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Exploring the effects and implications of green innovation within the sustainable transition

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Introduction

Climate change, one of the most pressing societal challenges of our time, represents a profound and far-reaching transformation of the Earth's natural systems. Primarily through emissions of greenhouse gases (GHG), human activities such as fossil fuel use, deforestation, and industrial processes, have lead to an increase in global average temperatures by more than 1°C since the pre-industrial era (IPCC, 2023). In addition, we are currently on a path towards 3°C of global warming (UNEP, 2023). This phenomenon has triggered a cascade of environmental, social, and economic consequences, from more frequent and severe weather events to rising sea levels and disruptions in ecosystems. Therefore, fighting climate change is not just an environmental issue, but a global crisis with implications for public health, food security, and political stability.

Addressing climate change requires collective action, innovation, and a profound shift from current production and consumption patterns. Scientific assessments are ever clearer and more certain on climate change, its impacts and future risks and option for adaptation and mitigation (IPCC, 2023; UNEP, 2023). A green industrial transition of economies is needed, involving a radical change of current industrial systems towards more sustainable production methods. Several actions must be adopted to reduce GHG emissions and adapt to climate change. These are available now, but they need to be scaled up and mainstreamed through policies and increased financing: among them, the development and uptake of environmental innovations, also referred to as green and sustainable technologies or eco-innovations, is a key pillar. These innovations span from renewable energy technologies for replacing fossil fuels to the adoption of adaptation practices against adverse climatic events. Efforts towards large-scale adoption of these innovations have led to concrete results, such as sustained decreases in the cost of renewable energy (Lazard, 2023). Recently, various studies support the feasibility of a shift to energy systems relying 100% on renewable sources that can limit global warming to 1.5°C (Breyer et al., 2022).

However, a rapid and massive development of green technologies also entails risks, which may require policy intervention in order not only to ensure the completion of the green transition of economies, but also to make it socially sustainable. An important aspect is related to the dependence of green technologies on specific materials that are needed for their realisation. Examples are lithium used to make batteries implemented in electric vehicles and to store energy from renewable sources, rare earths used to make magnets employed in wind energy, and silicon used in the manufacturing of solar panels, among others. These raw inputs have a number of related concerns, such as risks of future shortages resulting from future supply not being able to meet the growth in demand driven by green technologies, or geopolitical tensions as well as risks of exacerbating existing inequalities resulting from their geographical distribution. Adding to this picture the economic importance, and often the absence of viable alternatives that characterise these resources, makes the dependence on raw materials a serious threat to slow down, if not completely undermine, the scaling up of eco-innovations.

These are complex phenomena, characterised by intricate challenges that cannot be effectively addressed by analyzing individual aspects separately or relying on conventional economic models designed to internalize climate-related externalities. Instead, a multidisciplinary approach is imperative, taking into account the complexity of climate change characteristics and of the possible strategies to cope with it. Climate change, with its global causes and consequences, long-term and potentially irreversible impacts, and significant uncertainties regarding future scenarios (Stern, 2007), requires nuanced solutions. Recognising the need for comprehensive strategies is essential, acknowledging the inherent complexity of both the challenges and solutions required to address climate change (Foxon et al., 2012).

Against this background, this thesis focuses on the analysis of multiple aspects connected to green technologies, and particularly bringing novelty to the effects and implications derived by their development. Specifically, two major issues will be explored. The first one regards the study of the effects that environmental innovation has on industrial production, looking at which sectors are the most affected by green technological areas by applying techniques from the Economic Complexity framework. The second one regards the investigation of the material content of green innovation exploring multiple directions, which span from the comparison with non-green counterparts to the construction of the geographical network juxtaposing countries where green technologies are adopted with those where materials are produced.

Environmental Innovation

The development of green technologies is a cornerstone of any possible strategy against climate change. These technologies fulfill several purposes, serving as mitigation tools aimed at reducing GHG emissions or as adaptive solutions to counteract the adverse impacts of climate change on human activities. More specifically, to achieve the transition of economies toward sustainability it is essential to employ technologies that harness energy from renewable sources. Additionally, there is a need for innovations in recycling materials, optimizing the management of product waste cycles, and enhancing the efficiency of existing infrastructures, production methods, agricultural processes, and the energy system. In a nutshell, green technologies can be defined as *"the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives"* (Kemp and Pearson, 2007).

Recently, a growing corpus of research studying green innovations has developed, focusing e.g. on defining their main characteristics (Barbieri, Marzucchi and Rizzo, 2020; Barbieri, Perruchas and Consoli, 2020; Perruchas et al., 2020), tracing their deployment across geographical areas (Barbieri et al., 2022; Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018), and exploring the importance of policies to promote them (Popp et al., 2010). Despite the beneficial effects, the widespread adoption of green technologies carries also potential risks, such as the impact on the labour market due to the potential shutdown of highly polluting industries (Saussay et al., 2022; Vandeplas et al., 2022), or the increased environmental degradation resulting from the opening of new mining sites for materials needed to build these innovations (Church and Crawford, 2018). If not properly addressed by policy intervention, these risks could hamper the achievement of the green transition.

In order to conduct empirical analyses on environmental innovation it is crucial to have good proxies to measure it; to this end, in this thesis we look at patent data. In particular, keeping in mind the related benefits and shortcomings (Arts et al., 2013; Griliches, 1998; Lanjouw et al., 1998), the use of patents to measure green innovative activities is well established in the literature, mainly due to the availability of patent data and the wealth of information they contain, such as the nature of the patented invention and the country of origin of the patent applicant (Dechezleprêtre et al., 2011). In particular, through the adoption of classification systems developed by patent offices, patents are associated with codes that identify the technological content of the patented invention. By doing this, it has been possible to identify climate change mitigation and adaptation technologies, related to e.g. energy generation, transportation, and waste management. Therefore, by using patents it is possible to distinguish which innovations have environmental purposes. This, combined with other factors such as the enormous amount of data available, makes patents a reliable source for conducting statistically robust empirical analyses on aspects related to green technologies.

Economic Complexity and green innovation

The transition towards net zero emissions is a pressuring challenge, which requires the design of appropriate policies triggering the development of technologies, products, and solutions while having access to the necessary funding and resources. It requires a structural change in economies involving not only many interconnected sectors, but also environmental and social aspects. Conventional approaches are not well suited to tackle this challenge since they lack in the characterisation of the inter-linkages among economic areas which will be affected. Therefore, there is the need for more integrated techniques, such as those adopted in the Economic Complexity (EC) framework (Pugliese and Tübke, 2019).

EC is a relative recent framework consisting in a bottom-up and data driven approach, drawing inspiration from the institutional and evolutionary literature (Dosi and Nelson, 1994; Teece et al., 1994) in describing economies as evolving and globally interconnected ecosystems, with the addition of insights from statistical physics, complex system analysis and network theory (Hidalgo et al., 2007; Tacchella et al., 2012). Going beyond aggregate measures of productive inputs and economic performance, and focusing instead on a more granular view of productive inputs, EC methods have proven to be successful in numerous policy relevant tasks such as forecasting (Tacchella et al., 2018) and explaining (Sbardella, Pugliese, Zaccaria and Scaramozzino, 2018) economic growth. In relation to environmental issues, several studies adopting EC techniques have been carried out. Consistently based on a data-driven approach, these studies have focused on the analysis and definition of environmental products (Fankhauser et al., 2013; Hamwey et al., 2013; Mealy and Teytelboym, 2020), technologies (Napolitano et al., 2022; Perruchas et al., 2020), jobs (Santoalha et al., 2021), and on the measure of the intangible capabilities needed for a country (Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018) or a region (Barbieri et al., 2022) to be competitive in a green technological domain.

In the wake of these studies, in Chapter 1 of this thesis we analyse how the development of green technologies correlates with product exports even years later, in order to be able to trace how green innovation unfolds into industrial production. In particular, differently from standard economic approaches, the adoption of EC methods allows us to characterise the relationship between green technologies and products at a very fine-grained level, and to validate the obtained outcomes with robust validation procedures.

Critical Raw Materials and green innovation

The development of environmental innovations requires a specific set of raw inputs, whose demand is expected to surge in the coming years in parallel with the global deployment of adaptation and mitigation technologies needed to achieve the sustainable transition. In this thesis, following the European Commission's work on the subject, these inputs are referred to as Critical Raw Materials (CRMs). In particular, the term CRMs originally refers to those materials that the Commission considers critical according to their economic importance and supply risks for Europe. The efforts of the Commission in identifying and monitoring these materials translate in a first list of 14 CRMs published in 2011 (European Commission, 2011) which has been updated every 3 years since then. The most recent list, published in 2023, includes 36 CRMs (European Commission, 2023*b*). Similar efforts in defining the mineral content of green technologies have been carried out by other international organisations such as the International Energy Agency (International Energy Agency, 2021, 2023*a*), World Bank (Hund et al., 2020), and OECD (Kowalski and Legendre, 2023). The main focuses of these reports regard the identification of the supply risks of different materials throughout the supply chain, the role they play in each technology, the exploration of both technological and material alternatives to the currently dominant ones, and the role of international and state policies, both in fostering investment and in placing barriers to materials trade. Similar topics have been the focus of countless papers published especially in recent years (Diemer et al., 2022; Grandell et al., 2016; Junne et al., 2020; Kushnir and Sandén, 2012; Valero et al., 2018; Watari et al., 2019; Yunxiong Li et al., 2024).

The dependence of green technologies is not just a matter of increasing the quantities available of CRMs in order to deliver the future amounts required to achieve the net zero emissions goal. Indeed, there are environmental concerns that arise in relation to a future increase in the extraction of CRMs, as the mining sector is frequently associated to negative externalities, such as increase in emissions and, especially at the local level, poor management of land, water and waste (Azadi et al., 2020; International Energy Agency, 2021). Additionally, the presence of these CRMs is often negative for the source countries, despite their undeniable global economic importance (Church and Crawford, 2018). Reference is in fact made to a resource curse which, in countries with weak institutions, can lead to an increase in corruption, violence, economic and gender inequality, and labour exploitation (Natural Resource Governance Institute, 2015; Robinson et al., 2006). The alternative path to mining, represented by increasing the recycling of CRMs, may not be sufficient to meet future demand given current recycling rates (International Energy Agency, 2021; United Nations Environment Programme, International Resource Panel, 2011). Therefore, policies aimed at addressing the issue of the materials required by green innovations cannot ignore its social and environmental implications.

The CRM dependency of green technologies is object of analysis in all the chapters of this thesis. Specifically, in Chapter 1 products connected with the production and processing of raw materials are some of the most influenced by the development of green technologies. In order to explore the issue further, in Chapter 2 and Chapter 3 the presence of CRMs in green technologies is directly explored through the adoption of text mining techniques in patents. In particular, after the preliminary exploration conducted in Chapter 2, where the CRM reliance of green technologies is explored in comparison with that of non-green counterparts, Chapter 3 discusses the geography of the CRM supply chain, particularly focusing on the materials with less diversified global production.

Structure of the thesis

This thesis consists of 3 main chapters, plus introduction and conclusion. Each chapter is self-contained and can be read independently. In particular:

- Chapter 1 - The trickle down from environmental innovation to productive complexity is based on a co-authored paper published in 2022 (de Cunzo et al., 2022). In this study, we analyse the relationship between green innovation and industrial production at a very fine grained level. First, we consider data on green patents and on exported products as proxies for green innovation and industrial production respectively. Second, we adopt existing Economic Complexity techniques (Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019) to build a bipartite network linking green technological domains to products. Each link between a green technology and a product in the network highlights a similarity in the technological and industrial hidden capabilities needed by a country to be competitive in both. Additionally, the analysis is conducted over a temporal dimension, so that we are able to explore the influence of green technologies over products both simultaneously and after some years.
  The results show that, when looking at the immediate effect, almost all green technologies exhibit some connections in the network. In contrast, products linked to these technologies belong to a few sectors, mainly related to the processing of raw materials. This reveals a pattern of parallel development of countries specialising in green technologies and in the processing sectors of the materials needed to realise them.
  Studying the effect of green innovation on industrial production with a 10-year time lag shows a stronger influence of green technologies on exports, indicated by an increase in the number of links in the network. From a qualitatively point of view instead, we observe higher complexity, i.e. higher and more specific requirements needed by countries to be competitive in them, of the green technologies and products in the network.
  Overall, this chapter opens for promising research developments, including e.g. assessing the effect of green innovation on other dimensions besides exports, such as employment in manufacturing sectors, or investigating in detail the raw material dependence of green technologies, as done in the remaining chapters of this

thesis.

- Chapter 2 - The Critical Raw Materials content of Innovation consists in an empirical analysis on the CRMs content of innovation activities. The main objective of this study is to identify the CRMs on which the realisation of green technologies depends the most, to evaluate how this dependence has evolved over time, and to draw a comparison with the CRMs dependence of non-green technologies, also establishing which technological domains, both green and non-green, are characterised by a considerable presence of CRMs. Additionally, a full description of the methodology adopted in both this and the third chapter is included. In particular, we employ text mining techniques over the abstracts of patents, which consist in the descriptions of the patented inventions, to detect the presence of CRMs. When a CRM is mentioned in a patent abstract, we assume that the invention's realisation depends on that material.
  The results show a predominance in green technologies of specific materials, which is often confirmed by their uses indicated in the existing literature. The comparison between the two types of technologies reveals a significantly higher presence of CRMs (almost double) in green technologies, which remains stable throughout the entire examined period. Finally, the last part of the analysis shows which technological domains are most characterised by the use of CRMs. Except for those related to metallurgy and chemistry, some non-green technological domains show complementarities with green innovative areas.
  On the whole, this chapter constitutes a preliminary approach to the topic of CRMs and the dependence of green technologies on these raw inputs. Starting from this analysis, several research developments and dimensions open up to be further explored. One of these, the geographical dimension, is considered in the concluding chapter of this thesis, where, adopting the same approach as in this chapter, we further shape the presence of CRMs in green technological domains.

- Chapter 3 - Mapping Critical Raw Materials in Green Technologies is based on a co-authored paper which has been submitted recently (de Cunzo et al., 2023). This chapter is a continuation of what discussed in Chapter 2. In particular, we further shape the presence of CRMs in green technologies by adopting text mining techniques over green patents. In line with Chapter 2, we explore the green technological domains which are most dependent on CRMs, also looking at the evolution of the level of dependence over time. Additionally, in depart from the previous chapter, we consider data on the CRMs production by country and geographical information on the countries where the green technologies are filed, i.e. where the patent applicants want to protect the invention and, therefore, where its adoption is likely to happen in the future. First, thanks to the use of CRMs production data, we further characterise our study with a dimension of materials scarcity, in terms of concentration of their production. Second, we investigate which countries rely the most on CRMs via their inventive activities, and therefore are more exposed to future shortages, and we compare them with countries where CRMs are produced.
  The results show that, among the most prevalent CRMs in green technologies, there are some materials such as rare earth elements, lithium, and cobalt, whose production is located only in a few countries, and therefore carries more supply

shortage risks. Additionally, when looking at countries where CRMs dependent green technologies are most prevalent, we find mainly high-income countries such as China, US, Japan, South Korea, and many European states. In contrast, when looking at countries where CRMs are produced, we find, with few exceptions, low-income Global South countries, which are additionally characterised by a lower or null presence of green technologies. This holds even for the most spatially concentrated, and therefore riskier, materials.

Hence, a pattern of inequality which is intrinsically embedded in the development of green technologies is observed. Countries producing the essential components of green innovations are almost excluded from the benefits of their diffusion. This in turn opens up interesting avenues for future research, such as quantifying the actual gains of producer countries from increased demand for CRMs, which may offer insights into the effectiveness of policies focused on increasing the supply of materials. The exploration of these avenues is not part of this thesis, but these are crucial aspects that raise questions about the actual environmental and social sustainability of the green transition as it is foreseen by current policy actions.

Chapter 1

The trickle down from environmental innovation to productive complexity

The content of this Chapter is based on de Cunzo et al. (2022).

Abstract

We study the empirical relationship between green technologies and industrial production at very fine-grained levels by employing Economic Complexity techniques. Firstly, we use patent data on green technology domains as a proxy for competitive green innovation and data on exported products as a proxy for competitive industrial production. Secondly, with the aim of observing how green technological development trickles down into industrial production, we build a bipartite directed network linking single green technologies at time t_1 to single products at time $t_2 \geq t_1$ on the basis of their time-lagged co-occurrences in the technological and industrial specialization profiles of countries. Thirdly, we filter the links in the network by employing a maximum entropy null-model. In particular, we find that the industrial sectors most connected to green technologies are related to the processing of raw materials, which we know to be crucial for the development of clean energy innovations. Furthermore, by looking at the evolution of the network over time, we observe a growing presence of more complex green technologies and high-tech products among the significant network links.

Keywords: *Green Technologies; Exports; Economic Complexity; Multi-partite network*

1.1 Introduction

The fight against climate change is at an unprecedented critical phase: the impact of human systems of production and consumption on the environment as well as the transition to a more sustainable economy are at the center of public attention and EU policy agenda (European Commission, 2019*b*; McMichael et al., 2006; World Economic Forum, 2018). In this context, the development of green technologies, which despite being relatively at an early stage of the life cycle has shown a great acceleration over recent years (OECD, 2011), might play a crucial role both towards containing and preventing greenhouse gas (GHG) emissions and in sustaining a shift towards less environmentally costly manufacturing processes (OECD, 2011; Popp et al., 2010; Stern, 2007). It is therefore of the greatest importance to investigate how green technologies are connected to the economy and, in particular, to industrial production. This is what motivates our paper. In particular, by adopting a complexity perspective, we aim at filling some gaps in the study of the interplay between green innovation and production by implementing a highly granular analysis that allows us to explore how individual green technologies unfold into industrial production.

Several aspects of the nexus between export and green technological development have been examined at the aggregate level. By exploring different directions of causality at the firm, industry and country level, a wide array of studies has focused on the export-green innovation nexus generally highlighting a positive relationship between (policy/regulation induced) eco-innovations and export competitiveness/performance (Brunnermeier and Cohenc, 2003; Costantini and Mazzanti, 2012), quality (Chai, 2022), propensity (Lodi and Bertarelli, 2022), or diversification (Wang et al., 2020) (for a review on the topic with a special focus on agrifood supply chains see Galera-Quiles et al. (2021)). However, previous research has largely looked at the link between overall green technological innovation and overall or sector specific export at highly aggregated levels -— i.e., by focusing respectively on green patent counts and export volumes (or intensity/participation rates etc.) -— overlooking the fact that a green technology may foster the export of a specific product or bundle of products, but this may not be true for all products, and a negative association with other exported goods could also be found.

Accordingly, we propose a novel quantitative framework rooted in the Economic Complexity (EC) literature (Hausmann et al., 2007; Hidalgo and Hausmann, 2009; Tacchella et al., 2012) that enables us to unpack the green innovation-export nexus by exploring how single green technological innovations, as proxied by patenting activity in climate change adaptation and mitigation technologies (CCMTs), trickle down into industrial production at the level of single products, as proxied by export data (Saltarelli et al., 2020). Our approach is particularly relevant when looking at green technologies, because, as they encompass different domains of know-how (Barbieri, Perruchas and Consoli, 2020), are designed to fulfill a broad range of functions (Perruchas et al., 2020), are heterogeneous across geographical areas (Barbieri et al., 2022; Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018) and linked in non-trivial ways to pre-existing knowledge bases (Barbieri, Marzucchi and Rizzo, 2020; Barbieri et al., 2022; Montresor and Quatraro, 2020), treating them as a homogeneous aggregated corpus may fail to disentangle the possibly differentiated effects of specific green innovations on specific products. This line of reasoning is resonant with the ambition of the Economic Complexity literature to "describe and compare economies in a manner that eschews aggregation" (Hausmann and Hidalgo, 2011). In fact, by combining insights from the evolutionary (Dosi and Nelson, 1994; Nelson and Winter, 1982) and structuralist approaches (Hirschman, 1958; Prebisch, 1950) in economics, EC describes the economy as a dynamic process of globally interconnected ecosystems and, in a departure from standard economic views, goes beyond aggregate indicators and measures of productive inputs. It considers instead a more granular view of the productive possibilities of an economy by emphasizing the importance of the composition of export baskets for long-run growth (Cristelli et al., 2017; Hausmann et al., 2006, 2007; Tacchella et al., 2018). In particular, the methodology we propose is based on the Economic Fitness and Complexity (EFC) approach (Cristelli et al., 2013; Tacchella et al., 2012; Zaccaria et al., 2014). EFC is part of the burgeoning literature on EC and is a multidisciplinary approach to economic big data where the informational content of different types of empirical networks is maximized by using ad hoc algorithms which optimize the signal-to-noise ratio. EFC has proved highly successful in forecasting (Tacchella et al., 2018) and explaining (Sbardella, Pugliese, Zaccaria and Scaramozzino, 2018) economic growth, and has been adopted by both the World Bank[1] and the European Commission[2].

Recently, some promising attempts to draw insights from the EC literature to analyse environmental issues have been put forth, with focus on environmental products (Fankhauser et al., 2013; Hamwey et al., 2013; Mealy and Teytelboym, 2020; Pérez-Hernández et al., 2021), technologies (Barbieri et al., 2022; Ferraz et al., 2021; Napolitano et al., 2022; Perruchas et al., 2020; Santoalha and Boschma, 2021; Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018; Sbardella et al., 2022) and jobs (Santoalha et al., 2021), setting the basis for a study of the productive or technological capabilities that are relevant to the green economy. Bearing in mind the benefits and the shortcomings of using patent data for studying technological innovation and especially their limited coverage in developing economies (Arts et al., 2013; Griliches, 1998; Lanjouw et al., 1998), our empirical contribution builds on the Green Technology Fitness measure and green technology space proposed by Sbardella, Perruchas, Napolitano, Barbieri and Consoli (2018); Sbardella et al. (2022), Napolitano et al. (2022) and Barbieri et al. (2022). Moreover, our analysis is linked to studies on the coherence in firm-level patenting (Boschma et al., 2013; Breschi et al., 2003; Pugliese, Napolitano, Zaccaria and Pietronero, 2019), the product space (Hidalgo et al., 2007; Zaccaria et al., 2014), and especially to the technology-science-export multi-partite network of Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli (2019). However, with respect to the extant literature, the present work examines the not yet explored link between green patenting and industrial production and proposes a reliable methodology to assess the empirical connections between these two dimensions by employing a more solid network link statistical validation strategy.

In practice, the application of the EC toolbox that we propose allows us to construct a network linking single CCMTs, identified through the Y02 Cooperative Patent Classification (CPC) technology class (see Methods section), to single exported products, classified according to the Harmonized System (HS). This network is obtained by contracting over the geographical dimension the two bipartite networks connecting countries with comparative advantages in green technologies at time t_1 and countries with comparative advantages in exported products at time $t_2 \geq t_1$ respectively, with a time

[1] https://datacatalog.worldbank.org/search?q=economic%20fitness.

[2] https://iri.jrc.ec.europa.eu/complexity

lag between these two layers of $\Delta T \equiv t_2 - t_1$ (where ΔT could also be equal to zero). Once the co-occurrences in the same country of competitive patenting and export are identified, their statistical significance is assessed via an *ad hoc* maximum entropy null-model (Saracco et al., 2017). The final result is a green technology-product bipartite network, where each link represents the (statistically significant) conditional probability that if a generic country is proficient in a green technology τ at time t_1 , it will also be able to export competitively product π at time t_2 . Each link from a green technology to an exported product highlights the fact that they share similar underlying technological and productive capabilities, therefore indicating the existence of high probability of jumping from the green technology to the linked product. An important feature of the network is its time-dependency: the direction and magnitude of the information flow can change in time and different time lags (ΔT) between green patenting and product exports can be considered. Our findings show that green technologies are especially connected to the export of raw materials, such as mineral, metal, and chemical products. Their persistent presence and importance in our network resonate with the literature on the raw material requirements that the green transition entails (European Commission, 2020*a*; Hund et al., 2020; International Energy Agency, 2021; Romare and Dahllöf, 2017; Valero et al., 2018). In fact, materials like lithium, cobalt, indium, nickel are key inputs for several green technologies, particularly in the domain of renewable energy generation/storage and electrical mobility. Hence, to deal with the climate and environmental crisis, it is crucial to carefully take into consideration the extent to which an increase in the development of green technologies could affect mineral demand, extraction processes and environmental inequality (European Commission, 2019*a*,*b*; Sovacool, Hook, Martiskainen, Brock and Turnheim, 2020). Among the goods significantly related to green technologies we also find different products related to the export of animals and vegetables -— mainly linked to technologies for GHG capture and storage —- and machinery and electrical products -— mainly linked to CCMTs in information and communication technologies. Moreover, a key result of our analysis is that the network structure changes when switching from $\Delta T = 0$ to $\Delta T = 10$, as for $\Delta T = 10$ we register a growing presence of complex green technologies and products in the statistically validated network links, suggesting that more complex green know-how requires longer to unfold into industrial production.
By shedding light on the dynamic complementarity and interrelation between green technological development and specific production lines, our methodology identifies in a quantitative and replicable way the green footprint of each product. This might prove to be instrumental in informing policy on the potential entry points in which countries can compete in emerging green markets and on the eco-innovative domains that trickle down the most into industrial production, and accordingly in designing targeted policy interventions aimed at fostering more sustainable production practices.

1.2 Results

As mentioned above, the aim of this paper is to leverage statistically validated networks to explore the connections between green technologies and exported products, i.e. the trickle down from green technology innovation to industrial production. Each link between a green technology and a product suggests not only that being competitive in the two requires similar underlying capabilities, but also that a comparative advantage in the green technology is a good predictor for the development and successful export of the product. We compute the validated links for two different aggregations of the data on exported products, moving from a broader level of description -— consisting of 97 so-called product chapters, labeled with 2-digit codes -— to a more detailed one -— consisting of 5053 product subheadings, labeled with 6-digit codes. Moreover, we are able to assess the evolution of the green technology-product network by taking into account the effect of a time lag of 10 years between the development of green technologies and the export of the products.

1.2.1 Green technology - product connections: general remarks

In order to build the bipartite network in which green technologies are linked to exported products, we start by considering two binary networks: the first connects countries to the green technologies they patent competitively, the second connects countries to the products they export competitively. By summing over the geographical dimension we then build the so-called *Assist Matrix* (Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019; Zaccaria et al., 2014), i.e. in our case the adjacency matrix of the green technology-exported product network, in the following way:

$$A_{\tau,\pi}(t_1,t_2) = \frac{1}{u_\tau(t_1)} \sum_c \frac{M_{c\tau}(t_1) M_{c\pi}(t_2)}{d_c(t_2)}, \text{ with } \begin{cases} d_c(t_2) = \sum_{\pi'} M_{c\pi'}(t_2) \\ \\ u_\tau(t_1) = \sum_{c'} M_{c'\tau}(t_1) \end{cases} \tag{1.1}$$

where the $\mathbf{M}$ matrices define the bipartite networks where countries are linked to the green technologies or exported products in which they have a comparative advantage (see Methods section). That is, we are counting suitably normalized co-occurrences, with the normalization factors being the product diversification of country c at year t_2 $d_c(t_2)$ – i.e. the number of products included in the export basket of that specific country – and the ubiquity of the green technology τ at year t_1 $u_\tau(t_1)$ – i.e. the number of countries that are patenting in that specific technological sector. The resulting green technology-product links are then statistically validated by using the Bipartite Configuration Model (Saracco et al., 2017; Squartini and Garlaschelli, 2011). We set at 95% the minimum significance threshold with which we validate our results, as we consider this to be a reasonable compromise between the number of observed links and their robustness. The details of the validation procedure can be found in the Methods section.

Aggregated analysis

Initially here we consider simultaneous normalized co-occurrences, that is with a time lag $\Delta T \equiv t_2 - t_1 = 0$ between the two network layers. Firstly, we investigate the links between green technologies and exported products at a 2-digit aggregation level. Figure 1.1 represents the adjacency matrix of the green technology-product network at a 95% statistical significance, where we find 46 significant links in total (i.e. 46 green rectangles in the figure). This figure allows us to provide some initial qualitative insights on which green technologies and exported products are connected and which are not. As regards green technologies we note that, although not uniformly, all technology

sub-classes (see Table 1.1 for CPC Y02 code descriptions) have some links to products and are present in the network. The same cannot be said for the exported product layer: some 2-digit product sections are almost completely disconnected, including e.g. *Foodstuffs, Plastics/Rubbers, Leather* and *Textiles*, while others have a considerable amount of links. In particular, product like *Mineral fuels, Nickel, Lead, Organic* and *Inorganic chemicals* are highly connected with green technologies such as *Technologies for adaptation to climate change* (Y02A) and *CCMTs in information and communication technologies* (Y02D), indicating that a relatively high number of countries are active in both. This hints at an overlapping of the green technological know-how and the productive capabilities needed for being proficient in both, suggesting that countries that do patent in technology sub-classes as Y02A and Y02D not only are more likely to export raw material products, but also that different types of metals and chemicals are highly connected to R&D in CCMTs, and thus new sustainable avenues in their production could be explored. The topic of raw material products and a specific case study will be discussed more in detail below.
In Figure 1.2 we offer an alternative representation in which we show the directed network between green technologies and exported products, with the node size being proportional to the node degree and the thickness of the edges to the corresponding Assist Matrix entry. The network representation permits a clear distinction between the disconnected components (such as the two nodes relative to air transport in the bottom left) and the large connected component in the center. For instance, it is interesting to notice the energy-related cluster on the left portion of the plot, where green technologies aimed at improving efficiency in computing, in wire-line and wireless communication networks and in the electric power management are linked to the export of raw material products and optical and electrical products, which are important inputs for these kinds of technologies.

