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Sustainable Innovations: Green Patent Acquisition and Corporate Environmental Performance

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Part I

Introduction

The United Nations Climate Change Conference set in Paris in 2015 has been held as a landmark international accord on climate change mitigation, aiming to reduce countries greenhouse gas emissions by 55% by 2030, and reach net zero by 2050. However almost nine years after the Paris Climate Agreement was signed, the world isn't on track to meet its target of limiting global warming [94], emphasizing how the commitment of governments can only be part of the effort to solve the climate crisis. Private enterprises, driven by market incentives and the imperative to remain competitive, are uniquely positioned to develop and deploy sustainable solutions at scale. This thesis aims to study the relationship between firms' acquisition of environmental technologies and their environmental performances, by tracking transactions of patents deemed as "green" to try to answer three research questions :

1. *How does the development or acquisition of green patents impact a firm's environmental performance? Are certain green technologies more influential than others?*

2. *Does a firm's environmental performance influence its decision to obtain green patents?*

3. *What is the direction of causality? Are firms acquiring patents in response to their environmental performances, or are their performances driven by the acquisition of patents?*

To answer these research questions this thesis is articulated into five main parts, including this introduction. Part II examines the role of environmental innovation (EI) in combating climate change, highlighting the peculiarities of green technologies and emphasizing the pivotal role of private firms in driving sustainability efforts. A definition of "green" in the context of businesses and technology is then provided, followed by a discussion on the phenomenon of greenwashing and its repercussions on environmental innovation. The focus shifts then to green patents, the differences among their international classifications, their significance in measuring green innovative activism, and how different processes of acquisition can carry different information. Section 3 examines measures of firms' sustainability, including the different performance indicators of environmental impact, methods for comparing different indexes, and how the disclosure of environmental and social data can influence firm performance. Finally the antecedents, blockers, and results of EI in corporate settings are analyzed by reviewing the current state of the literature.

Part III outlines the different methodologies and data sources used in the research. It gives details on the origin of all data utilized, covering patent data, patent transactions, corporate data, and how the final database was created. Moreover, it explains the procedures and models employed for the analysis, including statistical and econometric techniques such as fixed effects panel regression, the Hausman test, bivariate probit regression and the Dumitrescu–Hurlin test for Granger causality. Each model's section contains a brief explanation of its statistical workings, the libraries utilized for its application and examples of how each model has been applied in environmental innovation papers by the scientific community.

Part IV presents the research findings. Starting from the first model, which employs a series of fixed effects regressions on panel data to investigate the impact of green patent acquisition on various environmental variables, then a bivariate probit regression examines how environmental performances influence patent acquisitions and patent development, and finally a Dumitrescu–Hurlin test for Granger causality is used to investigate causal relationships between patent obtainment and green performance indicators in firms.

Part V summarizes the key findings of the thesis and draws conclusions based on the analysis conducted and the state of the literature. Overall this thesis tries to provide insights into the relationship between firms' environmental innovation activities and their environmental performance, drawing from scientific literature and employing rigorous methodologies for analysis and interpretation.

Part II

Overview on the topic and its scientific literature

1 The role of environmental innovation on climate change

Since 1950, both the global population and various societal and economic activities have experienced exponential growth. August 2nd marked the "Earth Overshoot Day" for the year 2023, meaning that humanity has exhausted the resources and services that the planet can regenerate in a full year within only 8 months. In 2024 Overshoot Day is scheduled for July 25th. The International Geosphere-Biosphere Programme and the Stockholm Resilience Centre have termed this phenomenon "The Great Acceleration" and have compiled a dashboard comprising 24 indicators showing the unbridled acceleration of human activities and their impacts on the Earth's ecosystem over the past two centuries. What emerges is a visible synchronicity in the escalation of economic and environmental trends from the 50s to the present day. These cumulative trends are monitored by 12 socio-economic and 12 Earth system indicators spanning from 1750 to the present, and provide compelling evidence of a fundamental shift in the Earth system's state. The economic advancement of prominent nations worldwide has led to increased prosperity and a heightened appetite for consumption, thereby influencing consumer behavior, a shift that is reflected by changes in the Earth's natural systems, starting from climate (greenhouse gas levels, global temperature), ocean acidification, terrestrial biosphere degradation and fish capture.

The discourse in environmental economics and policy has been increasingly connected with issues regarding technological change. The process of technological change brings a paradigm shift with profound implications, as it is both one of the causes of the "Great Acceleration" and the key to stop its disastrous consequences. For years now scholars like Jaffe [66] have stressed the need to study and understand Technological advancements because they significantly shape the environmental impact of social and economic activities and have the potential to either worsen existing environmental issues, by contributing to increased pollution, or offer solutions by mitigating or replacing polluting practices. Considering that many environmental challenges and policy responses are evaluated over long time horizons spanning decades or even centuries, the cumulative effects of technological changes are likely to be substantial.

What the scientific community is trying to study is a way to use eco-innovation to break the link between economic growth and environmental degradation, striving instead for enhanced resource efficiency and sustainable development. This multifaceted concept strives to optimize the utilization of resources throughout the entire lifecycle of products, aiming to achieve more with less [105]. At its essence, eco-innovation entails a concerted effort to diminish the resource intensity of products and services while fostering the emergence of new business models that are not only competitive but also environmentally responsible. By integrating sustainability principles into every stage of the value chain, eco-innovation endeavors to generate value while respecting ecological boundaries.

All the current sustainability challenges, including climate change, resource scarcity and environmental degradation, pressures companies to reconsider their operational strategies. Adhering to the 'Business as usual' mindset will render companies ill-equipped to tackle rising resource costs, supply chain disruptions, or shifts in regulations. The OECD has already highlighted the significant economic, social, and environmental costs of inaction, with potential business benefits of implementing known improvement measures estimated at 3 trillion USD (McKinsey, 2011). Consequently, there is a growing imperative to explore alternative approaches that not only address sustainability concerns but also present opportunities for growth, cost reduction, and competitive advantage.

Scholars like Barbieri [9] argue that unlike other factors contributing to enhanced environmental quality, such as a reduction in the scale of the economy or shifts in production and consumption patterns towards cleaner sectors, technological advancements aimed at environmental improvement also lower the societal cost of achieving environmental goals. Consequently, environmental technological innovation holds the potential to create win-win scenarios where improvements in environmental quality and economic growth are mutually beneficial. It's not a coincidence that an increasingly large share of government budgets is being employed by policymakers to stimulate the generation and diffusion of environmentally beneficial technologies (Fig. 1) trying to capture these potential win-win outcomes.

The realm of eco-innovation offers a vast array of opportunities for transformative change spanning from the development of low-carbon solutions across various economic sectors to the creation of green products and innovative business models. Additionally, eco-innovation extends to ambitious initiatives such as the establishment of zero-waste cities, the implementation of smart infrastructures, and the promotion of sustainable ecosystem management and lifestyles. Plenty of examples showcase successful applications of eco-innovation across various domains like processes, products, organizations, marketing methods, and institutions. For instance, the automotive and transport industry has taken several steps to reduce CO2 emissions and other environmental impacts, notably those associated with fossil-fuel combustion. Meanwhile the iron and steel industry, driven by increasing prices and scarcity of raw materials has made a significant increase in performance by a number of energy-saving modifications and redesigns of various production processes. Energy-saving tires exemplify eco-innovation targeting product enhancement, while Bike sharing systems in cities worldwide represent an institutional eco-innovation initiative. These examples unequivocally illustrate the symbiotic relationship between environmental sustainability and business profitability, serving as inspiration for other companies and institutions to adopt eco-innovative solutions.

1.1 Challenges of environmental innovation

The nature of environmental innovation poses peculiar roadblocks that make its implementation a challenging task due to the precarious balance between benefits and costs. Solving environmental problems often results in diffuse public benefits but concentrated private costs. This disparity makes the beneficiaries of EI less likely to use their capital for the benefit of the collective, while those facing losses are incentivized to resist the

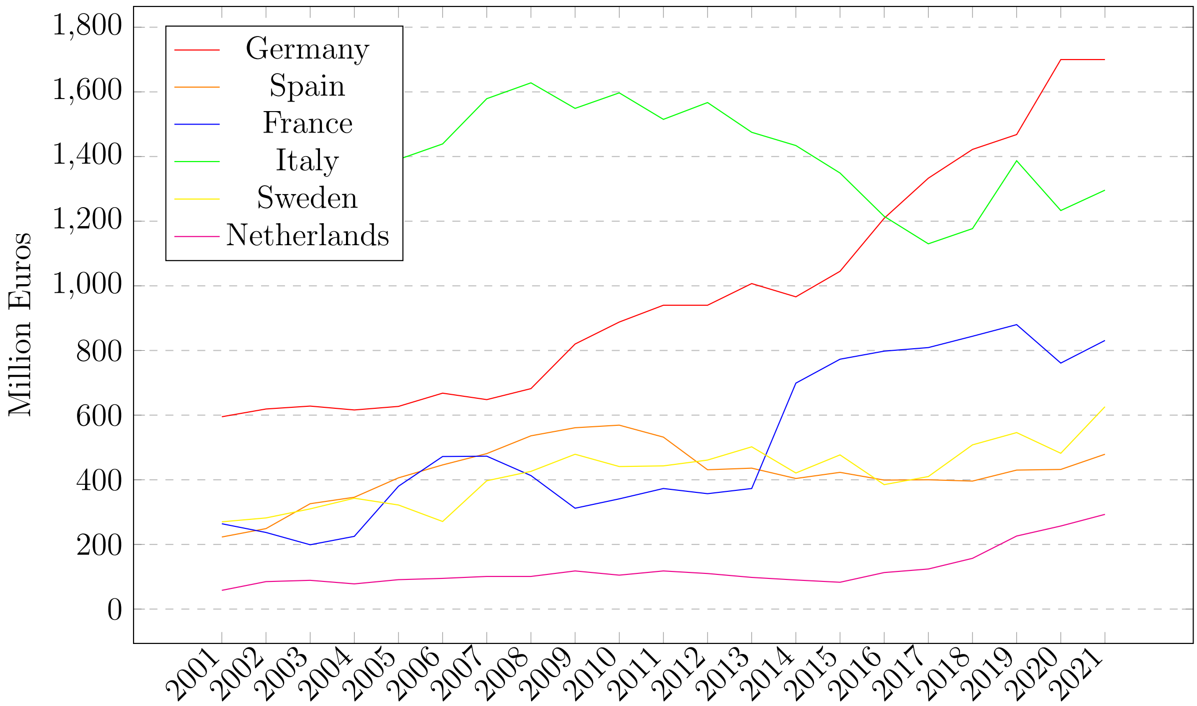

Figure 1: Major European nations environmental protection R&D expenditures by year. Source : Eurostat 2023

change. Gerbash [48] names this problem the "double free riding of environmental innovation". On one hand entities benefit from the emissions reductions achieved by others without contributing equally, a dynamic that disincentivizes them from undertaking costly mitigation efforts themselves. On the other hand leaving innovation solely to market forces leads to suboptimal outcomes globally. While new technologies enable emission reduction at lower costs. Countries are hesitant to pay for licenses due to their free-riding in abatement and have low demand for these superior technologies, resulting in market forces being unable to drive efficient levels of technological advancement. This suppressed demand significantly dampens the potential rewards for innovation, hindering the development of better solutions. The effect of these two sources of free-riding is of mutual reinforcement, makeing slowing down global warming a particularly difficult problem.

Adding to the problem, the contribution of technological innovation may be limited over several decades due to the substantial investment in research and development over extended periods that are required to maintain new technologies. This holds particularly true for environmental innovations, which often necessitate advancements in fundamental knowledge, and may not easily find large markets due to the aforementioned social rather than private benefits. Moreover, the large focus of EI on processes rather than products, makes it less attractive to consumers. For instance, "green electricity" may not appear different from electricity produced with fossil fuels and may lack commercial value or consumer appeal. Consequently, significant environmental innovations aimed at reducing greenhouse gas emissions are likely to take considerable time to materialize [108]. Despite the difficulties, given the rapid pace of climate change, the crucial question is not whether innovative solutions will be found in the future, but whether they can be implemented rapidly enough to address the urgent challenges at hand.

1.2 Innovation

The modern concept of technological change finds its roots in the theories of Josef Schumpeter (1942) [104], who regarded innovation as a defining feature of modern capitalistic systems. In his theories, innovation is mainly driven by entrepreneurs, who are motivated by the prospect of gaining temporary market dominance through new products or processes. If successful the process leads to significant profits for a period, until the old innovations are eventually supplanted by newer and more efficient innovations, a cycle Schumpeter famously named "creative destruction". As delineated by Schumpeter the cycle of dissemination of a new and superior technology throughout the market is composed of three key stages. The first stage, *invention*, involves the initial development of a scientifically or technically novel product or process. While some of these inventions may result in a patent, many remain unpatented. Not all inventions progress to the next stage, *innovation*, that occurs when the new product or process is successfully commercialized and made available to the market. This means that a firm can innovate without being the original inventor by identifying a previously uncommercialized technical idea and bringing it to market in a new product or process. Both the invention and innovation stages typically occur within private firms through research and development activities. At the end of the cycle a successful innovation undergoes *diffusion*, and gradually becomes more and more accessible for use in various applications as it is adopted by firms or individuals. Diffusion is crucial in realizing the cumulative economic or environmental impact of new technologies.

