "user" layer, which provides user interface and visualization tools to mainly serve governments, consumers, NGOs and enterprises [87]. Blockchain technology and smart devices have also been proposed for innovative reputation-based ETS solutions [89]. An application of this approach has been implemented on a case study in fashion apparel manufacturing industry [88].

Without a doubt, the integration of Blockchain and IoT is valuable for LCA and life cycle inventory. Nevertheless, some issues may hamper the beneficial traits of these new technologies. First of all, one issue is related to data manipulation: before data and records are uploaded, enterprises may alter and change them on purpose or by accident. To solve this problem, it is possible to design a system that directly uploads in the blockchain network data collected by sensors excluding the enterprise, otherwise, it is possible to involve a third party or an NGO to guarantee data integrity. A subsequent issue involves the storage dilemma. When implementing a blockchain-based LCA system, increasing the size and number of blocks leads to storage scalability problems. Advantage storage management or cloud computing can solve this impasse. An additional challenge is the one related to degradation of data, due to transmission performance, and network congestion that may occur when transferring records. 5th generation network technology can be exploited to improve the quality of real-time transmission, and, with the intention of preventing network congestion, periodical data transmission can be favour with respect to real-time alternatives, so as to operate when the network is idle or less occupied.

Recently, an elegant white paper has proposed something similar to what has emerged from this research [85]. This is introduced in the next sub-chapter.

5.3. Introducing BitCO$_2$

Today's challenge of mitigating the effects of climate change involves strategies to reduce greenhouse gas emissions into the atmosphere. Since only a part of developed countries have historically taken an active role in this direction, the question arises whether efforts done so far are addressing global emission reduction. Applying multiple policy approaches within diverse socio-economic contexts shaped the proposal of innovative carbon emission reduction mechanisms called BitCO$_2$. This work explores the current regulatory and methodological framework of life cycle assessment to evaluate and propose a blockchain-managed system for the issuance of CO_2 emissions reduction tokens, called BitCO$_2$ tokens.

The proposed framework aims to drive consumer preferences by granting an economic incentive, proportional to the emissions avoided, by choosing a certified product whose impact is lower than the carbon footprint of an average product that covers the same functional unit.

As it emerges from the literature review and from the results of the applications, the following are its key characteristics:

- **Individual**: *activities* produce *commodities* because there is a *need* demand from each of us, acting like final individual consumers. National schemes can for sure have a beneficial effect on curbing carbon emission, but very often political priorities changes, leaving behind the groups of all the individuals distributed all over the world that would participate in a carbon emission reduction scheme.
- **Consumption-based**: emission burdens are allocated to agents considering all the emissions that took place all over the world to produce the *commodity* that is needed by the final demander. However, a lot of care must be taken when designing a consumption-based carbon policy: it is not currently possible to track all the flows of all the real products consumed within the economy. That is why a comparative approach should be adopted,

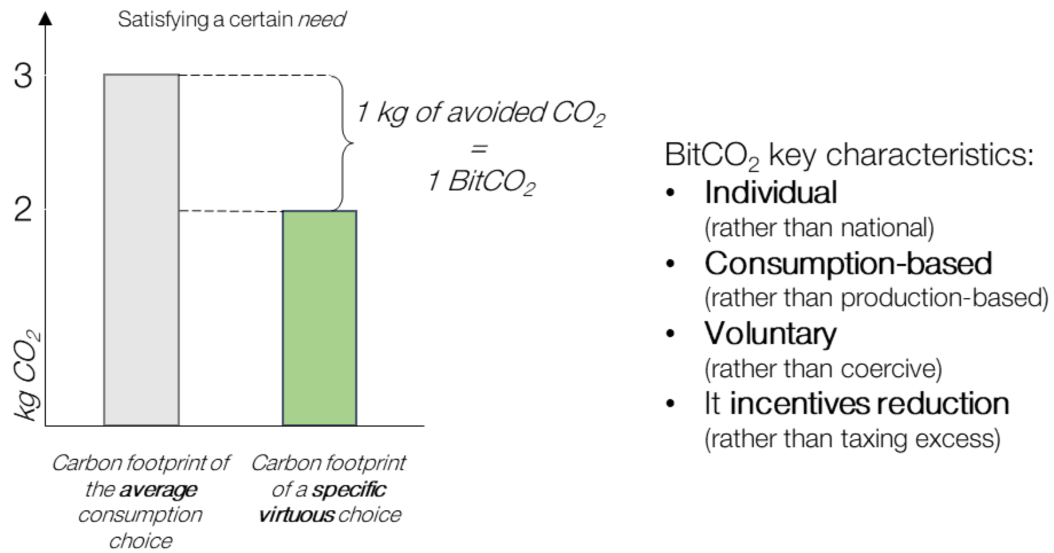
allowing for a gradual inclusion of a few *commodities* serving the same *need*, starting from the most carbon-intensive.

- **Voluntary**: if low-carbon consumption choices are incentivized, it would be possible to reward beneficial behaviour which is usually better perceived by consumers with respect to imposing taxes or levies on the ones that keep having the baseline behaviour.

Having an individual (vs. national), consumption-based (vs. production-based), and incentivizing (vs. coercive) carbon emission reduction mechanisms offer multiple advantages that can justify its practical implementation. Moreover, other consumption-based mechanisms have been proposed in the past [298], but they would implicitly require overnight tracking of the carbon footprints of all the *commodities* of the economy, something that would require – at least – a slow and gradual inclusion.

As it is going to be presented in the 5.4 sub-chapter, this has been tested for a specific carbon-intensive and hard-to-abate sector (i.e. Italian private transportation) adopting an SD model and an LCA methodology developed for the purpose. See Figure 5.2 for a visual representation of the mechanisms and for a resume of BitCO2 key characteristics.

Figure 5.2 – How BitCO2 is built and its key characteristics.



Understanding BitCO2 following the 4 steps of life-cycle assessment

Each sub-section, corresponding to each step of the LCA methodology, is accompanied by a practical example of the application for electric vehicle purchase and usage.

Goal and scope definition

The goal of BitCO2 is to provide the information and economic incentive to the consumer regarding the quantity of GHG emissions avoided by the purchase of a specific product (i.e. *commodity*) that covers a specific functional unit (i.e. *need*), compared to the average product (i.e. *commodity*) that could have been purchased in the same market to cover the same functional unit (i.e. *need*). Assuming to involve a company producing electric cars and a company supplying electricity from renewable sources, we would identify as functional units a vehicle of a certain size and category purchase (for its purchase) and the single km travelled (for its use).

Inventory analysis

This application requires two inventory analyses to be carried out in parallel. Specifically, on the one hand, an inventory analysis will be carried out in real time thanks to the adoption of smart meters (joint use of RFID and timestamping) at each stage of the supply chain that can automatically provide the necessary inventory data. On the other hand, starting from the same product category in which the object of the LCA analysis is included, an average product of the same market in which it competes is identified. Clearly, ambiguous functional units and choices in allocation methods may bring to ambiguity in LCA results [94]. Several allocation methods exist and LCA guidelines have been established and databases, such as ecoinvent, provide multiple system models [95]. Therefore, it would be possible to choose the same system model for both the average comparison product in the market mix and the real-time specific supply chain of BitCO_2 network members. In the case of the car manufacturer, real-time tracking would require the introduction of multiple smart meters capable of tracking information on actual GHG emissions. For a less complex supply chain such as electricity production, it would be sufficient to monitor the energy mix referred to the electricity supplier. At this point there would be, on the one hand, the information necessary to estimate the quantity of equivalent CO_2 emitted to produce and deliver the vehicle in question and the electrical kWh in medium voltage as fuel and, on the other hand, the average references for the same product categories in the same market.

Impact assessment

The impact assessment part is carried out between the two macro-areas of the BitCO_2 network, upstream and downstream of the consumer's purchase of the good or service under analysis. The impacts of GHG emissions related to the specific and average reference product are aggregated and weighted according to the global warming potentials (GWP) identified by the IPCC [299]. At this stage, the need for complete comparability between the two analyses is evidently unveiled. In fact, in order to trigger a virtuous circle between consumers, producers, and final buyers of the BitCO_2 tokens, the difference between the two GHG impacts is computed. In this way, it will be possible to quantify the number of emissions avoided (or added) by buying the product under analysis compared to the corresponding average alternative product.

In the car market example, the buyer of the specific electric car in question would thus become the owner of both the car and a title that identifies the avoided emissions. For each refuelling, if the buyer recharges his/her car through the supplier of electricity within the BitCO_2 network, he/she will be awarded additional proportional tokens. In particular, this will amount to the difference between the CO_2 emitted for recharging the vehicle with that specific supplier electricity mix and the CO_2 emitted by an average same category vehicle to cover the same distance travelable with that electricity.

Interpretation

The interpretation phase of the LCA analysis is usually aimed at identifying problems, completeness assessments, sensitivity and consistency checks. Although it is expected that these assessments will be conducted, for example, by deepening and updating the average inventory information based on technological progress, this part aims to highlight the incentive mechanism that this system is intended to trigger. In this sense, the interpretation phase is seen as an evaluation of the avoided CO_2 impact that the market depicts. To do this, it is essential to introduce the role of the third key stakeholder in this system (in addition to producer and consumer): insurance companies. Indeed, insurance companies have an interest in experiencing a reduction in global GHG emissions. In fact, these companies are already paying relevant damages due to the occurrence of extreme climate events that are likely to occur more frequently [28]. Although there is no universally agreed method to date to quantify the impact of the expected damage from the additional unit of CO_2 released into the atmosphere, each insurance company operating in this market needs to adopt its own assessment. Putting BitCO_2 into practice would require them to estimate the expected economic impact over a sufficiently long period of time of the amount of CO_2 they would like to avoid (e.g. 20 Gton in 10 years). In this perspective, it would be the insurance company that would issue the avoided emissions title, certifying the conformity of the comparative LCA analysis conducted and recognizing the ownership of the title to the person who actively made the ecologically virtuous purchase. At a later date, for example, one year after the issuance of the BitCO_2 tokens, the company will reabsorb them by means of rebates for insurance premiums. This results in a real market for avoided emissions. For this reason, it is necessary that the trading of this asset is regulated by a suitably robust blockchain model. It is useful to point out that one of the strongest value propositions of blockchain technology, does not lie in the traceability of the LCA process and its components - which as explained can be achieved with different and less intensive tools - but rather in accountability and exchange of the emission reduction tokens.