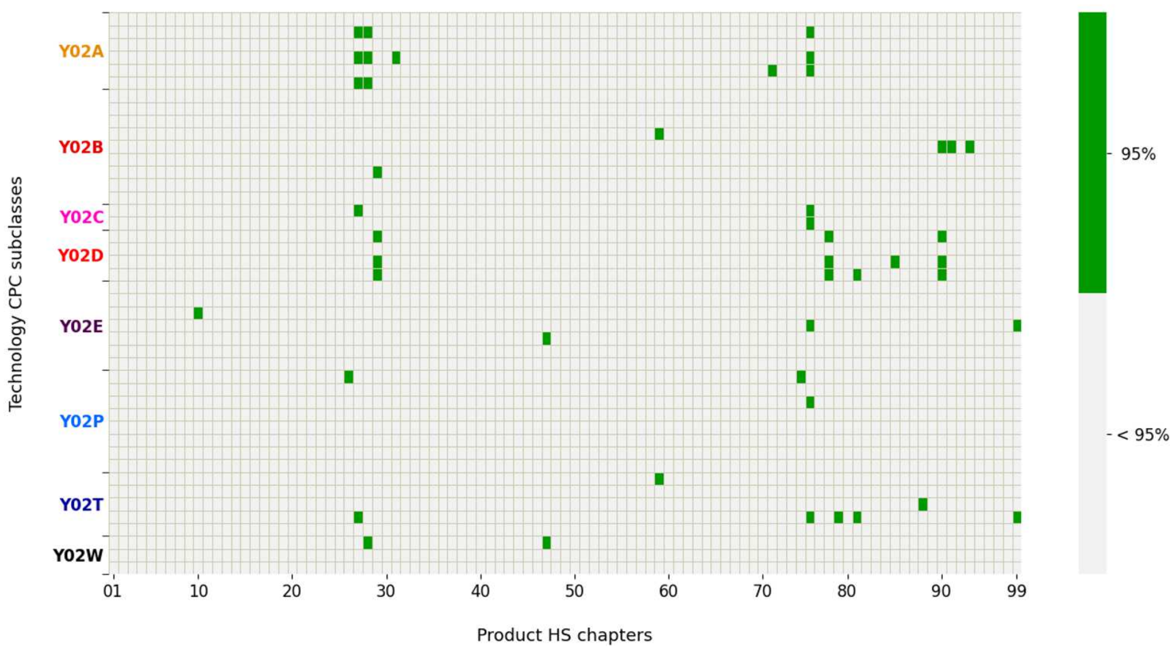


Figure 1.1: Heatmap representation of network links at 95% level of significance. Y-axis = CPC codes of green technology sub-classes; X-axis = 2-digit exported products. Each green rectangle corresponds to a link between the corresponding green technology on the y-axis and exported product on the x-axis.

Class or Sub-class	Title and description
Y02	**TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE**
Y02A	Technologies for adaptation to climate change
Y02B	Climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications, including the residential sector
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies, i.e. information and communication technologies aiming at the reduction of their own energy use
Y02E	Reduction of greenhouse gas (GHG) emissions, related to energy generation, transmission or distribution, including renewable energy, efficient combustion, biofuels, efficient transmission and distribution, energy storage, and hydrogen technology
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation, e.g. hybrid vehicles
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management

Table 1.1: CPC Y02 tagging scheme. Source: EPO (European Patenting Office, 2018). In the first column the CPC code identifying the Y02 technology sub-class is reported. The second column reports the corresponding description.

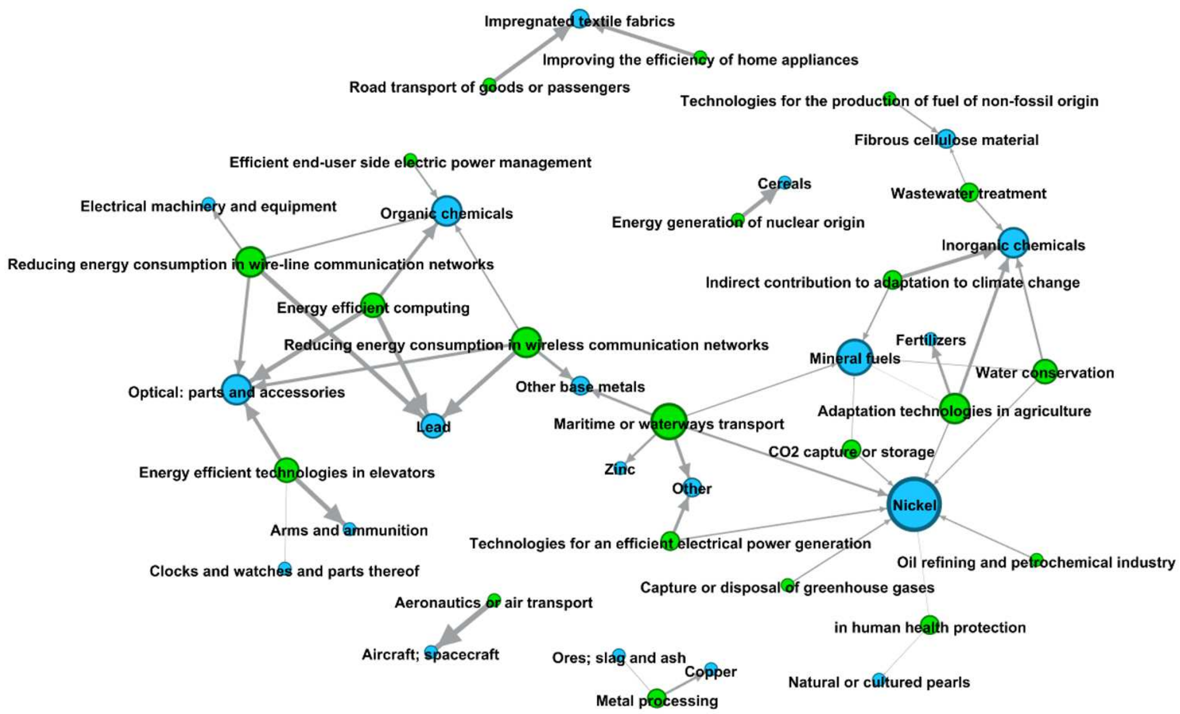


Figure 1.2: Directed network from green technologies to exported products for a time lag $\Delta T = 0$ and 2-digit product aggregation. Nodes' size depends on their degree; edges are weighted according to the value of the Assist matrix $A_{\tau\pi}$.

Fine-grained connections

We move forward into the analysis by considering the 5053 exported products present in the HS classification at 6-digit aggregation level. Increasing the level of data breakdown reveals the potential of our methodology, that can be easily applied to any level of data aggregation, and when applied to fine grained information can provide very punctual insights. Figure 1.3 represents the entire bipartite green technology-product network. The dimension of the nodes is proportional to their degree; the green ones correspond to green technologies, while all the others correspond to exported products and are coloured according to the product sections they belong to (see Table 1.2). We notice that, in line with the 2-digit product case, almost all green technologies (39 out of 44) are present in the network. This means that almost all green technologies are connected to the production of at least one product. However, depending on where the nodes are placed in the network, a green technology may be more or less integrated into the production system as a whole. More specifically, we can see that the periphery of the network is dominated by technologies related to services and transport, while the core of the network contains technologies belonging to sub-classes such as Y02A, which covers technologies for the adaption to the adverse effects of climate change in human, industrial (including agriculture and livestock) and economic activities, and Y02W, which covers CCMTs related to waste management.
In Table 1.2 we collect some descriptive information on the distribution of product nodes and edges in the network. More in detail, products belonging to primary sectors, such as animal and vegetable goods, show a large number of connections with green technologies. In particular, we observe links between different green technologies and the export of meat, fish, milling industry products and grains. All of these are largely connected with Y02A — especially with Y02A 40 - *adaptation technologies in agriculture, forestry, livestock or agroalimentary production* and Y02A 50 - *in human health protection* — and with Y02C - *Technologies for capture, storage, sequestration or disposal of GHG*. This is consistent with the high level of pollution and emissions that the agricultural and livestock sector is accountable for (Ritchie et al., 2020). Finally, consistently with the results obtained in the 2-digit product case, the subheadings belonging to minerals, chemicals and metals product sections are confirmed to be highly connected to green technologies. We elaborate on this by focusing on the export of cobalt in the following.

A case study: cobalt

An interesting product export example in our green technology-product network is that of *Cobalt and other intermediate products of cobalt metallurgy* (Harmonized System code 810520). Figure 1.4 layout highlights which technologies are significantly connected to the successful export of cobalt, with a level of confidence even above 95%. In the figure, three red concentric circles delimit the 99.9%, 99% and 95% level of significance. The blue peaks exceeding one of these circle in the figure denote that the export of cobalt is linked at the corresponding level of significance with the green technology labeled around the circular border. In particular, cobalt export is linked with *Technologies for adaptation to climate change* (Y02A), *related to transportation* (Y02T) and *waste treatment* (Y02W), *for energy generation, transmission and distribution* (Y02E), and with *CCMTs in in information and communication technologies* (Y02D) and *in the*

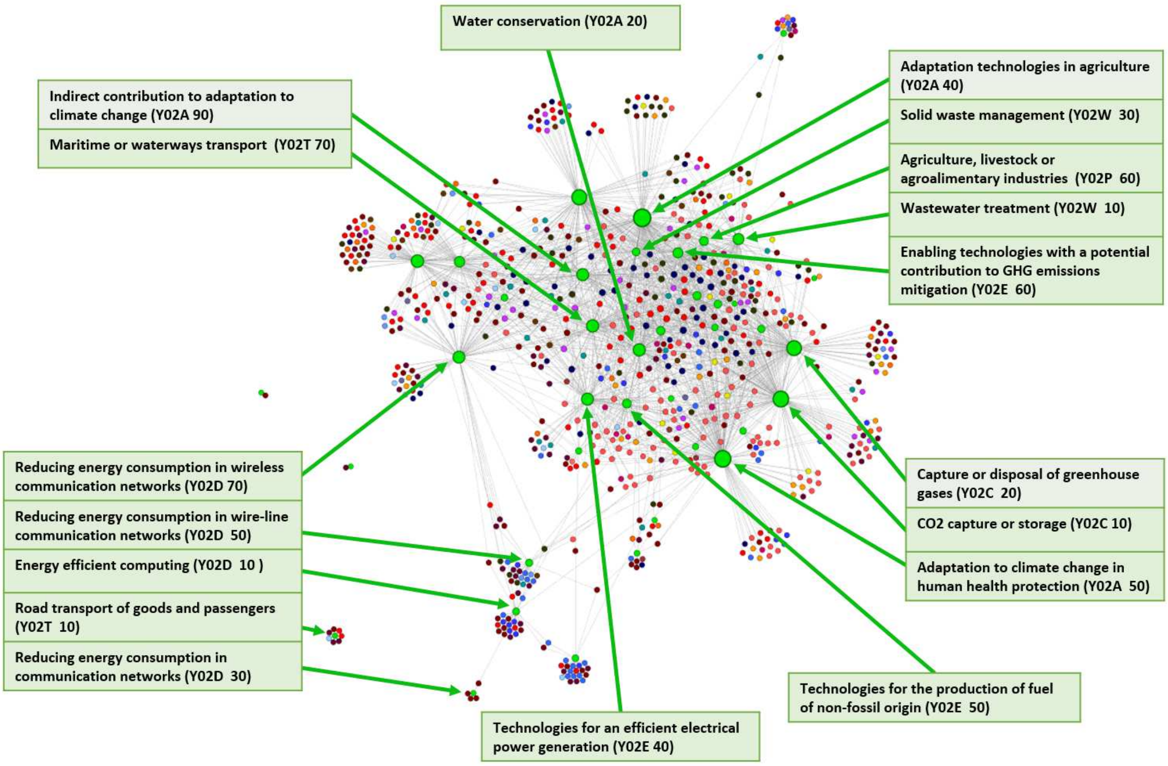


Figure 1.3: Directed network from green technologies to exported products for a time lag $\Delta T = 0$ and 6-digit products aggregation level. Nodes' size is proportional to their degree. Green nodes: green technologies with green arrows pointing to the description of some of them. All the other nodes: exported products (coloured according to Table 1.2).

Product Section	2-digit included	# of 6-digit products (%)	# of nodes in the network (%)	# of edges in the network (%)
Animal & animal products	01-05	228 (4.5%)	114 (15.6%)	424 (19.6%)
Vegetable products	06-14	256 (5.1%)	54 (7.4%)	151 (7.0%)
Fats, oils and waxes	15	45 (0.9%)	12 (1.6%)	35 (1.6%)
Foodstuffs	16-24	193 (3.8%)	30 (4.1%)	61 (2.8%)
Mineral products	25-27	148 (2.9%)	58 (8.0%)	355 (16.4%)
Chemicals & allied industries	28-38	789 (15.6%)	124 (17.0%)	295 (13.6%)
Plastics/Rubbers	39-40	211 (4.2%)	8 (1.1%)	11 (0.5%)
Leather	41-43	69 (1.4%)	14 (1.9%)	38 (1.8%)
Wood	44-46	93 (1.8%)	16 (2.2%)	42 (1.9%)
Paper	47-49	144 (2.9%)	30 (4.1%)	103 (4.8%)
Textiles	50-63	801 (15.9%)	24 (3.3%)	42 (1.9%)
Footwear/Headgear	64-67	49 (1.0%)	2 (0.3%)	2 (0.1%)
Stone/Glass	68-70	143 (2.8%)	11 (1.5%)	17 (0.8%)
Precious stones and metals	71	53 (1.1%)	24 (3.3%)	69 (3.2%)
Metals	72-83	568 (11.2%)	94 (12.9%)	326 (15.1%)
Machinery/Electrical	84-85	769 (15.2%)	58 (8.0%)	91 (4.2%)
Transportation	86-89	131 (2.6%)	17 (2.3%)	25 (1.1%)
Optical instruments	90-92	217 (4.3%)	31 (4.3%)	59 (2.7%)
Arms and ammunition	93	20 (0.4%)	4 (0.6%)	10 (0.5%)
Miscellaneous manufactured articles	94-96	118 (2.3%)	1 (0.1%)	1 (0.1%)
Works of art	97	7 (0.1%)	3 (0.4%)	6 (0.3%)
TOTAL	/	5052	729	2163

Table 1.2: Exported product sections. 1^{st} column: product section names; $2^{nd} - 3^{rd}$ columns: which 2-digit products and how many 6-digit products are included. $4^{th} - 5^{th}$ columns: number of nodes and edges in the network of Figure 1.3. The percentages between parenthesis are computed with respect to the total values reported in the final line. Note that product *999999: Commodities not specified according to kind* is not included.

production or processing of goods (Y02P).

The case of cobalt is useful to stress the consistent presence of raw materials among the exported products most linked to green technologies in our network. This is far from surprising: these materials are crucial for producing green technologies, such as photovoltaic panels, wind turbines, batteries and battery energy storage systems, etcetera; indeed, an emerging literature on the topic has made different attempts to estimate the mineral intensity of green technologies and to forecast how their proliferation will shape mineral demand in the years to come (Golroudbary et al., 2019; Herrington, 2021; International Energy Agency, 2021; Karali and Shah, 2022; Romare and Dahllöf, 2017; Valero et al., 2018). In particular, cobalt is considered a high-impact mineral for the sustainable transition and to meet expected future demand its production will need to increase up to nearly 500% of 2018 levels by 2050 (Hund et al., 2020). Cobalt is a key element in energy storage technologies, which for instance are used in the automotive sector to power electric vehicles and are needed to store energy from intermittent renewable sources, such as photovoltaic panels and wind turbines. Given that 64% of global cobalt supply comes from the Democratic Republic of Congo (European Commission, 2018*b*), the risks associated with meeting its demand -—- which will rise if certain climate targets are to be met —– and the cross-cutting way in which it is used in green technologies, have led to cobalt being placed on the European Commission's list of critical raw materials (CRMs) (European Commission, 2020*a*), which includes materials considered critical for their supply risk and economic importance. The list is updated every three years, and cobalt features in it since its first version published in 2011 (European Commission, 2011). It is worth noticing that REGPAT, the patenting dataset we employ, does not cover the Democratic Republic of Congo. However, even if cobalt main world supplier is missing, we still observe many connections between cobalt and cobalt metallurgy products and green technologies. In particular, these connections arise from the co-occurrences of several green technologies and cobalt product exports in countries like Australia, Belgium, Canada, Finland, Norway, Russia and South Africa, which are all important producers of raw and refined cobalt (Idoine et al., 2022; Sovacool, Hook, Martiskainen, Brock and Turnheim, 2020).

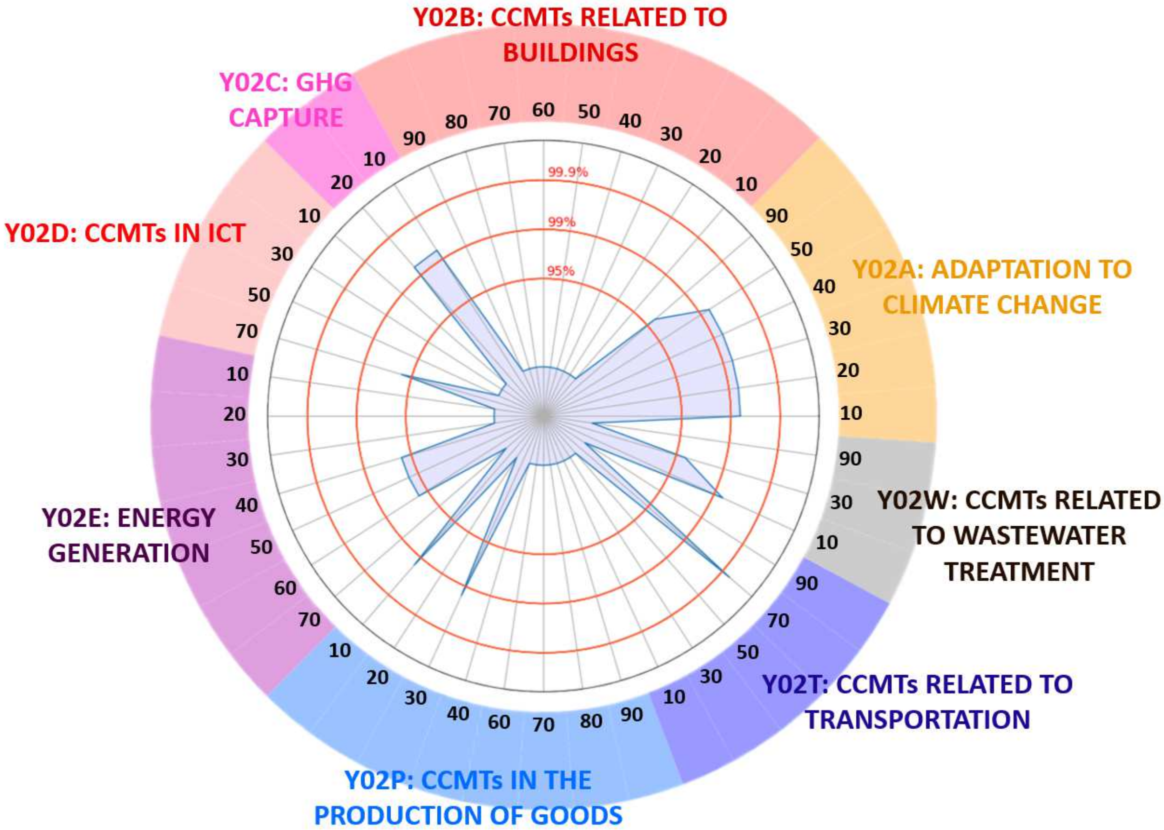


Figure 1.4: Focus on the export of *Cobalt and other intermediate products of cobalt metallurgy* (Harmonized System code 810520). Along the circular border of the figure, the CPC codes of the 44 green technology groups are labelled. Within the figure, three concentric circles delimit the significance levels of 99.9%, 99% and 95% respectively. Each peak in blue that exceeds the level delimited by one of the inner circles corresponds to a link that cobalt has with the green technology described in the border.

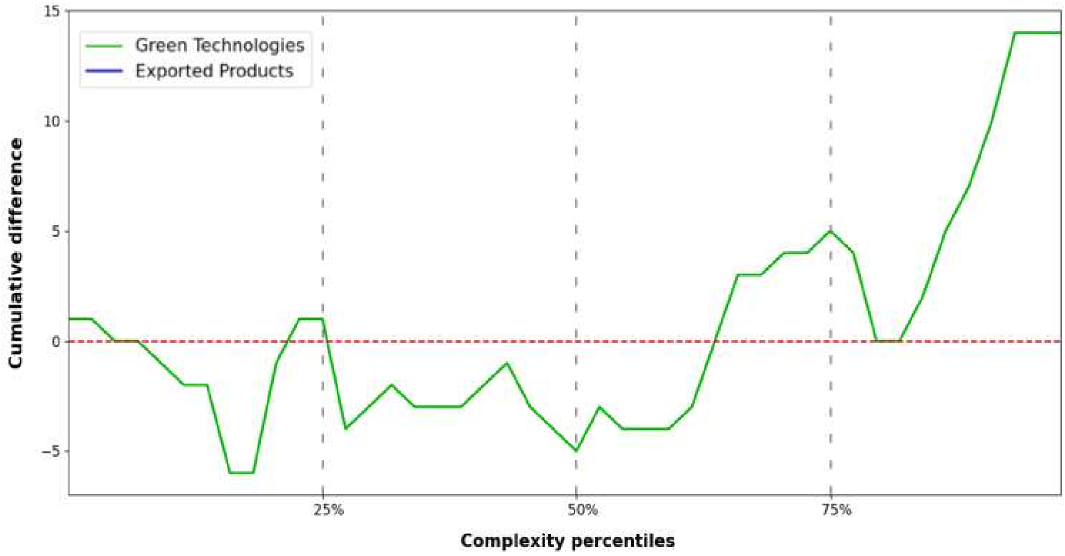
1.2.2 Connections in a 10 year horizon

With the aim of analysing whether the spectrum of green technologies needed to gain a comparative advantage in a variety of productive sectors changes over time, here we explore how the links between green technologies and exported products change, both in qualitative and quantitative terms, moving from a time lag between the green technology and exported product layers of $\Delta T \equiv t_2 - t_1 = 0$ to $\Delta T = 10$. In fact, our analysis can be conducted also by considering different values of ΔT allowing for a dynamic perspective on the green technology–production nexus.
When considering $\Delta T = 10$ from a quantitative point of view we observe a slight increase in the total number of links, both in the case of 2-digit and 6-digit products (from

46 to 60 links in the case of 2-digit products and from 2166 to 2354 links in the 6-digit case). This finding is coherent with the results presented in Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli (2019), in which the authors show that technological advancements on average anticipate export. The increase of roughly 10% of the resulting links suggests that green technologies are better integrated into the production process after a ten years digestion.
Regarding possible differences in the properties of the linked technologies and products for both time lags, in Figure 1.5 we plot the cumulative increment in the number of links for both green technologies and exported products. In particular, in the x-axis of the two plots we rank green technologies (top panel) and exported products (bottom panel) by increasing complexity, which is computed through the implementation of the Economic Fitness & Complexity (EFC) algorithm15 (see section A.3 in the Appendix). The green/blue line in the figures plots the cumulative difference between the number of links that each activity shows for $\Delta T = 10$ and $\Delta T = 0$ — in formula: $y_i = \sum_{j=lastranked}^{i^{th}ranked} n_j(\Delta T = 10) - n_j(\Delta T = 0)$, where y_i is the value corresponding to the i^{th} ranked green technology/product and $n_j(\Delta T)$ refers to the significant number of links that the j^{th} ranked green technology/product has at the corresponding ΔT. What emerges from the two plot layouts is significant: the new links that appear when the time lag is increased are relative to more complex products as well as to more complex green technologies. For example, we observe an increase in the number of significant links with high complexity products such as those related to the Machinery/Electrical and the Optical instruments sections and with complex climate change mitigation technologies in the following subclasses: Y02D 10 - *Energy efficient computing*, Y02D 70 - *Reducing energy consumption in wireless communication networks*, Y02T 30 - *Transportation of goods or passengers via railways* and Y02T 50 - *Aeronautics or air transport*. Therefore, it is likely that more complex potential spillover effects in industrial production deriving from the development of a green technology will manifest themselves at a later stage over time. This is in line with the idea that more complex green technological know-how requires more time to be transmitted to the productive sectors. Moreover, this finding is in agreement with Barbieri, Marzucchi and Rizzo (2020) and Barbieri, Perruchas and Consoli (2020) that study the relationship between green and non-green knowledge bases and argue that green technologies are generally complex and have a heterogeneous development process, involving different domains of know-how.

1.3 Discussion

To address the climate crisis it will be essential to change the way economies have grown and developed (European Commission, 2019*a*). Within this context, the development of eco-innovations aimed at reducing GHG emissions and their diffusion within global value chains can make important contributions towards decarbonization. However, it is important not to disregard the intrinsic limits of a "big technological fix" (Parkinson, 2010; Sarewitz and Nelson, 2008) and to be aware that science and technology can indeed provide effective tools to tackle the climate change, but they will be the more effective the more they will be accompanied by a project of radical transformation of current production and development models (European Commission, 2018*a*, 2019*b*).
Our work might provide valuable insights on understanding possible future scenarios resulting from the development of green technologies and on how trade may act as a



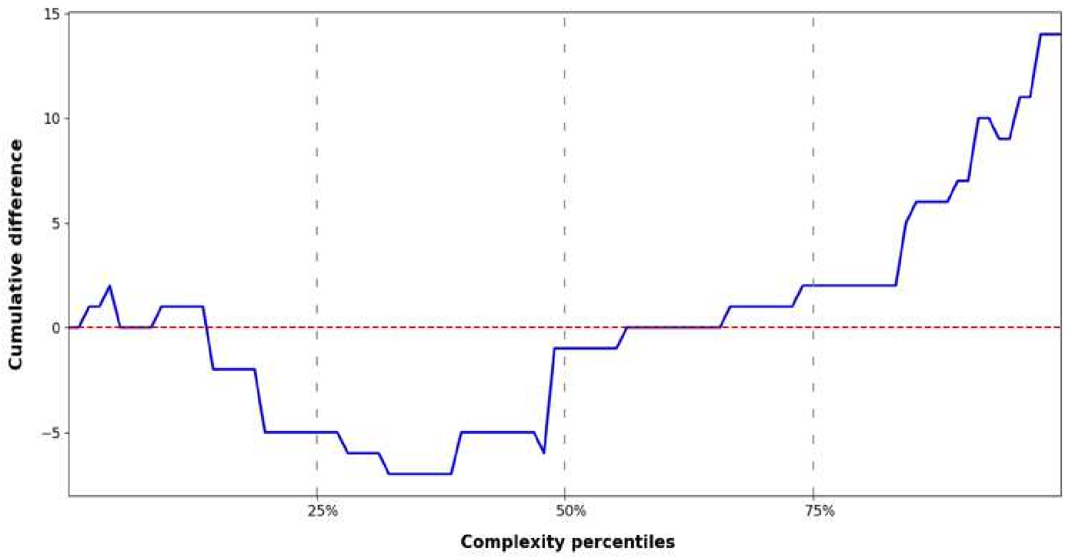


Figure 1.5: Cumulative difference between the number of node links for the time lag $\Delta T = 10$ and $\Delta T = 0$. The top panel refers to green technologies (green line), while the bottom panel (blue line) refers to the 2-digit exported products. In their respective panel, green technologies and exported products are sorted in order of increasing complexity ranking. The x-axis labels 25%, 50% and 75% delimit the first, second and third quartiles of the complexity ranking (moving from the last to the first position). If the y-value is below/above 0 (dashed red line), then the cumulative number of links delimited by the corresponding green technology or product in the x-axis is higher for $\Delta T = 0/\Delta T = 10$.

channel for green technology diffusion. To this end, we propose a novel application of the Economic Complexity framework and construct a network that links green technologies to exported products —– at a given statistical significance, time lag, and at any CPC and HS classification aggregation level — enabling us to investigate on a case-by-case basis how green technological know-how is transmitted, even years later, into industrial production. Our empirical analysis yields two main findings. When observing simultaneous co-occurrences between comparative advantages in green technologies and exported products, we emphasise a strong association between green technologies and the export of raw materials, especially mineral and metal products. In addition, we provide evidence on a relevant number of significant connections between products belonging to the agricultural and livestock sector, among the globally highest pollutant industries (Ritchie et al., 2020), such as *Animal & Animal products*, and green technologies aimed at GHG emissions capture and storage. Whereas, when considering time-lagged co-occurrences, for $\Delta T = 10$ we register a larger presence of significant links involving more complex green technologies and products (where complexity is assessed via the Economic Fitness & Complexity algorithm applied separately to products and green patents), such as green technologies related to transportation or used in ICTs, and machinery/electrical or optical instruments products. This suggests that the process that can lead to the development of the joint capabilities required for the development of complex green technologies and the competitive production of high-tech products is not instantaneous and may require years to unfold.

By emphasizing the heterogeneous, disaggregated effects that individual CCMT patents can have on the production and trade of single goods, our multi-level analysis may bear relevance to the green transition policy context. Our findings may provide support for short- and medium-term industrial policies by allowing to target, with high level of detail, green technologies that are more likely to leave larger footprints in industrial production or mitigate the impact of polluting industries on the basis of each country's green technological capabilities. Accounting for differentiated effects also over time through the dynamic observation of the green technology-product network, our approach might be of help in uncovering the time window required by more complex green technological know-how to be transmitted into production, and thus in designing policies acting on different time horizons. Furthermore, since monitoring the trade of environmental goods is a central objective on the global policy agenda (Sauvage, 2014; WTO, 2001), by identifying green footprints in products, our work might contribute to classifying environmental products. In fact, whilst the introduction in the Harmonized System of several 6-digit subheadings including new environmental goods was announced (Steenblik, 2020) in 2020, the updated classification is not yet available, and currently a clear-cut identification of environmental goods within existing product classifications constitutes a difficult task —– as for instance it is impossible to distinguish between combustion engine and electrical cars.

With respect to the Economic Complexity literature that focuses on various aspects of the green economy, this work introduces different elements of novelty. In fact, previous works analyse green technologies and industrial production separately, either without exploring the connections between green patents and exported products or by analysing it ex-post (Fankhauser et al., 2013; Mealy and Teytelboym, 2020; Pérez-Hernández et al., 2021; Santoalha and Boschma, 2021; Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018). Moreover, extant research (Hamwey et al., 2013; Mealy and Teytelboym, 2020; Montresor and Quatraro, 2020; Santoalha and Boschma, 2021; Pérez-Hernández et al., 2021) proposes a number of versions of the green product or technology space, however without considering any dynamic element, as well as without using any validation strategy of network links and thus possibly considering spurious associations, that fail to account for the ubiquity of products/technologies and the diversification of countries, as we are instead able to do in this contribution.

This paper opens up different possibilities of extension of our empirical framework that might contribute to broadening our understanding of the complex interactions that the path towards the sustainability transition entails. First, we believe it would be of interest to explore the interplay of green technological and productive capabilities with other important dimensions of human activity, in particular by looking at the relationship between green technology development, industrial production and (1) the labour market (including e.g. data on employment and wages at sectoral and occupational levels); (2) the scientific production of countries through academic publication data (Patelli et al., 2017). Second, if new data will become available, analysing longer time spans might increase the observed signal (Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019), thus helping to better characterise the structural relationships that link green technologies to production. Third, by geolocalising the co-occurrences that we have identified, we plan to define a measure of green technology-product relatedness that might shed light on the green footprints in the specialisation profiles of each country or region. Finally, as mentioned above, our findings call attention to the strong connection between the development of green technologies and the trade of metals and minerals they require to be successfully realized and deployed. The critical raw materials intensity of these technologies is a core issue in the policy debate (European Commission, 2011; Hund et al., 2020; International Energy Agency, 2021): CRM extraction contributes importantly to GHG emissions (Azadi et al., 2020; Norgate and Haque, 2010; Romare and Dahllöf, 2017), with the risk of thwarting the efforts towards the promotion of less polluting energy sources by shifting emissions upstream in the energy generation process and increasingly relocating environmental negative externalities in the Global South (Karali and Shah, 2022; Okafor-Yarwood and Adewumi, 2020; Sovacool, Hook, Martiskainen, Brock and Turnheim, 2020). Accordingly, future research should delve deeper into such CRM dependency. Our next project points in this direction and aims at mapping mineral and metal inputs in green technologies through keyword search on patent texts. On a larger scale, we believe it would be of paramount importance to direct future research and policy towards preserving the stability of the raw materials value chain by limiting the supply dependence on and the over exploitation of specific areas, as well as promoting recycling practices, more transparent and fairer raw material extraction activities, while also fostering the development of eco-innovations less dependent on critical raw materials.