Kemp and Pearson [69], along with other scholars, have emphasized that innovation persists even during the diffusion stage of the innovation process, since it offers opportunities for discovering new uses and users for the innovation while it spreads. Technological advancements, augmented R&D endeavors and feedback from users and suppliers, collectively contribute to sellers' efforts to enhance their products and, combined with competitive forces, often drive down the price of innovative products further facilitating their adoption and diffusion within the market. The innovation process, its outcomes, its impacts on the economy and the environment are influenced by a multitude of aspects that coexist in a broader framework made up by the values, beliefs, knowledge and networks of individuals involved, existing technologies, economic growth patterns, market conditions for both products and factors of production, the state of the education and training system, physical infrastructure, and the macroeconomic and regulatory environment.

Since the impacts of innovation are co-produced, occurring at both micro and macro levels, assessing the macro-level performance of EI is incredibly complex due to factors such as income effects and the diffusion of knowledge and preferences. However, it is feasible to compare the performance of an innovation against relevant alternatives in an initial analysis by examining material consumption, emissions and waste generation to gauge the relative merits of different innovations. Collectively, these three stages—invention, innovation, and diffusion—constitute the process of technological change, which plays a pivotal role in shaping economic and environmental landscapes.

1.3 Defining Green

In itself, defining what "Green" means (in the context of economics) is a challenging task. A macroeconomic definition of "green investment" is given in a 2011 IMF paper, as *"the investment necessary to reduce greenhouse gas and air pollutant emissions, without significantly reducing the production and consumption of non-energy goods"* [41], this refers to both public and private investment. The authors specify three main categories of green investment : Low emission energy supply, energy efficiency and carbon capture.

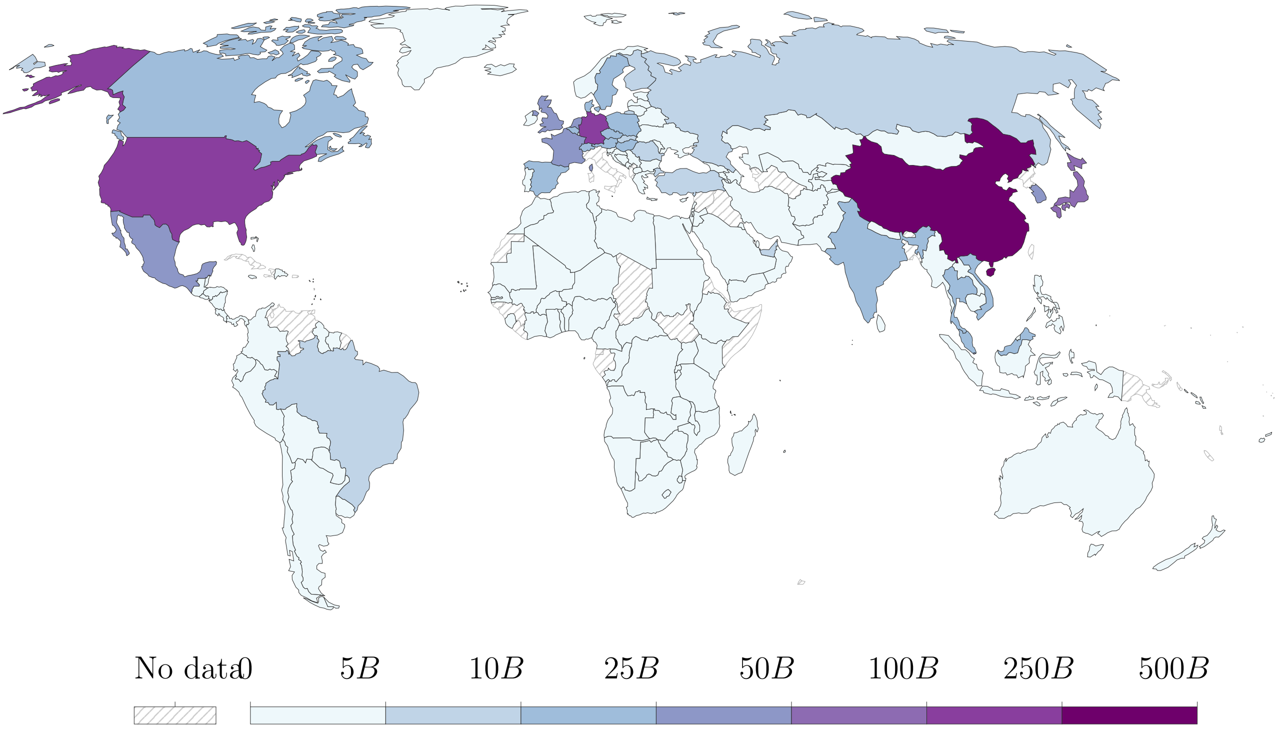

Figure 2: Export of environmentally sound technologies in billion dollars
source : UN Statistics division, 2020

This view differs from the financial view, in which a green investment is *the purchase of securities of firms aligned with environmentally friendly business practices and the conservation of natural resources.* Since a standard for environmentally friendly business practices has not been set yet, the broadness of those definitions leaves room for an infinite amount of different interpretations, resulting in a scattered and confusing scientific literature on the topic.

To address this issue, various frameworks have been developed to classify environmental friendliness. One of the most developed frameworks is the EU Taxonomy for Sustainable Activities [45], regulated under EU2020/852 of the European Parliament and of the Council of 18 June 2020. It divides economic sectors between ones that have an impact on climate change mitigation and ones that have an impact on climate change adaptation, resulting in a list of industry sectors and their NACE codes. Other public (like China, the UK, Russia and Canada), and private (Net-Zero Banking Alliance) institutions have established their taxonomies, with different degrees of strictness and clarity. Green indexes have been created in recent years to select and monitor the performance of green sectors, businesses and investments. Examples of such indexes are the NASDAQ OMX Green Economy and the S&P Paris-Aligned & Climate Transition Indexes. The criteria for choosing green companies for these indexes are usually clear, but the methods for defining "green" is disputed [87]. Considering the variations in green investment policies across different asset classes, a 2012 OECD Working Paper [46] suggests that it may be useful to define "green" in relation to different asset classes separately. By acknowledging these distinctions, a more cohesive and comprehensive understanding of green investment can be achieved.

The definitions become even more unclear in the scientific literature. Papers like *Beauer et. al (2023)* or [11] use the term "green stocks" even if not referring to Equities of firms that work in one of the sector proposed as green in taxonomy, nor referring to stocks of companies found in green indexes, but simply because these stocks where found to be the *"greenest"* when compared to others. This is mostly due to the lack of data regarding sustainable finance, and the absence of a common academic vocabulary.

The same uncertainty can be found when applying the green label to technology. Kemp and Pearson [69] decided to base the definition of eco-innovation on environmental performance instead of on environmental aim because it is not the aim that is of interest but whether there are positive environmental effects related to its use. They arrive at the following definition :

> *"The production, assimilation or exploitation of a product, production process, service or management or business methods that is novel to the firm [or organization] 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"*

1.4 Greenwashing

"Greenwashing" refers to the deceptive practice of conveying a false or misleading impression of a company's environmental responsibility or sustainability efforts to gain social or economic benefits. By employing greenwashing companies aims to attract investors who prioritize ESG considerations and wish to support projects or organizations that align with their values. For instance in green debt instruments greenwashing involves the issuance of debt with an additional promise by the issuer that some, or all, the funds raised are to be allocated for a green cause or to achieve certain sustainability targets. Firms might benefit from this promise as it can affect the interest rate and reduce the cost of capital. This phenomenon is aided by the voluntary nature of many green standards and the reliance on self-labeling, which creates the risks of unsubstantiated claims of greenness, leading to greenwashing [77]. This means that companies may exaggerate or falsely represent the environmental benefits of their actions, thereby misleading investors and the public. The risks of greenwashing can persist over time due to failures in reporting, monitoring, and impact assessment. If firms fail to provide accurate and transparent information on how the funds are used or the actual environmental impact of financed projects, it becomes difficult for investors to assess the true sustainability and green merits of their investments. In addition Hu and Wang [63] argue that the proliferation of frameworks and standards could mine the impact of green innovation in firms with higher greenwashing. When multiple standards available, each with its own criteria and requirements, the market becomes complex and fragmented, aiding ill-intentioned companies to select the standards that result in a greener image.

But greenwashing might not just hamper green innovation, it can substitute it. "Innovation washing" is the term coined by Xing [111] to describe the tactical trick employed by firms in the presence of environmental information intangibility to develop and employ low quality green innovation to appeal to resource providers. This complexity adds to the aforementioned problems making it even harder for investors to navigate and evaluate the environmental credentials in the market. It also opens the door for issuers to selectively choose the framework or standard that best aligns with their desired image, potentially undermining the credibility of green certifications. To mitigate greenwashing risks, ongoing efforts should focus on strengthening transparency, implementing robust reporting and verification mechanisms, and fostering harmonization and standardization across the market.

2 Green Patents

After having discussed innovation and its role in the fight against climate change, the next section covers how EI can be tangibly measured by studying patents. A patent is an intellectual property right that is granted by a county's government as a territorial right for a limited time period (usually of 20 years) to protect inventions. The main idea behind patenting is that granting a monopoly to generate income from a certain inventive activity is expected to spur inventions, but at the same time disclosing the invention adds to the stock of knowledge of the collective, thereby enabling further discovery.

Advancement and dissemination of novel technologies, whether they usher in revolutionary changes or de-carbonize existing ones has been deemed critically essential by governments worldwide. This is particularly true in addressing climate change while meeting escalating global demands for energy and natural resources. A robust and widely adopted industrial property system, with a specific emphasis on the patent framework, serves as a catalyst for innovation as it fosters the development of new technologies. The role of institutions on growth, and especially the influence of Intellectual Property Rights, has been integrated into the Schumpeterian Growth Framework; By securing the rewards of successful innovators and thereby motivating R&D efforts, intellectual property rights (IPRs) protection plays a central role in endogenous growth theory as theorized by Lewis Davis and Fuat Sener [33]. In the case of green patents, the new technologies might be crucial for effectively combating climate change and the promotion and growth of the green economy [55].

Environmental Innovation (EI), when protected via a patent, might also help the firm to obtain a competitive advantage in a resource-based view approach to strategic management. Researchers have long understood that competitive advantage depends upon the match between distinctive internal (organizational) capabilities and changing external (environmental) circumstances [10]. Starting from the mid '90s natural and environmental constraints have been included in this framework [54] making green patents a surrogate for inimitable and non-substitutable resources.

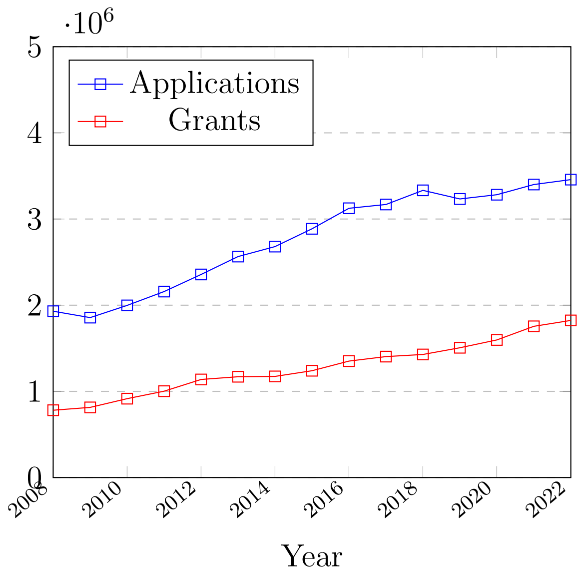

Figure 3: Patents Applications and Grants, worldwide data.
Source : WIPO Statistical Database August 2023 [110]

2.1 Classification of green patents

In recent years, numerous international organizations, including the European Patent Office (EPO), the World Intellectual Property Organization (WIPO), and the Organization for Economic Cooperation and Development (OECD), have directed significant attention to studying the role of patents in advancing and disseminating sustainable technologies. Before diving deep in specific classifications it's important to understand the difference between these technologies :

- **Climate Change Mitigation Technologies** (CCMTs) [67] are a spectrum of technologies and applications dedicated to diminishing the impact of climate change or adapting to it. These technologies operate by managing, decreasing, or preventing anthropogenic greenhouse gas (GHG) emissions, with a particular focus on CO_2. This category includes all those measures whose goal is to radically modify the production process, not integrating it but transforming it at the level of technology used.
- **Environmentally sound Technologies** (ESTs), cataloged by the United Nations Framework Convention on Climate Change (UNFCCC) [37] are a set of

> techniques and technologies able to reduce environment damages through processes and materials that generate fewer potentially harmful substances, recover such substances from emissions prior to discharge, or utilize and recycle production residues.

Starting in 2009 the European Patent Office has undertaken comprehensive monitoring of inventions in sustainable technologies by collecting, processing, and analyzing statistical data pertaining to patents in CCMTs. Since January 1 2013, the EPO has implemented a dedicated coding scheme named the "Y0X" tagging scheme for patent documents involving climate change mitigation technologies, based on the CPC classification (an extension of the IPC jointly managed by the EPO and the US Patent and Trademark Office). Y0X introduces Section Y, a new category alongside the standard Sections A-H of the international classification and further divides it into two classes : Y02 identifying technologies and applications for climate change mitigation and Y04 which concerns information or communication technologies that have an impact on other technological areas.

A committee of Experts guided by the World Intellectual Property Organization developed in 2010 the "IPC Green Inventory" methodology. It is based on a set of essential ESTs identified by the Secretariat of the United Nations Framework Convention on Climate Change (UNFCCC) and leverages the general purpose classification scheme provided by the IPC system to create a specialized scheme aimed at facilitating the retrieval of patent information on green technologies. The IPC system divides all fields of technology into hierarchical sets of sections, classes, subclasses and groups. It is an indispensable tool for industrial offices, in conducting searches to establish the novelty of an invention, or to determine the state of the art in a particular area of technology.