Nowadays, LCA is increasingly adopted to provide information on the impacts associated with consumer goods. Although there are still issues of comparability and access to the inventory information needed for analysis, the use of new industry 4.0 technologies together with new standards and benchmarks can allow for a system of incentives to facilitate the decarbonisation challenge undertaken today. The adoption of a suitably strong and neutral blockchain model would unleash potential economic value enclosed in information about the lower climate-changing impact of a product compared to an alternative that meets the same need of the consumer. BitCO_2, the solution presented in this work, would involve three entwined economic actors in a mechanism that would make it beneficial to reduce overall GHG associated with the production and consumption of a specific category of consumer goods. In particular, the insurance company would see long-term cost savings from the issuance of security recognising ownership of a unit of avoided emissions, which it would recognise at a present cost. The supply chain actors involved in the production and delivery process of a given product involved in the BitCO_2 network would have an incentive to decarbonize its supply chain as much as possible, thus attracting an increasing volume of clients. In fact, the already growing environmental awareness and preference of consumers would be reinforced by the relative economic advantage of choosing low-carbon options. Finally, the adoption of the described application would consequently enhance LCA spread and classification development.

On the blockchain technology

Deepening the BitCO_2 value proposition's technical and economic rationale requires a better understanding of the concept and definition of the term *blockchain*, as well as its extensive usage, which may be incorrectly used or applied as a substitute for well-established technologies.

Blockchain is not a standalone technological innovation, rather it's a data structure comprised of blocks. With other critical components, it may create a real-world application. These various components may create a system that includes blockchain. It may function as a technological metaphor, substituting one element for the whole thing. Blockchain is a mechanism for handling digital data that establishes ownership of both tangible and intangible goods and services (e.g., property rights upon physical goods or cryptocurrencies). In fact, distributed systems are utilised to give individual parties control, ownership, and creation of digital data that represent ownership of both tangible and intangible goods and services.

The key distinction between past times when distributed technologies had not been invented is that a common agreement for data ownership - e.g. a consensus - must be set up and enforced by a *trusted third party* (either by choice of the participants or via law). This *trusted third party* would be in charge of providing the infrastructure, establishing the rules, validating the data, and resolving potential disputes among the participants of the agreement. When using distributed systems, a single individual can now handle and perform more of the previous tasks that required a *trusted third party* without one. The recording of digital data, ownership rights, and modification (i.e. transactions) are just a few of the tasks that can be accomplished using this approach. Protocol rules are embedded and enforced in each client program (a node) to make distributed technologies work (code is law philosophy). It is crucial for nodes to make extensive use of two critical information technology tools: cryptography and *consensus rules* to achieve distributed consensus. Digital signatures guarantee the ownership of a specific asset demonstrating it, while *consensus rules* assure consistency and reliability. For example they can regulate:

- the correct communication and acceptance between nodes;
- the time ordering of the operation executed by the nodes on the data;
- the updated common state of the information shared by the nodes.

Every node adheres to the *consensus rules* when exchanging data with other nodes during data exchanges. If a data exchange violates the rules, the receiving node will reject it. If a broader violation of the rules occurs among nodes in two groups, a split (i.e. a fork) may occur.

The timing of data operations exchanged between distributed nodes is important. In particular, the ordering of data operations is essential when two entities of the consensus communicate scarce digital representation. When a double spending occurs, which of the two transactions is legitimate? If a *trusted third party* exists, for instance, the valid transaction is the one that is listed chronologically after with respect to *trusted third party*'s time reference. As a result of a distributed validation process, *consensus rules* may include several mechanisms to coordinate the ordering of transactions.

The Proof-of-Work (PoW) [300] is one of the most innovative and most trustworthy distributed network providers, thanks to which nodes may validate transactions by demonstrating the greatest amount of computational effort. PoW consensus attempts to provide clear economic incentives to miners (validators) who are forced to invest in validation infrastructure in advance and compete with existing and potential new validators. Because validation activity is permitted without any limitations, inefficient validators will not be able to compete and will soon leave the market. To secure the network, hardware and energy expenditure will be wasted, since profits are only gained by properly conducting the validation activity. An unscrupulous miner, who alters data to suit his or her own advantage, would be detected and punished by all the nodes in the network, which would be an irrecoverable investment. In contrast, other consensus mechanisms might exist, but with a different level of trustlessness and network security. In particular, Proof-of-Stake (PoS) and Delegated PoS, which recognize validators as those who hold the greatest share of the digital asset underlying the consensus, must be mentioned. In order to validate a distributed system, a priori a set of users is chosen to form a federation whose votes decide the "right" history of data according to a predefined majority rule embedded in the protocol.

A blockchain system's data structure contains data about ownership in the form of blocks connected on a chain of increasing size. This sort of data structure is well-suited to the validation process and ordering operations on data, but it is heavy, non-scalable, and must be replicated throughout all of a network's nodes to ensure security and anonymity. It is particularly slow, non-growing, and must be replicated across all of a network's nodes to ensure security and impartiality. By using a different data structure (e.g., a cryptographically signed database), it might be possible to achieve scalability, speed, and less storage space. PoS allows for a more efficient use of energy per transaction, as recently reported also by main-stream media commenting on the recent shift from PoW to PoS in the Ethereum system [301]. The issue of energy – and consequently emission – savings is fundamental for the case of BitCO_2 due to the relevance of its emission reduction nature driving the whole proposal.

5.4. Process-based LCA and System Dynamics for modelling a novel carbon emission reduction mechanism

This chapter is intended as an application of the novel carbon reduction mechanism described in 5.1, called BitCO_2. The chapter is formed by two different studies regarding the same sector, the Italian private transport one. The first study targets the evaluation of a credible estimate of the greenhouse gas emissions (GHG) released during the production and combustion of fuels and embedded in the production of internal combustion engine vehicles (ICEVs) and battery electric vehicles (BEVs). The approach employs a process-based LCA methodology, combining different pieces of information to get footprints for every vehicle registered in 2019 in Italy. The second one takes advantage of the estimates of the first one to model an application of BitCO_2 within the Italian private passenger car market. This second application is based on a System Dynamics model of vehicle adoption in which the role of BitCO_2 is modelled as a way to decrease the total cost of ownership of BEVs over ICEVs.

5.4.1. Comparing LCA GHG emissions of new passenger car sales of over a million battery electric vehicles and internal combustion engine vehicles in Italy

Introduction

During 2021, 1.46 million cars were sold in Italy still showing a slow recovery from pre-pandemic levels. Passenger car market sales in 2020 and 2021 respectively displayed a contraction of -35% and -31% with respect to 2019 data. Despite the overall car sales decrease, electric vehicles (EV) – i.e. cars that are equipped with any type of electric propulsion, even partial – have been witnessing a relentless rise. The yearly sale shares of electrified powertrains in the period 2019-2021 are respectively: 0.8%, 4.3%, and 9.4%. In 2021, the new battery electric vehicle (BEV) – i.e. cars which are only taking electricity as fuel – registrations amounted to 67.3 thousand units versus 11.0 thousand vehicles in 2019 [302]. The upward trend in EV adoption remarkably increased worldwide passing from 2.5% in 2019 to 4.2% in 2020. To date, the adoption of this technology is limited mainly by higher purchase costs with respect to the corresponding fossil fuel-based powertrain, range, and refuelling times – still not at the level of an internal combustion engine vehicle (ICEV). Nevertheless, the stated pledges of Western governments to significantly reduce greenhouse gas (GHG) emissions is driving investments and consumer preferences toward electric vehicles. Moreover, it is worth noting the progress in cutting component costs. Relentless technological improvements are making the obstacles to the adoption of this technology less and less relevant, paving the way to a total cost of ownership comparable between BEVs and ICEVs. The possibility of making these vehicles partially or totally autonomous might reduce the costs of transport in the future, allowing a greater utilization rate of passenger vehicles, an underutilized asset to date. Despite these important advantages, the GHG emissions needed to deliver the average EV are usually higher than the corresponding average ICEV. In this regard, in Italy, there is still a debate about the actual emission savings that a BEV can allow compared to an ICEV [303]. Indeed, it has been pointed out that the emissions associated with production, together with charging with largely fossil-based electricity, may not be sufficient to reduce GHG emissions for the average Italian private transport demand.
Many researchers performed GHG impact assessment studies regarding private passenger vehicles based on different powertrains. However, the industry of electric cars and the most expensive components needed for its realization (i.e., lithium-ion battery) are continuously evolving. This strongly impacts GHG estimations per kWh of battery capacity as highlighted by comparing several studies [286]. The authors found a range between 30 kgCO_2eq/kWh and 250 kgCO_2eq/kWh for

battery capacity manufacturing showing a general trend towards smaller estimates for more recent studies. Two of the most recent and authoritative studies show the advantages of EVs over ICEVs in terms of vehicle lifecycle emissions. Hoekstra emphasizes the relevance of the assumptions underlying comparative studies, showing ~60% savings for manufacturing and driving an EV over an ICEV, implying a GHG pay-back distance within 25 thousand km [304]. A recent study by ICCT confirms this upper boundary, providing estimates for different powertrain types as well [305]. A high level of uncertainty, associated with the vehicle segment and the alternatives present within the same market, leads to a debatable quantification of the emissions actually avoided by purchasing and driving a BEV compared to an ICEV in Italy. The present study attempts to address this research question.

Methodology

In this study, the two main phases of a car life cycle are considered. The first one refers to the GHG footprint associated with vehicle production while the second one includes the operational emissions. For the production stage the functional unit is the vehicle itself while, for the operational phase, 1 km of travelled distance is chosen. Every car has been assigned with a vehicle segment (Utility, Small, Medium, Large, and SUV) through an algorithm based on proximity with 10 car archetypes (one for every segment for both BEV and ICEV) described on the basis of displacement, power, and mass values.

In order to investigate the potential of BEVs in decarbonizing private transport in Italy, the GHG emissions required for the manufacturing and use of all the cars registered in 2019 have been estimated. Most of the needed information has been taken from a database openly made available by the Ministry of Infrastructure and Transport (MIT) [306].