1.4 Methods

1.4.1 Data

We use data on patent applications in environment-related domains as a proxy for environment-related innovation, and data on exported products as a proxy for production (Saltarelli et al., 2020). Both datasets consist of single data collections recorded annually at a country level. We use information on patent applications on 44 green technological fields —– corresponding to the Coperative Patent Classification groups listed in Table A.2 in the Appendix — for 48 countries between 1995 and 2019; and on product exports —– classified according to the Harmonized System and whose number depends on the level of aggregation considered: 97 in the 2-digit case, 5053 in the 6-digit one —– measured in US dollars for 169 countries between 2007 and 2017. As explained more in detail in the next section, our methodology requires selecting the countries in common between the two data collections, which turn out to be 47. All data can be represented as matrices: we denote by $\mathbf{W}(t)$ and $\mathbf{V}(t)$ the matrices corresponding respectively to the data on green patents and exported products in year t. Each matrix has a number of rows and columns equal to the number of countries c and activities a respectively, where the latter refer to either green technologies τ and exported products π. A more comprehensive description of the two datasets we use, including also a list of all countries at our disposal, is reported in section A.1 in the Appendix.

1.4.2 Data preprocessing

Temporal aggregation

The information on both exported products and the patented inventions is collected yearly; it is then possible to investigate the connections at different time scales. While annual data can offer more detailed results, i.e. distinct for each year considered, it may also supply them with more noise. In fact, data can fluctuate significantly from one year to another. In order to minimize the possibility that the detected green technology-product connections are the result of data fluctuations, we consider the total volume of products and patents produced in given time intervals. For our analysis, we compute the matrices $\mathbf{W}(\delta, t)$ and $\mathbf{V}(\delta, t)$, corresponding to the time interval of δ years ending in the year t. To this aim, we sum the yearly matrices $\mathbf{V}(t)$ and $\mathbf{W}(t)$ over δ:

$$\begin{aligned} \mathbf{V}(\delta, t) &= \sum_{t'=t-\delta+1}^{t} \mathbf{V}(t') \\ \mathbf{W}(\delta, t) &= \sum_{t'=t-\delta+1}^{t} \mathbf{W}(t') \end{aligned} \tag{1.2}$$

Summing data over a time window of δ years reduces the noise in our results, giving more weight to patents and exports that are consistently registered several times in nearby years. Given the years present in the employed datasets, we sum the matrices over 5 years ($\delta = 5$). Starting from the layer of exported products, we select the two most recent 5-year aggregate matrices available to us, with the condition that the years included in the two sets are not overlapping. Therefore, the two resulting matrices are $\mathbf{V}(\delta, t) = \{\mathbf{V}(5, 2012); \mathbf{V}(5, 2017)\}$. Next, depending on which time lag ΔT we consider between the two layers, we select the green patents matrices. Thus, for the time lag $\Delta T = 0$, the corresponding matrices are $\mathbf{W}(\delta, t) = \{\mathbf{W}(5, 2012); \mathbf{W}(5, 2017)\}$, while for$\Delta T = 10$, when we consider green patenting as a "predecessor" of exporting, they are $\mathbf{W}(\delta, t) = \{\mathbf{W}(5, 2002); \mathbf{W}(5, 2007)\}$. To simplify the notation, hereinafter we omit the δ dependency of the data matrices, however all our results are produced from the analysis of the aggregated 5-year data collections mentioned above. Choosing the most recent time frame available in the data allows us to obtain more relevant implications from our work. However, to avoid any possible bias due to our choice of time window, we have conducted different robustness checks on the network links using both different aggregation time intervals δ and final year t, and we have concluded that the green technology-product links we find are robust to such changes in the parameters. These tests can be found in section A.4 in the Appendix.

Revealed Comparative Advantage

Both exports and patents' matrices strongly depend on the total size of the economy or sector. In order to remove this size correlation, we compute Balassa's Revealed Comparative Advantage (RCA) (Balassa, 1965) of both activities. The RCA is computed as the ratio between the weight of activity a (be it a patent in a technology field τ or the export of a product π) in the portfolio of country c and the weight of that same activity with respect to the world volume, as reported in the following equation:

$$RCA_{ca} = \frac{\frac{X_{ca}}{\sum_{a'} X_{ca}}}{\frac{\sum_{c'} X_{c'a}}{\sum_{c'a'} X_{c'a'}}} \tag{1.3}$$

Where the element X_{ca} refers to both $W_{c\tau}$ and $V_{c\pi}$, i.e. the elements of the country-green technology and country-exported product matrices (for a more detail description on how the matrices are built, we refer to the Appendix section A.4). The next step is the computation of the binary matrices $\mathbf{M} = \mathbf{M}_{ca} = \{\mathbf{M}_{c\tau}; \mathbf{M}_{c\pi}\}$, whose elements are set to 1 if the value of $RCA_{ca} \geq 1$ and to 0 otherwise, i.e. when that country c is not competitive in activity a. The RCA metric is frequently used in the Economic Complexity framework to assess whether a country is a significant exporter of a product (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009). The extension of its use to the patent layer (Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019) allows us to compare patent and export data in a coherent way as presented in the following sections.

1.4.3 Construction of the validated network

Full technology-product network

Starting from the binary matrices $\mathbf{M}$ described above, that summarise the comparative advantages in the products and technologies of different countries, a network linking green technologies to products can be derived. The method adopted here has been widely exploited in the Economic Complexity framework (Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019): the idea is to count how many countries have competitively developed a given green technology at time t_1 and are also competitive in the export of a product at time t_2. This number thus quantifies the empirical green technology-product co-occurrences (Teece et al., 1994). In practice, however, the co-occurrences should be suitably normalized to take into account the nested structure of the bipartite networks: countries with high diversification d_c and technologies with high ubiquity u_τ provide less information and for this reason the weight of the corresponding co-occurrences is lowered. The result of this normalization is called Assist Matrix

(Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019; Zaccaria et al., 2014). The co-occurrences can be obtained from the contraction of the binary country-technology and country-product matrices. The assist matrix element $A_{\tau\pi}$ depends on both the year t_1 relative to the patenting of the technology τ and the year t_2 of the subsequent export of product π. In formula:

$$A_{\tau\pi}(t_1, t_2) = \frac{1}{u_\tau(t_1)} \sum_c \frac{M_{c\tau}(t_1) M_{c\pi}(t_2)}{d_c(t_2)}, \text{ with } \begin{cases} d_c(t_2) = \sum_{\pi'} M_{c\pi'}(t_2) \\ \\ u_\tau(t_1) = \sum_{c'} M_{c'\tau}(t_1) \end{cases} \tag{1.4}$$

By counting the co-occurrences between green technologies and exported products –— while weighing them with the degree (or ubiquity) of the green technology u_τ and the country degree (or diversification) in the exports d_c —– each element of the matrix $A_{\tau\pi}(t_1, t_2)$ provides a quantitative measure of how likely is to have a comparative advantage in exporting product π in year t_2, conditional on having a comparative advantage in green technology τ in year t_1. Therefore, t_1 and t_2 indicate that in the formula it is considered the possibility that the link couples patents developed in a given year with products exported in a different year. Finally, it is important to notice that while a statistically significant link between a green technological class and a product is established on the basis of the empirical conditional probability that having a comparative advantage in the green technology will lead to a comparative advantage the export of a specific product, we are in no way arguing that there is a causal relationship that links green patenting to subsequent product export. After the computation of the Assist Matrix, we statistically validate the empirical results expressed by each node $A_{\tau\pi}(t_1, t_2)$ through the implementation of a null model which we present in the following section.

Statistical validation of the network using a null model

The matrix elements computed in Equation (1.4) need to be validated by a statistical test able to distinguish meaningful links from noise and to supply a confidence level for assessing the probability that two nodes share a statistically significant number of co-occurrences. In particular, here we rely on the filtering procedure, based on the Bipartite Configuration Model (BiCM) (Squartini and Garlaschelli, 2011), developed by Saracco et al. (2017) for the projection of bipartite networks into monopartite networks, and subsequently adapted to a multi-partite setting by Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli (2019). It must be however noted that no absolute criteria exists for the choice of the model, and that different null models can yield different outcomes (Cimini et al., 2022). Here, we use a null model for the binary matrices $\mathbf{M}$, in which the matrices are randomised except for some constraints we impose (Saracco et al., 2015) —– in this case the average degrees of the nodes. The use of BiCM allows for a stricter filtering procedure with respect to other null models (Cimini et al., 2022) and correctly takes into account the possible noise present in the input data (Cimini et al., 2022; Saracco et al., 2015, 2017). This class of models is based on the maximum entropy principle (Jaynes, 1957), which leads to the realisation of an ensemble Ω of bipartite networks $\tilde{\mathbf{M}}$, where links are random but maximize the number of possible configurations which satisfy the imposed constraints. In the present case the entropy function:

$$S = -\sum_{\tilde{M} \in \Omega} P(\tilde{M}) \ln P(\tilde{M}) \tag{1.5}$$

is maximized under the constraint that the ensemble averages $\langle \dots \rangle_\Omega$ of the ubiquity of activities a (i.e. of green technologies τ and exported products π) and of countries diversification of the random networks, $\tilde{u}_a(t)$ and $\tilde{d}_c(t)$ respectively, must be equal the observed ones (labeled without the tilde symbol):

$$\begin{aligned} \langle \tilde{d}_c(t) \rangle_\Omega &= d_c(t) \\ \langle \tilde{u}_a(t) \rangle_\Omega &= u_a(t) \end{aligned} \tag{1.6}$$

Hence, these networks are random but preserve the information present in the empirical degrees.
The maximization procedure yields a probability distribution for each possible pair of country-activity nodes to be linked. Then, we use them to perform a direct sampling of the ensemble Ω. The ensemble is composed of a number of realisations of the null model; the number of realizations is established by considering the p-value threshold with which we choose to validate the links in the technology-product network. In particular, since our results are mostly set to a statistical significance of 95%, we construct ensembles consisting of 10000 realisations of the null model. In such a way, a rough but conservative estimate yields a sampling error of 5 ‰. For each pair of null model realizations $\{\tilde{M}_{c\tau}(t_1); \tilde{M}_{c\pi}(t_2)\}$ related to the green technology and exported product layers, we compute the corresponding null Assist Matrix of element $\tilde{A}_{\tau\pi}(t_1, t_2)$ through a contraction as in Equation (1.4) and therefore build an ensemble of 10000 realizations of null Assist matrices. Finally, for each possible green technology-product τ-π link we compare the empirical value $A_{\tau\pi}(t_1, t_2)$ with the 10000 null values of that same link. We are thus able to assess the statistical significance of our results: for example, if we want to select 95% significant links, we consider only those links with the empirical value higher than the corresponding null ones in at least 9500 cases out of 10000.

Validation of the results for a specific time lag

As already stressed, our methodology allows us to build different networks linking green technologies to exported products by varying the temporal dimension. We express the time dependence of the analysis through the time lag ΔT, the difference between the year t_2 of the country-product matrix and the year t_1 of the country-green technology matrix. Given the years present in the two data collections we employ, in our analysis we consider two time lags: $\Delta T = 0$ and $\Delta T = 10$. We recall that our matrices refer to sums over 5-year intervals. To each of the two considered time lags we associate two different pairs of 5-year aggregate technology-product matrices: $\mathbf{W}(2012) - \mathbf{V}(2012)$ and $\mathbf{W}(2017) - \mathbf{V}(2017)$ for $\Delta T = 0$; $\mathbf{W}(2002) - \mathbf{V}(2012)$ and $\mathbf{W}(2007) - \mathbf{V}(2017)$ for $\Delta T = 10$, where, by following Equation(1.2), the number in parenthesis represents the last year in the five year interval. For each pair of matrices we follow all the steps described above —– i.e., RCA and Assist Matrix computation, and statistical validation of the links through the null model at a selected p-value —– and we consider only the links that are statistical significant in both of them. For instance, the links represented in Figure 1.2 are those that show 95% statistical significance in both the networks obtained from $\mathbf{W}(2012) - \mathbf{V}(2012)$ and $\mathbf{W}(2017) - \mathbf{V}(2017)$. Therefore, we consider two levels of significance to validate our results. The first is the assessment of the links' statistical significance through the null model that allows us to assign a confidence interval within which we exclude that the links are solely the result of noise. The second is the condition according to which we only consider links validated at a certain statistical threshold in both the pairs of green technology-product matrices for the selected ΔT: we believe this to be an important step for arguing that the know-how of a specific technology is transmitted to a product immediately or requires a time lag of 10 years, regardless of the specific years we are considering. Finally, it provides additional robustness to the analysis of our network beyond the adoption of the null model.

Chapter 2

The Critical Raw Materials content of Innovation

Part of this chapter is based on de Cunzo et al. (2023).

Abstract

This paper presents an empirical investigation in patents to assess the dependence from Critical Raw Materials (CRMs) in green and non-green technologies. By employing text mining techniques on patent descriptions, we are able to detect the presence of CRMs in green and non-green innovations. Overall, green technologies exhibit higher reliance on CRMs, and particularly on materials like silicon, aluminium, lithium, and copper. However, a closer examination of the most CRMs-dependent technological domains unveils similarities between green and non-green technologies, despite the evident gap in the overall dependency. In the broader context of the eco-sustainable transition of economies, which largely depends on the extensive adoption of environmental innovations, this paper serves as a preliminary descriptive analysis of the raw material dependence of technological domains.

Keywords: *Critical Raw Materials; Text Mining; Patents*

2.1 Introduction

Numerous studies have identified the widespread adoption of environmental innovations, also referred to as green and sustainable technologies or eco-innovations, as a crucial step in reducing greenhouse gas (GHG) emissions and, consequently, mitigating the impact of climate change (OECD, 2011; Stern, 2007). As a result, significant attention has been devoted to studying these technologies, focusing e.g. on the examination of their distinguishing characteristics, also in comparison to conventional innovations (Barbieri, Marzucchi and Rizzo, 2020; Barbieri, Perruchas and Consoli, 2020; Perruchas et al., 2020), and on the role of policies for their implementation (Johnstone et al., 2012; Popp et al., 2010), always taking into account the different levels of national and regional expertise on environmental technologies (Barbieri et al., 2022; Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018). In this paper, we will delve further into the implications of green innovation within the broader context of the sustainable transition. In particular, our main focus will be on the raw material requirements of green technologies (Herrington, 2021). Keeping in the background the underlying limitations of a "technological fix" to climate change (Sarewitz and Nelson, 2008), our exploration will extend to potential economic and social implications stemming from an extensive adoption of green technologies.

In order to discuss environmental innovations, we should start from the general concept of innovation. In particular, innovation can be defined as the introduction of novelty in the economic realm. Therefore, the implementation of a new good, service or methodology in the production process of a certain product, the adoption of a new managerial practice in a firm, or a new marketing method, are all examples of innovation. When we move to environmental innovation, it is not immediate to come up with its definition. Following Kemp and Pearson (2007), environmental innovations can be defined in a very general way as *"the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives"*. Therefore, within the scope of this comprehensive definition, all innovations that result in positive environmental effects when compared to their alternatives are included, regardless of whether they were explicitly designed for having such effects.

Given the importance and urgency of cutting GHG emissions, particular focus has been given to climate change mitigation technologies (CCMT). In particular, climate change mitigation refers to efforts to reduce or prevent emission of greenhouse gases. According to the United Nations Environment Programme (UNEP) *"Mitigation can mean using new technologies and renewable energies, making older equipment more energy efficient, or changing consumer behavior"*[1]. However, facing climate change is not only, or at least not anymore, about mitigating its negative effects to human life and wellbeing by reducing emissions. In fact, certain impacts such as temperature increases, extreme weather events, and deforestation leading to soil degradation, are already being experienced in numerous regions across the globe. Therefore, adaptation actions should enter the picture too. In practice, adaptation is the response available for the impacts of climate change that will occur in the next decades before the mitigation will have

[1] see https://www.unep.org/explore-topics/climate-action/what-we-do/mitigation

some effect (Stern, 2007). Adaptation measures could both happen naturally at the individual level as a response to environmental changes and pushed by the government and the public sector.

Either way, environmental technologies have a pivotal role towards the adoption of both mitigation — through e.g. renewable energy technologies such as solar panels and wind turbines, and batteries — and adaptation — through e.g. instruments to improve the air quality or to monitor and control water pollution —- practices, and for these reasons numerous studies have outlined their key attributes. First of all, green technologies have a certain degree of heterogeneity, and should not be considered as a single homogeneous block. Several studies have grasped this heterogeneity aspect, focusing on different properties of green innovations, also comparing them with respect to non-green ones. In fact, while green and non-green technologies may compete between them — for e.g. financial resources or human capital — they also exhibit complementarities: in particular, the development of green green technologies relies on advances in specific non-green technology domains (Barbieri et al., 2022, 2023). In Barbieri, Marzucchi and Rizzo (2020) green and non-green technologies are investigated and compared adopting ex-ante and ex-post perspectives: with the former it is possible to explore the nature of technologies by focusing on the knowledge recombination process that leads to the invention, while with the latter it is possible to investigate the impact of innovations on subsequent inventive activities. The results suggests that green technologies appear to be more complex and novel in terms of the composition of their know-how compared to non-green ones. In addition, they generate more knowledge spillovers, thus having a stronger impact on subsequent innovations. The variety and complexity knowledge inputs of green technologies resonate with the fact that they are innovations relatively at the early stage of their life cycle, whose development is positively correlated with local knowledge base that is diversified across unrelated innovative fields, as discussed in Barbieri, Perruchas and Consoli (2020). Another important aspect is related to policies, which are fundamental in promoting green technology adoption (Barbieri et al., 2016; Popp et al., 2010). In fact, in the absence of proper environmental policies, firms have almost no incentive to install or further develop environmental innovations. This is mainly due to the fact that both the environmental and knowledge benefits arising from green technologies adoption are not exclusively experienced by the economic actor (firm, country) that invested in them. Policies should not be limited at increasing upstream R&D expenditures; rather, they should be shaped according to the main features of green technologies and of the knowledge base of countries that adopt them. In fact, as discussed in Perruchas et al. (2020), countries tend to diversify and specialise into technological domains that are close to their existing knowledge base. Moreover, the level of green technological capabilities substantially differs across geographical areas, due to the combination of multiple factors such as their income level or their openness to trade (Barbieri et al., 2022; Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018). Adding to this picture the increased urgency of climate mitigation in emerging countries (Bathiany et al., 2018), where technological development often lags behind, it is important that tailored policies are crafted for each country, taking into account both its specific knowledge base and climate needs.

What provided so far demonstrates how the predominant emphasis in innovation studies has been on the exploration and analysis of the benefits stemming from the development of eco-innovations, as well as on the design of appropriate policies to promote for their widespread use (Barbieri et al., 2016; Popp et al., 2010). Comparatively, less attention has been given to potential drawbacks. Indeed, most of the existing literature tends to focus on discussing the gains arising from green technology adoption, overlooking aspects that could lead to negative side effects and undermine the mitigation and adaptation purposes of such technologies. One particular instance in this sense regards the dependency of green technologies on a specific set of minerals and metals, to which we refer as Critical Raw Materials (CRMs). These materials are essential components in the realisation of several eco-innovations. Therefore, due to the huge increase in the uptake of green technologies expected in the coming years, the demand for CRMs will certainly escalate. Combining this with the absence of relevant alternatives on the one hand, and with supply risks due to scarcity or geopolitical reasons on the other, has thrust the issue of CRMs into the forefront of countries' political agendas (European Commission, 2020*a*; Hund et al., 2020; International Energy Agency, 2021). Accordingly, in the last years several studies have been conducted on CRMs issues, focusing on e.g assessing their future supply risks (Grandell et al., 2016; Valero et al., 2018), and shaping their presence in technological domains (Diemer et al., 2022; Yunxiong Li et al., 2024).

Following this line, we propose an empirical investigation aimed at identifying and quantifying the presence of CRMs in green technologies, while comparing their utilisation in non-green counterparts. We address the following research questions:

1. Which CRMs are most present in green technologies?

2. Is the dependence on CRMs different between green and non-green technologies?

3. Which are the most CRMs dependent green and non-green technological areas?

With the first question we aim at giving a detailed empirical characterisation of CRMs in green technologies. The second and third questions take inspiration from the above mentioned studies where green and non-green innovations are compared (Barbieri, Marzucchi and Rizzo, 2020; Barbieri, Perruchas and Consoli, 2020). In particular, we will explore their differences and similarities both looking at which CRMs they rely the most and at which the most material intensive technological domains.

In what follows, in Section 2.2 - Using patents to measure innovation we provide an overview of the use of patents as a proxy for green and non-green innovation measurement. Next, Section 2.3 - The CRM content of green innovation gives a more generalized context to the topic of CRMs. In Section 2.4 - Empirical Strategy we present the methodology we use to investigate the presence of CRMs in green and non-green technologies, starting from the discussion of the information we extract from patents and moving to the construction of the dataset and the full list of CRMs we investigate. Finally, we present our main findings in Section 2.5 - Results, and Section 2.6 - Conclusion concludes.

2.2 Using patents to measure innovation

The capacity to empirically analyse green and non-green technologies relies on the availability of effective methods for measuring innovation. There is more than one option when it comes to choose an established metric to proxy for innovation. Examples include looking at survey data that monitor firms' environmental efforts, at R&D expenditures, and at patent data. However, the difficulty of linking survey data with official statistics or other surveys on the one hand, and that of finding detailed and harmonised R&D expenditure data on the other, limits the use of the former two sources (Kemp and Pearson, 2007). Similarly, the use of patent data carries both benefits and limitations (Arts et al., 2013; Griliches, 1998; Lanjouw et al., 1998). For instance, potential drawbacks include the fact that patents primarily measure invention rather than innovation, therefore capturing only a limited proportion of all innovations. Additionally, not all inventions are patented, and the propensity to patent differs across sectors. Lastly, distinguishing between the values of different patents is not straightforward. However, despite these shortcomings, patents also offer several benefits, making them a good proxy for innovation and eco-innovation.

Firstly, patent data are publicly available and have long time series that make them well-suited for statistical examination. Secondly, a considerable amount of quantitative and qualitative information on both the applicants or inventors, including e.g. their geolocalisation both at the country and regional level, and the nature of the invention, is contained in patents. Regarding the invention's nature, patents can be classified according to their technological content following established classification systems, in which they are grouped into technological areas ranging from broad categories like *"Electricity"* to highly specific and detailed ones, such as *"Antenna arrays or systems"*. In particular, we refer to the International Patent Classification (IPC) system[2] and the Cooperative Patent Classification (CPC) system[3]. IPC has a longer history: it was established in 1971 by the World Intellectual Property Organisation (WIPO) and it consists in a hierarchical system spanning from 8 technological sections labeled alphabetically with single letters from A to H to approximately 70000 technological subdivisions labeled with alphanumeric codes. Instead, CPC was launched in 2013 by the European Patent Office (EPO) and the United States Patent and Trademark office (USPTO) in order to harmonise their existing classification systems. CPC is an extension of IPC. Indeed, the first 8 sections of CPC, labeled with A-H letters, coincide with those of IPC, while the 9^{th} section, labeled with the letter Y, tags cross-sectional technologies. CPC is highly detailed, comprising approximately 250000 classification entries, and is extremely useful for green technologies: in particular, within the Y section the subsection Y02 (Veefkind et al., 2012), tagging technologies or applications for mitigation or adaptation against climate change, is included. Therefore, in order to proxy for green innovations it is possible to consider separately the patents labeled with Y02-starting codes within the CPC system. This is a crucial aspect in our analysis, since it allows us to have a clear distinction between green and non-green patent datasets, which we use as proxies for green and non-green innovation respectively. Furthermore, Y02 takes into account adaptation and mitigation technologies, enabling us to encompass both these essential aspects of green innovation.

In practice, we retrieve green and non-green patents from the EPO Worldwide Patent Statistical Database (PATSTAT) (European Patent Office, 2020), and in particular from the PATSTAT 2020 version. In PATSTAT, information on more than 100 million patent documents from patent offices around the world are collected. From each patent contained in it we select multiple information regarding the patented in-

[2]see https://www.wipo.int/classifications/ipc/en/ to explore IPC

[3]see https://www.cooperativepatentclassification.org/home to explore CPC

vention which we then use in our analysis. The details on the overall dataset and the information extracted from patents are discussed in Section 2.4 - Empirical Strategy.

2.3 The CRM content of green innovation

Under the heading "Critical Raw Materials" (CRMs) we group a specific set of mineral and metal resources which are fundamental components for green technologies, and particularly renewable energy technologies, but also for products in digital, defence and aerospace technologies. Our main focus is on the green technologies dependence from these resources (Herrington, 2021). Some examples include lithium, which is crucial in the construction of batteries used in electric vehicles and as energy storage in renewable technologies, rare earth elements, which are key components of permanent magnets used in e.g. electric vehicles, digital technologies or wind generators, and base metals such as copper and aluminium, which are demanded heavily for electricity grids. These examples are not exhaustive of all the CRMs included in our study, which will be listed in the next section. With high future demand projections and the current lack of viable alternatives to be used for the development of green technologies, there are growing concerns surrounding CRMs among national governments and international institutions (European Commission, 2011; Hund et al., 2020; International Energy Agency, 2021). According to a recent report made by the European Commission, the global competition around these resources will become fierce in the coming decade, and today's dependence on oil may be replaced soon by dependence on CRMs (European Commission, 2023*b*).

Therefore, if not addressed properly, the risks carried by the mineral requirements of green technologies could hamper the efforts towards containing climate change. First, the expected growth in demand for many CRMs is so high that there may not be enough supply available to meet it. To illustrate the scale of this growth, according to the International Energy Agency (IEA), in order to reach net zero GHG emissions by 2050 the demand for lithium will increase by nearly 600% during the period 2021-2030 (International Energy Agency, 2023*a*), which is not far from similar predictions from the World Bank, estimating an increase of 500% of lithium demand just to have a 50% chance of limiting the average temperature increase to below 2°C by 2100 (Hund et al., 2020). Moreover, the pace at which these resources will be needed makes the risk of shortages not only a question of meeting the expected future cumulative demand within a certain year, but also of supplying them at the right time in order to avoid bottlenecks that, even if temporary, could still prevent the achievement of the established climate targets (Grandell et al., 2016; Kushnir and Sandén, 2012; Valero et al., 2018). Second, there exist geopolitical risks arising from the geographical distribution of CRMs which have the potential to undermine the resilience of the entire supply chain. In fact, in the last decade the global production of CRMs has become more concentrated among few producer countries, some of whom account for large shares of multiple materials. China is a major example of this, given its leading role in the global production of several CRMs at the processing stage (i.e. when the extracted ores are refined in order to achieve the chemical composition of the material required for its use), with heavy (100%) and light (85%) rare earth elements, gallium (94%), and magnesium (91%) holding the largest shares; other examples include South Africa, holding the 71% of global platinum production, and the Democratic Republic of Congo, with the 63% of cobalt production at the mining stage (European Commission, 2023*b*). The significant concentration of production in many CRMs is a major concern for importing countries, further exacerbated by the increase in export restrictions observed over the past decade (Kowalski and Legendre, 2023). The European Union is at the forefront on this issue, making great efforts to ensure a resilient supply chain of critical resources for its member states. The release and constant updating of a list of CRMs, defined as *"raw materials of high importance to the EU economy and of high risk associated with their supply"*[4], goes precisely in this direction. The first list has been published in 2011, and it is updated every 3 years since then (European Commission, 2011). The efforts made by the European Commission are extremely important in the context of this thesis, since, as explained in the next section, we investigate an expanded version of the 2020 CRMs list (European Commission, 2020*a*).

In line with the political agenda dictated by states and international organisations, a growing body of literature on the study of CRMs has developed in recent years. Many studies have concentrated on quantifying the material requirement for the green transition and identifying potential bottlenecks of future demand of CRMs, focusing on CRMs in general (Grandell et al., 2016; Valero et al., 2018) or on specific cases (Junne et al., 2020; Kushnir and Sandén, 2012; Sverdrup, 2016), as well as on specific technological areas (Watari et al., 2019). Within the innovation literature, pioneering empirical analyses have recently paved the way for the study of CRMs in technological domains, investigating the technological and geographical linkages between technological paradigms and some critical and conflict materials (Diemer et al., 2022) and exploring the technological dependence of new inventions on rare minerals (Yunxiong Li et al., 2024).

The increase in primary — i.e. extraction — and secondary — i.e. reuse and recycling — production of CRMs could counteract the risks of future supply shortages. However, both options carry potential shortcomings. In the case of primary production, the drawbacks arise from the controversies embedded in the mining sector. In fact, on the one hand, mineral development poses environmental threats, like e.g. GHG emissions arising from both mining and processing activities (Azadi et al., 2020; Norgate and Haque, 2010), water depletion and pollution, and waste-related contamination (Carmo et al., 2017; Gunson et al., 2012; Miller et al., 2018). On the other hand, it brings social negative impacts, such as increased corruption and misuse of government resources, human rights violations and the outbreak of violent conflicts (Berman et al., 2017; Christensen, 2018; Church and Crawford, 2018). On the other hand, regarding the increase of secondary production, the main limitations stem from the current insufficient recycling capacity of many CRMs (Jowitt et al., 2018; United Nations Environment Programme, International Resource Panel, 2011; Vikström et al., 2013), and other factors such as the lack of market incentives, which make recycling still far from being a feasible option (International Energy Agency, 2023*a*; Wang et al., 2014). Therefore, strategies to cope with the lack of CRMs are not straightforward, and should take into account both the potential negative consequences stemming from an increase in primary production and the intrinsic limits of recycling for many of these resources.