Lastly, in 2015 the OECD [56] developed a search strategy utilizing IPC and CPC codes jointly to select patents of environment-related technologies, although quoting directly the aforementioned paper : *"Due to their very nature, it is impossible to identify technologies with unequivocally positive environmental benefit; this is because the benefit of environmental-related technologies will ultimately depend on how they are used and applied in practice. Unlike for biotech, nanotech or ICT fields that can be defined using an objective criterion, there is no such objective for envtech. Indeed greenness is a*

C - CHEMISTRY
C10 - PETROLEUM, GAS OR COKE INDUSTRIES; TECHNICAL GASES CONTAINING CARBON MONOXIDE; FUELS; LUBRICANTS; PEAT
C10B - DESTRUCTIVE DISTILLATION OF CARBONACEUS MATERIALS FOR PRODUCTION OF GAS, COKE OR SIMILAR MATERIALS
C10B 53/ - Destructive distillation, specially adapted for particular solid raw materials or solid raw materials in special form
C10B 53/02 - of cellulose-containing material
C10L - FUELS NOT OTHERWISE PROVIDED FOR; NATURAL GAS; SYNTHETIC NATURAL GAS
C10L 5/ - Solid fuels
C10L 5/40 - essentially based on materials of non-mineral origin
C10L 5/42 - essentially based on animal substances or products obtained therefrom

Table 1: Example of IPC labeling

somewhat elusive concept and, consequently, it might sometimes be difficult to interpret such statistics for policy purposes".

2.2 Green patents as measure of green innovative activism

The use of patents as a reliable measure of innovative activity has been studied for decades by researchers, Acs and Audretsch find in their 1989 paper "Patents as a measure of Innovative activity" [65] a correlation between measures of knowledge like R&D expenditures and skilled labour to patented inventions similar to the one innovative activity has (although differences arise when accounting for capital intensity and unionization).

Since then (aided by the constantly growing number of patent applications worldwide, see Fig. 3.) the literature has highlighted more advantages patents can provide over other indicators, and researches regarding green patents specifically started to emerge. Such an example is 2015 "Patents as a measure for eco-innovation" [86] where the authors Oltra, Kemp and de Vires summarize green patents advantages in 5 main points:

- **Level of eco-incentive activities.** Since patent applications are generally filed in a beginning stage of the development cycle, they do not only measure inventive output, but are an indicator of the level of innovative activity itself [92].
- **International technology diffusion.** Patenting is costly, inventions tend to be protected in only a selected number of countries of the world. Given the

additional costs of filing abroad, Eaton and Kortum [40] propose that only the most valuable inventions are filed in several countries, signaling that the inventor expects the them to be profitable and have potential applications in that market. Furthermore, filings in different countries (Patent Families) could be used to track technology diffusion across countries, as found by Jhonstone in the case of wind-powered electric generating equipment [68].

- **Directions of research and technological competencies of organizations.** In order to be granted each patent needs a detailed description and an IPC or CPC classification, making it simple to track the technological trajectories of an organization compared to using self-reported R&D data.

- **Knowledge sources of eco-innovations.** Patents can act as a source of other pertinent bibliographic data. The identity and national origin of both the inventor and the assignee (or applicant) can empower researchers to discern the role of collaborative dynamics between public and private entities within a designated technology or IPC section. A private firm patent portfolio can highlight specific aspects of knowledge dynamics, like the proportion of patents from suppliers and component manufacturers, trends among sectors and patent applications.

- **Technological spillovers and knowledge flows.** To gauge the flow of spillovers from innovation-generating sectors and innovation-utilizing one various approaches have been suggested. Jaffe assesses the technological correlation among a subset of US firms by scrutinizing the distribution of their patents, Engelsman looks the simultaneous occurrence of IPC codes and Verspagen classifies intersectoral technology spillovers by considering both the main IPC code and supplementary ones. Alternatively, by employing patent citations, it's possible to study the utility of knowledge in a given patent by assuming that references to preceding patents are useful for developing novel knowledge in the citing patent.

This being said patents present consistent limits and weaknesses already highlighted by literature. On their own patents measure inventions, not innovation, which refers to the application of the invention itself. Only a subset of patents are commercially profitable, resulting in a highly skewed value distribution where the majority of patents have little or no commercial desirability, and are therefore less significant as a measure of innovation. According to Petruzzelli [89] this could be magnified for green patents. Green innovations seem to possess higher levels of complexity and novelty than other innovations, mostly due to the spectrum of environmental impact they try to obtain (energy consumption, waste reduction, materials innovation etc etc) and the different processes and cycles they can be applied to. Eco-patents only concern eco-innovations that are new to the world, or at least characterized by a degree of novelty, which is superior to the minimum degree of novelty necessary for an innovation to be patentable. This implies that eco-patents specifically pertain to a limited subset of eco-innovations distinguished by a notable degree of novelty. Contrary to intuition high level of novelty is not found to be correlated with a higher value (measured by the total number of citations the specific patent received within 5 years of the filing date, which has been demonstrated to correlate with returns by Trajtenberg [106]) possibly because by being too new green innovations need more time to be understood and adopted. In the same paper Petruzzelli finds that another driver for patent value are inter-organizational collaborations and technological complexity of the firm they are held at. The same patent can have a different value if possessed by a different firm, making patents less objective of an indicator.

Lastly, due to their own nature only primarily technical innovations are patented, making information on new business methods and organisational innovations not tracked via a patent portfolio analysis. Given that firms are more likely to patent research that results in new products, rather than research that results in new processes, research on environmental innovation that uses patent statistics is more likely to focus primarily on product eco-innovations (Popp, 2005 [92]).

2.3 Patent development and acquisition

Most papers cited in the previous section use data regarding patents directly developed by firms following the standard patent development process. This isn't however the only way for a firm to obtain a patent. The patents marketplace has seen a rapid growth in the last decades, finding accurate data on the topic is difficult but according to IAM Patents [79] the brokered patent market had reached 11 billion $ in sales in

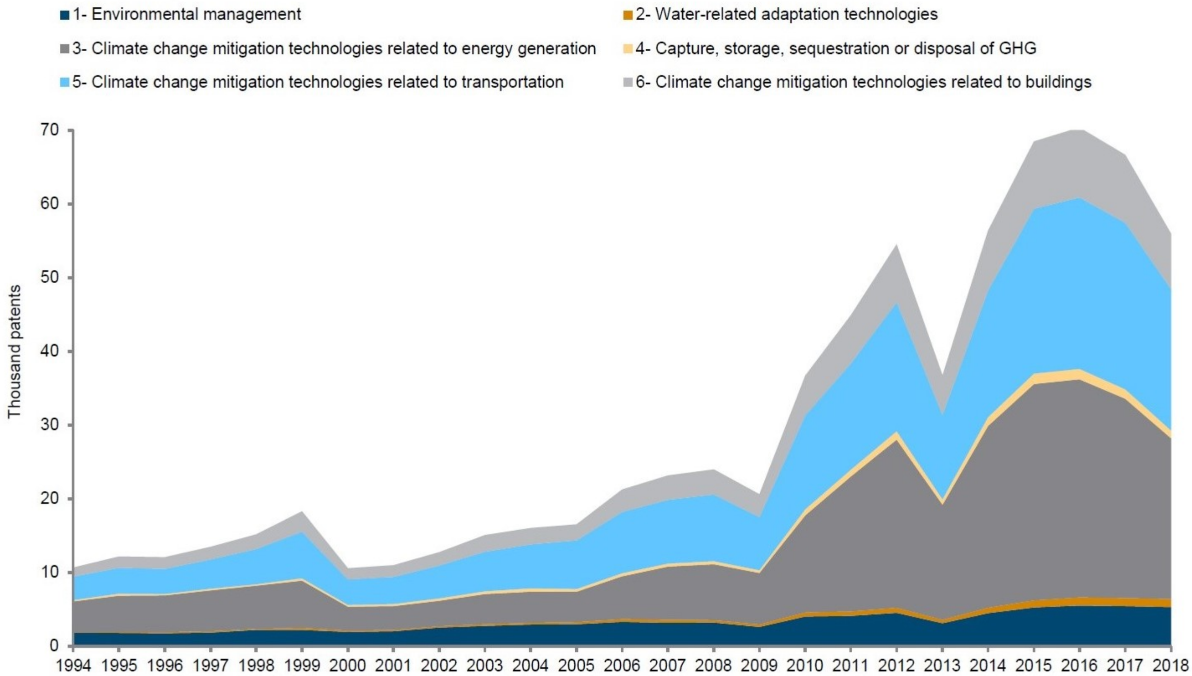

Figure 4: Number of patents granted globally in six categories of IPC green technologies. Source : Ghodsi and Mousavi [49]

2021. Deshpande [36] proposes that this growth goes hand to hand with the increased complexity of intellectual property, if the cost of R&D increases but only 30% [83] of the resulting intangible assets are exploited or commercialized by their owners, firms need a secondary market where to monetize their efforts. In addition to purchase, mergers and acquisition (M&A) are another valid strategy for technological acquisition. As stated in the 2006 work by Cloodt and Hagedorn *'Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries'* [29] the acquisition of related knowledge via M&A can have a positive impact on a firm innovative performance especially in high-tech settings, given that the acquirer patent portfolio and the acquired one have a significant knowledge overlap [52] to create opportunities for learning, but different enough to fill gaps in capabilities.

The method of acquisition of a patent might carry significant information on the commitment to the technology traded. Caviggioli, De Marco, Scellato and Ughetto [22] find that acquired patented technologies exhibit on average greater complexity, technical merit, legal robustness, are more closely aligned with basic research, and have a stronger technical focus than internally developed patented inventions. Patents acquired through the patent market tend to be more frequently associated with non-core technology areas compared to M&A patents for a given firm and are generally easier to trade. They also tend to have fewer backward scientific citations, claims, and inventors, indicating a lower level of complexity. Technological acquisitions through the market can be integrated into the portfolio of activities more seamlessly than those stemming from M&A processes.

3 Measures of firms sustainability

Once established what green investments are, and how patents can play a role in signaling a firm interest in ecological innovation, it's time to dive deep on the criteria used to assess green performances. Once again, the existence of multiple international frameworks and a lack of standardization on the field results in a significant number of developed indexes with a low frequency of usage in the literature [1] therefore this overview will analyze only the most used green performance indicators (GPIs) as suggested by bibliographical analysis of green researches like Tuni et. al. [107] or ones present in frameworks developed by already mentioned entities like the OECD.

To add another dimension to the analysis, indicators on specific substance usage and emissions (like greenhouse gasses or electric consumption) do not only consider the sheer volume of direct usage, but the degree of connection to business activities as well. In 2002 the Greenhouse Gas Protocol [95] formalized a concept already present in the literature, it distinguishes between three 'scopes' to help delineate direct and indirect emission sources :

- **Scope one emissions.** Occur from sources that are controlled directly or owned by the company, for example emissions from combustion in owned or controlled boilers, furnaces or vehicles, emissions from chemical production in owned or controlled process equipment, transportation of materials, products, waste, and employees and fugitive emissions (like equipment leaks from joints, seals, packing, and gaskets or methane emissions from coal mines and venting etc.)
- **Scope two emissions.** Accounts for greenhouse gasses (GHG) emissions from the generation of purchased electricity consumed by the company in its owned or

controlled equipment or operations. For many companies, purchased electricity represents one of the largest sources of GHG emissions and the most significant opportunity to reduce these emissions. Purchased electricity is defined as electricity that is purchased or otherwise brought into the organizational boundary of the company. Scope 2 emissions physically occur at the facility where electricity is generated.

- **Scope three emissions.** Scope 3 allows for the treatment of all other indirect emissions. Scope 3 emissions are a consequence of the activities of the company, but occur from sources not owned or controlled by the company. Some examples of scope 3 activities are extraction and production of purchased materials, transportation of purchased fuels, and use of sold products and services. Given the challenge posed by their estimation [98] these emissions are not mandatory in the GHG protocol, but are essential for a robust accounting [88].

3.1 Performance indicators for environmental impact

A Key Performance Indicator is *an item of information collected at regular intervals to track performance of an organization or system at any level that produces output using resources of different types* (Fantini 2015 [42]). Measurement of KPIs has no value per se but acquires utility when compared with the appropriate reference points, making tracking implementation of plans, assessing progress and adopting best practices possible. Given their purpose KPIs have been implemented in the quest for continuous green improvement. According to the European Commission's 2009 report on KPIs for ESG [102] environmental KPIs must illustrate a correlation to risk or success factors in corporate business, be significant and relevant for investment decisions, be firmly integrated into the corporate management system, be quantified, comparable, and illustrate dynamics from one reporting period to another. Sherif [100] identifies two main sources of sustainability KPIs. The first is made up of international organizations like the Global Report Initiative (GRI), Dow Jones Sustainability Index (DJSI), ISO 14031 environmental performance evaluation and many more; They develop both wide and sector-fitting indexes with the purpose of reporting environmental performances outside of the firm, giving little to none internal guidance on internal reporting. The second source are published research articles, which tend to be more specific to firms but with narrower spread and more difficulties when comparing different cases.