In order to isolate the data to perform the comparison between ICEVs and BEVSs, hybrid vehicles have not been considered, reducing the sample to 1.73 million vehicles. In fact, although the analysis has been conducted on hybrid vehicles as well, nothing that would enrich the debate on electrification of private transportation has emerged. For this reason, the analysis was limited to BEVs and ICEVs thus addressing the research question without including technologies that are in essence considered transitional and that would require further assumptions on real electricity to traditional fuel utilization rate. Furthermore, due to the large degree of uncertainty on lithium-ion battery lifetime and displacement impact, end-of-life emissions have been neglected in this analysis. At the time of writing, one of the largest BEV manufacturers claims to be able to derive 921 kWh from every 1’000 kWh worth of lithium battery through energy-intensive separation, enrichment, and purification processes [307]. However, the amount of batteries that are taken back and recyclable is still a small fraction of what has been produced due to high actual cycle numbers and possible second-life strategies.

The current study introduces two indicators computed comparing two segment-equivalent BEV and ICEV:

- the minimum travelled distance required to pay back the extra emissions usually needed for manufacturing the BEV (PBD – pay-back distance);
- minimum ownership time required to pay back the extra emissions usually needed for manufacturing the BEV (PBT – pay-back time).

Thanks to the spatial detail provided by the MIT database, the analysis is performed for each Italian region. Finally, 2 scenarios of BEVs adoption evolution from 2022 to 2032 are considered. The scenarios are compared in terms of avoided GHG emissions related to private passenger vehicles. The analysis aims at assessing whether the ICEV substitution with fully electric powertrains might lead to a remarkable decrease in GHG emissions at the fleet level.

Manufacturing the vehicle

The GREET2 model is used to estimate the impact of vehicle production. GREET2 is a tool able to simulate vehicle cycle emission output and energy use of vehicle manufacturing cycle, and it provides a consistent life-cycle analysis platform with reliable, widely accepted methods and protocols [308]. It performs a material-based life-cycle assessment capturing raw material extraction, processing, transport, and ultimately assembly into an automobile or light-duty truck. Among the many customizable parameters, a focal role is represented by emission factors, considering battery production and assembly location. These are set based on the region where the vehicle is most likely to have been produced. Marklines database is used for estimating these values [309]. In this manner, the model provides a measure of GHGs specific to vehicle weight for two different types of material used (conventional and lightweight, which has been adopted in this analysis), powertrain and vehicle manufacturer. Each vehicle of the considered fleet is mapped according to the same parameters. Regional energy mixes assumed in vehicles' manufacture are taken from the International Energy Agency and provided to GREET2 as an input. This is impacting region by region on production and assembly emissions which are considered in the same way across all considered powertrains. Outputs are provided on a per vehicle lifetime basis, implying values of emissions embedded in manufacturing a kWh of EV battery ranging from 22 to 54 kgCO2eq/kWh.

Driving the vehicle

Emissions reduction targets for the Road Transport sector consider direct emissions associated with vehicle use. The value of these emissions per km is provided directly from the MIT database. However, this measure only accounts for emissions released from vehicle tailpipe (Tank To Wheel, TTW), ignoring emissions accrued to fuel cycle (Well To Tank, WTT). Fuel cycle emissions are non-negative for both BEVs and ICEVs while TTW or tailpipe emissions for BEVs are null. Estimating the emission factors strongly impacts the analysis. In addition, although the impacts associated with fossil fuels have a limited variability, great uncertainty might affect the emission factors of electricity production that is dependent on the degree of achievement of one country's decarbonization goals. The model allows regional-based carbon intensity values (i) for the considered geography, Italy. For this research, 300 grCO_2eq/kWh has been assumed for every Italian region and has been kept constant for every driven km thus conservatively assuming no electricity mix evolution. For what concerns ICEVs, a JEC report has been used as reference both for fuel consumption and emission factors, deriving WTT and TTW emissions [310,311].

Table 5.2 summarizes the approach adopted in this study. In this table, m, b, and a stand for mass, manufacturer's brand, and fuel supply. Furthermore c_b^{BEV} represents the consumption of a BEV of a specific brand while f_b^{BEV} is the specific carbon footprint (in ton of CO_2eq per ton of vehicle) of the car manufactured by that same brand according to the approach explained above. The same applies for f_b^{ICEV}. Finally, c_a^{ICEV} stands for vehicle consumption characterised by its fuel supply, which is multiplied by the corresponding emission factor (e_a).

Table 5.2 – Map of the approach adopted in this study. All the mass units refer to CO_2 equivalent.

	Driving		**Manufacturing** [ton]
	WTT [gr/km]	**TTW** [gr/km]	
BEV (m,b)	$c_b^{BEV} * i$	0	$m * f_b^{BEV}$
ICEV (m,b,a)	$c_a^{ICEV} * e_a$	Already provided	$m * f_b^{ICEV}$

Evolution of passenger vehicle fleet

The potential of the electrification of the Italian passenger vehicle fleet from 2022 to 2032 has been assessed under the following simplifying assumptions:

- Fixed size of passenger vehicle fleet (40 million units)
- 9 thousand km driven by each car in the fleet
- New passenger vehicle registrations following a 10-years moving average pattern
- Every new registered vehicle displaced a vehicle characterized with the same emissions per km of the average car sold 10 years before [312]

Two scenarios are considered:

- *+10%BEVs*: it assumes no improvements in power system carbon intensity and an increase in the penetration of BEVs on new registration growing 10% per year
- *100%BEVs*: it assumes that 100% of new registrations are BEVs and that every year power carbon intensity decreases by 20 grCO_2eq/kWh, more than twice the current trend.

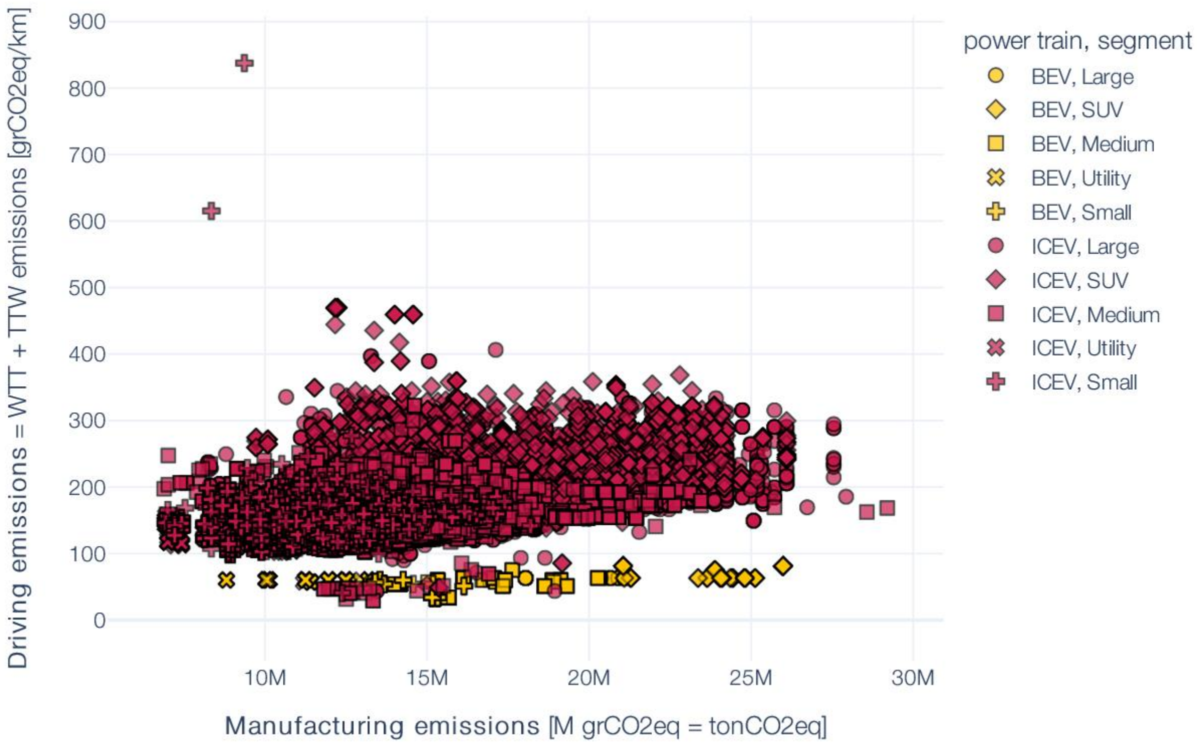
The code behind this analysis can be accessed at the following GitHub repository: github.com/mohammadamint/LCA_Transport_Italy.

Results

Life-cycle CO_2eq emissions by segment

The MIT database was expanded by adopting the methodology and assumptions described above. For each passenger vehicle registered in 2019, it is now possible to specify emissions embedded in the manufacture and linked to driving (WTT and TTW) (see Figure 5.3). This information can be aggregated from the 1.73 million rows to a geographic (region, province), technology (power train, fuel supply), or market (segment) perspective.

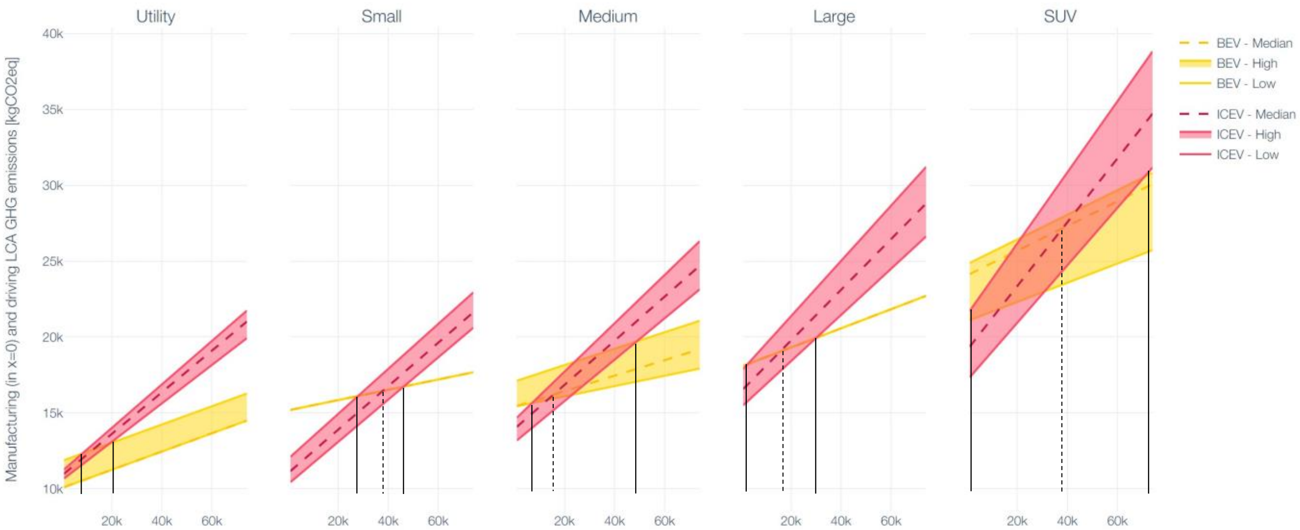
Figure 5.3 – Driving and manufacturing GHG emissions of 1.73 million vehicles registered in Italy in 2019.