[4]see https://...critical-raw-materials-en

2.4 Empirical Strategy

The main goal of our analysis is to explore the relationship between CRMs and green and non-green innovation. In order to do so, we rely on patents collected from PATSTAT (European Patent Office, 2020). For each patent recorded in PATSTAT, there is plenty of information about the patented invention that is extremely useful for the purposes of our analysis. More specifically, the information we extract from each patent includes:

- **patent application ID**: a unique code which serves as a patent identification;
- **patent abstract**: description of the invention that has to be patented;
- **inpadoc family ID**: identification code of the family associated to the patent. A patent family covers the set of patents related to the same invention. In fact, the intellectual property associated with an invention can be protected by several patent applications[5]. Therefore, there might be multiple patent IDs that cover the same invention associated to the same family ID;
- **technology code**: label following IPC (for non-green technologies) or CPC (for green technologies) systems with which patents are classified according to the technological content of the invention;
- **filing year**: year of the patent registration in PATSTAT;

The above list includes all the information we need when analysing patents in this study. Depending on which task we carry, we consider all or only a subset of this information. Finally, there is additional information associated to patents that is not considered here but that could be useful for similar studies, such as the geographical information regarding the country where the patent is filed (i.e. where the intellectual property of the invention is protected) and the country of origin of the inventor(s).

2.4.1 Construction of the dataset

The first step is to distinguish between green and non-green patent datasets. In particular, in the green dataset all the patents tagged with Y02 codes of the CPC system are included; the remaining patents form the non-green dataset. In Table 2.1 and Table 2.2 we report the description of the 8 IPC sections labeled alphabetically from A to H and the Y02 class decomposed in the corresponding 8 green technology sub-classes.

In theory, we could consider only the CPC system in our analysis, since the A-H sections with which non-green technologies are tagged are included in both CPC and IPC systems, while the Y02 class is included in CPC only. However, due to the fact that not all patent offices assign CPC codes to the inventions, many non-green patents in PATSTAT do not have a CPC tag. Therefore, in order to include as much patents as possible in our study, we use the IPC tagging scheme for the non-green dataset. Nevertheless, the use of different classification systems depending on which of the two datasets (green and non-green) we are analysing does not limit our study. In fact, at

[5] The reason for this lies in the fact that, for example, for the same invention there are as many patent applications as the number of countries or geographical organisations where the applicants want their invention protected. Another possible reason is that legal frameworks of patent offices also offer mechanisms to extent the rights of protection over an invention, which lead to more patent applications.

Label	Description
A	Human necessities
B	Performing operations; Transporting
C	Chemistry; Metallurgy
D	Textiles; Paper
E	Fixed constructions
F	Mechanical engineering; Lighting; Heating; Weapons; Blasting
G	Physics
H	Electricity

Table 2.1: IPC technology sections. The first column lists the letters from A to H with which each section is labeled, while the second column lists the corresponding descriptions.

Label	Description
Y02	**TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE**
Y02A	Technologies for adaptation to climate change
Y02B	Climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications, including the residential sector
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies, i.e. information and communication technologies aiming at the reduction of their own energy use
Y02E	Reduction of greenhouse gas (GHG) emissions, related to energy generation, transmission or distribution, including renewable energy, efficient combustion, biofuels, efficient transmission and distribution, energy storage, and hydrogen technology
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation, e.g. hybrid vehicles
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management

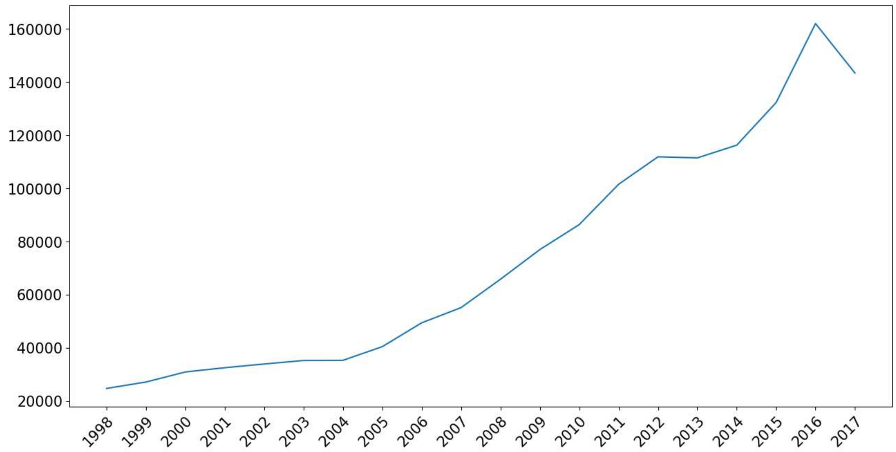
Table 2.2: Y02 green technology class. The first column lists the labels associated with each green technology category, starting from the whole of Y02 down to its 8 sub-classes, while the second column lists the corresponding descriptions.

the levels of aggregation we work with, the CPC and IPC classifications coincide in the technologies tagged with codes belonging to the A-H sections. Therefore, considering the IPC codes for the non-green technologies only brings the advantage of having more patents to analyse, as all patent offices assign IPC codes, whereas they may not do so with CPC codes if the patented invention is not green.

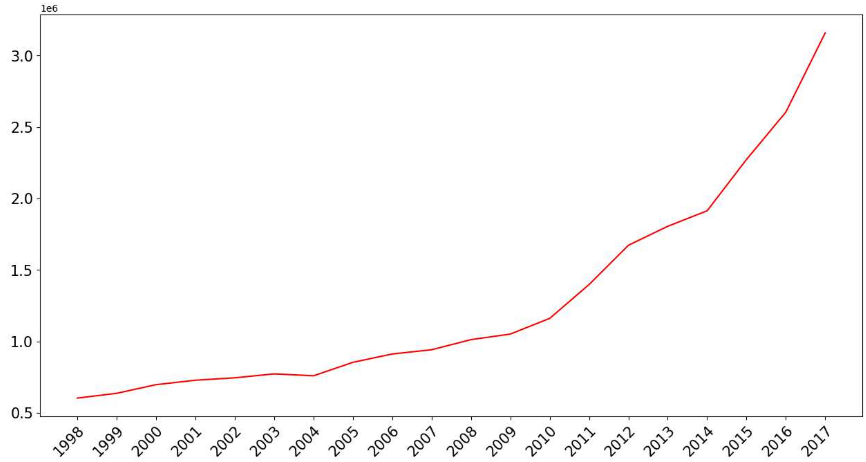
Starting from the two distinct datasets, we move to the selection of the time period. In particular, we focus on the 20 year period 1998-2017, which allows us to be as much recent as possible by including the year 2017, given the version of PATSTAT available to us. In fact, patent applications can be published in PATSTAT even few years (usually up to 3) after their filing date. For this reason, we decided to stop our analysis at the year 2017. In addition, we set the starting year to 1998 so that the entire 20 year period 1998-2017 would capture the development of green technologies from a long perspective, also taking into account the dynamics around some of the major climate agreements (European Commission, 2019*a*; United Nations, 1997, 2015).

Once the time period has been set, we select only the patents with the filing year within it. Then, a second selection has been done considering only the patents with the abstracts written in English. Finally, we exclude the patents for which the information related to the technological IPC and CPC codes is missing. We conduct these selection processes to both green and non-green patent datasets. The resulting datasets comprise 1473320 and 25708295 inpadoc families IDs corresponding to inventions classified as green and non-green technologies respectively. In Figure 2.1 a general descriptive of the two datasets is reported. In the top panels (Figure 2.1a and Figure 2.1b) the annual evolution of the number of green and non-green patent families is reported for the entire period 1998-2017. In both figures we notice a considerable increase in the patenting activity, particularly in the last 10 years of the time interval. If we compare these trends in relative terms, it is possible to see how the increase in green patents has been higher compared to that in non-green ones (see Figure 2.1c). To remove possible annual data fluctuations in the figure and capture the overall trend, we divide the entire 1998-2017 period in four 5-year intervals and we average the number of patent families within each period. The figure shows that the average number of green patents in the last 5-year interval (2013-2017) increased by 346% with respect to the starting value in the interval 1998-2002. The corresponding increase for non-green patents is about 244%. The huge increase registered particularly for green patents confirms the great acceleration in green technologies witnessed in recent years (OECD, 2011).

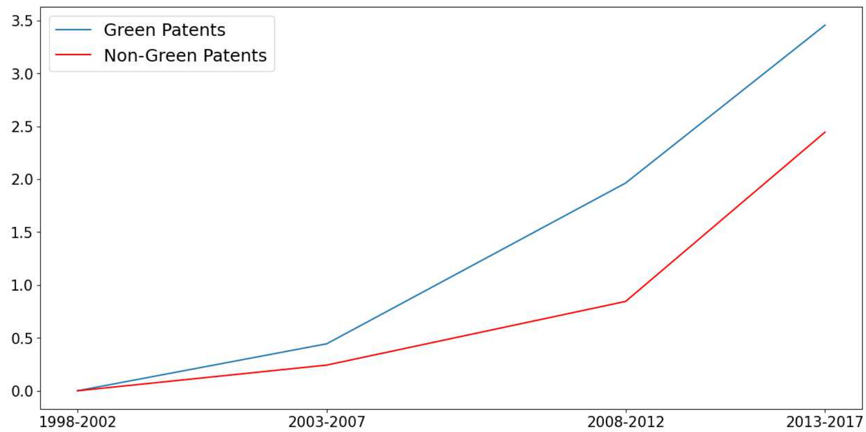
Before moving to the next section, it is important to note that, in order to avoid multiple counting of the same invention, all our results will refer to the inpadoc family ID level of aggregation, as in Figure 2.1. However, the text mining process is conducted at the application ID level, since some applications can differ in their content (and therefore have different abstracts) even though they refer to the same patent family.



(a) Number of Green patent families



(b) Number of Non-Green patent families



(c) 5-years percentage increase

Figure 2.1: Preliminary descriptive on patent datasets. (a) - (b): Annual number of green and non-green patent families in the period 1998-2017. (c): 5-years percentage increase of the number of green and non-green patent families with respect to the average in the initial period 1998-2002.

2.4.2 Text Mining in patent abstracts

In order to define the sample of CRMs we look for in patent abstracts, we start by considering an extended version of the 2020 European Commission list of CRMs (European Commission, 2020*a*), in which the main minerals investigated in the IEA report of 2021 (International Energy Agency, 2021) are added. This summarises to a list of 44 materials reported in Table 2.3.

aluminium, antimony, arsenic, baryte, bauxite, beryllium, bismuth, borate, boron, cadmium, chromium, cobalt, copper, fluorspar, gallium, germanium, graphite, hafnium, indium, iridium, lead, lithium, magnesium, manganese, molybdenum, nickle, niobium, palladium, phosphate rock, phosphorus, platinum, rare earth elements (REEs), selenium, silicon, silver, strontium, tantalum, tellurium, tin, titanium, tungsten, vanadium, zinc, zirconium.

Table 2.3: List of all the materials mentioned in European Commission (2020*a*) and International Energy Agency (2021).

Starting from this list we make some additional modifications in order to end up with the final list of keywords for the text mining process. Firstly, regarding REEs, we investigate for the presence of all the single elements belonging to this category that are mentioned in at least one of the two source documents (European Commission, 2020*a*; International Energy Agency, 2021): this sub-group comprises dysprosium, lanthanum, neodymium, praseodymium, samarium, scandium, yttrium, and terbium. Secondly, we also investigate for the presence of the element symbols of all CRMs, except for those symbols that can have a different meaning or are single letters (i.e *In* for indium, *As* for arsenic, *W* for tungsten, *B* for boron, etc.). Thirdly, for some CRMs we do not only search for keywords, but also check the terms preceding and following the CRM in the abstract in order to avoid wrong counts. More specifically, we apply this third step for silicon and lead. In the case of lead, because it can refer to other meanings that the actual metal lead[6]; in the case of silicon, we want to keep only the observations associated to silicon metal, as it is silicon metal, and not silicon, that is explicitly mentioned in the Commission's CRM list. Silicon metal is an high silicon alloy that can be further refined in order to obtain extremely pure silicon, which is widely used in high-tech products such as semiconductors or photovoltaics. To keep only silicon metal detections, we discard the patents where silicon is preceded or followed by words pointing to a less pure form of the material[7].

We start the text mining process by identifying all the CRMs listed in Table 2.3. Subsequently, we group together the detections of specific CRMs. In particular, since they are considered as unified groups in many related statistics or information like e.g. production data, we group iridium, palladium and platinum under the Platinum Group Metals (PGM), all the rare earth elements under the REE label, hafnium and zirconium under zirconium, phosphate rock and phosphorus under phosphorus, and borate and boron under boron. The resulting Table 2.4 encompasses the final list of 39 CRMs

[6] To make some examples, lead used as the verb to lead, components like lead wire and lead screw which are not made of lead, and lead in the sense of the expression leading.

[7] The less pure versions of silicon include e.g. silicon oxides, ferrosilicon, quartz, etc.

for which we present all figures and results derived from our analysis. In the table, the element symbols that we investigate in patent abstracts are indicated after the corresponding CRM.

Critical Raw Materials final list				
Aluminium (Al)	Antimony (Sb)	Arsenic	Baryte	Bauxite
Beryllium (Be)	Bismuth (Bi)	Boron[I]	Cadmium (Cd)	Chromium (Cr)
Cobalt (Co)	Copper (Cu)	Fluorspar	Gallium (Ga)	Germanium (Ge)
Graphite	Indium	Lead (Pb)	Lithium (Li)	Magnesium (Mg)
Manganese (Mn)	Molybdenum (Mo)	Nickel (Ni)	Niobium (Nb)	Phosphorus[II]
PGM[III]	REE[IV]	Selenium (Se)	Silicon (Si)	Silver (Ag)
Strontium (Sr)	Tantalum (Ta)	Tellurium (Te)	Tin (Sn)	Titanium (Ti)
Tungsten	Vanadium	Zinc (Zn)	Zirconium[V]	

[I] boron includes borate and boron detections
[II] phosphorus includes also phosphate rock detections
[III] PGM includes the detections associated to platinum (Pt), palladium (Pd) and iridium (Ir)
[IV] REE includes the detections associated to the following list of keywords/materials: ree, rare earth, dysprosium (Dy), lanthanum (La), neodymium (Nd), praseodymium (Pr), samarium (Sm), scandium (Sc), terbium (Tb), and yttrium
[V] zirconium includes zirconium (Zr) and hafnium (Hf) detections

Table 2.4: Final list of CRMs against which we express our results. Between parentheses we indicate those element symbols that we investigate in patent abstracts in addition to the CRM extended keywords.

2.4.3 Methodology in a nutshell

The entire text mining process can be summarised through Figure 2.2. For each patent contained in either the green or the non-green dataset, we process its abstract looking for the presence of the CRMs listed in the previous section. When we find a CRM mentioned in an abstract, we associate the respective patented invention with it, claiming that its realisation depends on that CRM. Combining this with the multiple information contained in PATSTAT allows us to perform multiple tasks. For instance, by using the IPC and CPC tagging schemes, we are able to link CRMs to specific technological areas even at fine grained level of details. In addition, even if not addressed explicitly in this study, the geographical information on the country where the invention is filed could allow us to explore the geographical distribution of CRM dependent inventions. Finally, the filing year of the patent allows us to study particular properties looking at their evolution over time.

Before presenting the results of the analysis, it is important to make an additional consideration. When a CRM is mentioned in a patent abstract, we assume that the patented invention needs that CRM in order to be realised and/or successfully employed. However, the presence of a CRM in a patent abstract could be due to other reasons

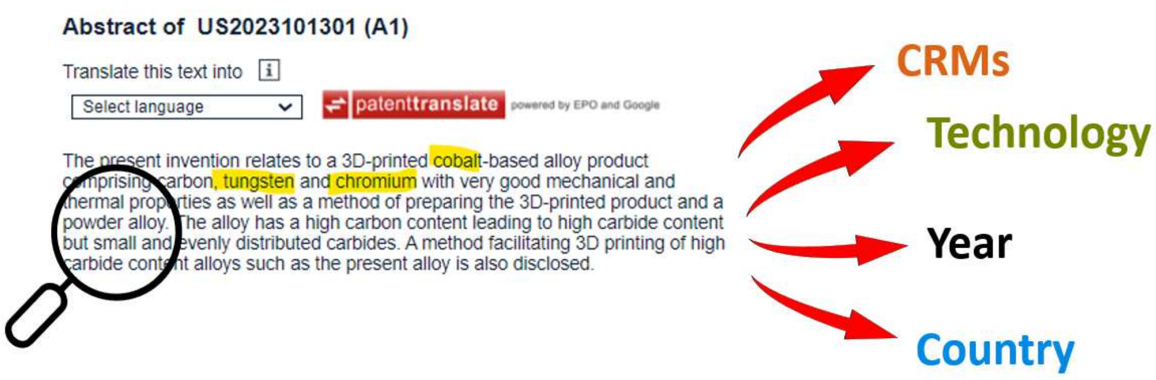


Figure 2.2: Text Mining methodology scheme.

than the actual use of that material. Indeed, some inventions might aim at the refining, recycling, or even at the removal of some CRMs. This, particularly in the case of removing, is a limitation of our analysis which could result in an overestimation of the presence of CRMs in patents. Nevertheless, following what have been already done in previous studies (Biggi et al., 2022; Diemer et al., 2022; Fifarek et al., 2007; Yunxiong Li et al., 2024), we consider text mining of CRMs in patents as a good proxy for how much green and non-green technologies depend on them. That said, future research should be devoted to refining these methods, perhaps by adopting natural language processing techniques (Montobbio et al., 2022; Rughi et al., 2023).

2.5 Results

In this section, we report the main outcomes of the text mining investigation in green and non-green technologies. First, Section 2.5.1 - CRMs presence in green technologies presents the main results associated with the screening of green patents. Second, in Section 2.5.2 - CRMs presence: comparison between green and non-green technologies we introduce the comparison of the aggregate results for green and non-green technologies, focusing on the presence of CRMs throughout the entire period 1998-2017. Third, the comparison between green and non-green technologies is further explored in Section 2.5.3 - CRMs dependence of technological domains, where the dependence of specific green and non-green technological areas is discussed.

2.5.1 CRMs presence in green technologies

The text mining screening of green patents leads to 292689 CRM detections in 167236 patent families. Given the total number of families in the green patent dataset (1473320), this translates into an average presence of CRMs in green technologies of 11.35% (i.e. 167236/1473320). This means that the 11.35% of green inventions exhibit a dependence from at least one of the CRMs under investigation. To better grasp the presence of CRMs in green technologies, in Figure 2.3 we show the distribution of the CRM detections. In the figure, each bar of the histogram reports the share of observations for the corresponding CRM labeled in the y-axis.

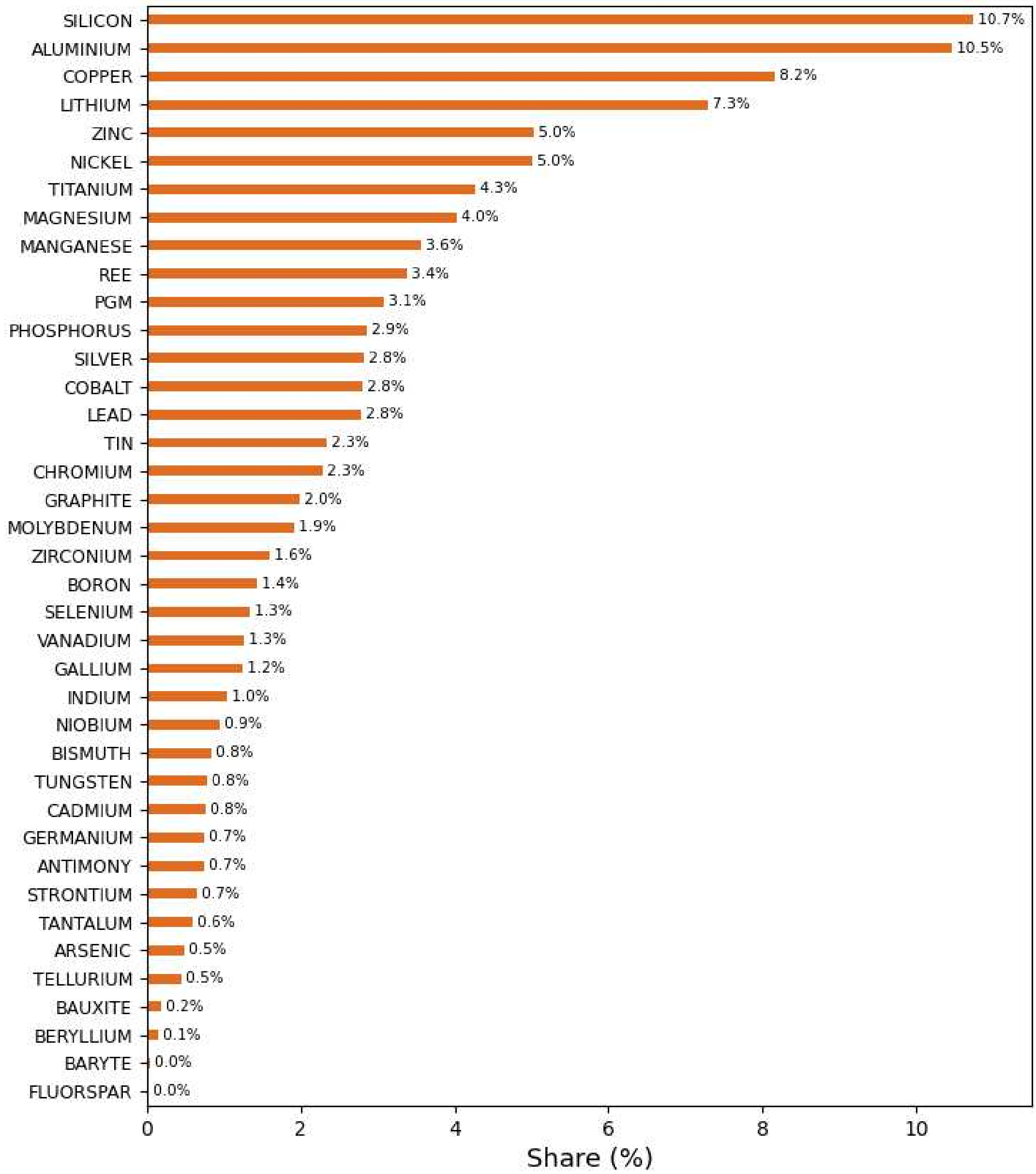


Figure 2.3: Distribution of CRM detections in green patents. CRMs are ordered in the y-axis according to the number of corresponding detections in green patents. Detection share values are indicated next to each bar in percentages.

Observing the histogram in the figure reveals an uneven distribution. Specifically, 62% of the observations pertain to 10 materials (i.e. the top 10 materials in the y-axis). Among these, around 37% are accounted for by silicon, aluminum, copper, and lithium, with the remaining 25% attributed to zinc, nickel, titanium, magnesium, manganese, and rare earths. The predominance of some of these materials in green technologies is confirmed by the literature, as we also mentioned in Section 2.3. For instance, aluminium and copper are implemented for electricity transmission, and aluminium is also incorporated into metal alloys for constructing electric vehicles. Silicon serves as the foundational material for nearly all solar-related technologies. Additionally, lithium is a crucial component in the manufacture of batteries, which are essential for electric transportation and for storing energy from renewable sources. Other significant materials used in batteries include nickel, manganese and rare earth elements (REEs), with the latter being essential for constructing magnets used in wind energy too. In general, information on possible end-use applications for each CRM can be found in the CRM factsheets report of the European Commission (European Commission, 2020).

In Figure 2.4 we further explore the distribution of CRM detections in green patent abstracts by adding the temporal dimension. In particular, we first divide the time period of the analysis into four 5-years sub-intervals: 1998-2002, 2003-2007, 2008-2012, and 2013-2017. Then, for each CRM, we plot the evolution of its relative presence in green patents (i.e. given a time interval, the number of CRM detections divided by the number of patent families) with respect to the initial value in 1998-2002.

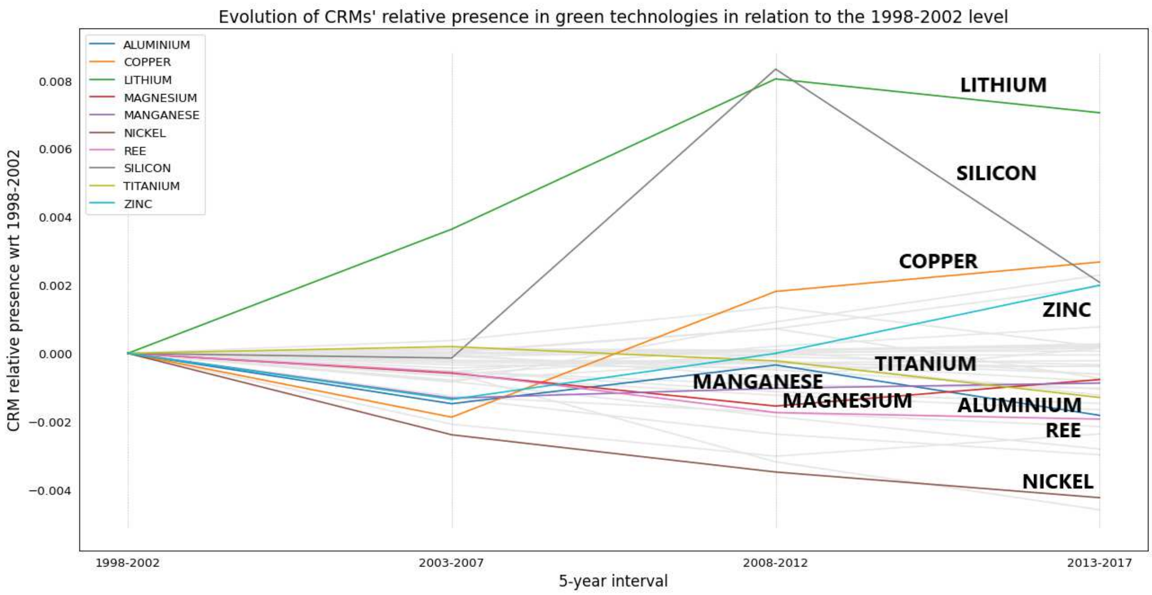


Figure 2.4: Evolution of CRMs presence in green technologies. The materials highlighted correspond to the first 10 materials of the histogram in Figure 2.3

In the figure we highlighted the 10 leading CRMs in terms of detections in green patents, i.e. the top 10 materials of Figure 2.3. For many of them, the level of presence in green technologies does not exhibit major changes during the period under analysis. Yet, there are few exceptions. In particular, lithium's presence in green technologies has increased the most, probably driven by a massive development in lithium batteries, which are set to accelerate rapidly over the coming decades (International Energy Agency, 2021). A more irregular pattern is the one concerning silicon, with a huge increase experienced before the last interval, characterised instead by a sharp decline: this pattern could follow the evolution of photovoltaic technologies, with the period of the increase indicating the reach of the level of maturity of silicon solar cells, while the decline might point to the search for alternative materials to be used in solar technologies. Regarding the remaining CRMs, while for some of them, namely zinc and copper, we notice an increasing trend in the last period, the majority exhibits a stable or decreasing pattern. However, this does not diminish their importance in green technology development in absolute terms, as we pointed previously in Figure 2.3.

2.5.2 CRMs presence: comparison between green and non-green technologies

In this section we start to compare the presence of CRMs between green and non-green patents, i.e. the number of CRM detections in green/non-green patent abstracts divided by the number of green/non-green patent families. More in detail, we compare the main outcomes of the text mining process in non-green patent abstracts with those obtained for green patents which we already presented partially in the previous section.

The overall presence of CRMs is significantly higher in green patents, underlining the peculiarity of green technologies in depending on these materials. In particular, as summarised in Table 2.5, the average CRM presence in non-green patents is 6.63%, which is almost half of the CRM presence in green technologies (11.35%).

	CRM Families	**Tot Families**	**Avg CRM Presence**
Green	167236	1473320	11.35%
Non-green	1705304	25708295	6.63%

Table 2.5: CRMs presence in green and non-green technologies. In particular, column *CRM families* refers to the number of patent families with at least one CRM detection; column *Tot Families* refers to the total number of patent families in the green and non-green datasets; column *Avg CRM Presence* refers to the average presence of CRMs for both datasets, and it's given by the ratio of the other two column values

The trends of the CRMs presence over the entire period are illustrated in Figure 2.5. This figure not only allows us to visually depict the disparity in CRMs dependence between green and non-green technologies, but also reveals the similarity in the patterns, with a high correlation of 86.5%.

Figure 2.5: Overall CRM presence evolution in green and non-green technologies. The green line shows the trend for green technologies, while the red line shows that of non-green technologies.

Finally, in Figure 2.6 we plot the evolution of the ratio between the presence of CRMs in green and non-green technologies. Although it may seem very irregular at first glance, looking at the y-axis we notice that the variation of the ratio throughout the period is minimal; this is expected, given the high level of correlation between the two trends represented in Figure 2.5, and it is also confirmed by the plot of the cumulative ratio (i.e. the dashed grey line in Figure 2.6).

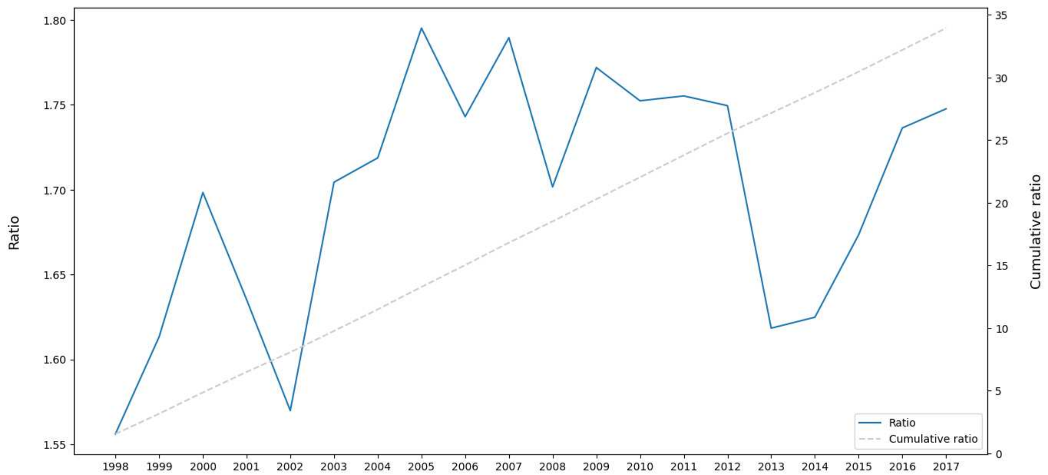


Figure 2.6: Ratio between the presence of CRMs in green and non-green patents. The grey dashed line plots the cumulative of the ratio.

Summing up, the comparison conducted in this section reveals a substantially higher significance (almost double) of CRMs in green technologies than in non-green technologies, which remains relatively stable throughout the period considered.