3.1.1 Emissions and Carbon Footprint

The scientific consensus points toward a clear relationship between increased greenhouse gasses in the atmosphere and a warming planet. Out of the seven GHG defined in the Kyoto Protocol, CO2 made up 71.6% of all emissions in 2023 [31] and it's therefore not a surprise that CO2 emissions are the most utilized indicator of green performances [19]. It is so ubiquitous that methods have been developed to convert emissions of other GHGs to CO2 emissions. The Intergovernmental Panel on Climate Change (an intergovernmental body of the United Nations tasked with advancing scientific knowledge about climate change caused by human activities) used the ton of CO2 as basic unit of measurement in the Global Warming Potential Scale (GWP) [8], developed to compare the global warming impact of different gasses by comparing how much energy a ton of gas will absorb over a given period of time, relative to the emissions of 1 ton of carbon dioxide (for example Nitrous Oxide has a GWP of 273 over a 100-year time scale while Methane is between 27 and 30). Utilizing the GMP value it is possible to calculate carbon dioxide equivalents (CO2e) by multiplying the tons of a given emitted GHG by its GMP [15]. The previously mentioned Greenhouse Gas Initiative utilizes equivalent tons of CO2 to measure scope one, two and three emissions.

Conceptually, by summing emissions of different GHGs (using CO2 equivalents) and accounting for their different provenances (using scopes) on a fixed time frame it is possible to calculate the *carbon footprint* of a firm. Even if a single, widely-adopted procedure for this operation is not set, Peters [88] proposes that the methods used to determine the carbon footprint should not be specified in the definition, quote : *"The 'carbon footprint' of a functional unit is the climate impact under a specified metric that considers all relevant emission sources, sinks, and storage in both consumption and production within the specified spatial and temporal system boundary"*. Footprint practitioners commonly employ two methods to assess the life cycle-wide impacts of organizations: process analysis and economic input-output (EIO) analysis. These approaches differ in the depth and scope of analysis and have distinct data requirements.

A conventional process analysis like life cycle analysis (LCA) relies on bottom-up data from specific production processes, while it yields more precise results for direct on-site impacts, it introduces significant systematic errors due to the the omission of resource requirements or pollutant releases of higher-order upstream stages of the production process. [74]. On the other hand, EIO (based on the method developed by the Nobel Prize-winning economist Wassily Leontief [58]) uses aggregate sector-level data to quantify the environmental transactions between different sectors considering both direct and indirect effects. When extended with national environmental and social accounts it can handle infinite supply chain systems and avoids truncation errors but tends to inadequately describe production processes specific to many small-scale and medium-scale applications.

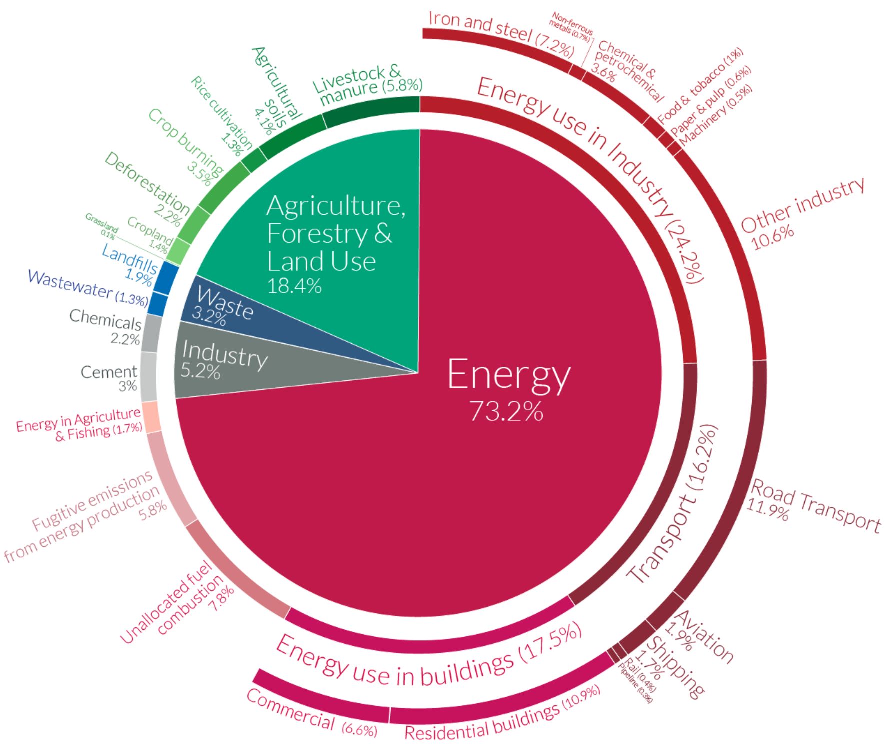

Figure 5: Breakdown of global greenhouse gas emissions in 2020, Source : Climate Watch and the World Resources Institute. Licensed under CC-BY by the author Anna Ritchie (2020) [97]

3.1.2 Energy usage

Energy indicators gained in relevance during the periods of crisis in the energy sector, being subjected to the societal and political context and, therefore, varying over time

[59]. Olsthoorn [85] argues that while emissions are intrinsically an environmental indicator (because they are concerned with the measurement and tracking of firm output to the physical environment) energy consumption should be viewed as a physical indicator that is neither good nor bad in itself but has to be evaluated. For example Energy flows offer valuable insights into the efficiency of energy use, but fall short in depicting the environmental impacts stemming from the consumption of various energy sources. These impacts encompass the depletion of abiotic resources, land use, ozone depletion, global warming, toxicity, acidification and eutrophication, among others. Similarly to carbon dioxide, energy consumption can be divided in direct and indirect energy use. The first refers to the energy purchased by the firm to operate their machinery, making and selling products, heating environments etc; while the second is the energy used in the manufacture of supplies and in the services purchased by the company [90]. Huijbregts [64] identified significant correlations between fossil Cumulative Energy Demand (CED, the direct and indirect energy use throughout the life cycle) and various midpoint impacts for products falling within categories like energy production, material production, and transport. Such relationships are well-established in scientific literature, extending beyond fossil fuels to include renewable energy sources. While using CED as a screening indicator can simplify environmental assessments, it cannot fully replace exhaustive Life Cycle Assessment when in-depth analyses are necessary.

From an environmental responsibility perspective, Goldenberg [50] finds electricity derived from renewable resources is generally considered beneficial due to the minimal or non-existent combustion of fuels that avoids contributing to climate change or air pollution. According to Bruckner [16] biomass and hydropower emerge as the primary contributors of green energy consumption, while wind, solar, and geothermal energy play a comparatively smaller role globally. The type of energy consumed is a significant point of discussion, particularly in the context of firms' environmental disclosure documents, which frequently incorporate indicators on renewable energy [2], as each source contributes differently to environmental health but might be given the same weight in some environmental frameworks. Moreover, despite its advantages, renewable energy sources still have multiple limitations. First of all historically their production and utilization have incurred higher economic costs compared to fossil fuels, although recent advancements have improved cost-effectiveness [50]. Secondly renewable resources are often located in remote areas, making the construction of power lines to urban centers, where electricity demand is high, a costly endeavor. But most importantly the utilization of renewable sources is hindered by their intermittent availability, like the reduced capacity of solar power on cloudy days, wind power on calm days, and the limitations of hydropower when water availability is compromised.

The current emission accounting standards allow companies to claim emission reductions through the acquisition of renewable energy certificates (also called RECS), that certify that one megawatt-hour of electricity was generated from a renewable source and fed into the grid, enabling the REC owner to claim the environmental benefits. The trade of RECS makes the "clean energy label" a tradable asset that can be applied to brown energy. This practice operates on the assumption that these certificates will stimulate increased investments in renewable energy generation, leading to a subsequent reduction in emissions from electricity production. However, existing research provides limited empirical evidence to support this assumption [13]. Consequently, the corporate procurement of certificates may lead to overstated estimates of emission reductions.

3.1.3 Waste production

As highlighted by the European Chemical Industry Council waste is a tangible indicator of inefficiencies within the production process, studying waste production is useful to understand shortcomings in both process and product design; Addressing environmental concerns necessitates the development of novel techniques for waste treatment and disposal. Since 2001 various stakeholders, including universities, governments, businesses, and NGOs, are actively engaged in advancing and implementing a zero waste strategy, aspiring toward comprehensive sustainability objectives outlined by the Zero Waste Alliance. These objectives encompass achieving 100% resource efficiency, eliminating solid and hazardous waste, eradicating emissions to air, water, or soil, eliminating waste in production and product lifecycles, as well as minimizing toxic substances. Companies striving for sustainability recognize that waste elimination is paramount, leading to reduced extraction from natural resources, diminished waste output, enhanced economic efficiency, and increased resource availability for all.

Business metric	Description
Unit of production	Business output in physical units; no consideration in monetary terms
Turnover (or sales)	Value of the company's production step in the value chain plus all upstream business activities; considers cradle-to-gate value creation
Total costs	Expenses for generating the business output; considers company's costs, including all expenses in the profit and loss statement
Costs of goods sold	Expenses that exclude indirect costs, such as office costs; shows direct expenses incurred in producing the company's output
Value added	Sales less intermediate costs for purchased goods and services; emphasisis put on the company's production step within the value chain
Earnings before interest and taxes (EBIT)	Approximate measure of a company's operating cash flow; focal point is the profitability of the company
Market capitalization or equity	Market value of a company or value of equity; emphasis is put on the value of the company as a whole
Number of employees	Proxy for the manufacturing activity; Might be influenced by different labour intensities in different sectors and/or different countries.
Total investments	May be taken as a substitute to either turnover or value added; Reflects only a part of the activity

Table 2: Summary of business metrics relevant to environmental indicators.
Source : Hoffmann 2008 [60], Olsthoorn 2001 [85]

3.2 Index comparability

The absence of standardization among subjects, sources and reporting methods emphasizes the importance of selecting similarly obtained data when comparing the performances of different entities. Obviously, companies have different sizes, have different numbers of facilities, employ more or fewer people, and have a smaller or larger network of suppliers. Absolute numbers of impacts need to be put in perspective or are otherwise meaningless. The absolute carbon usage is useful for aggregate trends on a sector-wide or macroeconomic view but makes comparing singular companies prone to biases [72], in contrast relating emissions to a business metric allows for more transparent relations and can have different explanatory powers depending on the business metric chosen (see Tab 2.).

From this starting point Hoffmann [60] identifies four comprehensive and systematic corporate carbon performance indicators deriving from a combination of physical or monetary units and static or dynamic time frames : carbon intensity which represents a company's carbon use in relation to a business metric, carbon dependency which illustrates the change in physical carbon performance within a given time period, carbon exposure which reveals the financial implications of using and emitting carbon and carbon risk which estimates the change in financial implications of carbon usage within a given time period. Depending on the way carbon usage is calculated a firm's carbon input or output can be assessed using their material flow and the cost of the said carbon can be estimated by averaging the price of carbon allowances (see Tab 3.). Following the same framework of reference the same definitions can be applied to other environmental variables like energy and water consumption.

A more general approach is offered by Olsthoorn et al.[85], who's study aggregates years of green literature and proposes standardized approaches to data. The first hurdle lies within comparability, environmental data are frequently presented without established standardization or conversion factors. Additionally, there is limited information available regarding the specific references or inclusions within the data. To enhance transparency of performance and bolster credibility Olsthoorn proposes normalization of all environmental data, making sure that information is converted to units that is compatible with a chosen standard or baseline. After this step, the data can be standardized and/or aggregated toward specific indicators to meet particular information needs. Summary indicators in the form of aggregated physical metrics provide an overview of total resource use, emissions, and waste without being relative to production. The more data is aggregated the easyest it is to present larger production units in a comprehensive manner, capturing the interaction and interdependence of environmental effects. Nevertheless, greater data aggregation leads to reduced relevance for local or highly specific environmental issues. This sequence is expected to enhance data comparability through standardization, simplify data complexity, and enhance the usability and suitability of the data through aggregation. Additionally, this sequence facilitates tailoring information to specific stakeholders by employing different standardization bases or methods.

	Static	**Dynamic**
Physical	*Carbon Intensity :* $CI = \frac{\sum_{k=1}^{K} C_{k,t}}{BM}$	*Carbon Dependency :* $CD_{i,\Delta t} = \frac{CI_{i,t_1}}{CI_{i,t_0}} * 100$
Monetary	*Carbon Exposure :* $CE_{i,t} = \frac{\sum_{k=1}^{K} CI_{k,t} * p_{k,t}}{BM}$	*Carbon Risk :* $CR_{i,\Delta t} = (\frac{CE_{i,t_1}}{CE_{i,t_0}} - 1) * 100$

Table 3: List of Hoffmann indicators. Where k = emission source, BM = business measure, t = time period, i = scope, p = price

3.3 Impact of firms environmental disclosure

Environmental disclosure began to be part of annual reports from the 1970s when disclosures were in narrative form, about half page and provided incomplete details of environmental performance. [84] But by the 20s, most large publicly traded U.S. firms had converged around voluntary standalone ESG reports as a primary means of documenting their ESG activities [99]. This growth makes these reports among the fastest growing voluntary disclosures in history and might be explained by two major theories, legitimacy theory and stakeholder theory [76]. Legitimacy theory asserts that firms must align their operations with societal norms and expectations to attain legitimacy. Empirical evidence on the relationship between environmental performance and the extent of environmental disclosures has yielded mixed results. In the United States, environmental disclosures are largely voluntary, and companies utilize various channels such as company websites, annual reports, or standalone non-financial reports for disclosure. Research indicates that firms tend to disclose more environmental information on their websites during environmental crises and more in annual reports when they possess a positive environmental reputation [35]. Managers explain their crisis in a cost effective way to outside stakeholders (such as environmental activists, local community groups, government agencies, journalists and the general public) in order to show they are taking appropriate action and to thereby avoid political actions, such as consumer boycotts or additional regulation. Firms demonstrating commendable environmental performance, coupled with high levels of environmental disclosure, signal to the public their accountability and emphasize that positive environmental practices do not come at the expense of stakeholders. Conversely, companies with subpar environmental performance tend to disclose less about their environmental activities. Guthrie and Parker [53] propose that even with regulatory frameworks, underperforming firms may be reluctant to disclose their environmental performance.