In order to clearly distinguish between different ICEV and BEV models, the LCA emissions of these two different technologies by the same market segment are shown in the Figure 2. The data reported in the figure presents variability bands that correspond to 25% and 75% of the distribution of the segment emissions. The associated variability is due to the effects of vehicle manufacturers, electricity emission factors and fuel emission factors. The median value is reported with a dashed line. Narrow variability bands of small and large BEVs are due to the market share of such segment coinciding with specific vehicle models, respectively Renault for Small and Tesla for Large segments. Moreover, the figure shows the range of travelled distance for which driving a BEV might contribute less to carbon emissions with respect to a homologue ICEV. The travelled distance is varied between 0 and 75 thousand km.

Firstly, a preliminary result – in line with what has been anticipated in the literature – is observed: nearly in all cases, BEVs present between 2 and 5 tonCO2eq more emissions embedded in the manufacturing stage.

Figure 5.4 – Emission embedded in manufacturing and driving same market segment BEV or ICEV. The x values of the intersections between the two areas identify minimum and maximum values of km to be driven to offset the additional emission usually necessary to manufacture a BEV over the same segment ICEV.



The more the vehicle is driven, the more the difference between ICEV and BEV driving emissions becomes relevant over manufacturing ones. Considering the least favourable values, the maximum travelled distance needed to make BEVs less carbon-intensive than ICEV is 50 thousand km for all vehicle segments except for the SUV segment. Using median values the PBD is about 13 thousand km for Utility vehicles, 38 thousand km for Small, 35 thousand km for Medium, 16 thousand km for Large and 41 thousand km for SUV.

Carbon emissions pay-back time by region

Results consider the different number of km driven by the average car in each region. This value enables to illustrate how different shares of registered vehicles per manufacturing brand and different amounts of km driven per year can affect the assessment of PBT. Figure 5.5 (which can be accessed interactively here: public.flourish.studio/visualisation/8975487) shows the PBT values for each region comparing the average value for BEV and ICEV of Medium segment (the one with the highest share among segments at the national level). For every region, medium vehicle PBT stays within 2.2 years, highlighting how the contribution of BEVs is beneficial in terms of GHG reduction already from the third year of use.

Figure 5.5 – Average time needed to pay-back the additional emission embedded in Medium BEV with respect to same segment ICEV by region.

Evolution of vehicle fleet emissions

In both *+10%BEVs* and *100%BEVs* scenarios, the contribution of BEVs to the reduction of emissions released annually by the passenger vehicle fleet does not even come close to zero emissions. In 2032, emissions could be reduced by 9% and 31% with respect to 2022 levels in the *+10%BEVs* and *100%BEVs* scenario respectively. In fact, even if all new car registrations were BEVs, the majority of the remaining emissions would still need to be reduced, mainly due to a still relatively old fleet of passenger vehicles, about 52% of which would still be ICEVs by 2032. As anticipated in the literature, this consideration underscores electric vehicles potential in solving alone the problem of emission reduction in the private auto transport sector.

Multiple actions could contribute to make electric vehicle diffusion more effective in reaching the long-term goal of a net zero-emitting passenger vehicle fleet. In particular, increasing the number of kilometres travelled per year by vehicles with the lowest carbon intensity would avoid the issue of underutilizing highly costly to the environment technologies. This may be fostered by large-scale development of autonomous driving, up to the development of the so-called autonomous Mobility as a Service (MaaS). Moreover, given the prolonged permanence of gasoline and diesel vehicles in the Italian car stock, an important contribution could be played by bio-fuels. However, significant difficulties in the scalability of these products' volume, the uncertainty about their indirect life-cycle emission impacts, and the debated availability are limiting this solution.

Conclusions

The current global scenario, marked by winds of war, rising cases of COVID-19 and consequent lockdowns in China (the largest producer of lithium batteries), and supply chain issues, make extremely difficult to predict how the share of BEVs in the stock of circulating cars in Italy will evolve. Nevertheless, the present analysis clarifies the positive role of BEVs in mitigating carbon emissions in the private passenger segment.

The role of BEVs in decarbonizing the transport sector has been assessed by developing a coding procedure that integrates information from multiple sources and models (such as GREET), being able to calculate LCA GHG emissions for all the new Italian car registration for 2019. BEVs' LCA GHG emissions are already better than ICEV for virtually any car segment, even if uncertainties are still in place for very diverse market segments such as the one of SUV. However, considering the

most bought car segment (i.e., Medium), circa 2 years of BEV adoption over ICEV are enough to pay back the additional emission usually associated with BEV manufacturing for most of the Italian regions.
Yet, BEVs alone cannot make the on-road private passenger sector carbon-free in the near future. Even considering all the new registration from today to the next 10 years were BEVs, more than 48% will be ICEVs. That could allow for a reduction over today's level of up to 31%, still far from net zero. This underlines the necessity of increasing the amount of km driven each year by BEVs over older and more carbon-intensive ICEVs. In this challenge, autonomous driving could play a disruptive role. Finally, a solution for the remaining vast majority of vehicles that will last for another 10 years should be put in place. Given the prominent role of gasoline and diesel-powered vehicles, biofuel development should be seen as an important milestone for passenger vehicle decarbonization in the transitional stages.
The analysis could be expanded, refined, and upscaled from the Italian to the European Union market. More transparent information on vehicle manufacturing data would improve the reliability of the similar analysis, by relaxing a big share of needed assumptions.

5.4.2. Modelling an individual market-based carbon emission reduction mechanism within the Italian private transport sector

Introduction

Climate change is posing huge risks to the economy, human health, and ecosystems, thus reducing greenhouse gases (GHGs) is one of the main global challenges for the next decades [313]. The GHG emissions embedded in European Union (EU) countries' private transportation represent a large hard-to-abate share of global carbon emissions. Carbon pricing mechanisms are instruments that attribute a price to GHG emissions expressed as a value per ton of carbon dioxide equivalent (tonCO_2eq). There are many ways to implement carbon pricing initiatives, but most of them are rooted in a carbon tax or ETS scheme, covering 21.5% of global carbon emissions [30]. Considering that the demand for European private transport is not expected to decrease and given the existence of battery electric vehicle (BEV) technology which is capable of satisfying this need while reducing CO_2 emissions, a carbon pricing mechanism in this sector could be useful to reduce global emissions. For this reason, this work aims at proposing and simulating the impact of a market-based mechanism related to the private transport sector in Italy, one of the largest EU private passenger's car markets. The objective is to test the role of this mechanism in enhancing the adoption of BEV over internal combustion engine vehicles (ICEVs), thus reducing global emissions. Avoiding emissions is intertwined with the generation of a token, called BitCO_2, that assumes an economic value through market dynamics. To prove that this mechanism is self-sustainable, it must be tested with a modelling approach. The scope of the mechanism presented is to outline a market scheme that promotes a behavioural change in consumers' habits to reduce GHG emitted by private passengers' cars. It is applied to the Italian scenario and focused on the choice between an ICEV and a BEV. The proposed mechanism has been modelled and tested for the Italian automotive sector. In Italy, the purchase of diesel cars faced a peak in 2017 and began to decrease. Sales of petrol vehicles, instead, reached their maximum value in 2019. In 2020 their sales decreased by about 39%, also due to the COVID-19 pandemic [314]. Nevertheless, petrol vehicles still retain the lead as the most popular type of vehicle, with a share of 37.8% of total sales in 2020. Electric car sales have continuously increased over the last years, reaching in 2020 a percentage of +204% [314]. Reducing the total cost of ownership by introducing an additional source of revenues for BEV owners may accelerate the adoption rate of this technology and their contribution to global carbon emission reduction.

Description of BitCO₂ mechanism within the private transport sector

Consumers' decision on choosing the most convenient private transport mode is the driver of the mechanism. The main barriers that prevent people from adopting a BEV are identified and considered in the definition of its rate of diffusion and purchase. They are range limitation, high purchase price, and too long charging time [315,316]. The mechanism intents to attribute tokens to those who purchase the least carbon-intensive solution. They are assigned at each electric recharge of the vehicle after it has reached the condition of emission parity (i.e. greenhouse gas pay-back time – GHG-PBT). This occurs when the total CO_2 emitted by BEV equals the impact caused by the adoption of a similar ICEV and is determined through life-cycle assessment (LCA). Related to this, the evidence shows that the CO_2 embedded in the manufacturing phase of a BEV is higher than the ICEV's one. Contrarily, the BEV emits less than the alternative during its operational phase. Therefore, a $BitCO_2$ token is assigned every time a certain amount of CO_2 is not emitted because the virtuous option was chosen instead of the more carbon-intensive one. Then, car owners can sell their $BitCO_2$ in a dedicated market that is simulated with a clearing mechanism every three months. By participating in this market, BEV owners can earn money, which represents a monetary incentive to lower the purchase price adoption barrier. These $BitCO_2$ tokens can be bought by individuals and firms that in turn can use this to pay for insurance coverage against climate damages. More specifically insured people can exchange the tokens with insurance companies in a market that is simulating the collection and the burning of the tokens at the end of every year. Therefore, insured people can effectively obtain a discount on the insurance premium. The insurance company set a discount established on a prevision, based on the social cost of carbon, of how many insured damages will not take place in the future thanks to the GHGs that are not emitted due to the mechanism. The insurance company can also benefit from this market-based incentive mechanism by acquiring a better reputation in terms of environmental care. This may lead to an increasing share of consumers interested in subscribing to this type of insurance contract.