2.5.3 CRMs dependence of technological domains

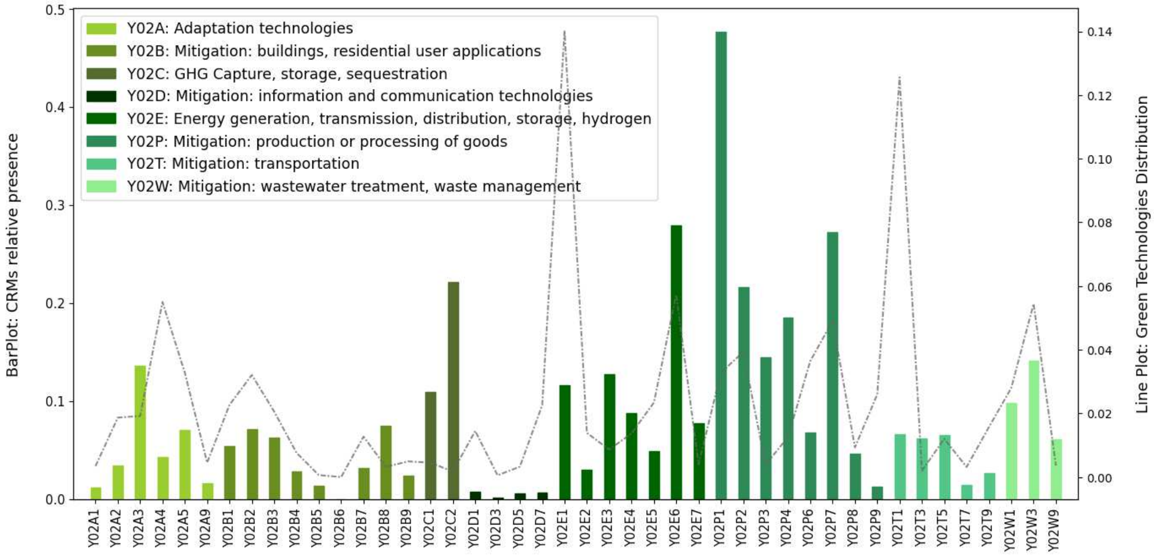
We further elaborate on the comparison between green and non-green technologies by investigating which particular technological areas exhibit more reliance on CRMs. On the one hand, we are interested in which green and non-green technological domains register the highest predominance of CRMs; on the other hand, we want to spot any difference or similarity between these domains. In addition, thanks to the hierarchical structure of the IPC and CPC systems with which patent are classified, our exploration can be conducted at multiple level of aggregations.

Starting from the most aggregated level of our data, represented by the A-H sections of Table 2.1 and the Y02 sub-classes of Table 2.2, we report the level of CRM dependence of each green and non-green technology in Table 2.6. Regarding green technologies, the highest levels of CRM penetration (last column of the table) are exhibited by *Y02P - CCMT in the production or processing of goods* (21% of CRM presence, i.e. the 21% of the total families in the dataset are associated with at least one CRM mention), *Y02E - Energy generation, transmission and distribution technologies* (14.3% of CRM presence), *Y02C - GHG capture, storage and sequestration technologies* (14.1% of CRM presence), and *Y02W - CCMT in wastewater and waste management* (12.5% of CRM presence). While the outcome for *Y02E* is somehow expected, as it covers all the main clean energy technologies, the high levels of CRM dependence in Y02P and Y02C require more discussion. *Y02P* covers CCMT in any kind of industrial processing or production activity, including e.g. green technologies used in metal (*Y02P1*) or mineral (*Y02P4*) processing, and related to chemical industry (*Y02P2*). These technologies are therefore directly connected to processes involving a direct or indirect use of CRMs, like e.g. for creating chemical mixtures to be used as catalysts, or to improve the material efficiency of certain instruments. Regarding *Y02C* instead, we must notice that, despite a 14.1% penetration of CRMs in this technology domain, the number of capture and storage green technologies is the lowest one in the dataset (they represent the 0.4% of the families in the green patent dataset). This reflects the low level of technological maturity of carbon capturing. Hence, even if they are technologies which rely heavily on CRMs throughout all their operations during the capture, transportation and storage stages, there is uncertainty on the actual implications for the future demand of these resources. Finally, the presence of CRMs in *Y02W* is probably determined by the material content of specific processes dealing with the refinement or recycling of products at the end of their life cycle. Turning to non-green technologies, the dependence on CRMs is much lower, with the levels of almost all technologies below 10%. The exception is section *C - Chemistry; Metallurgy*, where the presence of CRMs covers 21.6% of patent families. This is not surprising, since the manufacture and treatment of e.g. metallurgy alloys, or specific inorganic and organic compounds, are covered by this section. Although having levels of CRM presence below 10%, other technology sections such as *H - electricity* or *B - Performing operations; Transporting* deserve further investigation at a more disaggregated level of technological domains, given the high number of patents they hold in the dataset.

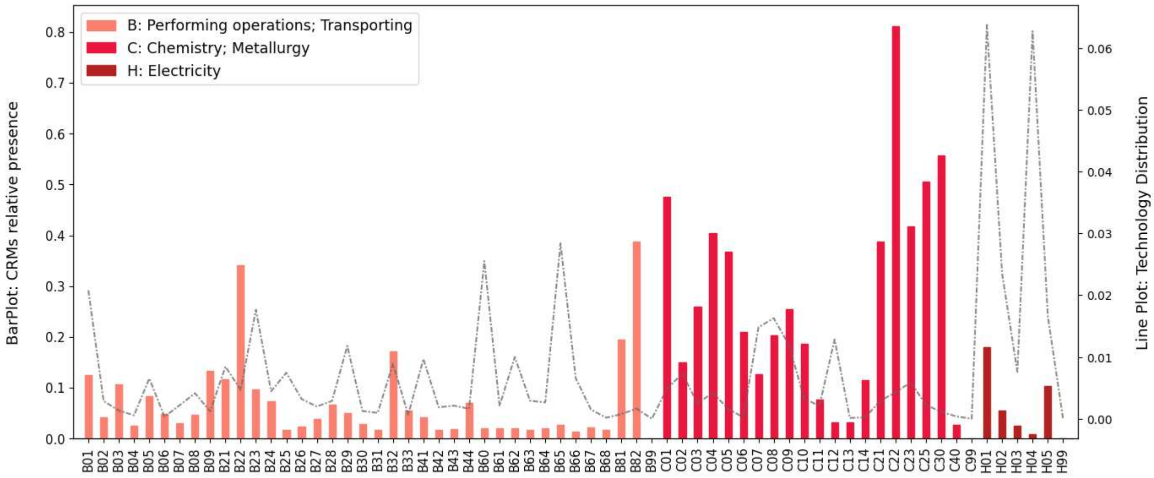
Label	Description	Families with CRM	Tot Families (dataset share)	CRM Presence
		GREEN TECHNOLOGIES		
Y02A	Adaptation technologies	13748	225776 (13.7%)	0.061
Y02B	Mitigation: buildings, residential user applications	9753	172407 (10.4%)	0.057
Y02C	GHG Capture, storage, sequestration	1444	10273 (0.4%)	0.141
Y02D	Mitigation: information and communication technologies	485	67106 (4.1%)	0.007
Y02E	Energy generation, transmission, distribution, storage, hydrogen	61645	431435 (26.1%)	0.143
Y02P	Mitigation: production or processing of goods	73568	350500 (21.2%)	0.210
Y02T	Mitigation: transportation	16133	250481 (15.1%)	0.064
Y02W	Mitigation: wastewater treatment, waste management	18166	145465 (8.8%)	0.125
		NON-GREEN TECHNOLOGIES		
A	Human necessities	159057	5146237 (15.2%)	0.031
B	Performing operations; Transporting	446246	7022131 (20.8%)	0.064
C	Chemistry; Metallurgy	719920	3327596 (9.8%)	0.216
D	Textiles; Paper	29214	470375 (1.4%)	0.062
E	Fixed Constructions	53624	1689268 (5.0%)	0.032
F	Mechanical engineering; Lighting; Heating; Weapons; Blasting	131963	3460419 (10.2%)	0.038
G	Physics	190646	6587153 (19.5%)	0.029
H	Electricity	503251	6091962 (18.0%)	0.083

Table 2.6: CRM dependence of Technological Domains (aggregate level). For each technology labeled with the code in the 1^{st} column, we report the corresponding description (2^{nd} column), the number of patent families with at least one CRM detection (3^{rd} column), the total number of patent families and the corresponding share in the dataset associated to that technology (4^{th} column), and the CRM presence (5^{th} column), given by the ratio of the families with CRM and the total number of families.

In Figure 2.7 we break down the technological domains at a more disaggregated level. In particular, in the top panel of the figure we report the CRM presence in 44 green technology sub-classes of the Y02 class, while in the lower panel we analyse the presence of CRMs in 65 non-green technologies labeled with 3-digit alphanumeric IPC codes, corresponding to the sub-categories belonging to sections *B*, *C* and *H*, i.e. the sections with the highest levels of dependence from CRMs, as it is shown in Table 2.6. However, a representation of the remaining technological sub-categories belonging to the other sections is available in section B.1 in the Appendix.



(a) Green technologies



(b) Non-green technologies (Sections B, C, and H)

Figure 2.7: CRM dependence of Technological Domains at a more disaggregated level. Panel (a) refers to 44 green technology categories belonging to the 8 sub-classes of Table 2.2. Panel (b) refers to 65 non-green technologies belonging to the sections B, C, and H of Table 2.1. In both panels, the histogram shows the level of CRM presence (left y-axis) in each technology labeled in the x-axis, while the grey dashed line plots the share (right y-axis) of each technology with respect to the total number of families in the green/non-green dataset.

Due to space constraints in the figure, technologies are indicated on the x-axis with the corresponding CPC and IPC codes, without indicating their descriptions. However, from the USPTO[8] and WIPO[9] websites for CPC and IPC codes respectively it is pos-

[8]see https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html
[9]see https://ipcpub.wipo.int

sible to directly explore the content of each green and non-green technological domain, from the 8 macro sections to the most detailed technological subdivisions. Here instead, we restrict ourselves to descriptions of the technologies we remark on.

Starting with green technologies, and confirming what we observed in the aggregated case, we note that the dependence on CRMs of *Y02P - CCMT in the production or processing of goods* is driven by technologies related to metal processing, chemical industry, and mineral processing (CPC codes *Y02P1, Y02P2, and Y02P4*), but also by *Y02P7 - CCMTs in the production process for final industrial or consumer products*, which can be explained by the several energy efficient measures characterised by manufacturing processes, e.g. for rolling metal or metal working, included in this category. Interestingly, the green energy (*Y02E*) technology with the highest material dependence is *Y02E6 - Enabling technologies*, which contains, among others, energy storage technologies, while *Y02E1 - Energy generation through renewable energy sources* registers a lower CRM dependence, although it is also the most prevalent technology in the entire dataset, with around 14% of all green patent families associated with it. Regarding non-green technologies (Figure 2.7b), the average low level of CRMs presence in the sections *B - Performing operations; Transporting* and *H - electricity* contrasts with the levels of single sub-sections like *B22 - Casting; Powder metallurgy*, *B82 - Nanotechnology*, and *H01 - Electric elements*. The latter is particularly interesting as it includes technologies such as batteries, magnets, resistors, semiconductors and solid state devices, suggesting an overlap with green technologies, as these are all fundamental components of environmental innovations where the use of CRMs is predominant. Deepening section *C - Chemistry; Metallurgy*, we note numerous technologies with a high presence of CRMs, with some having even more than 50% of the inventions mentioning materials. We refer in particular to *C01 - Inorganic Chemistry*, *C22 - Metallurgy, ferrous or non-ferrous alloys and their treatment*, *C30 - Crystal growth*, and *C25 - Electrolytic or electrophoretic processes*. Finally, in the figure the levels of presence of CRMs associated to technologies *B99*, *C99*, and *H99*, covering *subject matter not otherwise provided for* in the respective non-green technology sections, are not represented. This is due to the fact that the number of inpadoc families associated with these technologies is very low (below 0.001% of the total families in the dataset, i.e. 25708295). Therefore, we do not consider the number of CRM detections in these technologies a significant result.

2.6 Conclusion

The transition to a clean energy system, and more generally the large-scale adoption of green technologies as both mitigation and adaptation innovative practices, is a fundamental and necessary step in the fight against climate change. However, this requires an upsurge in resources, specifically metals and minerals, that serve as indispensable and often irreplaceable components for such technologies. We refer to these raw inputs as Critical Raw Materials (CRMs). Examples encompass lithium, a pivotal component in batteries, rare earths, utilized in manufacturing magnets for electric vehicles and wind turbines, silicon for solar panels, and aluminum and copper for electricity transmission, among others. Thus, the massive and rapid adoption of green technologies in economies entails a proportional surge in the demand for CRMs, heightening the risk of supply bottlenecks, which is further exacerbated by geopolitical tensions stemming from the geographical distribution of these resources. These challenges have prompted significant concerns among countries and international institutions, leading to a growing body of work dedicated to addressing these issues, particularly in recent years (European Commission, 2023*b*; Herrington, 2021; Hund et al., 2020; International Energy Agency, 2021; Kowalski and Legendre, 2023).

Against this background, we carry out an empirical analysis with the aim of shaping the dependence of green technologies on CRMs, and comparing it with that of non-green technologies. To this end, we conduct a text mining investigation on patents, where the use of patents as a proxy for innovation enables a clear distinction between green and non-green technologies. Our approach is grounded in a number of literature strands. Firstly, we draw from the literature on the study of CRMs and green technologies, which predominantly focuses on identifying potential bottlenecks (Grandell et al., 2016; Valero et al., 2018). Secondly, we refer to innovation studies which focus on discussing various facets of green technologies, also drawing comparisons with their non-green counterparts (Barbieri, Marzucchi and Rizzo, 2020; Barbieri, Perruchas and Consoli, 2020; Perruchas et al., 2020), and on exploring the CRM dependence of technological domains (Diemer et al., 2022; Yunxiong Li et al., 2024). The research questions guiding our analysis are threefold: (i) which CRMs are most present in green technologies? (ii) Is the dependence on CRMs different between green and non-green technologies? (iii) Which are the most CRMs dependent green and non-green technological areas?

Overall, the text mining analysis of patents reveals that silicon, aluminium, lithium and copper are the most extensively utilized materials in green technologies, collectively accounting for 37% of all detections. Another significant share of observations (25%) is associated with CRMs such as zinc, nickel, titanium, magnesium, manganese, and rare earths. The prevalence of these materials in green patents aligns with their documented uses in the literature. In particular, looking at the evolution of the observations over the time period considered, we note a remarkable growth for lithium. This underscores the increasing efforts to address the electrification of transport vehicles and the recent advancements in batteries (Castelvecchi, 2021; International Energy Agency, 2023*b*).

When comparing green and non-green technologies as a whole, we find a notable disparity in the presence of CRMs. Green technologies exhibit a substantially higher prevalence, with 11.35% of them having at least one CRM detection, in contrast to 6.63% for non-green technologies. Despite this difference, the trends in CRM presence are remarkably similar between the two types of technologies, showing a correlation of 86.5%. Overall, given the peculiarity of CRMs with green technologies, it is not unexpected that the latter have a relatively higher dependence. However, the similarity in trends implies a similarity in the materials detected in both types of technologies, albeit in relatively higher numbers for green patents compared to non-green ones, which is potentially driven by shared characteristics between certain green and non-green technologies. This resonates with previous studies exploring the complementarities of green and non-green technologies (Barbieri et al., 2022, 2023).

Finally, addressing the third research question, our exploration into the technology domains (both green and non-green) most dependent on CRMs yields interesting findings. These results further emphasize on the complementarities between green and non-green technologies. Specifically, when identifying non-green technology domains marked by a substantial CRMs presence (excluding those closely tied to metallurgy), we discover significant representation in electric elements. This includes semiconductors and solid-state devices, which point us back to pivotal components of clean energy storage technologies, and technology domains associated with crystal growth processes, which can be used in the production of homogeneous crystals, such as silicon crystals crucial for solar panels. Thus, in shaping the CRMs dependency of green and non-green technologies, while a quantitative distinction is evident in terms of overall material presence, we also find similarities as to which are the most material intensive technology areas. Even in the non-green case, these areas underscore the significance of key technological components within the context of the clean energy transition.

On the whole, this paper represents a preliminary step in the analysis of CRMs, with several unexplored aspects pointing towards interesting avenues for future research. First of all, there are potential advancements in data and methods that can enhance our understanding of CRM dynamics. For instance, overcoming text mining as the only means of establishing the presence of CRMs in technologies could help to distinguish the actual use of a material in inventions from other purposes, such as recycling, refining, or removal. While text mining of patents is acknowledged in the literature, the incorporation of text analysis algorithms could enhance precision. Additionally, patents contain a wealth of untapped information beyond what is considered in this study that can enrich this analysis. For instance, geolocalisation at the country level of patent protection could identify countries most exposed to increased CRMs demand through their inventive activities. Further, characterizations at the CRM level, including data on their production, could help assess whether materials with concentrated production in a few countries, and therefore riskier, are prevalent in patents.

These considerations offer only a glimpse into potential avenues for exploring the topic of the dependence of green innovations from CRMs, which poses challenges to achieving climate goals. While the resource-intensive nature of green technologies holds a central position in global political agendas, we argue that comprehensive empirical studies, like this one, are vital for shaping effective policies. These policies should not solely focus on increasing the production of CRMs at any cost, but should also take into account the related social and environmental aspects, such as the social and economic conditions in the main producing countries and the environmental impacts of the extraction and processing of raw materials.

Chapter 3

Mapping Critical Raw Materials in Green Technologies

The content of this Chapter is based on de Cunzo et al. (2023).

Abstract

The goal of this paper is to elaborate an empirical analysis of the relationship between Critical Raw Materials (CRMs) and environmental technologies. Using text mining techniques to parse and analyse patent descriptions, we provide a thorough empirical exploration of (i) the dependence of green technologies on CRMs; (ii) the countries that lead the demand of CRMs; and (iii) the countries that are more exposed to global demand for CRMs. Framed in the context of recent policy debates on the viability of the green transition, our study points to criticalities associated to both the evolution of green technology and to the spatial network of demand and supply of CRMs.

Keywords: *Critical Raw Materials; Green Technologies; Text Mining*

3.1 Introduction

The goal of this paper is to elaborate an empirical analysis of the relationship between Critical Raw Materials (CRMs) and environmental technologies. CRMs include a broad range of raw inputs that are necessary for the production of intermediate and final goods, and that are deemed critical on account of both their strategic importance for multiple sectors of the economy and of issues concerning availability and limited substitutability. The European Commission (EC) published the first comprehensive list of CRMs in 2011 (European Commission, 2011) and updated it every three years. For the purposes of the present study we rely on an expanded version on the 2020 list (European Commission, 2020*a*) that includes crucial inputs for the green transition (Herrington, 2021; Hund et al., 2020; International Energy Agency, 2021; Kowalski and Legendre, 2023). Our analysis explores three questions:

1. Which green technologies rely more intensively on CRMs?
2. Which countries rely more intensively on CRMs via their own green inventive activities?
3. Which countries are more exposed to green technology-driven demand for CRMs?

To put matters in context, meeting the climate change goals outlined in the Paris Agreement (1.5-2°C or below) will require scaling up the development and deployment of green technologies which, in turn, entails a significant expansion of production and trade of raw inputs that are critical for their operation (International Energy Agency, 2021; Kowalski and Legendre, 2023). The problem is that green technologies are already more mineral intensive than the fossil fuel counterparts. The International Energy Agency (2021) estimates that a standard electric car needs six times the mineral input of a conventional vehicle and that, under the Sustainable Development Goals scenario, demand for lithium, nickel and graphite – all key inputs for electric vehicles – will grow up to almost 30 times relative to 2020 levels. Likewise, the World Bank (Hund et al., 2020) estimates that meeting the 2°C scenario by 2050 for energy storage alone will require a 450% increase in the production of graphite, lithium and cobalt. Therefore, while implementing the green transition may contribute to reduce global dependence on fossil fuels, keeping up with current demand levels will shift the pressure towards production and trade of raw materials, neither of which is exempt from complications.

On the one hand, the availability of minerals depends upon a wide range of physical and sociopolitical issues. As regards the former, empirical evidence shows that current global reserves of CRMs are not sufficient to match projected demand levels (Herrington, 2021). In addition, the processing yield (viz. ore) of several inputs that are crucial for green technology has been declining over time, thus resulting in higher unitary extraction costs (Heijlen et al., 2021). A second set of issues concerns geopolitical tensions – such as e.g. the ongoing conflict in Ukraine – whereby energy dependence on few supplier countries may turn into vulnerability to input shortages and price oscillations, with far reaching social and economic impacts (Kowalski and Legendre, 2023). Further, prior research shows that mineral extraction correlates with negative socioeconomic outcomes in source countries, to name a few: environmental harm (Azadi et al., 2020; Norgate and Haque, 2010; Wanger, 2011; Romare and Dahllöf, 2017), lower agricultural productivity (Aragón and Rud, 2015), increased physical and psychosocial occupational health hazards (Sovacool, Ali, Bazilian, Radley, Nemery, Okatz and Mulvaney, 2020), as well as higher propensity towards violent conflicts (Berman et al., 2017; Christensen, 2018; Church and Crawford, 2018). What's more, these domestic issues often hamper suppliers' export security of minerals, thus adding to the globally uncertain outlook. Increasing secondary production of materials through reuse might be an alternative but the current recycling capacity of most CRMs remains inadequate (International Energy Agency, 2021; Jowitt et al., 2018; United Nations Environment Programme, International Resource Panel, 2011; Vikström et al., 2013), and there is still a long way to go before such an option becomes viable and profitable (International Energy Agency, 2023*a*; Wang et al., 2014).

Another major complication is that meeting current, or higher, levels of demand for energy and transportation requires extraction and processing infrastructure that has yet to be built. Indeed, many CRMs required for the green transition have not been mined in bulk quantities so far, and doing so will likely confront scalability issues due to (i) the need for massive amounts of fossil-fuel energy, (ii) the complexity of the underlying component inputs and (iii) the uncertainty of operating untested large-scale distribution systems – e.g., supplying clean energy that matches current standards of security, continuity and regularity (Azadi et al., 2020; Grandell et al., 2016; Michaux, 2021; Valero et al., 2018). One solution may be increasing mineral extraction both by improving current mining activities and by opening new sites, as outlined in the EC's Action Plan on Critical Raw Materials (European Commission, 2020*a*). But, in addition to the foretold socioeconomic drawbacks, setting up new extraction activities would not solve pressing supply issues considering that the average lead times from discovery to production of new mines is nine years – five for construction and start of production alone (International Energy Agency, 2023*a*). In sum, the problem is not just how much of each input is physically available but whether it is economically possible to extract, product and use them as intensively and rapidly as dictated by current policies — not least the European Green Deal.

These issues have surfaced in academic and policy debates only recently. A World Bank forecast casts a shadow on current projections of the timing of the switch to non-fossil fuel energy generation and storage due to global CRMs availability (Hund et al., 2020) and calls for closer collaboration between the climate community and mineral producers to facilitate 'smart mining strategies'. In a similar vein, a European Commission foresight exercise of the supply risks associated with the availability of and accessibility to CRMs (European Commission, 2020*b*) invokes a new industrial strategy based on the stipulation of strategic alliances to remove economic and technical barriers. Further, an International Energy Agency study on green energy technology supply chains identifies key bottlenecks to the scaling up of clean energy as per current policies (see i.e., International Energy Agency 2021, 2023*a*), and advocates for international producer-consumer relationships to shape new environmental, social and governance standards for mineral production and processing. Last but not least, an OECD (Kowalski and Legendre, 2023) assessment of possible shortcomings for technology development due to export restrictions of raw materials recommends a product-specific approach to guide policies for preventing or closing gaps and inconsistencies along green value chains. Common to these recent reports, besides the focus on the emerging socio-technical barriers, is the emphasis on policy that identify and prevent cross national or cross sectoral barriers.

In spite of growing attention in the policy arena, the literature on innovation studies has barely kept up with mounting evidence of growing, and imminent, criticalities in the path towards the green transition. Iammarino and coauthors took a first step by providing thorough empirical evidence of the technological dependence of new inventions on rare minerals (Yunxiong Li et al., 2024) and of technological and geographical linkages between technological paradigms and some critical and conflict materials (Diemer et al., 2022). Taking the cue from these pioneering studies, we propose an exploratory analysis of how green innovation activities map onto the demand for critical raw materials. Bearing in mind that under the broad umbrella of 'green technology' stands a vast terrain of target-specific domains (i.e., energy generation, transport, manufacturing), understanding how technology and sub-technology developments shape input material demand is crucial to inform the viability of different low-carbon scenarios, especially in view of the trade offs that may emerge as a result of the aforementioned bottlenecks. Furthermore, such an exercise carries a dual geographical connotation considering that both inventive activities and material inputs availability are spatially concentrated in specific territorial clusters, which obviously may or may not coincide. This is to say, a directed mapping of clean technology onto critical materials indirectly captures the complex web of cross-country demand and supply connections, thus providing a critical entry point into the wider socio-political opportunities and challenges associated with the green transition.

The empirical analysis proposed here relies on various methodologies and data sources. First, we employ text mining techniques to parse green patents' abstracts – source: European Patent Office (2020) – over the period 1998-2017. This allows us to identify the green technology classes that are more intensively associated to CRMs, thus addressing the first research question. Our methodology follows the cue of cited works by Iammarino and coauthors (Diemer et al., 2022; Yunxiong Li et al., 2024), as well as the pioneering study by Biggi et al. (2022) on the toxicity of chemical patents. Subsequently, using information on granted status and filing countries, we map spatial demand of CRMs based on each country's green patenting activity, thus addressing the second research question. These two issues are further articulated by considering the relative scarcity of materials, measured by means of a spatial concentration index. Lastly, data on the annual production of critical raw materials (source: *World Mining Data* (2023)) allows us to geolocalise the spatial distribution of these inputs. This addresses the third research question and yields the other side of the map, namely of the territories with higher exposure to green technology development by virtue of their endowment of critical materials.

The remainder of the paper is organised as follows. Section 3.2 - Data & Methods describes the data and the methodology. Section 3.3 - Results outlines and discusses the results, and is articulated in sub-sections, one for each of the research questions addressed in this paper. Section 3.4 - Conclusion concludes.

3.2 Data & Methods

3.2.1 Data

Green Patents

The primary source of our analysis is the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT) (European Patent Office, 2020), a comprehensive repository of information on more than 100 million documents from patent offices around the world. In spite of well-known shortcomings — i.e. not all inventions are patented, or that among those patented it is difficult to determine their true intrinsic value — patent data is still a reliable source due to wide availability and granularity of information (Arts et al., 2013; Dechezleprêtre et al., 2011; Griliches, 1998; Lanjouw et al., 1998). In the case at hand, we rely on information on the nature of the invention, as detailed in the abstract, and on the geolocalisation of applicants and inventors (Dechezleprêtre et al., 2011). Finally, patent data can be disaggregated into increasingly fine-grained technological areas, which facilitates our task of running keyword searches in specific technological domains (Haščič and Migotto, 2015).

Associated to each patent application in PATSTAT are the Cooperative Patent Classification (CPC) codes assigned by patent offices depending on the relevant technological domain of the invention. The CPC system encompasses five hierarchical levels spanning from 9 sections to around 250000 subgroups: codes starting with the letters A to H represent a traditional classification of innovative activity in technological fields, while the Y section[1] tags new cross-sectional technologies. Inside the Y section, the Y02 class (*Technologies or applications for mitigation or adaptation against climate change*) contains more than 1000 tags organised in 8 sub-classes concerning a wide range of technologies related to sustainability objectives, such as energy efficiency in buildings, energy generation from renewable sources, sustainable mobility, smart grids and many others, details of which can be found at a more aggregated level (hereafter CPC1 level) in Table 3.1 and at more disaggregated level (hereafter CPC2 level) in Table 3.2.

Our database includes 3.003.748 patent applications containing abstracts written in English and labeled with CPC codes under the Y02 class. Since an invention can be protected by several patent applications[2], we avoid multiple counting by grouping applications in *inpadoc* patent families, each representing a collection of documents related to the same invention. In our case, 3 million applications correspond to 1.839.600 patent families for each of which we retrieve information on the corresponding Y02 codes at CPC1 and CPC2 levels, the country of origin of the inventors, the country where the family is filed (i.e. where the owners of the invention want to protect it), and the earliest filing year of the family (i.e. the filing year of the earliest patent application belonging to the family). Regarding the latter, we only consider patents registered in PATSTAT no later than 2017 to account for lengthy lags between the compilation in patent offices and the data recorded and collected by EPO.

CRM Production Data

The other major source for our analysis is the World Mining Data (WMD) dataset (*World Mining Data*, 2023), from which we extract information on the annual production of all the relevant CRMs (see Table 3.3) to focus, in particular, on the annual material content in metric tons produced by each country for the period 1984-2020. Moreover, we compare WMD data with data from the British Geological Survey (BGS)

[1] https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html

[2] For example, for the same invention there are as many patent applications as the number of countries or geographical organisations where the applicants want their invention protected. Legal frameworks of patent offices also offer mechanisms to extent the rights of protection over an invention, which lead to more patent applications.

CPC label	Title and description
Y02	**TECHNOLOGIES OR APPLICATIONS FOR MITIGATION OR ADAPTATION AGAINST CLIMATE CHANGE**
Y02A	Technologies for adaptation to climate change
Y02B	Climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications, including the residential sector
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies, i.e. information and communication technologies aiming at the reduction of their own energy use
Y02E	Reduction of greenhouse gas (GHG) emissions, related to energy generation, transmission or distribution, including renewable energy, efficient combustion, biofuels, efficient transmission and distribution, energy storage, and hydrogen technology
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation, e.g. hybrid vehicles
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management

Table 3.1: CPC1 Y02 tagging scheme: green technology main classes.

(British Geological Survey, 2023) and the US Geological Survey (USGS) (U.S. Geological Survey, 2023) to cross-check for consistency. We consider WMD our main source because it covers most of the materials of interest. In fact, several CRMs are not found in elemental form but alloyed together with other elements in some minerals. Data on these CRMs can be expressed in terms of the produced quantities of the corresponding minerals: however, depending on the mineral, the CRMs are present in different percentages, which entails that it would be inaccurate to compare production data between countries. For example, lithium can be extracted from minerals with different lithium content. In BGS and USGS lithium production data is reported in terms of these minerals, which can be different depending on the producer country; in WMD on the other hand, lithium production data is expressed in terms of lithium oxide content (Li_2O) for all countries, which make it more accurate as a measure to compare.