Stakeholder theory asserts that environmental disclosures arise in response to stakeholder demands. When a firm's long-term survival relies on external stakeholder support managers provide environmental information that is belived to align with stakeholder expectations since addressing stakeholder demands becomes crucial. As emphasized by Smith et al. [109], a firm necessitates the support of all its stakeholders, leading management to address stakeholder demands through the implementation and disclosure of environmental strategies and activities. Environmental improvement initiatives might not only yield business benefits but also enhance the company's reputation. Therefore Smith hypothesizes, a positive relationship between environmental performance and environmental disclosure. Furthermore, the globalization of the economy has led to an increase in the internationalization of companies. International firms exert a growing influence on the social and ecological environments of both local and global communities. This expansion prompts a rising expectation for companies to be accountable to various stakeholder groups for the broader spectrum of their impacts [24].

An interesting viewpoint on the truthfulness of green disclosure comes from Cho and Patten [27]. Their findings support the contention that companies with poorer environmental performance employ language and verbal tone to manipulate the message conveyed in their financial report environmental disclosures. They observe, firstly, an association between worse environmental performance and the use of more optimistic language in the disclosures of their test companies. This suggests that the language and verbal tone in these disclosures more heavily emphasize reporting positive news and attributing favorable performance to the reporting companies' internal efforts, potentially obscuring responsibility for subpar performance compared to better-performing companies. Additionally, they identify a negative correlation between their environmental performance measure and the certainty scale of the disclosure. Consequently, it appears that companies with poorer environmental performance endeavor to conceal internal attributions for their unsatisfactory performance by employing convoluted and less certain language.

4 EI in firms

Now that the main topics regarding environmental innovation, how it can be studied via green patents and how it can be evaluated using environmental performance indicators have been discussed it's time to deep dive into the role that environmental innovation has took inside businesses, exploring its determinants, blockers and its actual impact on green performances by reviewing some of the scientific articles on the topic. Scholars like Pinget [91] have discussed whether EI is triggered by supply-push factors, demand-pull factors, regulations, or a mix of the three. Each one is going to be analyzed in the next subsections.

4.1 Technology-Push factors

"Innovation breeds innovation", is the phrase coined by the American economist William Baumol in his book *The free-market innovation machine* [12] and stands as a pillar of mainstream innovation theory. The existing technological possibilities of a firm, which encompass both the physical and knowledge-based capital stock, are essential for the development of new products and processes and serve as catalysts for driving further innovations. Acquiring and cultivating such a capital stock requires investments in research and development R&D activities as well as ongoing education and skill development for employees, and according to Baumol poises the company for continued success in innovation endeavors. This hypothesis is tested and confirmed by Jens Horbach [61] by running a random effect logit regression on a panel of German companies, confirming that the technological capabilities ("knowledge capital") by R&D is very important for environmental innovation and that general and environmental innovative firms in the past are also more likely to innovate in the present.

Another important study by Horbach [62] underscores how eco-innovations typically serve multiple objectives beyond environmental aims only. Organizations must prioritize competitiveness and productivity while striving to meet environmental regulatory standards, therefore their efficacy in developing and adopting eco-innovations is dependent on their ability to seamlessly integrate productive efficiency and product quality with environmental objectives. The adoption of eco-innovations is therefore more probable if the positive environmental outcomes align with cost-saving measures, especially when involving material and energy efficiencies. Other empirical studies underscore the pivotal role of cost savings and productivity enhancements as key drivers of eco-innovations, particularly in the realm of process innovations and clean technologies and emphasize that innovation in clean technology is typically propelled by cost considerations. Cost savings, particularly those that stem from the reductions in material and energy usage, assume an heightened significance in eco-innovations due to their potential to mitigate environmental impacts. For instance, reductions in material consumption inherently translate to diminished waste generation, while energy conservation measures often coincide with reductions in CO2 emissions.

This concept aligns with what Cainelli and Mazzanti [18] refer to as the "Complementarity as technical jointness" of environmental innovation. Quote : *" The intrinsic technical features of processes and products may define the specific, possibly unique, features of relevant technical jointness between intended and unintended effects of EIs".* For instance, consider EI aimed at enhancing energy efficiency, which generates a private appropriable benefit. In this scenario, the intended outcome of energy savings represents a valued private good, but it also yields an unintended positive externality in the form of emissions reduction, including greenhouse gases and other air pollutants. Thus, the private benefits derived from energy efficiency improvements carry a concurrent public good component, further illustrating the intricate interplay between private and public interests inherent in environmental innovation endeavors.

Businesses that engage in innovation-driven activities often try to mitigate the various expenses and risks by attracting additional partners to collaborate on data and asset sharing. Taking into account the interests of both internal and external stakeholders can help businesses to mitigate some of the potential challenges of EI and increase the benefits. A noteworthy aspect of environmental innovation is that it often demands expertise and capabilities that fall outside a firm's core competencies; Research and Development collaborations play a significant role in driving environmental innovation by facilitating economies of scale, particularly among firms operating within the same sector. Cainelli, Mazzanti, and Montresor [17] demonstrate that interfirm network connections are paramount drivers of EI, particularly for firms situated within a local production system. Moreover, their research underscores that EI is fostered through firms' engagements with "qualified partners" (e.g. universities and suppliers, but not customers or competing firms) indicating that interactions with specialized collaborators play a pivotal role in stimulating environmental innovation initiatives.

4.2 Demand-Pull factors

In the current landscape consumers are increasingly cognizant of the adverse impacts associated with the products they consume and consequently the demand for less polluting products with extended lifespans is growing. This shift in consumer behavior is driven by a heightened environmental consciousness among the public, coupled with stringent international regulations governing environmental protection. Chen [25] argues that cultivating a green image has become paramount for companies, given the prevailing trends in environmentalism among consumers. Empirical evidence shows that the pressure to eco-innovate is strongest in product markets that are close to final consumers. In these markets firms can easily communicate the added value of the innovation to the customer, and most importantly they can readily assess the willingness of consumers to pay an extra for green products. Being at the forefront of green innovation affords companies the first-mover advantage and allows them to command premium prices for their eco-friendly products, gaining a competitive edge in the market [26]. In addition, enterprises have begun integrating the concept of green products into the design and packaging of their offerings thereby enhancing the differentiation of their products and solidifying even futhter their market position. Beyond consumer demand, firms face mounting pressure from various other stakeholders, including governmental regulatory bodies, non-governmental organizations, industry rivals, and the media to transition towards environmentally friendly practices. Calls for adherence to green labeling standards, adoption of certifications from international organizations such as the International Organization for Standardization (ISO), and increased transparency through public disclosures regarding the use of materials and energy in their production processes [6] are common today, and are a manifestation of this growing pressure.

But demand-side factors can easily be turned into attempts of greenwashing (already treated in section 1.4). Kesidou and Demirel [70] observe that although engaged stakeholders and growing expectations for corporate social responsibility contribute significantly to the development of eco-innovative products and processes, they do not necessarily elevate the overall level of eco-innovation. Their study, based on UK data, reveals that firms respond to stakeholder pressures by investing in eco-innovation only to the extent necessary to project a "green image". In other words, the firms may prioritize surface-level eco-friendly initiatives that enhance their public perception without substantially advancing their actual environmental innovation efforts.

Overall the demand-pull factors of EI are coherent with stakeholder theory as argued by Cek and Erkantan in *The Relationship between Environmental Innovation, Sustainable Supply Chain Management, and Financial Performance: The Moderating Role of Environmental, Social and Corporate Governance* [23]. According to the stakeholder theory, businesses should consider the interests of all parties involved in the operation in addition to providing value and profit for proprietors or investors. Prioritizing social responsibility objectives and environmental stewardship not only meets the demands of stakeholders but also fosters stronger relationships between them and businesses. By aligning their actions with social responsibility and environmental preservation goals, businesses can effectively satisfy the diverse needs of stakeholders, ranging from employees and customers to investors and communities. This alignment not only enhances the overall reputation and credibility of businesses but also strengthens trust and loyalty among stakeholders.

4.3 Regulations

The literature widely acknowledges that environmental innovation is influenced not only by market demand and technological advancements but also by regulatory incentives. There is an ongoing discourse regarding the impact of regulation-driven environmental innovations on overall innovation and firm success. Specifically, the debate centers on whether firms can achieve market success with innovations stimulated by environmental regulations, comparable to innovations driven by market demand or technological advancements. The affirmative stance on this issue is proposed by Porter and van der Linde in 1995 [93] and is defined as the Porter hypothesis. According to this hypothesis, stringent environmental regulations can catalyze "innovation offsets". Essentially, increases in resource efficiency spurred by regulatory measures can ultimately lead to higher levels of economic efficiency, particularly over the long term.

Rennings and Rammer in *"The impact of regulation-driven environmental innovation on innovation success and firm performance"* sum up the role that Environmental regulations plays in stimulating innovation activities within firms through four key channels. First such regulations incentivize providers of environmental goods, services and technologies to innovate in environmental processes. This is mostly evident when existing technologies are insufficient to meet regulatory standards, prompting the development of new products and the enhancement of existing ones. As regulations alter the economic landscape, firms might perceive this as an opportunity to introduce new products or services that assist other businesses in complying with the new requirements. For example the introduction of mandatory packaging deposits could spur the creation of logistics services to aid retailers in managing returned packaging. Secondly environmental regulations encourage the development of innovative products in the realm of product-integrated environmental protection. This encases requirements related to the use or avoidance of certain materials, hazardous substances, or other product attributes such as recyclability, biodegradability, and improved energy efficiency, or reductions in emissions like air, wastewater, and noise. Thirdly, environmental regulations stimulate investment activities beyond mere compliance with standards, leading to the development of new or significantly improved processes for environmental protection. These efforts may focus on streamlining operations or enhancing quality in a broader context. Lastly, environmental regulations foster the growth of new services aimed at advising firms on environmental matters, like environmental consultants who specialize in certifications or assessing environmental policies. The introduction of new regulations often creates demand for advisory services tailored to help businesses navigate compliance and sustainability challenges effectively.

Overall, the convergence of consumer preferences, regulatory mandates, and stakeholder expectations is reshaping the business landscape by compelling organizations to embrace sustainability and green practices as integral components of their operations. This shift not only benefits the environment but also presents opportunities for companies to enhance their brand reputation, drive innovation, and secure a competitive advantage in the marketplace.

4.4 Blockers of EI in firms

Despite its numerous advantages, environmental innovation sits in a challenging spot where the normal roadblocks to innovation are reinforced by the inactive attitude of towards environmental activism shown by many firms. As pointed out by Slawinski [101] there is a fundamental short-termism problem in current management practices. Organization of firms that rely heavily on the use of management practices that emphasize short-term financial returns in their decision-making on climate change will be less likely to make significant investments that would contribute to absolute GHG emissions reductions, especially in light of the uncertainty associated with such investments and their long-term payoff periods.

The Oslo manual [32], developed by the OECD and EUROSTAT in 2005, identifies and categorizes various economic and cost-related barriers that may impede business innovation. Souto and Rodrigues in their study *"The problems of environmentally involved firms: innovation obstacles and essential issues in the achievement of environmental innovation"* [103] adapt this model to environmental innovation finding five main barriers that might stunt EI. On the revenue side, the first barrier pertains to the internal financial constraints of the company, such as insufficient share capital or reserves, a problem accentuated by the increased cost of EI, already discussed in section 1.1.

The second barrier involves external financing challenges. It includes a lack of funding from affiliated entities (subsidiaries or associates) as well as difficulties in obtaining loans from financial institutions or non-financial companies and difficulties in securing venture capital or accessing public funding through loans or grants from international or supranational organizations. A report from the World Economic Forum [4] highlights how in many instances investments in innovative clean technologies are marked by uncertainties surrounding factors like their durability and performance, which amplify their perceived risk. Additionally, these investments typically entail an high capital costs upfront, coupled with a considerable amount of time to bring a new solution to the market, resulting in a payback period for such investments that tends to be longer compared to more conventional investments. Environmental innovation continues to be viewed by investors as a nascent field with unfamiliar markets and business models, especially when contrasted with more established sectors like information and communication technology, biotechnology, or life sciences, all with already demonstrated significant financial returns. This perception of immaturity and uncertainty surrounding EI can act as a deterrent for investors, leading them to favor more established sectors with proven financial track records.

The third barrier are the prohibitively high costs associated with EI activities, for both the current expenditures on innovation and the investment in fixed capital dedicated to innovation efforts. The challenges related to funding become more pronounced in innovative start-ups and small-sized firms, entities that often face difficulties in accessing external funding due to their inconsistent and unstable income streams. Moreover, their internal funds are limited as they may not have built up reserves, primarily because they have not yet reached profitability. Additionally, these companies lack the experience and established track record necessary to instill confidence in investors and potential lenders, and consequently struggle to assure stakeholders. According to several scientific studies, these hurdles are found to be consistent across various countries.