Methodology

To simulate the effect that the proposed mechanism can have on the Italian private transportation sector the System Dynamics modelling framework was adopted and followed in all its steps. The initial step aims at defining the dynamical hypothesis on which the model relies. Then the simulation model is formulated, implemented, and tested. The software adopted for model development is Stella Architect.

Model hypothesis

BEVs are considered the least carbon-intensive option and compared to the most common choice of ICEV. The importance attributed to the vehicle type selection relies on the implication that the less GHG are emitted into the atmosphere, the less likely extreme weather events will increase their intensity, frequency, and ultimately their damages in absolute terms. The people that want to purchase a private vehicle and may decide on a BEV are called potential adopters. The decision itself is supposed to be influenced by three factors: BEV purchase cost, battery charging time, and BEV driving range. The demand for a BEV is expected to be negatively correlated to an increase in its price sale and its recharging time but positively linked to a rise in the kilometres range.

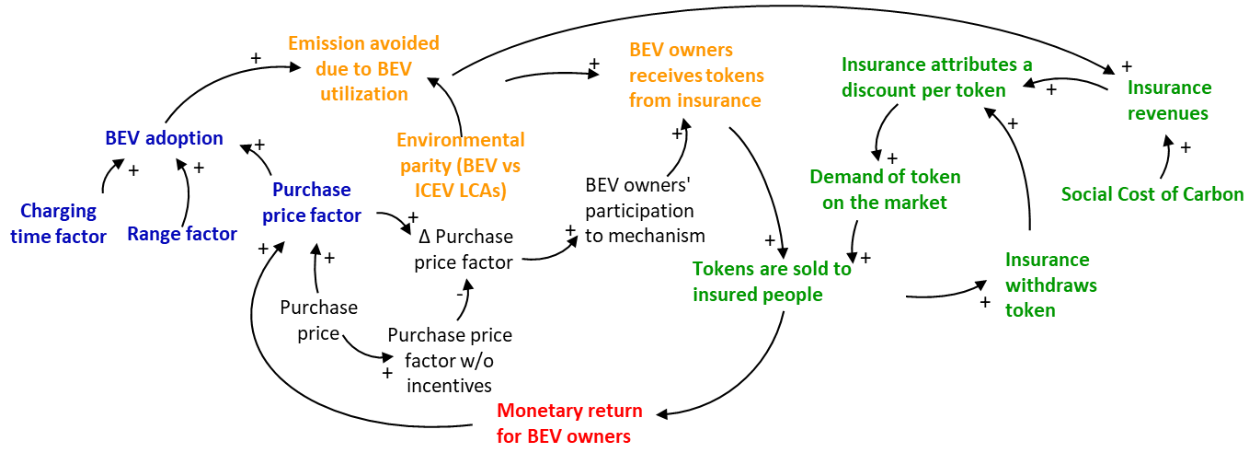
Formulating a simulation model

The SD model aimed at stimulating the mechanism is divided into four sections:

- BEV adoption
- BEV vs ICEV LCA
- Market mechanisms
- Incentive mechanisms

They are illustrated in Figure 5.6, where the main causal loops of the mechanism are represented. In the following paragraphs, all four subsections are discussed more in detail.

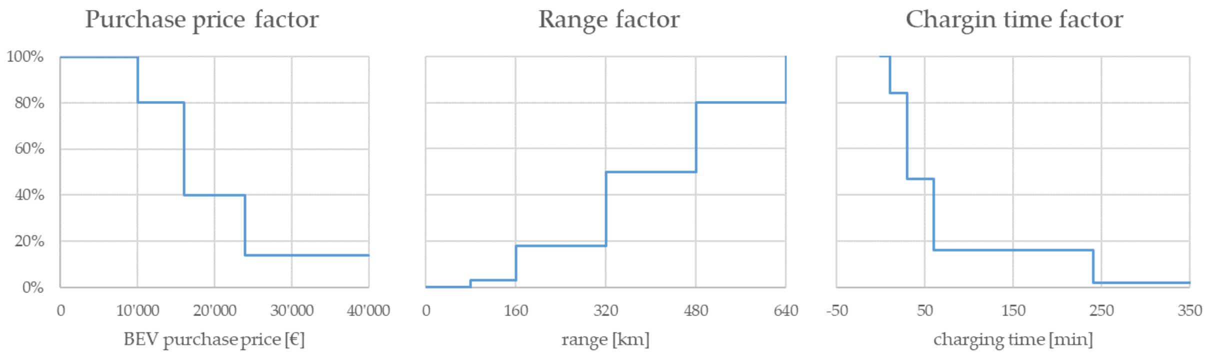
Figure 5.6 – Causal loop diagram describing the BitCO₂ mechanism



BEV adoption: the role of BitCO₂ in influencing one of the 3 main catalysts behind BEV adoption

The conceptualization of the mechanism is done by considering that in 2020, 974’328 people bought an ICEV [314], and assuming that the Italian automotive future sales will behave similarly to what is predicted to happen on the whole European car market from 2020 to 2025 [317]. Since the mechanism lasts 20 years, the data related to 2026-2040 are forecasted using linear regression. Potential adopters also vary accordingly to a projection of population growth [318]. The potential adopters become actual BEV adopters accordingly to the incidence of the three main adoption barriers, as shown in equation 1: *Purchase price*, *Range of km*, and *Charging time*. Each category represents the consumers' willingness to buy a medium-sized BEV over a corresponding ICEV considering different prices range [319], vehicle range in km, and charging time [320]. See Figure 5.7, for the assumed price range and charging time level factors.

Figure 5.7 – Adoption rate factors.



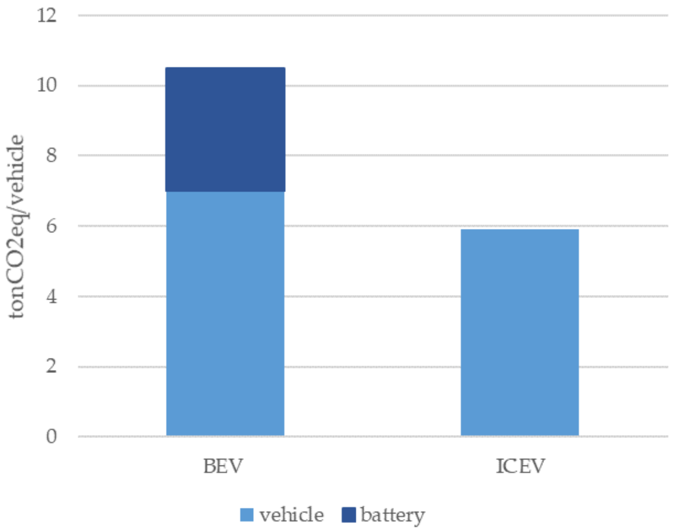
$$\begin{aligned} &Adoption\ fraction = \\ &Purchase\ Price\ Factor^{Price\ difference\ weighted\ factor} \cdot Range\ Factor^{Range\ weight\ factor} \\ &\cdot Charging\ time\ Factor^{Charging\ time\ weight\ factor} \end{aligned} \quad (1)$$

The exponential terms of equation 1 represent how much each of the three previously mentioned factors weights for Italian citizens when they have to choose whether to buy or not a BEV [316]. To fully define the adoption fraction the time-varying behaviour of purchase price, range of km, and charging time must be defined as inputs to the factor functions. Data projections on the purchase price are available starting from 2021 to 2030 [321]. To define future sales, a polynomial regression (2nd grade) is applied. The variable range of km driven with a fully charged battery is defined with the same procedure [322]. The charging time of a battery is defined considering the power of the most popular type of charging station: normal charging point with a power output of 10-22 kW in 2020 [323] and a fast one (22-50 kW) in 2030 [324]. Considering a battery of 65 kWh for a medium segment vehicle, it is possible to compute how long it is the actual charging time of a BEV. At this point the variable *adopters* are defined and can be modelled as stock in the simulation model: the inflow is the rate of adoption; the outflow is the discard rate. The fraction of adopters convinced to buy an electric vehicle through participation in the policy mechanism benefits from the emission of the tokens. The $BitCO_2$ tokens are attributed every time the car is recharged after it reaches the condition of emission parity compared to the ICEV, in other words every time the emission of a ton of CO_2 is avoided thanks to the fact that a BEV is being driven instead of an ICEV.

BEV vs ICEV LCA: tokenizing the avoided emissions embedded in purchasing and driving a BEV with respect to a similar ICEV

LCA analysis is carried out for both vehicle types, this comprises the emission released during the manufacture and end-of-life of the vehicle (Cradle-to-grave analysis) and those related to the fuel cycle, i.e. GHG related to the fuel production and direct emission attributable to the operation (well-to-wheel analysis). The manufacturing carbon footprint adopted in this case study is illustrated in Figure 5.8: BEV and ICEV car-cycle [325,326].

Figure 5.8 – Emissions embedded in manufacturing a BEV and ICEV. Values adopted in the System Dynamics model



The operational impact of the ICEV is 221.7 $grCO_2/km$, where WTT emissions are 44.6 $grCO_2/km$ [310], TTW are 177.1 $grCO_2/km$ [310]. It is assumed that the heating value of diesel is 34.9 MJ/l [310] and the fuel consumption of an average diesel middle-size car could be approximated to 6.7 l/100km [327].