However, WMD does not provide information for some CRMs, for example phosphate rock minerals, the only significant global resources of phosphorus according to USGS (U.S. Geological Survey, 2023), magnesium, silicon and strontium. To make up for these gaps, we rely on data from the BGS. An additional caveat is in order for silicon. Production data are included within the ferro-alloys, which comprise alloys that do not include silicon (like ferro-manganese, ferro-nickel, ferro-chrome and so on) or that have a variable and uncertain silicon content (like silicon metal, ferro-silicon, ferro-silico-chrome, ferro-silico-manganese). From all the ferro-alloys, we extract production data on silicon metal only, since it is from it that the high-purity silicon used in green technologies is typically obtained; in addition, in the list by the European Commission (2020a) silicon metal, and not generic silicon, is explicitly mentioned among the critical materials to be monitored for Europe. Finally, since starting from 2011 USA production data on silicon metal is reported together with ferro-silicon under the name "ferro-alloys", we estimate the annual silicon metal quantities produced by USA in the period 2011-2020 by weighting the reported ferro-alloys values with the average

CPC label		Description
Y02A	10	Adaptation to climate change at coastal zones; at river basins
	20	Water conservation; efficient water supply; efficient water use
	30	Adapting or protecting infrastructure or their operation
	40	Adaptation technologies in agriculture, livestock or agroalimentary production
	50	Adaptation in human health protection
	90	Having an indirect contribution to adaptation to climate change
Y02B	10	Integration of renewable energy sources in buildings
	20	Energy efficient lighting technologies
	30	Energy efficient heating, ventilation or air conditioning
	40	Improving the efficiency of home appliances
	50	Energy efficient technologies in elevators, escalators and moving walkways
	60	ICT aiming at the reduction of own energy use
	70	Technologies for an efficient end-user side electric power management and consumption
	80	Architectural or constructional elements improving the thermal performance of buildings
	90	Enabling technologies or with a potential contribution to GHG emissions mitigation
Y02C	10	CO_2 capture or storage
	20	Capture or disposal of greenhouse gases other than CO_2
Y02D	10	Energy efficient computing
	30	High level technologies for reducing energy consumption in communication networks
	50	Reducing energy consumption in wire-line communication networks
	70	Reducing energy consumption in wireless communication networks
Y02E	10	Energy generation through renewable energy sources
	20	Combustion technologies with mitigation potential
	30	Energy generation of nuclear origin
	40	Technologies for an efficient electrical power generation, transmission or distribution
	50	Technologies for the production of fuel of non-fossil origin
	60	Enabling technologies or with a potential contribution to GHG emissions mitigation
	70	Other energy conversion or management systems reducing GHG emissions
Y02P	10	Technologies related to metal processing
	20	Technologies relating to chemical industry
	30	Technologies relating to oil refining and petrochemical industry
	40	Technologies relating to the processing of minerals
	60	Technologies relating to agriculture, livestock or agroalimentary industries
	70	CCMT in the production process for final industrial or consumer products
	80	CCMT for sector-wide applications
	90	Enabling technologies with a potential contribution to GHG emissions mitigation
Y02T	10	Road transport of goods or passengers
	30	Transportation of goods or passengers via railways
	50	Aeronautics or air transport
	70	Maritime or waterways transport
	90	Enabling technologies or with a potential contribution to GHG emissions mitigation
Y02W	10	Technologies for wastewater treatment
	30	Technologies for solid waste management
	90	Enabling technologies or with a potential contribution to GHG emissions mitigation

Table 3.2: CPC2 tagging scheme: green technology sub-classes.

ratio silicon metal to ferro-silicon of the period 2001-2010.

3.2.2 Methods

Our analysis focuses on 1.473.320 patent families over the period 1998-2017, thus covering a 20 year time span that is both as recent as patent data allows but that also captures dynamics unfolding around milestone climate agreements (European Commission, 2019*a*; United Nations, 1997, 2015).

CRMs keyword search

As a first step in our analysis, we compile a list of critical raw materials that will be parsed in green patent abstracts. To do so, we rely on two main sources. The first is the European Commission's list of materials that are labeled as 'critical' in view of their importance for the future of European economies, especially in light of the commitments outlined in the Green Deal (European Commission, 2020*a*). This list, first created in 2011 (European Commission, 2011), is regularly updated every 3 years. For this study we use the 2020 update. The second source is the report of the International Energy Agency (IEA) on the role of minerals in the transition to clean energy sources (International Energy Agency, 2021), in which a wide range of minerals used in clean energy technologies is considered.

Using these resources as references, we run a keyword search of CRMs mentions in each patent's abstracts based on a newly created dictionary containing all the materials in the aforementioned reports (see the top panel *Disaggregated keywords* in Table 3.3). Each detection of a listed term implies an association between a patent application and one of the CRM[3]. The list of 39 CRMs with respect to which we express our results, is reported in the bottom panel (*Aggregated keywords*) of Table 3.3.

At this point, a caveat is in order. A green technology-CRM connection can signal a number of circumstances. For example, an input may be mentioned because it is directly used by the patented green technology but also because the technology is used in the manufacturing or refining processes of that material. Furthermore, a green patent might mention a material as the patented invention corresponds to a technology aimed at removing the material because it is harmful to the environment. The latter is especially important for our analysis. That said, following prior literature (Biggi et al., 2022; Diemer et al., 2022; Fifarek et al., 2007; Yunxiong Li et al., 2024) we consider that text mining is a reliable first approximation to detect the connection between CRMs and green technologies. In this spirit, we have also carried out additional checks as reported in Appendix C.1 - Manual Exploration of Patent Abstracts. No doubt, future research should be devoted to refining these methods, perhaps by adopting natural language processing techniques (Montobbio et al., 2022; Rughi et al., 2023).

[3]We perform a keyword search of both the extended names of CRMs and their element symbols when they have one, except when the latter may be associated with other meanings — e.g. 'In' which is the symbol for indium, 'As' for arsenic, single letter elements like B (boron), P (phosphorus), and so on. Moreover, we merge the results corresponding to materials that are grouped together when we look at their production information: these include rare earth elements (REEs) — for which we search both for the single materials and the 'rare earth' terms in the abstracts — platinum group metals (PGM), and hafnium with zirconium (labeled as zirconium only in the results).

Critical Raw Materials full list

Disaggregated keywords

Aluminium	Antimony	Arsenic	Baryte	Bauxite
Beryllium	Bismuth	Boron	Cadmium	Chromium
Cobalt	Copper	Dysprosium*	Fluorspar	Gallium
Germanium	Graphite	Hafnium***	Indium	Iridium**
Lanthanum*	Lead	Lithium	Magnesium	Manganese
Molybdenum	Neodymium*	Nickel	Niobium	Phosphorus
Palladium**	Platinum**	Praseodymium*	Samarium*	Scandium*
Selenium	Silicon	Silver	Strontium	Tantalum
Tellurium	Terbium*	Tin	Titanium	Tungsten
Vanadium	Yttrium*	Zinc	Zirconium***	

Aggregated keywords

Aluminium	Antimony	Arsenic	Baryte	Bauxite
Beryllium	Bismuth	Boron	Cadmium	Chromium
Cobalt	Copper	Fluorspar	Gallium	Germanium
Graphite	Indium	Lead	Lithium	Magnesium
Manganese	Molybdenum	Nickel	Niobium	PGM
Phosphorus	REE	Selenium	Silicon metal	Silver
Strontium	Tantalum	Tellurium	Tin	Titanium
Tungsten	Vanadium	Zinc	Zirconium	

Table 3.3: *Top panel*: list of all materials searched in patent abstracts. *Bottom panel*: list of 39 CRMs after aggregation. Legend: * rare earth elements (REE); ** platinum group metals (PGM); *** zirconium and hafnium (labeled under zirconium after the aggregation).

Herfindahl–Hirschman Index

We consider the time interval 1998-2017 both as a whole and divided into five-year blocks. Regardless of the time aggregation, the pre-processing of CRMs production information is the same, that is, we sum up the production data of the years included in the time interval considered. Therefore, for each period, and for each country-CRM couple, we consider the amount of CRM produced by the country in the years considered. In addition, from the summed data we compute the Herfindahl–Hirschman Index (HHI). Normally, HHI is a commonly accepted and used measure of market concentration computed by summing the squared market shares of all firms in a particular market. The resulting index ranges from 0 to 1: the higher the HHI, the greater the market power of the largest firms in the market. Here we employ the HHI to measure the concentration of producing countries for each CRM. In our case, the HHI takes into account the relative size and distribution of the CRM quantities produced by countries and it approaches zero when the CRM is produced in relatively equal size quantities by a large number of countries. Therefore, the higher the HHI, the greater the share of material output from the largest producing country. In formula:

$$HHI_m(t) = \sum_c \left(\frac{q_{mc}(t)}{\sum_c q_{mc}(t)} \right)^2, \tag{3.1}$$

where $q_{cm}(t)$ is the produced quantity (expressed in metric tons) of the CRM m from country c in time period t.

Network Construction

The last part of the analysis brings together all the preceding insights to explore jointly the network of relationships between (i) CRMs and green technologies (based on keyword search), (ii) countries and green technologies (based on where patents are filed), and (iii) between countries and materials (based on production data).

Depending on the relationship at hand, we follow different rules for the link construction between two nodes. In particular, we connect a CRM with a green technology when the number of detections in that green technology is greater than the average number of detections of all CRMs in the same green technology. We also connect a CRM with a country when the latter produces more than the average global production of that CRM. Lastly, we connect a country with a green technology when the number of filed green patent families corresponding to that green technology in the country is above the average number of filed families across all countries. The outcome of such an exercise is an undirected network of CRMs, green technologies and countries wherein each link represents a connection to which we associate different meanings: green technologies are connected with the materials on which they are most dependent and with the countries in which they are deployed, while a country is connected with a material if it is a major producer worldwide.

3.3 Results

Through a keyword search of materials over more than 3 millions green patent abstracts we examine at a very fined grained level the dependence of green technologies on the

39 CRMs listed in Table 3.3 (bottom panel) over the period 1998-2017. Searching for green patents in this time window yields 1473320 inpadoc documents. Overall, all the materials are detected at least once, while looking at the families where we have found at least one material, the only green technology to which none of them corresponds (and therefore the only one with which we find no connection to any material) is *Y02B6 - ICT aiming at the reduction of own energy use*, which is also the green technology least present in the entire dataset and has been removed from the CPC since 2018 (European Patent Office and U.S. Patent and Trademark Office, 2018).

3.3.1 CRMs presence in green technologies

We start by examining the outcome of the keyword search in green patents which yields 292689 CRM returns in 167236 inpadoc families; considering the total number of families in the period 1998-2017 (i.e. 1473320) this means that about 11.4% of patent families have at least one detection. Figure 3.1 shows these inputs ordered and labeled on the y-axis according to the total (in percentage terms) of detections in green patents. As expected, silicon and base metals like aluminium, copper, zinc and nickel are the most prominent, which resonates with their wide applicability in various sectors, both green and non-green. To put matters in context, crystalline silicon is key in the solar photovoltaic technology; electricity networks require a huge amount of copper and aluminium, with copper being a cornerstone for all electricity-related technologies; zinc is used in wind turbines as a protective coating against corrosion; nickel has an important role in energy storage technologies (Hund et al., 2020; International Energy Agency, 2021). In addition, we find a high number of returns for lithium, REE, cobalt, and graphite, all extremely important for the development of green technologies.

Figure 3.2 shows the evolution of CRM mentions in green technology patents over the period 1998-2017. In particular, we divid the time period into four 5-year intervals: 1998-2002, 2003-2007, 2008-2012 and 2013-2017. Subsequently, for each CRM and for each 5-year interval, the figure plots the total number of detections divided by the total number of patented green technologies. Finally, we report each CRM evolution using 1998-2002 as the base period. Therein the majority of CRMs exhibit a stable pattern, bar a few exceptions. One is lithium, which exhibits a constant increase from 2002 to 2012 and a slight decrease in 2013-2017. Such an input is known to be crucial for many green technologies like batteries for electric vehicles, which is a source of concern given the ongoing booming demand (Hund et al., 2020; International Energy Agency, 2021, 2023*a*; Kushnir and Sandén, 2012; Valero et al., 2018). Another noticeable feature is the rapid acceleration of silicon in the first sub-period followed by an equally strong decline afterwards. This can be ascribed to the evolution of patenting in solar panels – included in *Energy generation through renewable energy sources (Y02E1)* – following a pattern similar to that of silicon, which remains the dominant input for solar panels due to its abundance in the form of minerals such as silica or quartz in the Earth's crust. However, factors such as high manufacturing costs or sub-optimal reflection parameters of silicon have spurred efforts towards enhancing solar cell performance (Suman et al., 2020) thus increasing the range of materials used in solar panels and, consequently, reducing the relative importance of silicon. Therefore if the initial growth coincides with the full maturity of technologies such as monocrystalline or polycrystalline silicon photovoltaic (PV) cells, the recent decline reflects the emergence of technological alternatives to silicon. Other CRMs such as copper, phosphorus and zinc exhibit increasing trends in recent years. While for copper and zinc this may be due to wide applicability in various domains (i.e., wind turbines, solar panels, batteries) the growth of phosphorus might be due to technologies aimed at controlling its presence in wastewater processes (see also the focus on phosphorus in Appendix C.1 - Manual Exploration of Patent Abstracts). Lastly, even if the trends of CRMs such as aluminum, rare earth elements, lead and nickel are constant or mildly decreasing, this does imply that they are less relevant for green technologies, as shown in Figure 3.1.

Taking a closer look at green technology categories, Figure 3.3 shows the relative presence of CRMs in the first (1998-2007) and second (2008-2017) periods. For reference, the grey dashed line shows the size of each green technology patent class in the dataset. With very few exceptions, dependence on CRMs has increased between the first and the second period, with highest prevalence in *Mitigation technologies in the production or processing of goods (Y02P)*, *Energy generation, transmission or distribution (Y02E)* and *Capture, storage, sequestration or disposal of GHG (Y02C)*. Conversely the subgroup of *Technologies for Information and Communication Technologies (Y02D)* are at the bottom of this ranking. As expected, among the top ten green technologies are flagship domains often cited in the technical literature (European Commission, 2020a; International Energy Agency, 2021), such as *Energy generation through renewable energy sources (Y02E1)*, *Technologies for road transport of good or passengers (Y02T10)* and *Enabling technologies (Y02E60)*. Surprisingly, we also observe two adaptation technologies and four technologies related to the production of goods, three of which with significant higher dependency than the average on CRMs. Overall, the average dependence on CRMs of the top ten technologies in terms of number of patent families is higher than the mean of all technologies (16.6% versus 8.7% in the first period, 18.8% versus 9.4% in the second one). Moreover, these technologies are mostly in a mature stage of the life cycle, which indicates a broader geographical diffusion of their development (Barbieri, Perruchas and Consoli, 2020; Perruchas et al., 2020) and use. This lends support to the argument that policies for the development of green technologies should account for increases in demand for CRMs, either through the increase of primary production or the development of recycling in combination with the eco-design of processes and products.

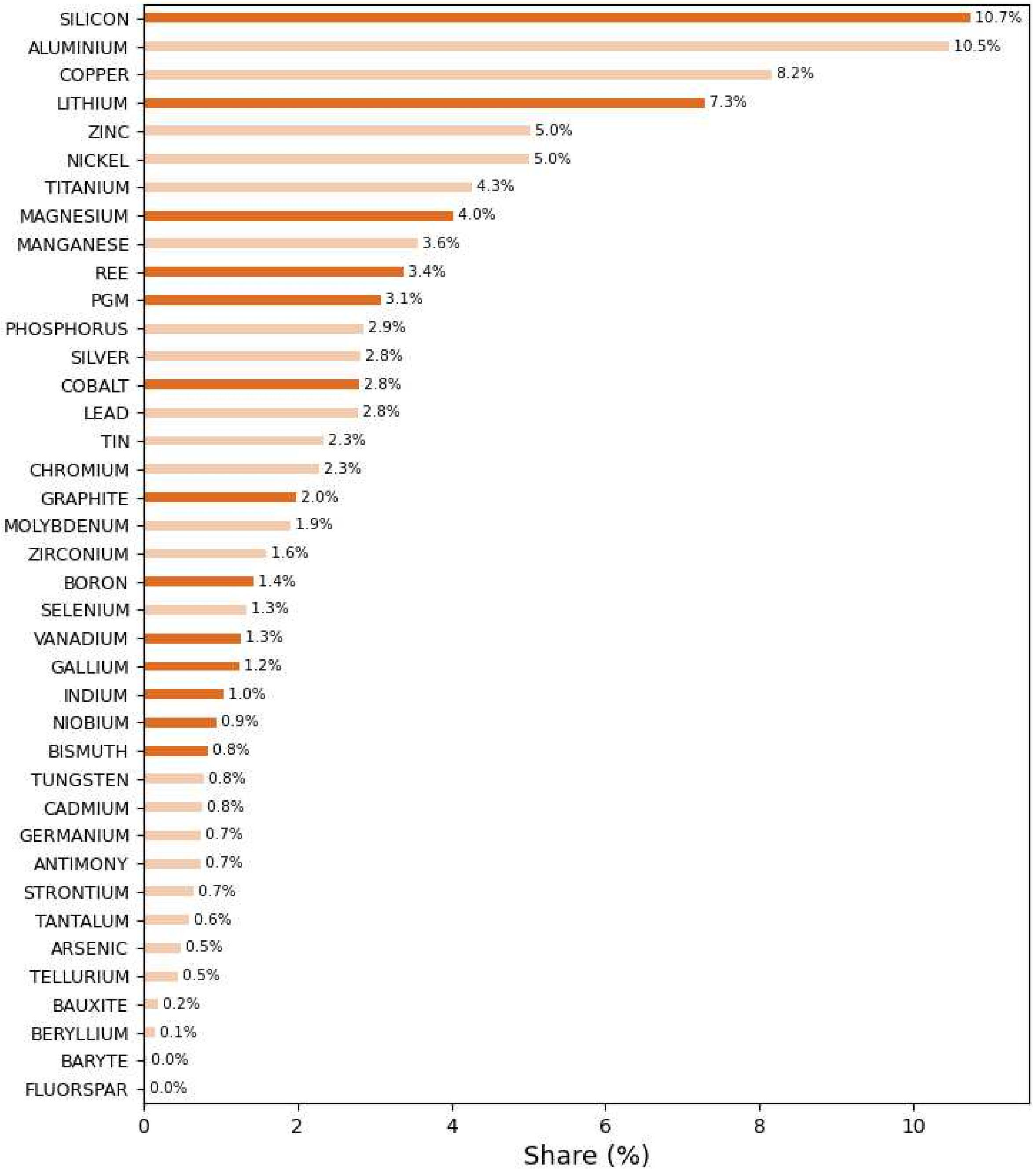


Figure 3.1: Shares of returns for each CRM in green patents. Dark orange bars indicate CRMs with HHI above the median, i.e., more geographically concentrated production, and connected to at least one green technology according to the methodology described in Section 3.2.2 - Network Construction.

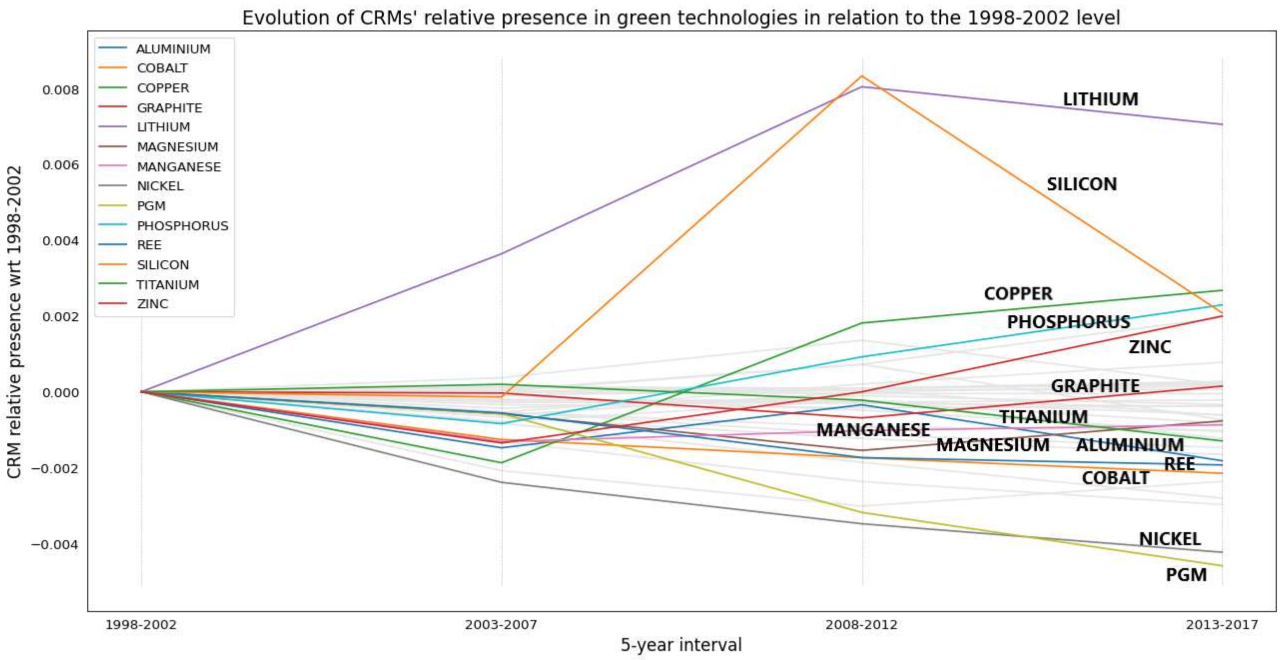


Figure 3.2: Evolution of CRMs' relative presence in green technologies over 5-year periods – base period: 1998-2002.

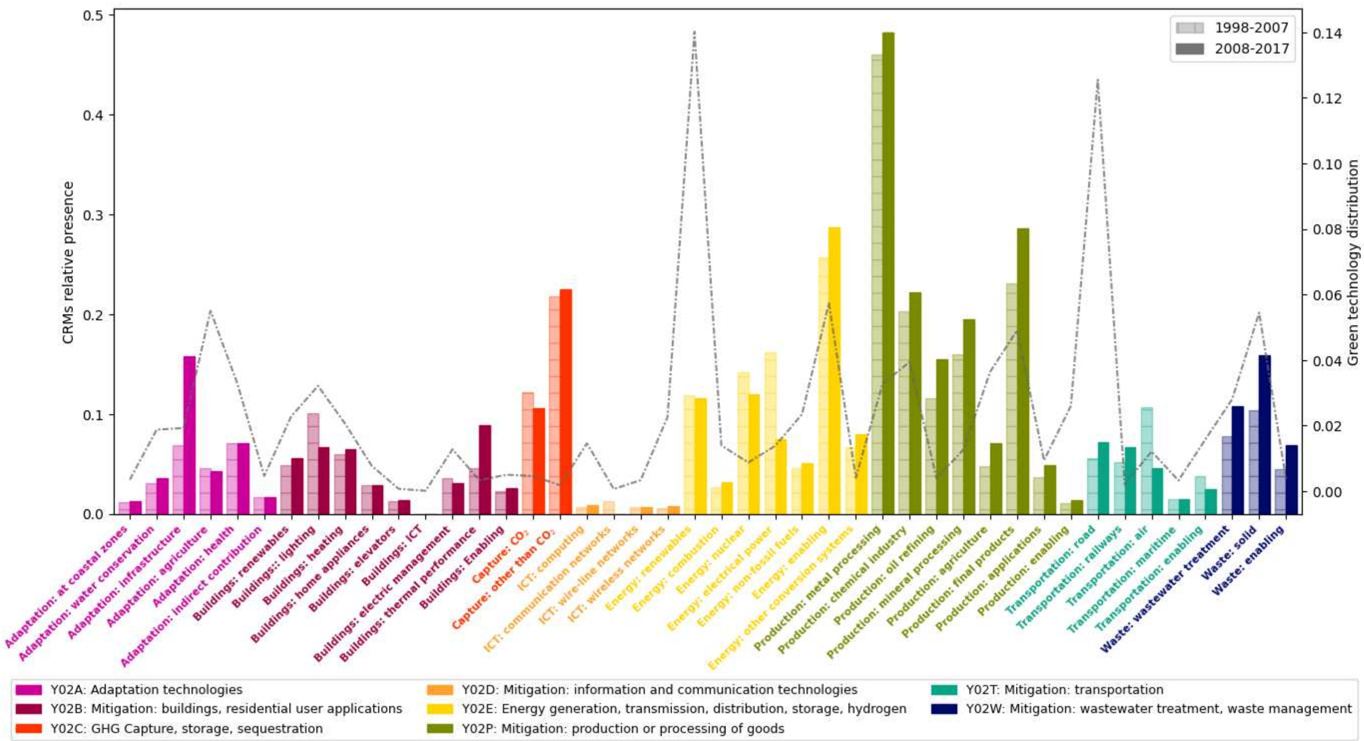


Figure 3.3: Relative presence of CRMs in green technologies (barplot) and green technology distribution (grey dashed line). Bars: left-hand side=1998-2007; right-hand side=2008-2017. Colour coding in the legend (see also Table 3.1 and 3.2).

3.3.2 Which green technologies rely more intensively on CRMs?

Using information on the annual production data allows us to compute CRM specific HHI index to measure the spatial concentration of material production. Table 3.4 shows

CRMs ranked by concentration (columns 1 and 2) as well as information on their share of detections in green patent abstracts (columns 3 and 4) – see Figure 3.1 for reference. Although most raw inputs mentioned in green patents exhibit a fairly wide geographical distribution, a closer look at the first half of the ranking (from boron upwards) indicates that even some of the most concentrated materials play a non negligible role. Among these are rare earth elements (REEs) – mostly produced in China –, silicon – the production of which in its purest form (i.e. silicon metal) is highly concentrated – , lithium – mostly concentrated in Chile, Argentina and Australia – and others like graphite, platinum group metals (PGMs), magnesium and cobalt. We will now focus on these materials that are not very diversified and yet play an important role in green technologies.

Figure 3.4 shows the connections between CRMs and CPC2 green technologies. Materials (rows) are ordered on the y-axis by increasing levels of geographic concentration of production activities (bottom to top) while green technologies (columns) are listed on the x-axis by increasing levels of patenting intensity (left to right). Each CRM-green technology pair cell is coloured according to the percentile range of CRM detections in each green technology, from dark red (high importance) to yellow (low). A cursory look at the graph reveals more clustering (red cells) on the right hand side, which indicates that the higher the frequency of patenting, the higher the material intensity. Further, clustering is higher on the centre to bottom right of the figure, thus suggesting that, in general, more in demand CRMs are also the less geographically concentrated.

Looking at individual items (rows), some CRMs stand out as more 'general purpose' than others, and thus exhibit strong connections with multiple green technology categories. Bearing in mind that CRMs are ranked by HHI (see Table 3.4 for reference), silicon, magnesium, lithium are among the most widely used CRMs with more spatially concentrated production (HHI above the median, top part of the figure). Conversely, aluminium, zinc, copper, lead, titanium and nickel are also in high demand but their production is more widely distributed in space (low HHI, bottom half of the graph). These findings resonate with the policy issues mentioned in the introduction, whereby green tech-CRM pairings that may be associated with shortages are in the center-top right hand side of the graph. Some of these problematic connections are well known.

The first is the co-occurrence of silicon (above median HHI as per Table 3.4) and *Renewable energy (Y02E1)*, which includes among its subclasses photovoltaic energy, thus also including crystalline and amorphous silicon PV cells (Suman et al., 2020). A second renowned connection is between silicon and *Enabling technologies for energy (Y02E6)*, including mainly energy storage technologies such as batteries, for which the use of silicon metal in the anodes is recently being ventured to increase their density (Eshetu et al., 2021; European Commission, 2020*b*). Lastly, silicon ranks high in patenting activities related to *solid waste management (Y02W3)*, which recent literature considers as a side effect of the rapid expansion of the photovoltaic industry (Guo et al., 2021).