Beyond financial constraints, the last two barriers are knowledge-related, due to the specific information and knowledge required by Environmental Innovation. In primis the absence of trained or qualified personnel, that is capable of developing innovative environmental solutions poses a significant challenge, as their associated skills are important for exploring new environmental technologies. Furthermore, finding partners willing to cooperate in EI activities can be daunting. The findings by De Marchi [34] indicate that certain types of partners play a more significant role in facilitating firms' co-innovation efforts compared to others. Notably, suppliers emerge as crucial collaborators, aligning with theories highlighting the presence of technological interdependencies that necessitate shared knowledge, skills, and resources in EI endeavors. Additionally, scientific entities such as universities, consultants, and research centers stand out as particularly influential cooperation partners, surpassing their importance in other "brown" innovation contexts. The complexity inherent in addressing sustainability challenges may compel firms to place greater reliance on these partners, who offer specialized expertise and knowledge-intensive competencies essential for navigating sustainability issues effectively. Poor management practices or the lack of internalized knowledge within a company can further complicate innovation efforts, underscoring the importance of a skilled workforce and effective collaboration in driving EI initiatives forward.

The blockers discussed so far might seem unmutable and inevitable, but in recent years the research on barriers to innovation has underscored the complexity of innovation dynamics, uncovering an intriguing phenomenon that challenges conventional wisdom. Studies like *Complementarities between obstacles to innovation: evidence from France* by Galia and Legreos [47] have found a positive correlation between firm's level of innovation and the intensity of barriers they face, meaning that the more innovation a company produces, the higher are their reported barriers. According to the authors, innovative firms encounter and address a greater and greater number of challenges the more they push the boundaries of innovation. The way those barriers are perceived may serve as a testament to a firm's success in navigating and overcoming innovation obstacles. These findings have prompted Galia to distinguish between "revealed" barriers and "deterring" barriers. The former are those challenges that firms encounter as they actively pursue innovation initiatives, and through the process of overcoming them, firms gain insights into the inherent difficulties of innovation, contributing to their experiential learning and awareness of innovation hurdles. In contrast, deterring barriers are obstacles that actively impede firms from engaging in innovation activities, posing significant challenges to their innovation efforts.

4.5 Economical impact of EI in firms

Even if it isn't the main focus of this thesis, understanding the current discussion on the economic benefits or drawbacks of environmental innovation is useful for contextualizing the role this activity plays in firms' strategies. In *"Does it pay to go green? The environmental innovation effect on corporate financial performance"* [43] authors Farza and Ftiti test the effect of EI on German company's financial performances by proxying environmental innovation with a series of variables like patents obtained, presence of energy-efficient buildings and environmental management systems certifications to test its influence on return on assets, return on capital employed and market to book ratio. According to their results, the positive effect of environmental innovation is more pronounced for the ROIC compared with the ROA, given that the difference between the ROA and the ROIC is the opportunity cost captured only by the ROIC measure they conclude that environmental innovation specifically reduces opportunity cost. Firms can, therefore, aim for several targets as they respond to environmental stakeholders' requirements while innovating for economic growth. In addition, EI helps in improving asset allocation efficiency and a firm's reinvestment ability.

However, as is the case for environmental impact, EI is most likely to be moderated by a series of contingent factors affecting the environmental–financial performance relationship. Andries [7] supports the positive argument for EI in firms' financial competitiveness but highlights how business size and reason to engage in EI are strong moderating factors. In line with predictions based on resource theory, larger firms benefit more from environmental innovations when they introduce these innovations in response to regulation or industry codes of conduct. Conversely, and in line with predictions from stakeholder theory, smaller firms benefit from introducing environmental innovations in response to customer demand.

4.6 Environmental impact of EI in firms

Now that we've explored the primary antecedents and blockers of environmental innovation in firms, it's essential to delve into its effects on the environmental performances of corporations. While studies on this topic are fewer compared to those focusing on its economic implications, the following section will highlight the main findings and open discussions on the matter.

4.6.1 Bolton, Kacperczyk and Wiedemann

In their 2023 study *"The CO2 Question : Technical Progress and the Climate Crisis"* [14] Bolton, Kacperczyk and Wiedemann analyze the impact of green innovation activity worldwide and its effects in reducing carbon emissions through the lenses of the *Jevons Paradox*. In the Jevons paradox, firstly noted on coal consumption by the economist William Stanley Jevons in 1865, improvements in resource efficiency can lead to an unexpected increase in resource consumption rather than the anticipated decrease. This paradox arises when technological advancements enhance the efficiency of resource utilization, thereby lowering the cost per unit of resource used. As a result, the reduced cost stimulates greater demand for the resource, offsetting any gains made in efficiency and leading to an overall increase in resource consumption. The authors argue that the same paradox can be applied to environmental innovation; Green technological progress might not necessarily be synonymous with carbon emission reductions as technological improvements that reduce fossil fuel energy reliance also boost economic activity.

Their findings reveal that firms experienced in brown technologies (as measured by the stock of patents improving the efficiency of brown technologies they already own) are less likely to engage in green innovation, and vice versa. Moreover, brown companies, particularly those with higher emissions and older age, tend to avoid green research and development. This is especially true when their scope 3 emissions are high, meaning that their supply chain partners are reliant on fossil-fuel-dependent technologies, and it implies that brown companies appear to be locked into fossil-fuel-dependent technologies through their production networks. The study also finds that green innovation has not significantly impacted future carbon emissions reductions in the short (one year) or medium (three to five years) term. This is consistent with the Jevos Paradox, while brown efficiency innovation leads to lower future carbon intensity, increased sales offset these gains resulting in higher overall emissions. Additionally, green innovation contributes minimally to corporate carbon emission reductions, comprising only 1% of the total reductions observed. Thus, while green innovation may be a necessary component of sustainability efforts, its current impact falls short of expectations, suggesting that a green industrial revolution has yet to materialize.

4.6.2 Cohen, Gurun and Nguyen

Different conclusions are reached by Cohen, Gurun and Nguyen in *The ESG innovation disconnect : Evidence from green patenting* [30]. Their paper focuses on companies in oil, gas, and energy-producing sectors, where firns have on average lower Environmental Social and Governance scores, and often excluded from ESG funds' investment portfolios. Despite this, the authors find that firms in these sectors play a significant role in driving innovation within the United States' green patent landscape. Traditional energy firms exhibit an higher levels of both quantity and quality (measured by patent citations) in green patenting activities. Surprisingly, these firms not only produce more green innovations but also generate higher quality patents compared to other sectors. Moreover, traditional energy firms often emerge as pioneers in various green technology domains, contributing foundational innovations that influence subsequent developments in the field, and are notably prominent in critical technology branches like carbon capture. Interestingly, the majority of their green patents are developed internally, indicating a strong emphasis on in-house research and development. These patents are highly cited and serve as foundational assets for innovation beyond the energy sector, with their language and structure often emulated by innovators outside the traditional energy industry. Despite their significant contributions to green innovation, these firms often face capital restrictions due to mandates and campaigns aimed at addressing environmental challenges.

Their final point centers around the presence of real investments in green actions after patent creation. Their findings indicate a significant and positive relationship between green patent intensity (measured as a percentage of green patents over total patents held by a firm) and green energy production, among firms in the energy industry. Specifically, a substantial increase of approximately 65% in green wattage production is found for every standard deviation increase in green patent intensity by energy firms. In contrast, no such relationship is observed for firms in other sectors. Their results suggest that energy companies that actively engage in green patenting also demonstrate higher levels of alternative energy production and indicate a strategic alignment between green patenting activities and tangible efforts to produce alternative energy.

4.6.3 Lee and Min

"Green R&D for eco-innovation and its impact on carbon emissions and firm performance" by Lee and Min [73] investigates the influence of green research and development investment on eco-innovation, environmental performance, and financial outcomes, drawing upon the resource-based view and the natural resource-based view models. The study uses data from Japanese manufacturing firms spanning from 2001 to 2010, and examines green R&D investment as a proxy for eco-innovation and its impact on CO2 Emissions Intensity and financial performance (proxied by Tobin's Q value).

Results from the models employed (see Table 4) show that, when R&D takes its mean value, green R&D investment is associated with a marginal reduction of approximately 4.5% in CO2 emissions, with a slightly greater effect observed compared to conventional R&D investment. The study also highlights a diminishing marginal reduction effect of green research investment on carbon emissions as firms increase their R&D expenditure. This implies that the negative effects of Green R&D on carbon emissions are attenuated when firms increase their R&D for non-environmental innovation. Intuitively, an increase in output resulting from non-green R&D can hinder environmental performance. Moreover, the study demonstrates a positive association between green R&D investment and firm financial performance, again with an attenuation effect between Green and standard R&D. This suggests that firms that invest in green R&D accumulate valuable resources and capabilities that contribute to superior overall firm performance, that however cannot materialize without unique organizational resources and capabilities to guide a proactive environmental strategy. Overall, the findings support the notion that green R&D investment plays a crucial role in reducing environmental impact while enhancing financial outcomes at the firm level.

4.6.4 Carrion-Flores and Innes

Our last analyzed study, titled *"Environmental innovation and environmental performance"* [21] inspects a panel of 127 manufacturing industries over the period 1989–2004 and identifies a bi-directional causal link between EI and toxic air pollution, utilized in

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Green_R&D	-0.061**	-0.052**	-0.176***	-0.314***	-0.116**	-0.204***
	(0.016)	(0.032)	(0.000)	(0.000)	(0.010)	(0.000)
R&D	-0.004	-0.005	-0.018*	-0.041***	-0.023***	-0.034***
	(0.634)	(0.565)	(0.071)	(0.003)	(0.005)	(0.006)
Green_R&DXR&D			0.002***	0.003***	0.002***	0.003***
			(0.002)	(0.000)	(0.001)	(0.000)
Energy_Intensive					4.362***	3.850***
					(0.000)	(0.000)
Green_R&DXR&DXEnergy_Intensive					0.002***	0.002***
					(0.000)	(0.000)
Capital intensity						0.140***
						(0.000)
Firm size						0.443***
						(0.000)
Leverage						0.034***
						(0.000)
Year-industry effect	No	Yes	Yes	Yes	Yes	Yes
Const	1.905***	2.385***	2.023***	-6.768***	-3.006***	-9.541***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	936	936	936	936	936	936
R^2	0.001	0.003	0.009	0.098	0.157	0.207

Dependent variable is CO2 scaled by asset. Numbers in ( ) adjusted p-values. Capital intensity is proxied by Asset scaled by sales. Firm size is proxied by the natural logarithm of sales. Leverage is defined as Debt divided by (Debt plus Equity). Energy intensive is a binary variable. *, **, *** refers to significance at the 10, 5, and 1% level respectively

Table 4: Effects of Green R&D and R&D on carbon as found in Lee and Min [73]

the paper as a proxy for regulatory stringency, by employing a series of time and industry fixed effect models. The paper underscores supports the efficacy of a linear feedback model in capturing the dynamic interplay between environmental policy and innovation. EI is utilized by firms as a mechanism to reduce the compliance costs brought up by stricter pollution standards imposed by government regulations or advocated by consumer or NGO pressure. At the same time the prospect of tighter pollution regulations amplifies the potential cost-saving benefits of environmental R&D, stimulating further innovation. However while the findings indicate a positive impact of tightened pollution standards on environmental research, the overall benefits appear modest. Moreover their results do not address the efficiency of environmental policies in promoting research, suggesting a potential gap between regulatory standards and their impact on research incentives. In the paper no conclusive evidence is found to suggest that regulators set tighter standards explicitly to spur innovation, as is proposed in the Porter's hypothesis.

4.7 Moderating factors in environmental innovation and firms' performance

One of the main recurring points found in this section of this thesis is the uncertainty still present in environmental innovation literature. EI is a relatively young field of study with a scarce, yet rapidly growing, amount of information and data. This results in a majority of EI papers analyzing only single territories or industries, skewing their conclusion. A number of meta-analysis on EI have emerged in recent years to catalog differences among papers and possible moderating factors influencing their results.

Liao and Liu [75] analyze 33 different EI empirical studies, finding four main moderating effects that shape the relationship between environmental innovation and firms' performance : the economic development level of a country, cultural background, industry diversity, and data types.

- *Economic Development of a Country.* Scholars have been proposing for over a decade that the implementation of environmental innovation in developing would lead to an increase in opportunity cost. While developed countries are in the post-industrialization age, in which the service industry is the major thriving force and creates the resources necessary to protect the environment and society, developing countries are still in the industrialization age, in which manufacturing is the major industry. Liao and Liu find a positive correlation between environmental innovation and firms' financial performance in both developed and developing countries but with a correlation coefficient much higher for post-industrial economies. The relation was however found to be reversed for environmental performances, with industrial economies having an higher positive effect.

- *Cultural Background.* Liao and Liu hypothesize a difference in the impact of EI in Eastern and Western countries, adducing an higher demand for green products in the east due to its more pluralistic and groupist cultural background, compared to the more individualistic nature of western culture. Their results evidence a stronger positive effect of EI in eastern countries when it comes to financial performance, but see no differences on environmental accomplishments.

- *Industry diversity.* Many empirical studies on the outcome of environmental innovation have been carried out in a single industry, but the effect of EI might change across sectors. For instance manufacturing firms might be unproportionally effected by an increase in the efficiency of production processes, while services might benefit from the sustainable attractiveness created by green products. In their analysis no moderating impact was found neither for financial nor environmental performances.

- *Data types.* The authors divide data types found in EI studies between Subjective, like the ones obtained through questionnaires, and Objective, like the ones taken from financial statements or green reports. Like for industry diversity no significant differences emerge among the two studies.