The electric car use impact is determined by how electricity is produced. The electricity mix that is considered is the European one, and the corresponding GHG emission historically is 447 $grCO_2/kWh$ in 2013, and 396 $grCO_2/kWh$ in 2016 [310]. As a reference for the 2030 electricity mix, it is used the one defined by IEA in their New Policies Scenario (now Stated Policies Scenario) the same expectations are considered also by JRC [310]. This scenario assumes the emission to be 257 $grCO_2/kWh$ in 2030. This shows how the electricity is expected to become greener over the years. The trend for the years from 2030 to 2040 was projected with linear regression. Then, using a conversion factor equal to 0.161 kWh/km [304], the amount of $grCO_2/km$ consumed by a BEV is found. Therefore, once the emission parity is reached, the BEV owner sees $BitCO_2$ tokens accredited each time he recharges his car. The amount of tokens is related to the quantity of emission avoided by driving the electric car for the amount of kilometers it is able to travel with that charge, and converted into tokens through the factor 1 $BitCO_2/tonCO_2$. These tokens can be withdrawn by insurance companies in the following years. In this way, the companies are certain that the corresponding emission has been avoided and it can be attributed to a discount on the premium tariff for clients that own $BitCO_2$. Consequently, BEV drivers who have subscribed to an insurance policy with companies that join the program could directly give back the tokens earned to the insurance. Generally speaking, non all BEV owners are insured therefore they are given the choice of selling the $BitCO_2$ in the dedicated market where other individuals and firms who are interested can buy them. In this way two markets are formed: the first is performed between car owners and insured people, the second represents the exchange of $BitCO_2$ among insured people and insurance companies.

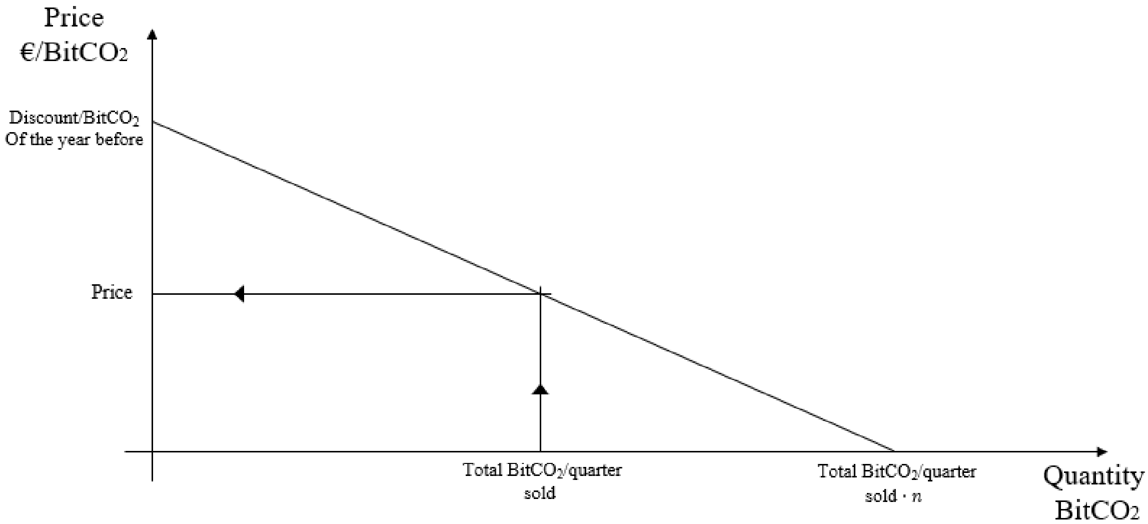
Market mechanisms: $BitCO_2$ price discovery within the first market

The first market is simulated to occur every three months. The dimension of the supply side of the market is subject to the quantity of $BitCO_2$ possessed by car owners. The demand is assumed as a linear function, characterized by two maximum values:

- the maximum quantity of tokens that insured people is willing to purchase at a price equal to 0. It is assumed to be about five times larger than the quantity of $BitCO_2$ emitted in the previous three months.
- the maximum price at which insured people are not willing to buy any token corresponds to the discount that the firm set in the second market.

Both the supply and the demand of this first market are now defined, and their encounter characterizes the price at which the token is sold.

Figure 5.9 – First market mechanism. Relation between the price of the token at its issuance and quantity of token sold.

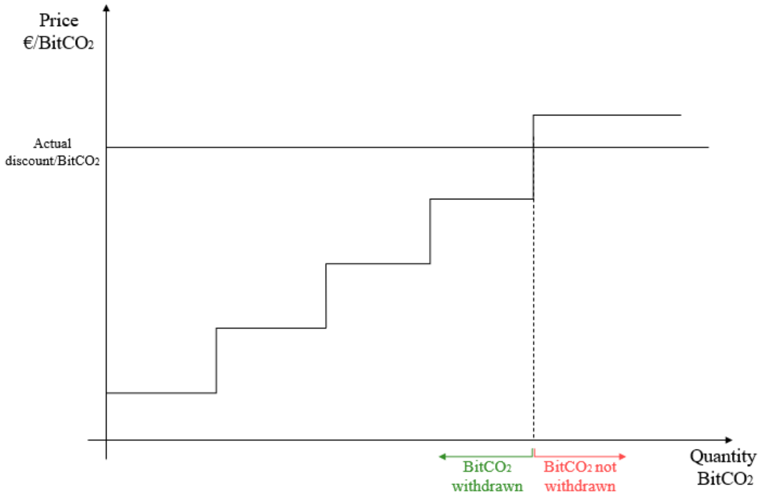


Insured people thus can buy the token at the price determined as in Figure 5.9 every three months. At the beginning of the year after they could deliver the $BitCO_2$ to the insurance companies to obtain a discount on the insurance premium.

Incentive mechanisms: $BitCO_2$ withdrawal price within the second market

The choice of whether to sell or not the $BitCO_2$ to an insurance company is taken by comparing the price at which they purchased the token with the one decided and adopted by insurance agents when they finally collect and burn the tokens. This second market is therefore characterized as in Figure 5.10, where the step function is made upon the token prices of the first market.

Figure 5.10 – Second market mechanism. Relation between the price of the token at its exchange and the quantity of available tokens.



Insurance companies intend to withdraw the tokens because it means that a certain quantity of CO_2 is avoided, and therefore, in the long run, they will pay less to compensate for climate change damages. The discount per token is set by the insurance agents each year and is computed by dividing the revenues that the insurance company has earned during the previous year by all the $BitCO_2$ present in the market. The revenues of the company correspond to the future money-saving that will interest the company itself, due to GHG emissions that have been avoided thanks to the mechanism implemented, and the corresponding avoided damages. The revenues are therefore computed considering the social cost of carbon in Italy, 9.22 €/tonCO2 [10], and the share of damages insured. This value assumes SSP2/RCP6.0 scenario, BHM LR damage function, and growth-adjusted discount rate (for details visit country-level-scc.github.io/explorer, accessed in 2021 for this study). These values are defined accordingly to the European situation where 39.7% of total climate-related economic damages are insured [42]. How revenues are computed is expressed by equation 2.

$$\frac{Expected\ Revenues}{tonCO_2} = SCC \cdot fraction\ of\ insured\ damages \quad (2)$$

The car owners that chose to buy a BEV, gain $BitCO_2$ and resell them to the insurance's clients. This denotes a monetary flow of revenues that last the whole lifetime of their car and act as an incentive by influencing the choice of the type of vehicle at the time of purchase. One barrier to BEV adoption is indeed positively affected, namely the purchase price. Thanks to the proposed mechanism the total cost of ownership is expected to reduce accordingly to the number of tokens the driver is going to earn along the BEV lifetime.

Results

In this chapter, the main results are discussed. Moreover, to show the solidity of the model, validation tests and sensitivity analysis are presented.

Testing the model

One of the most important steps of model development is to check its robustness. To do that, SD theory suggests twelve validation tests [137]. For this work, few validation tests were excluded because not compatible with the peculiarities of the model that was developed. Some of the tests, such as the *Boundary adequacy test*, *Structure assessment test*, and *Parameter assessment*, were completed during the modelling phase to evaluate the appropriateness of model boundary according to physical laws and aggregation level and to attribute to variables a real-life meaning. Additionally, the *Dimensional consistency test*, used to specify the unit of measure of each parameter, is proven through an automated dimensional analysis performed by Stella software. Two important checks that verify the stability of the model are the *Extreme condition test* and the *Behaviour anomaly test*. The former is done to assess whether the model behaviour is realistic even when extreme inputs are applied. For example, maximizing the adoption fraction parameter implies that all the potential adopters become BEV adopters, due to the absence of the barriers that limit the BEV purchase. Therefore, since no adoption barriers are present, the BitCO_2 policy mechanism becomes useless. This is what can be inferred from model results that show null BitCO_2 sold over the simulation time horizon, thus confirming the stability of the model. Indeed, The *Behaviour anomaly test* is aimed to evaluate if an anomalous behaviour appears when some loops or relationships are deleted or modified. If this happens, it means that the delated parameter or loop is significant for the model. For example, eliminating the charging time variable, one of the three barriers that limit the adoption fraction, leads to a higher willingness to buy a BEV, so a greater quantity of tokens are sold and a larger amount of emissions are avoided, almost 280% higher emission reduction with respect to the base case. Lastly, an *Integration error test* is performed to test the choice of time step (DT) for model simulation: changing DT or the integration method should not influence in a significant way the behaviour or the results. The golden rule is that the time step should be equal to or smaller than 1/3 of the shorter time constant in the model, thus the minimum delay [137]. Therefore, the DT in the base case is set to 1 month. To perform this validation test, DT is cut in half, so it is about 15 days (1/2 month). Once this change is implemented, the outcomes show the same trend as in the base case, except for little oscillations of some variables related to the BitCO_2 market mechanism due to the intrinsic operativity of the stocks in the model. Nonetheless, the behaviour of the model is on average the same thus confirming the success of the test.

Main results

As presented in *Formulating a simulation model*, the market-based BitCO_2 mechanism aims to foster BEV adoption, leading to a reduction of GHG emissions into the atmosphere. The adoption of EVs over the ICEVs is limited by three barriers: the purchase price, the range of km that a battery can sustain, and the charging time. Through the economic incentive, the total cost of ownership decreases, bringing the adoption fraction to reach higher values with respect to the one without the policy. Hence, starting from the potential adopters, the number of people that purchase a BEV is defined through the adoption fraction. At this point, understanding when the token will be assigned to each BEV owner is fundamental: it is performed by comparing the environmental impact of both cars.

Figure 5.11 – Number of additional BEVs purchased thanks to the BitCO2 mechanism and price of BitCO2 tokens by month.