Another critical cluster of potentially problematic pairings concerns lithium, which exhibits the peculiarity of being strongly represented in green technologies that are more material specific, meaning that they rely on average on less CRMs compared to other technologies in Figure 3.4. One instance is *Road transport (Y02T1)*, whereby batteries and energy storage devices rely extensively and almost exclusively on this input (Graham et al., 2021). Other lithium-intensive green technologies are *Energy*

CRM (label)	Rank HHI	HHI value	Rank Detections	% Detections
Niobium (Nb)	1	0.855	26	0.94%
REE (REE)	2	0.832	10	3.38%
Tungsten (W)	3	0.667	28	0.78%
Beryllium (Be)	4	0.662	37	0.15%
Antimony (Sb)	5	0.649	31	0.74%
Magnesium (Mg)	6	0.611	8	4.03%
Germanium (Ge)	7	0.461	30	0.74%
Gallium (Ga)	8	0.441	24	1.25%
Graphite (Gph)	9	0.415	18	1.99%
Bismuth (Bi)	10	0.411	27	0.84%
PGM (PGM)	11	0.406	11	3.08%
Fluorspar (F)	12	0.379	39	0.02%
Silicon (Si)	13	0.344	1	10.74%
Vanadium (Va)	14	0.319	23	1.27%
Arsenic (As)	15	0.309	34	0.48%
Indium (In)	16	0.29	25	1.03%
Lithium (Li)	17	0.281	4	7.29%
Cobalt (Co)	18	0.276	14	2.81%
Boron (B)	19	0.267	21	1.42%
Chromium (Cr)	20	0.255	17	2.28%
Zirconium (Zr)	21	0.254	20	1.60%
Strontium (Sr)	22	0.254	32	0.65%
Baryte (Ba)	23	0.244	38	0.03%
Molybdenum (Mo)	24	0.228	19	1.91%
Tin (Sn)	25	0.219	16	2.33%
Lead (Pb)	26	0.199	15	2.78%
Tellurium (Te)	27	0.194	35	0.45%
Phosphorus (P)	28	0.185	12	2.85%
Aluminium (Al)	29	0.168	2	10.46%
Bauxite (Bx)	30	0.157	36	0.18%
Selenium (Se)	31	0.148	22	1.34%
Tantalum (Ta)	32	0.142	33	0.60%
Copper (Cu)	33	0.14	3	8.16%
Manganese (Mn)	34	0.135	9	3.56%
Zinc (Zn)	35	0.13	5	5.02%
Titanium (Ti)	36	0.123	7	4.26%
Cadmium (Cd)	37	0.114	29	0.76%
Nickel (Ni)	38	0.101	6	5.00%
Silver (Ag)	39	0.094	13	2.82%

Table 3.4: For each CRM, this table reports information on its HHI (rank and value) and on the corresponding number of detections (rank and shares in percentage) which are also shown in Figure 3.1

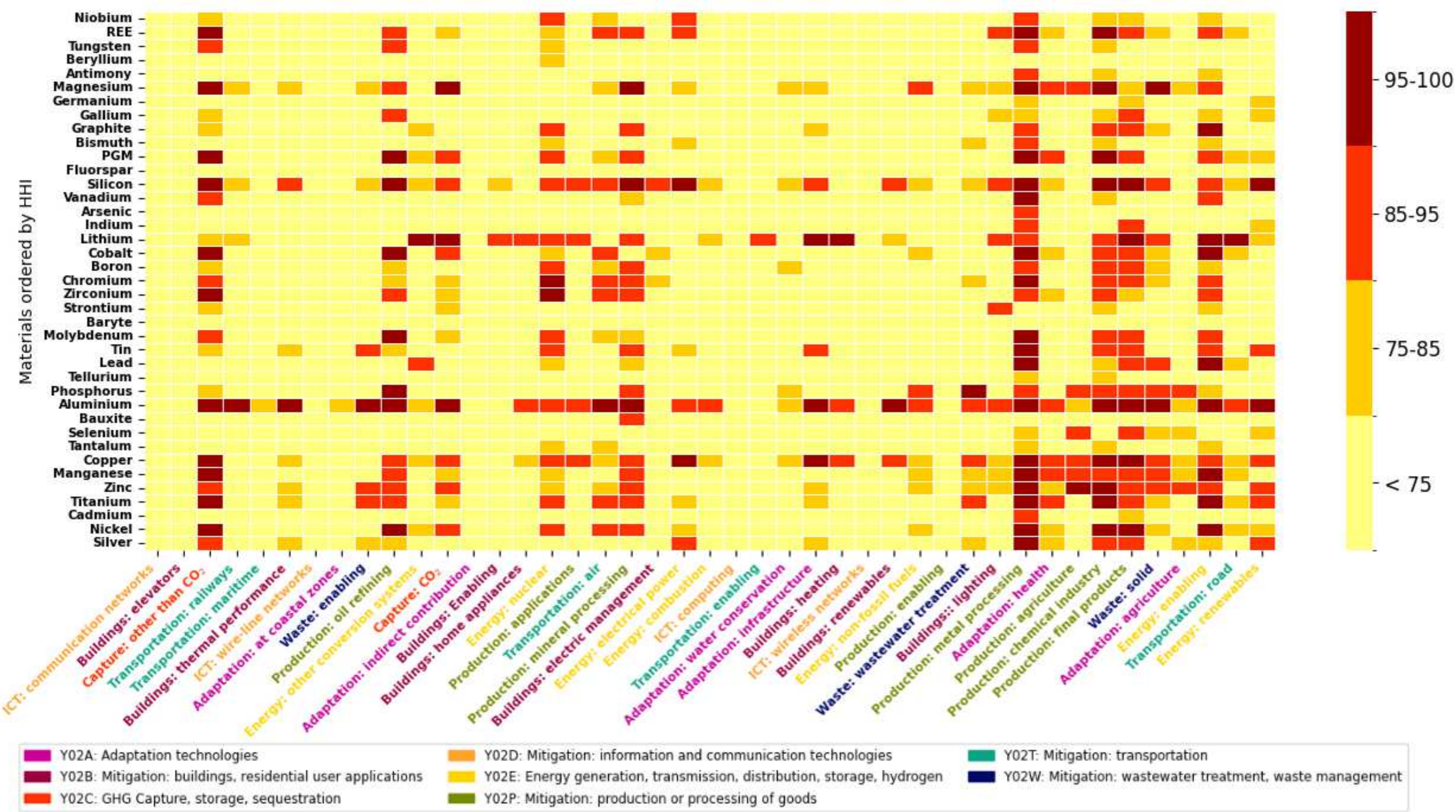


Figure 3.4: Relative presence of CRMs in green technology patents. CRMs are ordered by HHI (see Table 3.4). Green technologies are ordered by the frequency of each sub-class in the dataset, colour coding in the legend. Cells are coloured according to the relative importance of CRMs in each sub-class: dark red= above 95^{th} percentile; red=85^{th}-95^{th}; orange=75^{th}-85^{th}; yellow= below =75^{th}.

efficient heating, ventilation or air conditioning (Y02B3) and *Water conservation technologies (Y0A2)*. Finally, lithium is in high demand among the leading green technology patent categories that rely extensively on silicon, namely *Renewable energy (Y02E1)*, *Enabling technologies for energy (Y02E6)* and *Technologies for solid waste management (Y02W3)*. The common ground of the two inputs is batteries, by far the most important enabling component, which is crucial as a storage system in renewable energy plants and whose recovery through careful waste management is essential to avoid both shortages and environmental and health hazards (Richa et al., 2014; Scrosati and Garche, 2010).

Focusing on the green technology categories (columns), *Production or processing of goods (Y02P)* emerges as the most 'material intensive' class, which is plausible considering that sub-components domains include *Metal processing (Y02P1)*, *Chemical industry (Y02P2)*, *Oil refining and petrochemical industry (Y02P3)* as well as *Final consumer products (Y02P7)*. Other categories that stand out are *Capture or disposal of GHGs other than* CO_2 *(Y02C2)* and *Enabling technologies for energy (Y02E6)*. The high dependence of these technologies on CRMs has many connotations. As mentioned, *Y02P* comprises green technologies for processing metals, minerals, chemical compounds, etc, which clearly leads to a high number of detections in the abstracts[4]. Regarding other patenting domains, the dependence of enabling technologies like batteries and energy storage devices in general as well as fuel cells' on CRMs is well documented (Hund et al., 2020; International Energy Agency, 2021). Finally, regarding the high dependence of *Y02C2*, according to the World Bank report (Hund et al., 2020) the materials involved throughout all the steps (i.e. capture, transport and storage) of the GHG capture process can be manifold and used in a variety of ways, such as nickel and manganese used either in capturing and in the steel alloys needed for the capture plant. However, as evidenced also by the limited number of patents associated with Y02C in our dataset (see Figure 3.3), carbon capture and storage is still at early-stages, which casts uncertainty as to the role it will play in the green transition, not least in terms of the actual quantities of CRMs that will be required for its development and deployment.

3.3.3 Which green patenting countries rely more intensively on CRMs?

The next step of the analysis focuses on the geographical dimension to identify where CRM-dependent green inventions are patented. To obtain a better proxy of the future successful deployment of each invention, we consider only granted green patents[5] which is a sample of 941878 patent families – about 64% of the total number of families over the period 1998-2017. In turn, these families correspond to 1672966 observations of filing countries. If instead we look only at patent families mentioning at least one CRM, we obtain 104028 granted families corresponding to 193585 filing country observations. Therefore, when looking only at granted inventions, the world average relative presence of CRMs in green technologies is 11% (i.e., 104028/941878).

[4]It is important to reiterate that materials might be mentioned in patent abstracts both as inputs but also because of the functionality the technology is aimed at, for example refining, recovery, recycling, etc. Therefore, our count method might overestimate the actual dependence of *Y02P*.

[5]In the case of international patent offices such as WIPO or EPO, we consider a patent application granted in a country when it was reported in PATSTAT or when the patent fees were paid at least once in the country.

Table 3.5 shows the top 20 countries that jointly account for 92% of total filing country observations (i.e. 1540643 out of 1672966): for each country we report the total green patent families (column 2), the number of families with at least one CRM detection (column 3) and the relative presence of CRMs in the country's patenting activity (column 4). Therein, China emerges as the global leader by a margin followed by the United States (US), Japan, South Korea and Germany (cumulatively, they account for 69% of all country observations). The next block includes France, the United Kingdom, Russia, Italy, Taiwan and Spain (cumulatively, 84% of all country observations). On the whole, this ranking highlights the dominance of Asian countries (4 in the top 10) together with the US, as well as the lower profile of Northern European countries, the majority of which are at the bottom of the table – jointly accounting for 5% of country observations – Netherlands to Austria in Table 3.5. A closer look reveals that average CRM dependence is higher in the top 10 relative to the bottom half (12% vs 11.3%). Therein, Russia and Taiwan stand out with the highest relative presence of CRMs in green patents (about 16-17%, well above the world average of 11% and the top 20 average of 11.7%), followed by South Africa and Belgium (about 14-15%), Japan and South Korea (about 13%). The more 'virtuous' countries are Denmark, Germany, France, UK, Sweden, Austria and the US (all around 10%).

Country	**TOT families**	**TOT families with CRMs**	**Relative presence of CRMs**
China	548723	64241	11.7%
United States	212267	19729	9.3%
Japan	184653	23913	13.0%
South Korea	115360	15131	13.1%
Germany	95452	9024	9.5%
France	71207	7139	10.0%
United Kingdom	60050	6002	10.0%
Russia	34422	5771	16.8%
Italy	29160	3040	10.4%
Taiwan	27120	4352	16.0%
Spain	25052	2559	10.2%
Australia	23372	2885	12.3%
Canada	22681	2629	11.6%
Netherlands	20081	2213	11.0%
Sweden	14699	1483	10.1%
Switzerland	13077	1412	10.8%
Belgium	11632	1646	14.2%
Denmark	11083	854	7.7%
Austria	10929	1100	10.1%
South Africa	9623	1462	15.2%

Table 3.5: Descriptive of filed green patents by country

To gain further insights into the spatial distribution of material intensity, we break down information on the relative presence of materials in the top 20 countries by green technology domain (see Figure 3.5). Looking at green patent portfolios by *Y02* sub-classes it is possible to observe that the highest levels of CRM dependence of countries are driven by the most intensive technological categories. High CRM dependent countries like Russia, Taiwan, South Africa, Japan, South Korea and Belgium show multiple high level of dependence (far above average) in the related domains of *production (Y02P)* (Russia, South Africa, Taiwan and Japan in particular), *energy generation (Y02E)* (Taiwan, Japan and South Korea), and *carbon capture (Y02C)* (Taiwan). Russia exhibits high dependence in *waste management (Y02W)*, while Taiwan, Belgium and South Africa in *transportation (Y02T)*. Countries with lower CRM dependence, such as China, Australia and Canada (about 12-13%, see Table 3.5), display average levels of dependencies across all technology domains. Finally, countries such as the US, Germany, France and United Kingdom exhibit a more balanced level of CRM dependence in their green patent portfolios, with fewer technology domains featuring higher levels of dependence, that usually do not significantly exceed the average values reported in the last row of the figure.

	Y02A	Y02B	Y02C	Y02D	Y02E	Y02P	Y02T	Y02W
China	0,064	0,066	0,161	0,013	0,131	0,215	0,068	0,113
United States	0,053	0,042	0,122	0,006	0,171	0,191	0,065	0,110
Japan	0,063	0,053	0,161	0,008	0,212	0,244	0,088	0,110
South Korea	0,049	0,052	0,163	0,008	0,202	0,227	0,102	0,130
Germany	0,063	0,048	0,124	0,008	0,149	0,196	0,064	0,097
France	0,061	0,048	0,136	0,011	0,158	0,202	0,071	0,103
United Kingdom	0,071	0,048	0,134	0,009	0,146	0,199	0,078	0,113
Russia	0,079	0,067	0,157	0,018	0,134	0,320	0,070	0,170
Italy	0,066	0,048	0,129	0,014	0,141	0,189	0,073	0,109
Taiwan	0,077	0,059	0,229	0,013	0,245	0,244	0,166	0,142
Spain	0,062	0,048	0,129	0,017	0,096	0,201	0,075	0,104
Australia	0,060	0,064	0,095	0,037	0,120	0,243	0,085	0,136
Canada	0,068	0,054	0,086	0,020	0,114	0,221	0,083	0,120
Netherlands	0,060	0,051	0,127	0,016	0,113	0,206	0,099	0,103
Sweden	0,065	0,050	0,159	0,026	0,111	0,205	0,063	0,116
Switzerland	0,066	0,052	0,182	0,027	0,119	0,177	0,123	0,111
Belgium	0,067	0,049	0,192	0,030	0,132	0,239	0,148	0,129
Denmark	0,061	0,034	0,184	0,043	0,052	0,145	0,078	0,098
Austria	0,070	0,044	0,178	0,029	0,096	0,190	0,072	0,105
South Africa	0,071	0,069	0,168	0,030	0,094	0,266	0,178	0,124
Average	0,065	0,052	0,151	0,019	0,137	0,216	0,092	0,117

Figure 3.5: Relative CRMs presence in Y02 sub-classes in national green patent portfolios, x-axis ranked by total green patent families filed in the country (left to right).

Summing up, these insights on the relative input intensity and on the portfolio composition of green patenting, uncover the existence of three blocks. The first includes countries with *high CRM intensity* driven by high CRMs presence in multiple technology domains: Japan, South Korea, Russia, Taiwan, Belgium and South Africa. In the second are countries with *medium CRM intensity* driven by average CRMs presence over all the technology domains: China, Canada and Australia. Finally, the last block consists of countries with *low CRM intensity*, exhibiting below average CRM presence in multiple technology domains: US, Germany, France, United Kingdom, Italy, Spain, Netherlands, Sweden, Switzerland, Denmark, Austria.

3.3.4 Which countries are more exposed to global demand for CRMs?

Following the procedure detailed in Section 3.2.2 - Network Construction we build a network of connections between CRMs, green technologies and countries wherein countries can be green technology inventors and/or suppliers of materials (Figure 3.6). To construct such a network, we average over green technologies to establish links with CRMs and countries, focusing only on materials with high HHI concentration (CRMs from boron upwards according to Table 3.4) that are connected to at least one green technology. This leads us to a reduced list of 13 CRMs, i.e., the materials highlighted with darker bars in Figure 3.1.

In the network layout nodes are grouped in four columns, from the left to the right: countries (1^{st} column, left-hand side), green technologies (2^{nd} column), CRMs (3^{rd} column), while in the right-hand side (4^{th} column) countries are connected to the network by virtue of CRM input production activities. The size of the nodes is proportional to their degree – i.e., each node's number of links with other nodes in the network – and, for the country and CRM columns, the highest degree nodes are at the center of the corresponding column. Instead, green technologies, positioned in the second column of the network, are grouped and colour coded according to the CPC1 sub-classes listed in Table 3.1.

Given the rules we follow to build the network links (see Section 3.2.2 - Network Construction) the main insights coming from this exercise center around the dual role of countries as both green innovator (1^{st} column) and producer (4^{th} column) actors. In fact, for what concerns the other 2 columns (green technologies and CRMs), it is important to note that they exhibit only minimal variation in their degree, and consequently in their importance in the network. This is due to the way we build the links. In fact, when we link a country or a CRM to a green technology, we first take each green technology, second look at the average number of filed green patents or of CRM detections, and third take the countries and CRMs that exceed these averages. Similarly, when we link CRMs to countries, for each CRM we link the countries that produce it more than the global average. Therefore, given the characteristics of this process, it is expected that, despite small variations, the nodes over which we average will have a similar number of connections[6].

Hence, while in the previous sections we focused on shaping the presence of CRMs in green technologies, the network provides insights on the role of countries in the global network of demand and supply for green technology inputs. With the exception of China, the global leader in terms of both green technologies and materials production, a divide emerges between countries at the two extremes of Fig. 3.6. The largest nodes connected to green technologies on the left-hand side are mainly high-income Global North countries – including the US, Germany, France, United Kingdom, Japan and

[6]To stress more on this, look e.g. at the $1^{st} - 2^{nd}$ column connections: for each green technology, we investigate the same set of countries and keep only those with a number of filed patents above the average. Therefore, since the set of countries is the same, the degree (number of countries) of each green technology will be similar, while the composition of its links (which countries) could potentially differ

South Korea – while the second tier of leading patenting countries, below the US in the first column of the network, comprises Italy, Spain, Australia, Russia, Canada and Taiwan.

On the right-hand side of the figure is a cluster of the producers of the most spatially concentrated CRMs. This features a diverse mix with both top patenting countries – such as China, US, Russia and Australia – and countries weakly connected or not linked at all to the green technology nodes, e.g. Turkey, Chile, Argentina, the Democratic Republic of Congo, and India. Brazil (BRA) is a good case in point. It is the second largest producer of CRMs behind China, top supplier of niobium but also of two pivotal and yet relatively scarce inputs like graphite and silicon – the reader will recall their importance from Section 3.3.2 - Which green technologies rely more intensively on CRMs?. The only other producers of silicon (intended as silicon metal) besides Brazil are China, the US and, to a lower extent, Norway. Yet Brazil's participation in green patenting is limited to *oil refining and petrochemical industry (Y02P3)*, a relatively small class of technologies (see Fig. 3.4). Likewise, South Africa (ZAF) is the top producer of highly sought after and relatively scarce platinum group metals (PGM) together with Russia. While this input is used in a wide range of technologies, most notably *chemical industry (Y02P2)* (8^{th} technology domain by patent intensity – see Fig. 3.4), South Africa is only weakly connected to the green patents cluster. Last but not least, the diagram shows that, coherently with the policy reports cited earlier (European Commission, 2020*a*), European countries are rather absent from the right-hand side of the diagram, and the only two that are present, Austria and Norway, are not connected to green technologies as prominently as leading players like France, Germany and United Kingdom.

Let us conclude by drawing attention to a handful of countries that are mere producers and thus exist in this network only by virtue of their capacity to supply CRMs to other patenting countries (red font on the right-hand side of Fig. 3.6). These include Argentina, Cuba, Chile, the Democratic Republic of Congo, India, Turkey and Zambia. With the exception of a few marginal inputs for green technologies – i.e., Boron produced by Chile, Argentina and Turkey – in most cases these countries play an important role in the global green technology enterprise. A striking example is lithium, of which Chile and Argentina are the only producers together with Australia. Yet another is cobalt, produced by various countries including the Democratic Republic of Congo, Cuba, and Zambia, which are not among green technology inventor countries. Finally is graphite, produced by India together with Brazil and China. Lithium, cobalt and graphite are therefore relatively scarce materials (i.e., high HHI) produced by countries that are at best marginal in the domain of green patenting. Therefore, a clear divergence emerges between the countries producing the CRMs necessary for the development of green technologies and those where such technologies are developed.

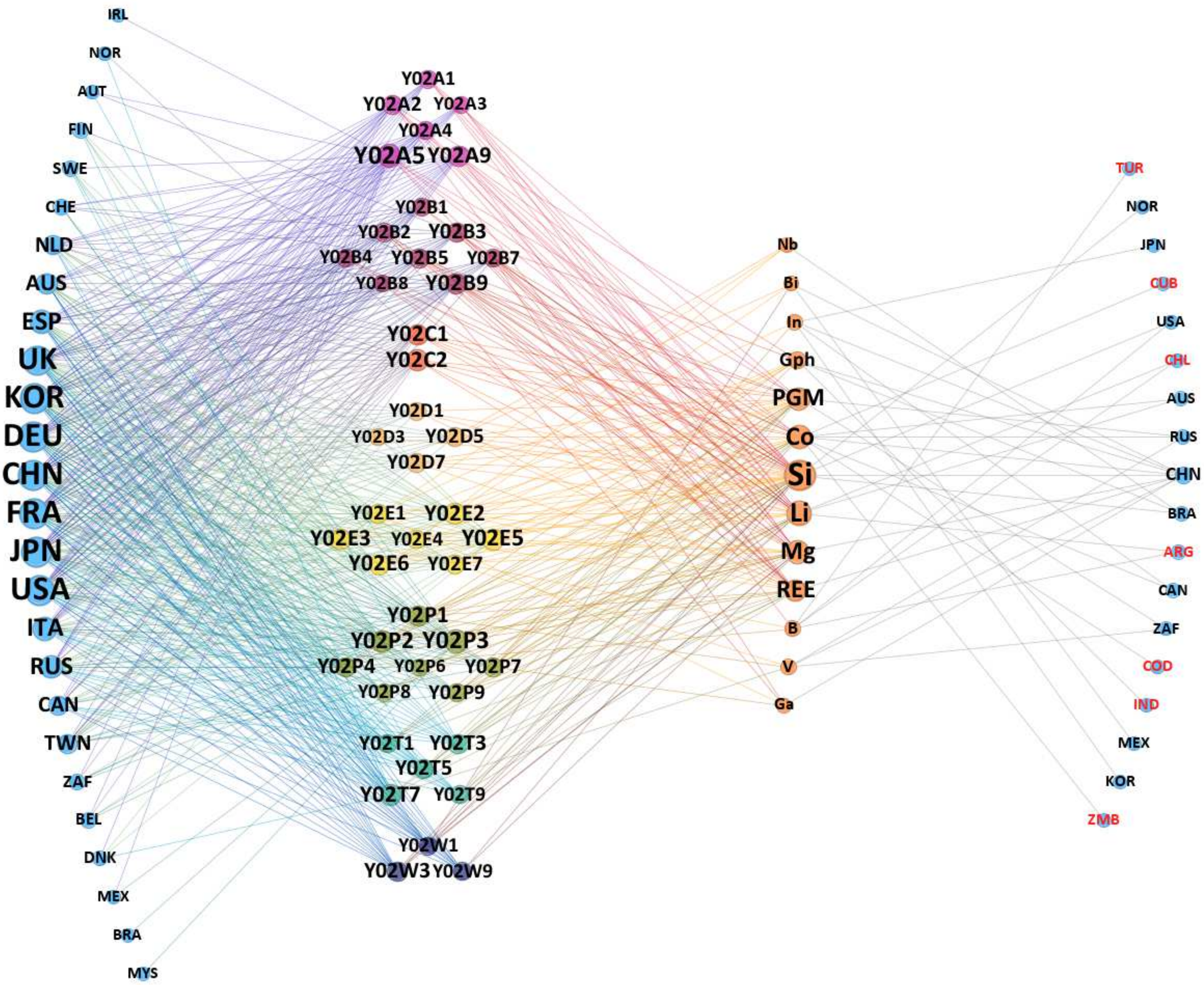


Figure 3.6: Network of CRMs-green technology-countries. Node size is proportional to their degree. Green technologies: from top to bottom according to CPC1 class. Materials: we select only those with above median HHI (i.e. above Boron in Table 3.4). Countries and materials are organised so that the higher the degree of the node, the closer to the centre of the respective column. 1^{st} (left) column reports the countries connected to green technologies (2^{nd} column; 3^{rd} column is the CRMs and the 4^{th} is the countries that produce them.

3.4 Conclusion

This paper has elaborated an empirical analysis of the relationship between Critical Raw Materials and environmental technologies motivated by a growing debate about the feasibility of the green transition which, in its current form, relies heavily on rapid and sizeable scaling up of green technology development and deployment. But this requires an expansion of production and trade of raw inputs which, in spite of policy proclaims, physical availability and state-of-the-art mining capacity simply do not warrant. While the policy debate has started to address these issues, the literature on innovation studies still lags behind. We propose to fills this gap by addressing three questions: (i) which green technologies rely more intensively on CRMs? (ii) which countries rely more intensively on CRMs via their own green inventive activities? And (iii) which countries are more exposed to green technology-driven demand for CRMs?

Our empirical analysis shows that in absolute terms mature green technologies, such as are Metal Processing, Production of goods and Enabling technologies for energy generation, are also more CRM intensive. This is not surprising considering that these were designed and developed when limited resource availability due to excess demand was not an issue. Yet another material intensive domain is the relatively less mature carbon capture, a highly contentious activity due to the uncertainty surrounding both input intensity as well as the observed environmental benefits (IPCC, 2022; Jacobson, 2019). When resource availability (proxied by the HHI index) enters the equation, we identify critical input-green technology pairings. The first is the use of silicon in renewable energy, both for generation and storage, as well as solid waste management. The second concerns the employment of lithium, which is prominent in green technology domains that exhibit higher dependency on specific inputs, namely: batteries and energy storage devices, energy efficient air conditioning and water conservation. Crucially, we also find co-dependence between these two CRMs, as both lithium and silicon are essential to flagship domains such as renewable energy and solid waste management.

Addressing the second question reveals the spatial distribution of green technology specialisation brings to the fore interesting peculiarities. In the top 20 patenting countries are two main groups: one with high CRMs dependence and narrower green tech specialisation, the other with low CRMs dependence and more balanced green technology portfolios. By and large, global leaders in the top 10 have more balanced patent portfolios, with higher prominence of less CRM intensive domains. Interestingly, the top 3 countries exhibit different patterns whereby China, the global leader, is a hybrid (i.e., the only one with high critical input intensity but also a balanced portfolio), the US (2^{nd} ranking) belongs to the former group while Japan (3^{rd} ranking) to the latter. On the whole such an exercise underlines the leadership of the US, the established role of Asia (three countries in the top 5, four in the top 10) as well as the consolidated role of some European countries – albeit only one EU country appears in the top 5.

Lastly, we focus on the geographical exposure to green patenting by considering the dual role of countries in the demand (via patents) and supply of CRMs (via production activities). Such an exercise brings to the fore a noticeable divide between innovators and predominantly low or middle income countries that participate in the global CRMs network only by virtue of their endowment of natural resources that are necessary to meet the demand for inputs that high income countries need to push the green technology frontier. In this picture, Europe stands out primarily as a user of CRMs due to its small volume of production. In contrast, 'mere suppliers' like Argentina, Cuba, Chile, the Democratic Republic of Congo, India, Turkey and Zambia are in the front line of providing critical inputs such as lithium (Chile and Argentina), cobalt (Democratic Republic of Congo, Cuba, and Zambia) and graphite (India) but do not engage any innovation activity.

Before concluding we reiterate that the goal of this paper was to identify criticalities and provide a roadmap for future research on topics that have received so far little attention among innovation scholars. While limits to the physical availability of critical minerals are not new, what has changed is that recent policy pledges have shortened the time frame of the green transition so that ambitious plans to accelerate the shift to e.g., renewable energy or electric vehicle transport may well run into bottlenecks. The first problem is that some critical minerals are in scarce supply, and for some of them mining in bulk quantities is still untested. Even if established targets of new recycling schemes and new extraction activities were met, supply issues would still stand in the way. The second problem is of scalability. Building and operating the infrastructures that are necessary to extract and process the desired volumes of materials, and to subsequently employ them in specific domains of use, is by and large unexplored territory. This uncertainty casts doubts on the feasibility of environmental targets that rely on efficient large-scale systems, especially if subjected to strict standards of security, continuity and regularity as is the case for clean energy supply. The last problem concerns the spatial distribution of natural inputs which connects with, on the one hand, the role of geopolitical relations in the trade of critical materials and, on the other hand, with the importance of accounting for socioeconomic and labour market outcomes in source countries. The lack of balance between the global demand of materials from more industrialised countries and resource availability raises ethical concerns, especially for European producers of green technologies whose future prospects depend on mining resources in other, often less developed, world regions that are already coping with substandard environmental and socioeconomic circumstances. The compelling evidence concerning the uncertainty and the high costs associated with CRM extraction indicate that current green policies are on track to exacerbate disparities and, further down the line, possibly undermine the perceptions and the commitment to tackling climate change. These are complex issues which cannot be addressed by a single paper, but we hope that the present study will contribute to spur such an important debate within the flourishing stream of literature on the green transition.

Conclusions

Main findings and contribution to the literature

This thesis is framed within the general context of the green transition, which implies structural changes towards non-emitting economies. More specifically, it focuses on green innovations, recognised as a crucial pillar for achieving the transition, exploring the possible effects and implications associated with their massive and rapid deployment. These types of phenomena are characterised by a certain degree of complexity and uncertainty. To give some examples, the goal of reducing emissions entails the closure of some sectors that are too polluting and the creation of new, more sustainable ones, with social implications at the geographical level, favouring countries with skills related to the new sectors, and at the employment level, with the reallocation of workers towards less environmentally impactful professions. In addition, the supply chain of green technologies — starting with the extraction and production of basic materials, then moving on to the manufacturing stage and finally ending with distribution and actual use — is particularly articulated at the geographical level. Taken together, if not addressed or poorly managed, these implications can increase the level of inequality between and within countries, threatening the achievement of a just transition, which *"happens in a fair way leaving no one behind"*[7]. Against this background, the 3 chapters of this dissertation contribute to further explore the implications arising from the development of environmental innovations. Specifically, two main topics are discussed. The first concerns the effects of green innovation on industrial production, and is addressed in Chapter 1; the second concerns the dependence of green technologies on raw materials, and is addressed in Chapter 2 and Chapter 3. Overall, the aim of the thesis is to contribute through empirical studies to the successful management of a massive adoption of green technologies in order to prevent negative environmental and social consequences.

How green innovation unfolds into industrial production

Chapter 1 investigates the effects of green innovation on industrial production, by looking at the co-occurrences in countries between the successful patenting of green inventions and the export of products. Through the adoption of techniques belonging to the Economic Complexity (EC) framework (Pugliese, Cimini, Patelli, Zaccaria, Pietronero and Gabrielli, 2019), this chapter brings novelty in the characterisation of the sectors most influenced by green innovation. In particular, building a bipartite network in which green technologies are connected to products whenever they share similar capa-

[7] https://commission.europa.eu/.../just-transition-mechanism_en

bilities needed for a country to be competitive in both, we explore how green innovation unfolds into industrial production at a very fine grained level of detail. Specifically, in the following the main findings for each of the research questions are reported.

- **Which products are most affected by green technology development?**

Looking at the network connecting green technologies to products, we observe a regular distribution of green technologies across all the technological domains. In contrast, when looking at the production side, products are much more irregularly distributed. In particular, a strong association emerges between green technologies and mineral and metal products, which are essential components of these innovations. This suggests the existence of a parallel process involving, on the one hand, the development of green innovations and, on the other hand, the specialisation in processing sectors of the raw inputs required to realise them.

- **How does a 10-year time lag between green technology development and product export alter their relationship?**

Investigating the evolution of the bipartite network when 10 years elapse between the development of green technologies and the export of products provides additional insights. In particular, again with the support of techniques rooted in the EC framework, we observe a larger presence of more complex green technologies and products in the network, suggesting that the process leading to the evolution of the joint capabilities required for the development of complex green technologies and the competitive production of high-tech products is not instantaneous and may require years to unfold.

The Critical Raw Materials dependency of green innovation

Chapter 2 and Chapter 3 delve into the study of the Critical Raw Materials (CRMs) dependency of green and non-green technologies through the adoption of text mining techniques, used to detect the presence of these metal and mineral resources in green and non-green patents. In particular, both chapters consist in exploratory empirical analyses on different dimensions related to the use of CRMs in green and non-green innovations, such as which materials prevail in patents, in which technologies they are most prevalent, and which countries adopt these technologies. Following the path traced by previous studies (Diemer et al., 2022; Yunxiong Li et al., 2024), the aim is to provide an overall picture of the technological dependence on these resources, as it involves numerous risks related to e.g. the actual availability of CRMs in the quantities deemed necessary to cover future demand, and geopolitical factors due to how many (often few) and which countries control the production of CRMs. Similarly to the previous section, in the following the main findings for each of the research questions associated to the CRMs investigation in patents are reported.