Part III

Materials and methods

5 Data source and database creation

The following section contains a breakdown of how the final database used in the various analyses was created, the main data sources, and a summary of the variable employed.

5.1 Patent Data

Data about patents was gathered from Orbis IP, a global database that links patent data to the companies and groups that hold them for intellectual property research and strategy. Orbis IP provides essential information on patents such as publication details, ownership, industry classifications, patent classifications (including IPC and CPC), opposition records, and patent valuation metrics. The employed dataset comprises 264,702 rows, each one representing a distinct patent in wide format, allowing for multiple entries for IPC, CPC, and owners, resulting in a total of 604 columns. To facilitate future analysis on the dataset, a Python script was employed to reformat it by consolidating IPC, CPC, and owner data into comma-separated values rather than separate columns, thereby reducing the total number of columns from 604 to 26. Subsequently, the IPC codes of each patent were compared against the "WIPO IPC Green Inventory" classification as referenced in Section 2.1, utilizing the IPC Green codes consistent with those used by Favot and Vesnic [44]. A subset of patents containing at least one IPC green code was then extracted from the original database, resulting in 148,559 patents originating from various regions across the globe, encompassing technologies spanning all major subclasses of the IPC Green Inventory classification. Most patents also contain the BvD ID of the company they were developed by, and an ID for the current owner of the patent on the date the database was created (mid 2023).

5.2 Patent Transactions

Data regarding patent transactions is also sourced from the Orbis IP database, encompassing all distinct transactions involving the green patents from the preceding section. This dataset comprises 60,900 distinct rows, each one containing pertinent information such as the patent ID (publication number), transaction date, transaction type, vendor BvD code, acquirer BvD code, and internal database ID. Notably, there are 23,711 unique patent IDs, indicating an average of 2.57 transactions per patent. The ”transaction type” variable encompasses nine unique values, and describes the method of obtainment : ’Intra-company’ (31.86% of occurrences) denotes transfers within entities under the same global ultimate owner for tax/legal purposes; ’Corporate acquisition’ (28.58%) refers to acquisitions between practicing entities excluding universities, banks, investment funds, law groups, and NPEs; ’M&A’ (16.75%) signifies patent transfers within M&A deals; ’Assignment as collateral’ (16.44%) denotes transfers involving entities such as banks or funding agencies; ’Release of collateral’ (3.02%) involves transactions with entities like banks or funding agencies; ’Government’ (1.77%) pertains to assets acquired or reassigned to government agencies; ’Research and innovation partnership’ (1.35%) involves transfers between innovation institutes or universities and other entities; ’Others’ (0.05%) encompasses miscellaneous transactions; and ’Non-practicing entities’ (0.02%) denotes transactions involving NPEs as acquirers.

Each transaction was then linked with the corresponding entry in the green patent database, selecting only the most recent transaction in cases of multiple occurrences. A new column titled ’Acquisition method’ was introduced for each patent, indicating the method through which it was acquired, be it one of the aforementioned transaction types or direct development by the firm if no transactions were identified. Given the purpose of this thesis, the only relevant transaction types are ’M&A’, ’Corporate Acquisition’ which for clarity is going to be renamed ’Patent Purchase’ from now on, and the newly-created ’Patent Development’.

Since each BvD code comprises a two-letter ISO 3166-2 code representing the firm’s nation and a numeric identifier for the firm, a visualization (refer to Fig.6) was created to map the buyer and seller nations, tallying the occurrences of each tuple and connecting them using the GeoPandas library in Python, with line widths adjusted based on occurrence frequency.

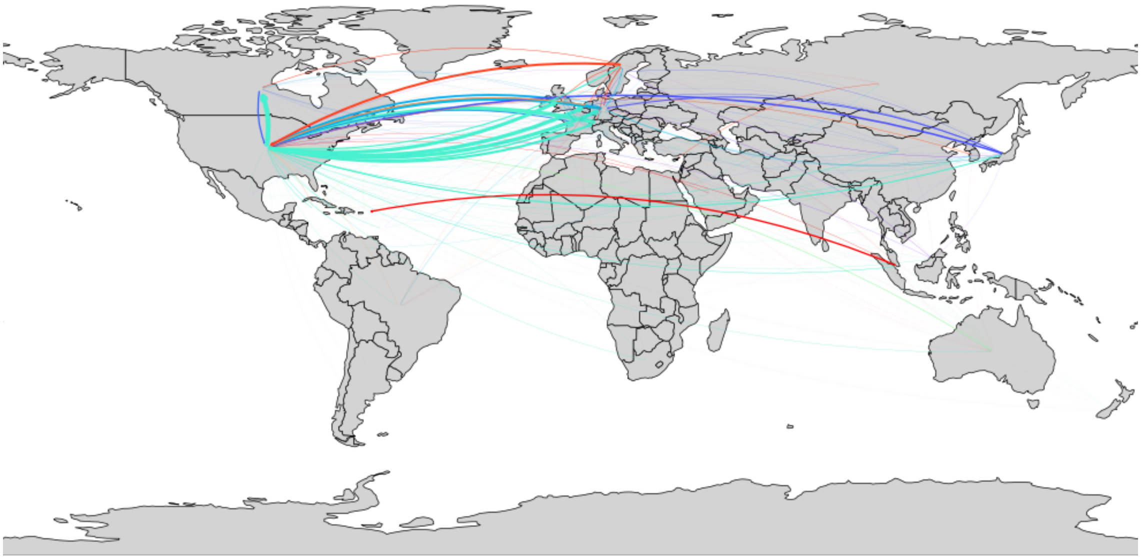

Figure 6: Visualization of patent transactions excluding intra-national transactions

5.3 Corporate Data

A majority of corporate data is sourced from Eikon, a suite of software products designed for financial professionals to monitor and analyze financial information, introduced by Thomson Reuters in 2010. Eikon offers real-time access to market data, news, analytics and trading tools across various asset classes, but most importantly for this analysis, it contains the largest ESG content collection in the world with 630 ESG measures for over 15000 companies around the world. For this analysis five ESG metrics have been chosen to characterize the environmental impact of firms : CO2 Equivalent Scope 1,2 and 3 emissions, Total Energy consumption and Total Waste production. A full breakdown of each variable can be found in table 17 of Appendix. To capture relevant information on firms, the following financial attributes were extracted as well : total assets, number of employees, total revenues, expenditures in research and development and total Property, Plant, and Equipment. Again a full breakdown can be found in table 16 of Appendix. These indicators were collected using the Screener tool in Eikon, starting from the list of corporations that have acquired or developed a patent from the Patents Transactions database, and selecting the previous 20 years starting from the last available data for each firm. Unfortunately the patents databases reference firms by their BvD ID which is specific to the Bureau van Dijk suite, but Eikon works with different IDs. Therefore a lookup table had to be utilized to translate BvD IDs to ISINs. Not all the BvDs had an equivalent ISIN, resulting in a loss of data.

Some of the analyses in the latter parts of this document account for the economical sector in which firms operate in as a control variable. To augment the database with this info the BvD ids of selected companies were passed through Orbis, and the NACE rev 2 [20] code was extracted. NACE stands for Statistical Classification of Economic Activities in the European Community, was established by Regulation (EC) No 1893/2006 and it's the European implementation of the UN classification ISIC. NACE comprises 4 hierarchical levels : Sections, Division, Groups and Classes, each more granular than the other.

Sector	NACE Rev 2 Name
Sector C	Manufacturing
Sector D	Electricity, Gas, Steam and Air Conditioning Supply
Sector E	Water Supply, Sewerage, Waste Management and Remediation Activities
Sector F	Construction
Sector G	Wholesale and Retail Trade
Sector H	Transporting and Storage
Sector J	Information and Communication
Sector K	Financial and Insurance Activities
Sector M	Professional, Scientific and Technical Activities
Sector N	Administrative and Support Service Activities

Table 5: Nace Rev 2 section full name

5.4 Database Creation

Once all the data was gathered, the Python's library Pandas was employed to create a dataframe that could be used for the analysis. We began by grouping the Patent Transactions database by ISIN, year, and acquisition type. This resulted in each row containing, for each firm and year, a new column indicating the count of green patents obtained through M&A, Purchase, or Development. Three additional columns were generated by converting these numbers into boolean variables, assigning the value 1 if at least one patent was obtained using the specific method, and 0 otherwise. This database was then full-joined with the Corporate Data database, filling rows with zeros if no transaction was found in that year for that firm. Table 6 describes the final variables, some of which were obtained either by dividing the original values by total assets, resulting in an Intensity measure, or by employing a natural logarithm.

Name	Description
Revenue_ln	Natural logarithm of revenues from all of a company's operating activities.
ROA	Company's net income prior to financing costs over total assets.
Tangibility	Company's Property Plant and Equipment value over total assets.
RnD_Intensity	Total Research and Development expenses over total assets.
EPS_index	Country specific and internetionally comparable index that measures the stringency of environmental policies.
CO2Scope1_ln	Natural logarithm of scope 1 CO2 equivalent emissions in Tonnes from sources that are owned or controlled by the company.
CO2Scope2_ln	Natural logarithm of scope 2 CO2 equivalent emissions in Tonnes from consumption of purchased electricity, heat or steam.
CO2Scope3_ln	Natural logarithm of scope 3 CO2 equivalent emissions in Tonnes from assets not controlled or owned by the company, but that are indirectly affected by its value chain.
EnergyTotal_ln	Natural logarithm of total direct and indirect energy consumed by the company.
WasteTotal_ln	Natural logarithm of total waste produced by the company.
CO2Scope1_Intensity	CO2 Scope 1 equivalent emissions over total assets.
CO2Scope2_Intensity	CO2 Scope 2 equivalent emissions over total assets.
CO2Scope3_Intensity	CO2 Scope 3 equivalent emissions over total assets.
EnergyTotal_Intensity	Total energy consumed over total assets.
WasteTotal_Intensity	Total waste produced over total assets.
Acquired	Boolean value indicating the obtainment by the firm of at least one green patent by purchase or as part of an M&A deal.
Developed	Boolean value indicating that at least one green patent was granted to the company by a patent office.

Table 6: Brief description of the variables used in the models

	count	mean	std	min	25%	50%	75%	max
ROA	19682	0.05	0.15	-8.21	0.02	0.05	0.08	5.32
Revenue_ln	39679	20.73	2.43	6.79	19.23	20.87	22.41	27.13
Tangibility	34749	1.76	7.79	-0.05	0.48	1.02	2.04	1360.20
Assets_ln	39369	20.25	2.23	2.06	18.88	20.34	21.76	27.06
RnD_Intensity	23069	92.02	668.33	0.00	15.67	36.92	75.88	48800
CO2Scope1_ln	7719	12.91	2.81	0.69	11.03	12.79	14.83	19.75
CO2Scope2_ln	7346	12.59	2.04	0.18	11.46	12.77	13.91	19.82
CO2Scope3_ln	4867	13.74	3.45	0.06	11.01	14.07	16.38	21.22
EnergyTotal_ln	8884	16.12	2.24	3.18	14.72	16.15	17.52	26.75
WasteTotal_ln	8084	11.54	2.28	0.44	10.13	11.46	12.86	20.79
CO2Scope1_Intensity	7277	1.02	3.49	0.00	0.01	0.05	0.64	74.63
CO2Scope2_Intensity	6925	0.17	0.50	0.00	0.02	0.05	0.17	21.23
CO2Scope3_Intensity	4527	2.41	7.60	0.00	0.01	0.26	1.75	169.94
EnergyTotal_Intensity	8456	32.47	826.89	0.00	0.49	1.58	8.64	50879.38
WasteTotal_Intensity	7805	0.75	7.04	0.00	0.01	0.02	0.05	155.03

Table 7: Summary of the main attributes of the variables utilized in the final dataset

6 Data and Methodology

To analyze the effect of patent acquisitions on corporate environmental performances three different models and tests have been utilized. First the panel dataset described in the previous sections has been used to run a Fixed Effect regression model linking different methods of patent acquisitions with a change in a select number of environmental indices. Then a bivariate probit is employed to investigate the main factors influencing the decision to acquire or develop a patent, and finally the Dumitrescu-Hurlin test checks for Granger causality between environmental variables and the decision to acquire a patent and vice versa. After every model is discussed in depth, a brief description of the R or Python function used is given, and a sample of relevant environmental literature is discussed to show how similar models have been used by scholars.

6.1 Panel Regression

The main advantage of panel data over cross-sectional or time-series data is its ability to control for unobserved heterogeneity (a term that describes the existence of unobserved differences between samples that are associated with the observed variables of interest) by accounting for both time-invariant and time-varying individual-specific effects, thereby producing more reliable and robust estimates of the relationships of interest that couldn't be achieved whiteout longitudinal measures. In the literature, this is achieved predominantly by employing one of two models : fixed effects and random effects models.

Several factors come into play When choosing between the two, as explained in Paul Allison's book "Fixed Effects Regression Models for Categorical Data" [5]. Firstly, the presence and nature of omitted variables are important, when no omitted variables are present, or if they are uncorrelated with the explanatory variables, a random effects model is often preferred because it yields unbiased estimates with smaller standard errors. However, if omitted variables are correlated with the variables in the model, fixed effects models can be useful for controlling for bias, the idea e is that whatever effects the omitted variables have on the subject at one time, they will also have the same effect at a later time (hence their effects will be constant or "fixed."). Secondly, the variability within subjects is a crucial consideration. Fixed effects models rely on within-subject variability, which means they may not work well if subjects show little change over time. Conversely, random effects models tend to have smaller standard errors, but they may introduce bias if there is insufficient within-subject variability. Lastly, the choice depends on whether we want to estimate the effects of time-invariant variables or merely control for them. Fixed effects models do not estimate the effects of such variables; instead, they control for them. On the other hand, random effects models estimate these effects, but they may suffer from bias due to uncontrolled omitted variables. Understanding these factors is essential for selecting the most appropriate model and ensuring accurate estimation in panel data analysis.