During the production phase, the BEV generates more quantity of CO_2 than the ICEV due to the presence of the battery, while driving, the trends are reversed. Thus, after a certain amount of km, the total CO_2 emitted by BEV (considering both construction and operation) is equal to the one of ICEV: the emission parity is reached. After that, the BitCO2 tokens are generated automatically every time the electric vehicle is recharged, according to the number of emissions avoided. In the first period of the simulation horizon, the number of km to reach the parity is equal to 27'770 km, then these variable experiences a decreasing behaviour because the electricity necessary to recharge a BEV is expected to become greener over the years, so the quantity of grCO2 produced to drive one km should reduce. At the end of the policy time horizon, this variable reaches the value of 23.530 km. The difference between the number of BEVs that reach the emission parity in the scenario with the incentive and the ones in the scenario without it represents the number of people that decide to choose to buy and drive a BEV over an ICEV thanks to the economic incentive embedded in BitCO2. These cars are represented in the variable BEV attracted which trend is reported in Figure 7. The owners of such cars are involved in the BitCO2 market-based mechanism, necessary to attribute a price to the token. They reach a maximum of around 40 thousand people after the 10th year of the mechanism.

Overall CO_2 emissions reduction achieved thanks to BitCO2 mechanism implementation is about 970 ktonCO2eq over 20 years of operation. There is a correlation between these emissions and the amount of token emitted by the insurance each month since one token corresponds to one ton of CO_2 not emitted.

The market mechanism engages three major stakeholders:

- BEV owners, who want to sell the token acquired thanks to their consumption choice;
- insured people, who buy it from them to resell the BitCO2 to insurance companies gaining a discount on the yearly fee paid to the firm;
- insurance companies, that collect and burn the token, meaning that a certain amount of emissions are avoided.

Starting from the variable *Total actual BitCO2/quarter* and crossing the demand of insured people with the supply of car owners, the price of the token is defined (see Figure 5.11). It varies between 6.4 and 2.4 €/BitCO2.

At the beginning of each year, insurance clients may choose to give the $BitCO_2$ to the insurance company to obtain a discount on the fee that they need to pay. They may decide to sell them if what they paid for the token is lower than the discount given by the firm. Despite the costs that the insurance has to pay due to the generation of tokens, the revenues, linked to the Social Cost of Carbon, set at 9.2 €/tonCO_2, and the policy avoided emissions, overcoming expenses, generating a profit for the firm. In the end, the incentive for future BEV owners is computed considering the price of the token earned during the lifetime of the car, discounted to the year of purchase of the vehicle. In the first years of the market, it reaches values around 200 €, then it stabilizes around 80 €. As already shown, this incentive is then decurted from the variable Purchase price, which represents one of the main barriers to the adoption of a BEV. Base scenario values are compared with best and worst scenarios in the next chapter's figures.

Sensitivity analysis

Sensitivity analysis is an important tool to test the robustness of the model's results subject to the variation of input parameters within their range of possible variation. According to System Dynamic theory, sensitivity analysis must be executed on variables that are both highly uncertain and likely to be influential [137]. The ranges of possible variation are defined through scientific articles and web research. The values' ranges are reported in Table 1. Then, performing sensitivity analysis on each parameter, worst and best values are identified to give the least/most favorable policy outcome, in terms of policy total avoided emissions.

Table 5.3 – Sensitivity analysis values.

	Range	*worst*	*best*	Unit	Source
Charging time	139 – 289	289	139	min	[328]
Range of km	140 – 425	140	425	km	[329]
Purchase price	26'000 – 42'000	31'111	32'222	€	[329]
Mileage	150'000 – 250'000	150'000	250'000	km	[325]
km/year driven	800 – 1'117	800	1'011	km	[330]
Sales prediction	1'553'988 – 1'798'541	1'553'988	1'798'540	cars	[331]
g_{CO_2}/km ICE	218 -228	218	228	gCO_2/km	[327]
CO_2/ICE	5 – 7.4	7.4	5	ton/vehicle	MIN: [326] MAX: [332]
CO_2/BEV	8 -14	14	11.33	ton/vehicle	[326]
g_{CO_2}/km BEV	45 – 65	65	45	gCO_2/km	MIN: [305] MAX: [332]
Social cost of carbon	2.13 – 22.3	2.13	22.30	€	[333]
Fraction of insured damages	0,36 – 0,447	0,36	0,44	-	[334]

Note that not all the parameters' range extremes coincide with *worst* and *best* values. That is the case with BEV purchase price. On the one hand, if the price of the BEV is too low, the role of $BitCO_2$ is not relevant in driving consumer choice; on the other hand, if the price of BEV is too high, the maximum assumed SSC cannot make the choice convenient. Therefore, *worst* and *best* values fall within range extremes.

The outcomes are in line with what is expected: in the *worst* scenario the adoption fraction is the lowest and the difference with the one generated without the incentive is small, leading to engaging few people. Thus, the market mechanism involves little quantities of tokens and small prices, moreover, the actual discount imposed by insurance reaches values around 0.6 € due to the low social cost of carbon. Therefore, the incentive for BEV owners is linked to the economic value of the BitCO$_2$, which is on average around 20 €, with a peak of 38 €. As a consequence, a tiny amount of emissions are avoided: 68.9 ktonCO$_2$ (-93% with respect to the *base* case) at the end of the policy time horizon. On the contrary, applying the values that give the most favorable scenario, the output of the model shows a huge growth in the adoption fraction due to the higher incentive and less stringent barriers. Hence, the number of people that make the virtuous choice increases, in particular, the BEV purchased thanks to the policy discount reaches a value of 189.000 cars. This means that the insurance generates a massive number of tokens, which implies avoiding a lot of emissions. In this case, the market mechanism begins earlier, driven by the scenarios' assumption of electricity's carbon intensity reduction, and the BitCO$_2$ assumes high prices due to the huge values of the discount set by the firm. Despite the elevated costs that the insurance has to pay, the social cost of carbon is so high (around 22 €) that the revenues overcome expenses, generating a massive profit. In the end, the policy results were very effective: a total of 5'240 ktonCO$_2$ are avoided, +440% with respect to the base case. Figure 8 to Figure 11 shows the results for sensitivity analysis, the base case is reported in red while best and worst scenarios are reported in sky-blue and red respectively.

Figure 5.12 – Number of BEV attracted by scenario and month

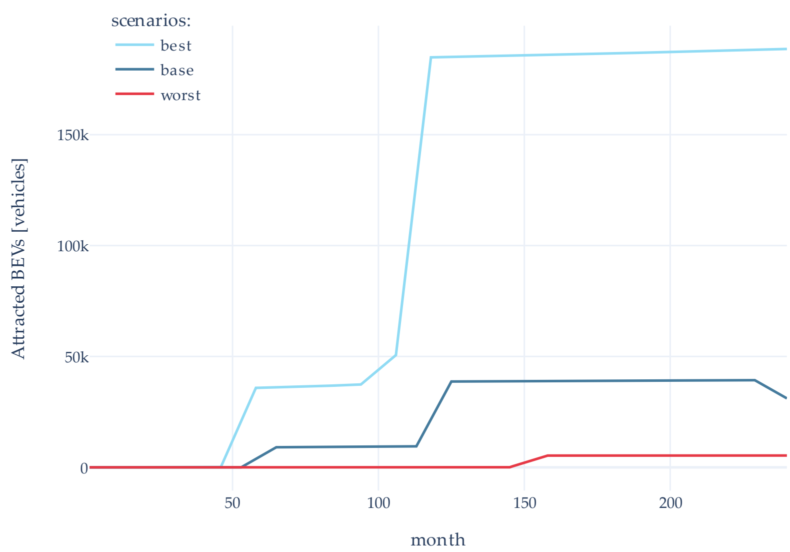


Figure 5.13 – BitCO2 price by scenario and month

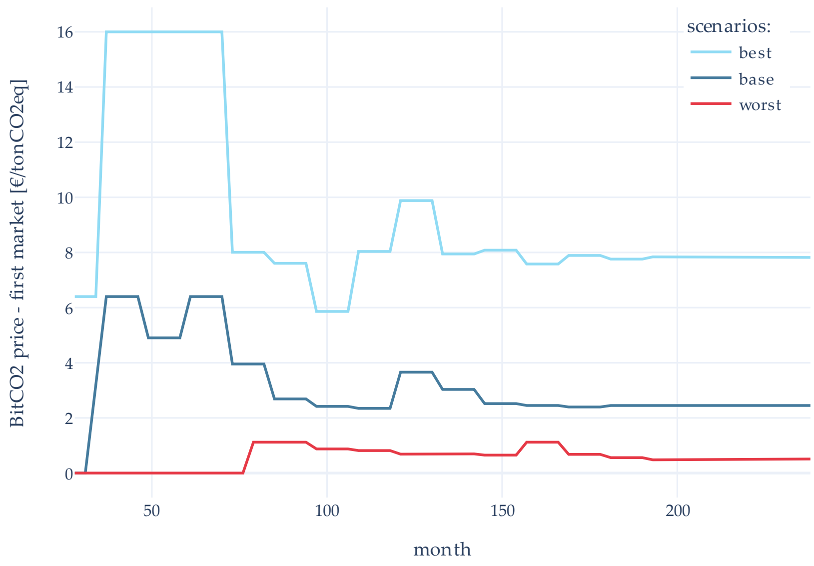


Figure 5.14 – Implicit reduction of the purchasing price of BEV by scenario and month