- **Which CRMs are most present in green technologies?**

- **Which green technologies rely more intensively on CRMs?**

These preliminary descriptive questions are addressed in both Chapter 2 and Chapter 3. In particular, the most prevalent CRMs in green patents are mainly silicon, lithium, and base metals such as aluminium, copper, zinc and nickel. Additionally, in Chapter 3 we also look at the concentration of production of CRMs, focusing on the most concentrated materials and thus with the greatest vulnerabilities along the supply chain. Restricting to these CRMs, besides the already mentioned silicon and lithium, other materials such as magnesium, rare earths, platinum group metals, cobalt and graphite have an important number of observations. The use of all CRMs mentioned so far is confirmed in various applications by the literature. Therefore, especially with regard to the most concentrated materials, there is a risk of future supply shortages hampering the spread of green technologies.

Analysing the occurrence of materials in different technological domains, we observe a strong presence of CRMs in technologies related to power generation, and particularly in enabling technologies that include energy storage inventions, demonstrating both the centrality of CRMs such as lithium used in lithium-ion batteries, but also the search for viable alternatives in batteries that rely on other CRMs. Futhermore, the green technologies characterised by the highest predominance of CRMs are those connected to the production or processing of goods, and particularly those related to metal and mineral processing, chemical industry, and to production processes for final industrial or consumer products. Despite the risks that CRMs in these particular technology classes are mentioned for other purposes than actual use, like e.g. recycling or removing, the robustness analysis conducted in the appendix of Chapter 3 points to an actual dependency relationship. Finally, other green technologies which particularly rely on the adoption of CRMs are carbon capturing and storage technologies and those connected to waste management.

- **Is the dependence on CRMs different between green and non-green technologies?**

The comparison between green and non-green technologies in terms of their reliance on CRMs is conducted in Chapter 2. Even if the topic of CRMs is peculiar to green technologies, the comparison with the non-green ones is a standard procedure in the literature, as several studies have focused on the characterisation of differences, similarities, and complementarities between green and non-green technological domains. Overall, the relative presence of CRMs in green technologies is almost double compared to that in non-green ones, also experiencing a greater increase over the time period under analysis. Regarding the technological domains, those exhibiting higher dependence from the use of CRMs are chemistry and metallurgy, electricity, and performing operations and transporting. Specifically, not considering the technological classes which are directly connected to mineral and metal related processes, some CRM intensive non-green technologies show similarities with green counterparts in some applications, such as batteries, magnets, resistors, semiconductors, and solid state devices, which are therefore important components in both green and non-green technological domains.

- **Which countries rely more intensively on CRMs via their own green inventive activities?**

- **Which countries are more exposed to green technology-driven demand for CRMs?**

The geographical dimension embedded in these two research question is explored in Chapter 3, through the use of the information contained in patents on the countries where green inventions are filed on the one hand, and the consideration of annual production data of CRMs on the other. What emerges is a stark disparity between countries where green inventions are filed, and therefore eventually implemented, and countries producing the CRMs required by these inventions in order to be realised. Specifically, the diffusion of green technologies mainly occurs in high-income countries, especially China, the United States, Japan, South Korea, and many European states such as Germany, France, and the United Kingdom. These countries, with the exception of China and partly the United States, are hardly among the main producers of CRMs, whose production is instead associated in most cases with low-income countries in the Global South. In addition, this disparity also characterises CRMs with a key role in green technologies, such as lithium, of which countries like Chile and Argentina are among the main producers, and cobalt, whose global production is mostly concentrated in the Democratic Republic of Congo. Hence, the development of green technologies relies on materials whose production is concentrated in countries that often do not benefit from this development, thus revealing a pattern of inequality which is intrinsically embedded in the sustainable transition via the deployment of green technologies.

Concluding remarks

This thesis revolves around the exploration of complex and potentially controversial aspects of the green transition that are often oversimplified and not challenged. The "Green Innovation-Good" paradigm is usually never questioned by policymakers, who promote the idea that more green innovation is better while neglecting the controversial aspects of the green transition. While, on the one hand, new industrial sectors, related to e.g. renewables, will emerge and grow, on the other hand polluting sectors will be closed down, with economic and social repercussions for the geographical areas specialised in them. Thus, while the transition offers new economic opportunities for environmentally sustainable growth, it also entails challenges with social and economic repercussions. The inherent contradictions of the green transition are also evident in the issue of the dependence of green technologies on Critical Raw Materials (CRMs), addressed in all the chapters of this thesis. The mitigation benefits brought by green technologies are counteracted by potential damages to soil, water, and emissions, caused by an increase in the extraction of the raw materials needed to realise them. Additionally, the production of CRMs is often concentrated in a few countries. This firstly raises geopolitical concerns due to the vulnerability of the supply chains. Secondly, it raises ethical and social concerns, as producer countries are often excluded from the distribution, and hence the related environmental benefits, of green technologies. In fact, low-income countries are often among the leading CRM producers, which are also characterised by a low (if any) level of green technology deployment.

In such a fragmented context, which differs for each country and each region depending on their knowledge level and skills, the implementation policies and, consequently, the long-term political vision with which the green transition is to be carried out, play a key role. Relatedly, it is worth discussing the European strategy on CRMs, taking the critical raw material action plan of 2023 as a reference (European Commission, 2023*a*). In order to ensure a sustainable, affordable and diversified supply of CRMs to succeed in its green and digital transition, the EU outlines a number of actions to be taken, including the development of a CRMs value chain in Europe and increasing diversification to reduce dependence on third countries, while promoting sustainable sourcing and circularity practices. Above all, the main focus is on promoting "green mining", i.e. resource extraction that can be green, and non-destructive, to the environment. In particular, to foster the increase of domestic CRMs capacity, the EU is committed to promoting investment in exploration and extraction of materials, through direct funding and faster licensing in the mining sector. This raises some concerns. First, because of the difficult convergence of the mining sector towards sustainable practices, which would overturn past evidence of its negative environmental impact (Azadi et al., 2020; Berman et al., 2017; Church and Crawford, 2018; Norgate and Haque, 2010). Second, because of the places where these mines would be developed within Europe. In a repetition of existing global patterns, with many CRM mines located in Global South countries, the new mines would not be near large cities, but in peripheral areas of Europe, often close to communities with a low consumption impact, and which would therefore not particularly benefit from the development of green innovations (Marin, 2021*a*,*b*). Therefore, in advancing green transition policies there is the risk of a significant worsening of inequalities also within Europe.

The bottom line is not to discredit the benefits of environmental innovations or to question their absolute centrality to reducing emissions. Nor is it to criticise a priori the pursuit of increasing the supply of CRMs to realise these innovations. The point is that underestimating, ignoring, and even worse denying, the existence of the risks discussed here can jeopardise the realisation of the green transition. The climate crisis cannot be addressed in isolation from the social crisis, not least because ignoring the social dimension is counterproductive to the climate cause itself. Emissions cannot be tackled while disregarding social and economic inequalities (Ritchie, 2023). For example, not taking into account the negative impacts of mining on local communities could increase the level of inequality between different regions, ultimately fostering support for anti-climate theses, and thus establishing a vicious circle whereby pro-environment policies would have negative repercussions for the environment itself. This phenomenon is already beginning to occur today (Rodríguez-Pose and Bartalucci, 2023).

Therefore, with regard to CRMs, the level of accountability of mining companies must increase, and local communities must be endowed with the right to express themselves and possibly oppose the opening of new mines (Marin, 2023). On the whole, however, a global vision of climate and social justice should be adopted, that decisively promotes circular industrial policies, and that perhaps revisits the feasibility of certain goals related to economic growth regardless, especially in already developed countries. As partly done in this thesis, also thanks to the approaches adopted, future research should deal with green innovation in a heterogeneous manner, e.g. by separately assessing and analysing the effects and implications associated with different areas of innovation, discussing the related benefits but also the potential limitations, and differentiating the investigation by geographical areas in order to calibrate specific policies.

Appendix A

Chapter 1 Appendix

A.1 Data Features

A.1.1 Green Patents

In this paper we look at patent data as a proxy of environment-related innovation (to which we will also refer to as green technologies) that is increasingly becoming the golden standard in the literature to measure green innovative activities, as it is widely available, it can provide an array of quantitative information on the nature of the invention and its applicant or inventor, including their geographical location, affording in such away to easily geo-localise patents both at country and local levels (Dechezleprêtre et al., 2011). Moreover, and very importantly, patent data can be disaggregated into increasingly fine-grained technological areas, allowing very specific green technologies to be identified, also through keyword searches (Haščič and Migotto, 2015). Green technology is particularly interesting because it shows distinctive features with respect to non-green technologies, appears to be heterogeneous and encompasses many domains of know-how. It has in fact been proven that the knowledge generation process behind the development of these technologies substantially differ from non-green ones (Barbieri, Perruchas and Consoli, 2020) and across geographical areas (Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018), but is linked in non-trivial ways to the pre-existing knowledge base (Barbieri, Marzucchi and Rizzo, 2020).
As a response to the increasing attention and concern about climate change and renewable energy generation, we are witnessing a large increase of patent applications in environment-related domains: according to the European Patent Office (EPO), in the last years there have been around 1.5 million patent applications in sustainable technologies (European Patenting Office, 2013). Searching for environment-related patent documents has, therefore, been a challenge, especially because in the past documents relating to sustainable technologies did not fall into one single classification. In 2013 the EPO and the United States Patent and Trademark Office (USPTO) agreed to harmonise their patent classification practices and developed the Cooperative Patent Classification (CPC) system, which encompasses five hierarchical levels spanning from 9 sections to around 250000 subgroups and where codes starting with the letters A to H represent a traditional classification of innovative activity in technological fields, while the Y section[1] tags cross-sectional technologies. Here in particular we employ the

[1] https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html

Y02–*Technologies or applications for mitigation or adaptation against climate change* retrieved from the OECD REGPAT database (Maraut et al., 2008). The Y02 class consists of more than 1000 tags organised in 9 sub-classes and includes patents related to climate change adaptation and mitigation (CCMT)[2] technologies concerning a wide range of technologies related to sustainability objectives, such as energy efficiency in buildings, energy generation from renewable sources, sustainable mobility, smart grids and many others, the details of which can be found in Table A.2 below and, in a more synthetic fashion, in Table 1 of the manuscript.
Following the notation given in the manuscript, we have matrices $\mathbf{W}(t)$ from 1995 to 2019. The number of countries (i.e. the number of rows in each matrix) are 48 (see Table A.1). The number of columns are 44 technological fields corresponding to the CPC groups listed in Table SA.2. To build such matrices, each patent family — i.e. each collection of patent applications covering the same or similar technical content — counting as a unit and recorded in REGPAT is divided between all technology codes τ and all countries c with which it is associated, following the procedure adopted in Napolitano et al. (2022) and Barbieri et al. (2022). Therefore, each element $W_{c\tau}(t)$ of the matrix represents the fraction of patent families associated with the country-technology pair $c - \tau$ in year t.

A.1.2 Exported products

For the export data we resort to the UN-COMTRADE database[3], which provides the yearly trade flows between countries, expressed in US Dollars. This information is provided at the product level, so that it is possible to study in detail which countries are exporting a given amount of a given product in a chosen year. The products in the dataset are classified according to the Harmonized System, a hierarchical classification that allows to disaggregate the economic sectors from two digits (about 100 different product chapters) up to six digits (about 5000 different product subheadings) codes. This degree of freedom is key to investigate the effect of technological innovations at different levels of detail: in fact, we move from the links that green technologies have with the export of entire product categories such as those related to the Machinery/Electrical sector to those that they have with the export of detailed single products such as electric motors. We point out that since importers' and exporters' declarations do not precisely coincide, suitable reconstruction algorithms are needed in order to achieve a coherent and cleaned dataset. In order to do so, we adopt a global Bayesian optimization approach to obtain a denoised dataset. The goodness of this procedure is empirically confirmed by Tacchella et al. (2018), who, by employing the denoised dataset, obtained a sizeable increase in GDP forecasting performance.
From the trade flows we obtain the export matrices $\mathbf{V}(t)$, where t ranges from 2007 to 2017: the number of rows, corresponding to the number of countries, is equal to 169

[2] According to the United Nations Environmental Program (UNEP): "Climate Change Mitigation refers to efforts to reduce or prevent emission of greenhouse gases. Mitigation can mean using new technologies and renewable energies, making older equipment more energy efficient, or changing management practices or consumer behavior" (United Nations Environmental Program (UNEP), 2016). However, it is important to notice that mitigation does not necessarily goes hand in hand with sustainable and "green" practices. Some CCMTs, such as nuclear technologies, might also pose threats on the environment or be polluting.

[3] https://comtrade.un.org/

(see Table SA.1), while the number of columns, corresponding to the exported products, depends on the level of aggregation considered (97 in the 2-digit case, 5053 in the 6-digit one). Thus, each element $V_{c\pi}(t)$ represents the volume of exports of the product π, expressed in thousands of dollars, by the country c in year t.

A.1.3 Country list

Depending on which step of our analysis we deal with, we consider all countries included in each collection or only those in common. In particular, the computation of the Revealed Comparative Advantage (RCA) is done separately for patents and exports, thus including all countries in the respective datasets. On the contrary, the calculation of the assist matrix is done by contracting the patent and export data over the geographical dimension, and therefore we only consider those in common. In Table SA.1 we collect all the countries included in both datasets, also writing their names in different colours depending on whether they are part of the 47 common countries between the two datasets or they are only present in one of them.

Country full list			
Afghanistan	Albania	Algeria	Andorra
Angola	Argentina	Armenia	Australia
Austria	Azerbaijan	Bahrain	Bangladesh
Belarus	Belgium	Belize	Benin
Bhutan	Bolivia	Bosnia Herzegovina	Botswana
Brazil	Brunei	Bulgaria	Burkina Faso
Burundi	Cambodia	Cameroon	Canada
Cape Verde	Central African Republic	Chad	Chile
China	Colombia	Congo	Costa Rica
Croatia	Cuba	Cyprus	Czech Republic
Democratic Republic Congo	Denmark	Dominican Republic	Ecuador
Egypt	El Salvador	Equatorial Guinea	Eritrea
Estonia	Ethiopia	Fiji	Finland
France	French Polynesia	Gabon	Gambia
Georgia	Germany	Ghana	Greece
Greenland	Guatemala	Guinea	Guinea-Bissau
Guyana	Haiti	Honduras	Hungary
Iceland	India	Indonesia	Iran
Iraq	Ireland	Israel	Italy
Ivory Coast	Jamaica	Japan	Jordan
Kazakhstan	Kenya	Kuwait	Kyrgyzstan
Laos	Latvia	Lebanon	Lesotho
Liberia	Libya	Liechtenstein	Lithuania
Luxembourg	Macedonia	Madagascar	Malawi
Malaysia	Maldives	Mali	Malta
Mauritania	Mauritius	Mexico	Moldova
Mongolia	Montenegro	Morocco	Mozambique
Myanmar	Namibia	Nepal	Netherlands
New Zealand	Nicaragua	Niger	Nigeria
North Korea	Norway	Oman	Pakistan
Panama	Papua New Guinea	Paraguay	Peru
Philippines	Poland	Portugal	Qatar
Romania	Russia	Rwanda	Saudi Arabia
Senegal	Serbia	Seychelles	Sierra Leone
Singapore	Slovakia	Slovenia	Somalia
South Africa	South Korea	South Sudan	Spain
Sri Lanka	Sudan	Suriname	Swaziland
Sweden	Switzerland	Syria	Tajikistan
Tanzania	Thailand	Togo	Tunisia
Turkey	Turkmenistan	Uganda	Ukraine
United Arab Emirates	United Kingdom	Uruguay	USA
Uzbekistan	Venezuela	Vietnam	Yemen
Zambia	Zimbabwe		

Table A.1: All country list.
Legend: "Red-labelled country": included in both datasets (47 in total); "Green-labelled country": included in green patents dataset only (1 in total); "Black-labelled country": included in exported products dataset only (122 in total).

A.2 Table S2: Y02-CPC detailed descriptions

As mentioned, we employ the Y02 class of the CPC patent classification to identify climate change mitigation technologies and we thus have information on patent applications for 44 green technology groups. These are in turn grouped into 8 subclasses, which are reported in Table 1 of the manuscript. In Table SA.2, we report the codes and descriptions at the group aggregation level.

CPC subclass		Description
Y02A	10	Adaptation to climate change at coastal zones
	20	Water conservation
	30	Adapting infrastructure
	40	Adaptation technologies in agriculture
	50	in human health protection
	90	Indirect contribution to adaptation to climate change
Y02B	10	Integration of renewable energy sources in buildings
	20	Energy efficient lighting technologies
	30	Energy efficient heating
	40	Improving the efficiency of home appliances
	50	Energy efficient technologies in elevators
	60	ICT aiming at the reduction of own energy use
	70	Efficient end-user side electric power management
	80	Improving the thermal performance of buildings
	90	GHG emissions mitigation [Buildings]
Y02C	10	CO2 capture or storage
	20	Capture or disposal of greenhouse gases
Y02D	10	Energy efficient computing
	30	Reducing energy consumption in communication networks
	50	Reducing energy consumption in wire-line communication networks
	70	Reducing energy consumption in wireless communication networks
Y02E	10	Energy generation through renewable energy sources
	20	Combustion technologies with mitigation potential
	30	Energy generation of nuclear origin
	40	Technologies for an efficient electrical power generation
	50	Technologies for the production of fuel of non-fossil origin
	60	Enabling technologies
	70	Other energy conversion systems reducing GHG emissions
Y02P	10	Metal processing
	20	Chemical industry
	30	Oil refining and petrochemical industry
	40	Processing of minerals
	60	Agriculture
	70	CCMT in the production process for final products
	80	CCMT for sector-wide applications
	90	GHG emissions mitigation [Production]
Y02T	10	Road transport of goods or passengers
	30	Transportation of goods or passengers via railways
	50	Aeronautics or air transport
	70	Maritime or waterways transport
	90	GHG emissions mitigation [Transportation]
Y02W	10	Wastewater treatment
	30	Solid waste management
	90	GHG emissions mitigation [Wastewater]

Table A.2: Descriptions of environmental technology groups. In the first column (divided in turn into two sub-columns) the CPC code identifying the technology group is reported. The second column adds the corresponding group descriptions.

A.3 Economic Fitness & Complexity algorithm

In Fig. 5 of the mauscript we order the codes related to green technologies and exported products according to their level of complexity. The latter is intended as an algorithmic assessment of the number and the sophistication of the capabilities needed to be competitive in a given activity. To compute it, we use the Economic Fitness & Complexity (EFC) algorithm product (Tacchella et al., 2012, 2013), originally introduced for exports but also applied to green patents (Sbardella, Perruchas, Napolitano, Barbieri and Consoli, 2018). More in detail, it consists of a non-linear iterative algorithm that, starting from the binary matrices $\mathbf{M}_{ca}(t)$ obtained through the implementation of RCA detailed in the manuscript in the Methods section, allows to quantify the complexity of the activities Q_a and the competitiveness of the countries, namely their fitness F_c, that perform in them. The mathematical formulation of the algorithm at each iteration n is as follows:

$$\begin{cases} \tilde{F}_c^{(n)} & = \sum_a M_{ca} Q_a^{(n-1)} \\ \tilde{Q}_a^{(n)} & = \dfrac{1}{\sum_c M_{ca} \dfrac{1}{F_c^{(n-1)}}} \end{cases} \rightarrow \begin{cases} F_c^{(n)} & = \dfrac{\tilde{F}_c^{(n)}}{\left\langle \tilde{F}_c^{(n)} \right\rangle_c} \\ Q_a^{(n)} & = \dfrac{\tilde{Q}_a^{(n)}}{\left\langle \tilde{Q}_a^{(n)} \right\rangle_a} \end{cases} \tag{A.1}$$

where, in the left-hand bracket, the calculation of the fitness and complexity parameters for all countries and activities is shown, while in the right-hand one is the following normalisation step. The non-linear structure of the algorithm causes the activities in the baskets of less competitive countries (i.e. with low fitness) to be assigned a low level of complexity. The most competitive countries turn out to be those with more diversified activity baskets. Given the convergence properties of the algorithm, discussed in Pugliese et al. (2016), we do not consider the complexity values but their rankings. In particular, the ranking are computed using the most recent 5-year aggregate matrices given the years of the data we considered in the analysis: thus, we use $\mathbf{M}_{c\tau}(5, 2017)$ for green patents and $\mathbf{M}_{c\pi}(5, 2017)$ for exported products.

A.4 Robustness test

In the manuscript we build the green technology-product bipartite network starting with two important preliminary steps: firstly, we summed the yearly data collections at our disposal over 5 years; secondly, depending on the time lag ΔT we consider, we select specific 5-year aggregate matrices. In particular, we select the two most recent exported product matrices available to us that do not overlap each other — i.e. $\mathbf{V}(\delta, t) = \{\mathbf{V}(5, 2012); \mathbf{V}(5, 2017)\}$, where δ corresponds to the interval of years over which the individual yearly matrices are summed up (in this case 5), while the year t explicitly indicated corresponds to the last year of the interval. Since the data collections of exported products are fixed for both time lags, we select the aggregated 5-year green patent collections depending on which of the latter we consider : therefore, we select the matrices $\mathbf{W}(\delta, t) = \{\mathbf{W}(5, 2012); \mathbf{W}(5, 2017)\}$ for $\Delta T = 0$ and $\mathbf{W}(\delta, t) = \{\mathbf{W}(5, 2002); \mathbf{W}(5, 2007)\}$ for $\Delta T = 10$.
In this section we want to show that our results do not depend on the choices of the years considered nor on the parameter δ. To this aim, we conduct a robustness test

in which we repeat our analysis for both different values of δ and years considered. In particular, we replicate our results for a 2-digit level of product aggregation and for the time lag $\Delta T = 0$. Considering the 10 years covered by the two 5-years summed data collections we consider in the analysis for $\Delta T = 0$ — i.e. from 2008 to 2017 — we create a dataset composed by 32 matrices (16 for green patents and 16 for exported products) aggregated at 3,4 and 10 years, so that $\delta = \{3, 5, 10\}$. The dataset is reported In Table SA.3: each $\mathbf{M}(\delta, t)$ in the table stands for a corresponding couple of technology-product matrices $\mathbf{W}(\delta, t) - \mathbf{V}(\delta, t)$ for which we process the full analysis, meaning RCA, assist matrix and null model computations. We consider as a benchmark of this test the 46 links validated at a 95% level of significance in the manuscript. The results we obtain can be summarized as follows:

- Considering only the aggregation over 3-year intervals, on average 73% of the 46 links are present at a 95% significance level. This percentage increases to 87% if we consider a 90% level of significance for the 3-year results.
- Considering only the aggregation over 4-year intervals, on average 80% of the 46 links are present at a 95% significance level. This percentage increases to 92% if we consider a 90% level of significance for the 4-year results.
- 85% of the 46 links are present at a 95% significance level for the unique pair of technology-product matrices with the 10-year time aggregation. This percentage increases to 98% (45 links out of 46) if we consider a 90% level of significance for the 10-year result.

Based on the above summary, we consider the robustness test successful. Therefore, we interpret the results reported in the manuscript as showing a real link of interdependence between the acquisition of green technological capabilities and the development of productive ones.

Time aggregation δ	**Data collections $\mathbf{M}(\delta, \mathbf{t})$**
3	M(3, 2010), M(3, 2011), M(3, 2012), M(3, 2013) M(3, 2014), M(3, 2015), M(3, 2016), M(3, 2017)
4	M(4, 2011), M(4, 2012), M(4, 2013), M(4, 2014) M(4, 2015), M(4, 2016), M(4, 2017)
10	M(10,2017)

Table A.3: Composition of the dataset we use for the robustness test of our results. Since we consider the time lag $\Delta T = 0$, data collections refer to both green patents and exported products.

Appendix B

Chapter 2 Appendix

B.1 Technology dependence on CRMs

In Section 2.5.3 - CRMs dependence of technological domains of the manuscript we investigated the dependence from CRMs of specific green and non-green technological domains, taken at multiple level of aggregation. At the disaggregated level for the non-green technologies, we focus on the most CRMs dependent technology sections, namely *B - Performing operations; Transporting*, *C - Chemistry; Metallurgy*, and *H - electricity*. For the sake of completeness, in Figure B.1 we show the presence of CRMs in the missing sections, i.e. *A - Human necessities*, *D - Textiles; Paper*, *E - Fixed constructions*, *F - Mechanical engineering; Lighting; Heating; Weapons; Blasting*, and *G - Physics*

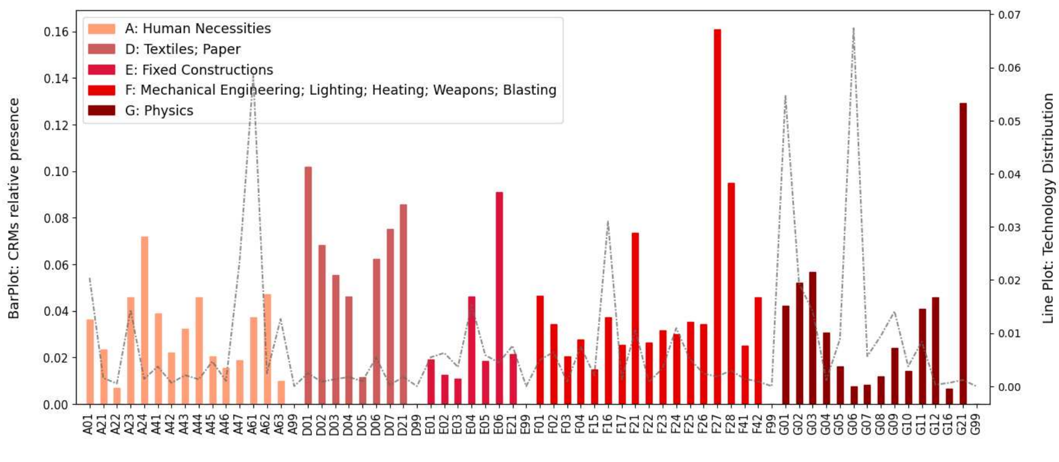


Figure B.1: Presence of CRMs in non-green technologies (sections A, D, E, F, G)

Appendix C

Chapter 3 Appendix

C.1 Manual Exploration of Patent Abstracts

Part of our methodology consists in the detection of a list of CRM keywords in patent abstracts, the presence of CRM implying that there is a connection between CRM and green technologies. As discussed in Section 3.2.2 - CRMs keyword search, while the literature considers text mining of CRMs in patents a good proxy for how much technologies relies on them, we checked for possible inconsistencies or bias in the findings by reading a sample of abstracts. This process helped us to gain clearer understanding of the connection between CRMs and green technologies, and to refine the queries.

In each case, we selected a sample of patent abstracts randomly stratified by technologies and CRMs so as to have the same distribution of technologies and CRMs relative to that of the population. For each patent, we classified CRM mentions in 4 different categories:

- the CRM is used by the invention.
- the invention is useful to either recycle or refine the mineral.
- the patents describes a methodology to not use anymore or to remove a CRM.
- false positive.

The last category helped use to validate and improve queries. Reading each of the abstracts led us to detect a high number of false positives in lead and beryllium, due to the use of "lead" and beryllium symbol ("Be") in English. After several corrections[1], we concluded that the rate of incorrect detection is less than 3% in all the cases presented below. In the following, elaborate on special cases such as phosphorus and on the green technologies with the highest number of detections.

C.1.1 Use of phosphorus

Phosphorus is among the most mentioned CRM, with increasing frequency over time but rarely mentioned in technological reports as a determinant for the development of

[1] for example, we further examined the preceding and subsequent words of lead in the corresponding abstracts to exclude the detections where 'lead' was used as a verb or denoted tools like lead wire, lead screw, etc., while for 'Be' we eliminated the abstracts where 'Be' was detected at the beginning of a sentence

climate change mitigation or adaptation technologies. Hence, we checked a random sample of 208 patent abstracts (2.5% of the population) stratified by technologies to understand how phosphorus is effectively referred to in the documents. We found out that only 71,2% mention it for usage, and the second most frequent mention (14,4%) concern inventions that involve a methodology for actually removing the material. Such instances are mainly in adaptation technologies related to water quality and agriculture (*Y02W1 - Technologies for wastewater treatment*, *Y02A5 - Water conservation; Efficient water supply; Efficient water use*, *Y02A4 - Adaptation technologies in agriculture, forestry, livestock or agroalimentary production*) and aim at preventing excessive amounts of phosphorus coming from soil fertilization. Finally, 12% of the inventions recycle or refine phosphorus, mainly in *technologies for the production of fuel of non-fossil origin (Y02E5)*, *solid waste management (Y02W3)* and *technologies related to metal processing (Y02P1)*. Only 5 patents out of 208 were false positive, which gives an accurate rate of detection of 97,60%.

C.1.2 Technologies with a high presence of CRM

We checked technologies with high presence of CRM in order to verify how robust is the use of minerals occurrences in patent abstracts as the measure of CRM dependence. We obtained random samples of patent abstracts for the following technologies:

- *Capture or disposal of greenhouse gases other than CO_2 - Y02C2* (22 abstracts, 3.4% of the population)
- *Enabling technologies related to Energy, Technologies with a potential or indirect contribution to GHG emissions mitigation - Y02E6* (800 abstracts, 2.8% of the population)
- *Climate Change Mitigation Technologies related to metal processing - Y02P1* (652 abstracts, 2.4% of the population)
- *Climate Change Mitigation Technologies related to chemical industry - Y02P2* (396 abstracts, 2.7% of the population)
- *Climate change mitigation technologies in the production process for final industrial or consumer products - Y02P7* (711 abstracts, 3% of the population)

The rate of inventions mentioning a use of CRM is above 96% in all these technologies except in the case of *Y02P1*, where 63.1% of CRM mentions are related to a use, while 30.7% are related to recycling or refining CRM. The specificity of metal processing explains these differences. This difference is also present in abstracts proposing a method to remove CRM. While it is less than 2% in all other technologies, it represents 5.2% of *Y02P1* abstracts. The rate of false positives is between 0.8% and 1.5%.

Delving into *Y02P1* mentions of CRM, we found out that the ratio between use and refine/recycle in not stable across minerals. The highest mention of use is in the case of graphite, silicon, bauxite and titanium (above 85% of patent abstracts mentioning those CRM use them), while the highest mention of refine/recycle is for silver, lithium, cobalt and germanium (above 55% of patent abstracts mentioning those CRM is for refining/recycling). The latter could indicate technological developments to improve the availability of some minerals.

In other technologies, the distribution of these ratios is stable across CRM. Above 90% of use for all minerals except for cadmium in *Y02P7*, where 11.8% of patents of this technology propose a process to remove it, and for arsenic in *Y02P2* where this ratio is 25%, although the size of the sample (8 abstracts in Y02P2 mention arsenic) calls for caution. In the cadmium case, the development of cadmium-free products is related to its high toxicity for humans even at low exposure rate.

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