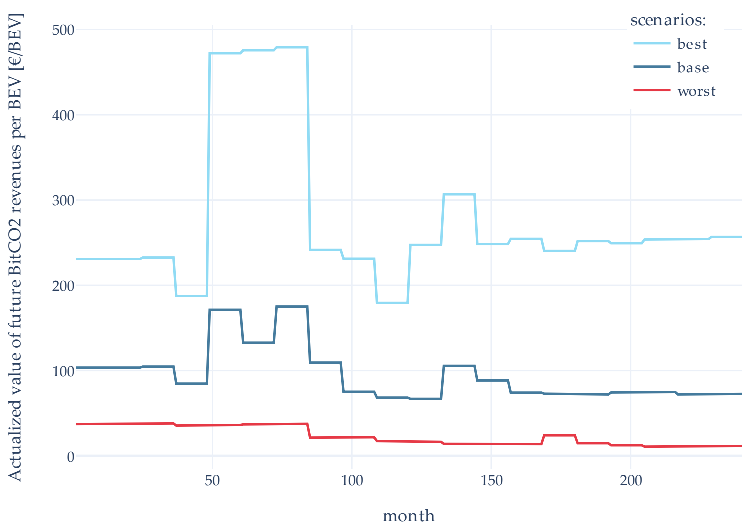
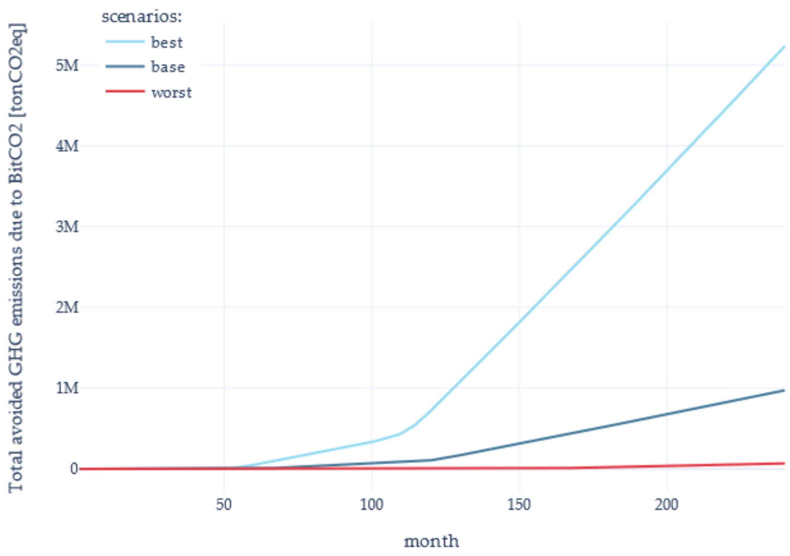


Figure 5.15 – Total cumulated avoided emissions by scenario and month



Conclusions

Human activities, such as burning fossil fuels for electricity generation, heating, and transport, are the primary drivers of the largest amount of GHG emissions. That's why active and willing participation of citizens in combatting climate change may be pivotal to checkmate this issue [5]. Thus, promoting sustainable development through virtuous people behavior might be at the center of policy makers' agenda to fight climate change through a just energy transition.

The purpose of the mechanism that has been presented is to decrease the current environmental impact of the Italian private road transport sector. The process is based on a consumption-based emission accounting method. System dynamic is selected as the most suited modeling approach. The role of consumers is a key factor in the mechanism: it ultimately relies upon the fact that they may choose to adopt a less carbon-intensive lifestyle, which is exemplified by the choice of the BEV over the ICEV. The decision, in this case, is promoted through monetary incentives. The market-based mechanism comprises a BEV adoption model. It considers several limiting barriers in the decision that a potential adopter has to face, such as the range limitation of an electric car, its charging time, and its high purchase price. Then the environmental implication of the vehicle choice is studied through the LCA of BEV and ICEV, which include both the emissions that are released during vehicle manufactory and the emission owing to the operational phase (well to wheel fuel assessment).

When people choose to purchase a BEV and they participate in the BitCO$_2$ market, they gain a monetary return. The incentive is supplied by insurance companies: they have an interest in decreasing GHG emission release into the atmosphere since it would also imply reducing the intensity and the frequency of future climate change damages they will eventually have to pay for.

The total quantity of emissions avoided due to the implemented mechanism during the 20 years of the policy is 973 ktonCO$_2$eq. It has to be taken into account that the yearly GHG emission in Italy is around 330 MtonCO$_2$eq [335]. From this perspective, the mechanism does not seem to attain a great achievement. The cause is probably the modest amount of people that chose the BEV due to the policy incentives, about 40 thousand people, thus making the participation in the market mechanism limited. The reason behind this phenomenon is the small monetary reward. The price attributed to the token in the markets can be identified as the bottleneck of the model: if the prices (and so the incentive) is not attractive, people are not motivated in taking part in the mechanism. The economic value is strictly related to the discount imposed by the insurance, which is linked to the social cost of carbon. The considered social cost of carbon is associated just with the climate change damages that occur inside Italian borders due to the emission of an additional ton of CO_2. However, the changes in climate due to the GHG are not related to where emissions are generated or avoided. Therefore, in this case, the Italian social cost of carbon does not consider the damages prevented outside Italy thanks to the policy. This can be considered a future improvement of the current work. The variation of the value related to the social cost of carbon is the key to having a different economic incentive, as presented in the Sensitivity analysis. Moreover, the model can be replicated by facing other virtuous alternatives. As far as the private transport sector is concerned, Plug-in Hybrid Electric vehicles or Hybrid Electric vehicles can be considered. Analyzing other economic sectors, greener substitutes can be represented by plant-based meet as the alternative to beef for what regards food sector, and electricity produced mostly by renewable sources instead that generated mainly by fossil fuel, related to the energy sector. For these new cases, new information linked to LCA and the main barriers that influence the adoption fraction has to be investigated.

6. Conclusions and future developments

This work started with a general research question: "What is the role of carbon emission reduction mechanisms (CERMs) in the Energy Transition?".

In Chapter 2, a significant part of the scientific literature was analysed with the aim of highlighting the problem of emission reduction and possible approaches useful for identifying solutions. This made it possible to select input-output (IO) models as the main methodological tool to enrich the literature with new applications aimed at modelling various CERMs trying to estimate their effect on greenhouse gas (GHG) emissions and other relevant indicators of sustainable development. Major aspects filtered through the literature analysis concern the relevance of policy instruments in achieving objectives that would otherwise be hardly attainable in an economic system that does not directly factor in impacts associated with environmental externalities such as those of GHG. In addition, the fragmentation of carbon pricing tools and some limitations of its implementations (e.g. carbon leakage, controversial role of some carbon credits, often low prices) emerge, which are often not included in most energy models that do not encompass a comprehensive representation of the economy as a whole.

Chapter 3 made the methodological contribution of this research explicit, focusing on the practical simplification and generalisation of the more sophisticated implementation of an input-output model. This led on the one hand to the design and co-development of a model for the multifunctional analysis of regions through input-output analysis (MARIO). On the other, a framework has been formalised that has enabled and will enable the modelling of virtually all types of IO analysis, from the application of the first models conceptualised by Leontief to more sophisticated dynamic IO models. The Technology-Activity-Commodity-Need (TACN) framework supports multi-regional analyses that can explicitly distinguish the production of goods and services over time from the activities that produce them, being able to consider their expandable capacity limits.

Expanding the Supply and Use framework into the so-called TACN framework and the availability of MARIO have allowed an easier implementation of IO models thus improving the application of Life-cycle Thinking studies. Some of them have been included in Chapter 4.

So, what emerges from the applications that can answer the starting question? The role of CERMs in the energy transition is, as noted in the literature, generally positive in reducing emissions per unit of service provided (i.e. carbon intensity, only one of the production factors in determining the total amount of emissions in Kaya's identity [49]). However, the following limitations or undesirable effects emerge:

- When considering CERMs that identify a lower limit of a technology's penetration into a mix, in cases where the technology is not yet industrially mature, not including the analysis of embedded emissions in production may lead to poor or worsening carbon intensities
- The role of end-user consumption choices can be decisive in achieving certain emission reduction targets, especially in those sectors where there is a large difference in carbon footprint between two alternative products that satisfy a given need
- If the level of emissions reduction becomes challenging (e.g. going to 0 net emissions within 2050; high carbon prices), the need to hedge against the risk of carbon leakage becomes more pressing, making the opportunity cost for companies much more skewed towards producing outside the jurisdictions that price carbon in a consumption-based approach
- Overlapping multiple purposes within the same incentive, without there being a direct relationship between incentive and negative externality reduction can lead to market distortions thus making the CERM inefficient

Overcoming these limitations led to the proposal of an innovative CERM inspired by the demand-driven nature typical of input-output models. If there is output, it is because there is non-zero final demand. By taking the incentive mechanism all the way to the consumer, by going to influence his or her consumption choices, it is possible to indirectly incentivize the supply chains of those activities that produce fewer emissions for the same amount of need satisfied, making them more favourable in the eyes of the consumer.

This increased attractiveness can turn into a real economic incentive if avoided emissions are estimated in a scientifically accurate and communicatively effective manner. In this sense, a token can be associated with each emission avoided through consumption of a particular good or service instead of alternatives. If there is economic value in carbon credits today, similarly the market may also find value in these tokens. The mechanism is called BitCO_2 and is explained more fully in Chapter 5. However, its modelling within the Italian private transport sector has shown promising results.

A new version of MARIO is currently under development. In fact, it will be expanded to integrate the TACN framework allowing for more complex studies like global dynamic models. Having access to such a framework would pave the way towards standardization of input-output studies and may favour the extension of information currently collected by national accounting offices, including explicit information on *technology* capacity, investment costs, and deployed units for every *sector* of the economy in every year. Current technological challenges would be more easily faced by entrepreneurs and policymakers if more transparent and explicit information on *technologies*, *activities*, *commodities*, and *needs* would be available. In fact, targeting the *needs* of industries and households while making national and supranational environment and socio-economic objectives explicit would automatically make policy-making technologically agnostic (e.g. there would be an issue of heating supply not necessary of natural gas supply).

The modelling implementation of BitCO_2 has proven its contribution even without considering the global social cost of carbon but just considering the estimation for Italy. In the near future, the SD model will be run assuming the global social cost of carbon. This represents the first milestone for the project which would require multiple simultaneous implementations to have a relevant global impact. Nevertheless, large-scale implementation of such projects would require the building of a proper blockchain information technology infrastructure which must be designed with care. In fact, if a superficial implementation of the BitCO_2 infrastructure is set, benefits deriving from the scheme may be offset by the carbon emissions embedded in operating and maintaining the infrastructure. Side chains of the most diffuse blockchains have been considered but detailed analysis is still ongoing.

Finally, a process-based LCA has been employed to estimate the footprints of different consumption choices in the BitCO_2 application here presented. However, the TACN framework can represent a standardized template for making the hypothesis around each footprinting study transparent and clear.

These ideas represent the starting point for the actual implementation of these methodologies within a private company initiative.

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