6.1.1 The Hausman test

It's clear that the decision between fixed and random effects models need to take into account various theoretical and practical considerations, and it's not an easy task. As a consequence researchers often employ a test specifically developed to make this decision easier, the Hausman specification test, introduced by J. Hausman in 1978 [57]. This test is intended to identify violations of the random effects modeling assumption, which asserts that the explanatory variables are uncorrelated with the unit effects (endogeneity). If there is no correlation between the independent variables and the unit effects, then estimates of β in the fixed effects model ($\hat{\beta_{FE}}$) should closely resemble estimates of β in the random effects model ($\hat{\beta_{RE}}$). The Hausman test statistic, denoted as H, quantifies the disparity between the two estimates:

$$H = (\hat{\beta_{RE}} - \hat{\beta_{FE}})'[Var(\hat{\beta_{FE}}) - Var(\hat{\beta_{RE}})]^{-1}(\hat{\beta_{RE}} - \hat{\beta_{FE}}) \tag{1}$$

Under the null hypothesis of orthogonality, H follows a chi-square distribution with degrees of freedom equal to the number of regressors in the model. A result where $p < 0.05$ is typically interpreted as evidence that, at conventional levels of significance, the two models exhibit sufficient divergence to reject the null hypothesis. Consequently, the random effects model is discarded in favor of the fixed effects model.

But as warned by Clark [28] if the Hausman test fails to indicate a significant difference ($p > 0.05$), it doesn't necessarily mean that the random effects estimator is completely free from bias and should therefore be favored over the fixed effects estimator. In most practical scenarios, there is typically some degree of correlation between the covariates and unit effects, even if it's not precisely zero. Thus, if the Hausman test doesn't reject the null hypothesis, it's more likely due to the test lacking sufficient statistical power to reliably detect deviations from the null, rather than indicating that the random effects estimator is unbiased. Even when using the random effects model, there may still be some bias (albeit potentially small) in the estimates of β, even if the Hausman test fails to reject the null hypothesis. However, in many cases, a biased estimator (such as the random effects model) can be preferable to an unbiased estimator (such as the fixed effects model) if the former offers sufficient reduction in variance over the latter, as previously discussed. It's important to note that the Hausman test doesn't help in evaluating this tradeoff between bias and variance reduction.

6.1.2 Fixed Effects

Let's now dive deeper on Fixed Effects models. Fixed effects panel models are a statistical approach used to analyze longitudinal data, where observations are collected over time for multiple entities (cross-sectional units). These models can incorporate both time fixed effects and entity fixed effects in addition to individual-specific characteristics. Time fixed effects capture time-specific effects that are common to all entities but vary across time periods, in this case they try to reflect environmental and corporate trends. Statistically this effect can be obtained either by including a set of dummy variables for each group in the dataset or by subtracting the time mean from each variable in the model and then estimating the resulting transformed model by Ordinary Least Squares, this procedure is known as "demeaning". Similarly, entity fixed effects capture entity-specific characteristics that do not change over time but may vary across entities, such as firm-specific management practices or individual-specific abilities. Again demenaing or dummy variables are applied for each entity in the regression model. By including both types of fixed effects in the model, the effects of time-varying independent variables on the outcome variable can be isolated while controlling for both time-specific and entity-specific factors. This allows for more reliable estimates of causal relationships in panel data by accounting for time-specific effects, entity-specific effects, and individual-specific characteristics simultaneously. The python library used to model the fixed effect regression in this thesis, linearmodels by Kevin Sheppard, utilizes demeaning in its panelOLS function, where it's possible to specify both entity and time fixed effects even with unbalanced data.

$$y_{i,t} - \bar{y}_i - \bar{y}_t = \beta(X_{i,t} - \bar{X}_i - \bar{X}_t) - (\bar{v} + \bar{u}) + (\epsilon_{i,t} - \bar{\epsilon}_i - \bar{\epsilon}_t) \tag{2}$$

Where :

- $y_{i,t}$ is is the dependent variable observed for individual i at time t.
- $\bar{y}_i = u_i + \bar{v} + \beta\bar{X}_i + \bar{e}_i$ is the first demean crossectionally.
- $\bar{y}_t = v_i + \bar{u} + \beta + \bar{X}_t\bar{e}_i$ is the second demean for each t.
- β is the matrix of parameters.
- $X_{i,t}$ is the time-entity regressor vector.
- $\bar{X}_i$ and $\bar{X}_t$ are obtained from the demean.
- $\bar{v}$ is the mean unobserved entity-invariant fixed effect.
- $\bar{u}$ is the mean unobserved time-invariant fixed effect.

- $\epsilon_{i,t}$, $\bar{\epsilon_i}$, $\bar{\epsilon_t}$ are the error terms.

A variety of studies utilize FE models to study environmental innovation at different levels. For instance the study covered in section 4.6.2 by Cohen, Gurun and Nguyen "The esg-innovation disconnect: evidence from green patenting" [30] uses it to study ESG scores and how they are associated with green patent production in firms of the energy sector. Similarly Khali and Khali [71] utilize a novel dataset of firm-specific ESG data from ten Asian countries to build an empirical model that explores the impact of both traditional and environmental innovation on companies' financial and environmental performance by running a FE model to estimate the impact of traditional and green R&D on CO2 emissions. Their analysis reveals that both traditional and environmental innovation contribute positively to enhanced financial performance, however traditional innovation alone has a comparatively weaker impact on environmental outcomes when compared to environmental innovation.

6.2 Bivariate Probit Regression

In statistics and econometrics the bivariate probit regression is a powerful tool to investigate two interdependent binary outcomes. A simple probit model is specifically designed to study response variables that have only two possible outcomes and utilizes maximum likelihood to estimate the parameters β. The bivariate approach extends the reach of the univariate probit model to analyze two interrelated binary dependent variables simultaneously. It proves particularly valuable when the choices or events under investigation are not independent, potentially influencing each other. The core objective of bivariate probit regression is estimating the joint probability of both outcomes occurring, taking into account their potential correlation. As it is the case for the normal probit model, the estimation process leverages explanatory variables to understand the factors influencing each outcome and their interplay. The model operates under the assumption that the underlying error terms of the two binary equations are not independent, thereby capturing the potential interdependence between the outcomes. This interdependence can arise from various sources, such as shared unobserved factors or inherent relationships within the system under study.

$$Y_1 = \begin{cases} 1 \text{ if } Y_1^* > 0 \\ 0 \text{ Otherwise} \end{cases} \quad (3) \qquad Y_2 = \begin{cases} 1 \text{ if } Y_2^* > 0 \\ 0 \text{ Otherwise} \end{cases} \quad (4)$$

$$\begin{cases} Y_1^* = \alpha_1 + \beta_1 X + \epsilon_1 \\ Y_2^* = \alpha_2 + \beta_2 X + \epsilon_2 \end{cases} \quad (5)$$

Given the absence of valid Python libraries to carry out this function properly the main database has been transferred to R where the package GJRM : Generalised Joint regression Model exists. This package provides a function for fitting various generalized joint regression models with several types of covariate effects and distributions. Many modelling options are supported and all parameters of the joint distribution can be specified as flexible functions of covariates. The primary fitting function is gjrm(): This function fits bivariate regression models with binary responses. It proves particularly beneficial for fitting bivariate binary models in instances of non-random sample selection, associated responses, endogeneity, or partial observability. Additionally, it accommodates bivariate models with binary, discrete, continuous, survival margins in the presence of associated responses or endogeneity, as well as bivariate sample selection models with continuous and discrete responses. Furthermore, it handles trivariate binary models, both with and without double sample selection.

Examples of bivariate probit models in environmental and innovation literature can be found in *The Effect of Knowledge Management on Environmental Innovation* by Stanovcic [**Stanovic2015**] that tests the relationship between knowledge management practices and environmental innovation by regressing the event of KM and the event of environmental innovation with multiple control variables. They find that KM could be considered as a significant tool to enhance environmental innovation performance and noticing that KM culture is more important for environmental innovation than KM policy. Or the usage of bivariate probit by Nguyen [82], indicating that environmental innovation activities are not associated with EMS implementation nor any other single policy instrument, reflect the perceptions of the survey respondents and, hence, should be interpreted as correlations rather than causal relationships. According to these perceptions, innovation behavior seems to be mainly correlated with the stringency of environmental policy.

6.3 Dumitrescu–Hurlin (non)Granger causality test

In a seminal article, nobel laureate Clive W.J. Granger [51] introduced a method for examining causal relationships within time series data. In the presence of two stationary series, x_t and y_t. Granger's approach allows to test whether changes in x cause changes in y. Put simply, if past values of x can reliably predict the current value of y, even after accounting for past values of y in the model, then it suggests that x is exerting a causal influence on y.

$$y_t = \alpha + \sum_{k=1}^{K} \gamma_k * y_{t-k} + \sum_{k=1}^{K} \beta_k * x_{t-k} + \epsilon_t \quad \text{with t = 1,..,T} \tag{6}$$

The standard Granger causality test involves a simple statistical examination : By comparing models with and without the inclusion of past values of x as predictors of y, it can be determined if the addition of x significantly improves the model's ability to predict y. If the model with x as a predictor significantly outperforms the model without it, it suggests that x Granger-causes y. Conversely, if including past values of y as predictors of x enhance the model's predictive power, it indicates that y Granger-causes x. Thanks to this process Granger causality testing provides a means to infer causal relationships between variables based on their historical patterns and interactions within a time series context. Using (5), one might easily investigate this causality based on an F test with the following null hypothesis:

$$H_0 : \beta_1 = ... = \beta_K = 0 \tag{7}$$

If H_0 is rejected, one can conclude that causality from x to y exists. The x and y variables can be interchanged to test for causality in the other direction, and it is possible to observe bidirectional causality (also called feedback). Granger causality, despite its name, doesn't always imply true causality, instead, it aligns with Hume's definition of causality, which associates cause-effect relationships with consistent conjunctions. As put by Marziarz in "A review of the Granger-causality fallacy" [81] if both

X and Y are influenced by a common third process with different time lags, the alternative hypothesis of Granger causality might not be rejected. However, manipulating one variable wouldn't necessarily affect the other. Potential sources of misleading test results include infrequent or overly frequent sampling, nonlinear causal relationships, nonstationarity and nonlinearity within time series data, and the existence of rational expectations. Granger causality tests are specifically designed for pairs of variables and can yield misleading outcomes when the true relationship involves three or more variables. Nevertheless, proponents argue that within a probabilistic view of causation, where A probabilistically causes B if A's occurrence increases the probability of B, Granger causality can be viewed as genuine causality [78]. For analyses involving multiple variables, a similar test can be conducted using vector autoregression, which extends the analysis beyond pairwise relationships.

Now that the properties of the Granger test are understood, it's clear from formula (5) that it is not suitable with panel data, therefore this thesis employs an extension to the test developed by Dumitrscu and Hurling [39] for unbalanced panels in order to capture all the information present in the data. This extension applies the same intuition as Granger but adapts the formula. Let's denote by x and y, two stationary variables observed for N individuals on T periods. For each individual i = 1, .., N, at time t = 1, .., T,the following linear model is considered:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} * y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} * x_{i,t-k} + \epsilon_{i,t} \tag{8}$$

This straightforward model, featuring two variables, lays the groundwork for exploring Granger causality within panel data contexts. While traditional causality tests in time series settings involve assessing linear restrictions on the vectors β_i, panel data analysis demands a more nuanced approach, particularly regarding individual heterogeneity. Individual heterogeneity manifests first through the inclusion of individual effects denoted by α_i, accounting for variability across individuals within the panel dataset. However, a more critical consideration lies in the heterogeneity of the parameters β_i. This form of heterogeneity directly challenges the concept of a representative agent, for example the effect of one variable on another may differ substantially between different groups or individuals, and thus influences the conclusions drawn regarding causal relationships. Understanding the nuances of panel data analysis is imperative for accurate inference about Granger causality. Given these observations the procedure to determine the existence of causality is to test for significant effects of past values of x on the present value of y like in the standard Granger test. The null hypothesis is therefore defined as:

$$H_0 : \beta_{i,1} = ... = \beta_{i,K} = 0 \quad \forall i = 1, ..., N \tag{9}$$

which corresponds to the absence of causality for all individuals in the panel. The Dumitrescu-Hurlin test assumes there can be causality for some individuals but not necessarily for all. Thus, the alternative hypothesis is :

$$\begin{cases} H_1 : \beta_{i,1} = ... = \beta_{i,K} = 0 \quad \forall i = 1, ..., N \\ \beta_{i,1} \neq 0 \text{ or } ... \text{ or } \beta_{i,K} \neq 0 \quad \forall i = N_1 + 1, ..., N \end{cases} \tag{10}$$

Similarly to the Bivariate case, the analysis was conducted in R due to an absence of suitable Python packages, to be more precise the PLM library created by Croissant, Millo and Tappe was chosen due to the presence of the pgrangertes() function, which utilizes Dumitrescu-Hurlin unbalanced test.

In "International trade and environmental performance in top ten-emitters countries: The role of eco-innovation and renewable energy consumption" [3], researchers Ali and Dogan investigate the influence of environmental innovation, trade dynamics, and renewable energy consumption on the relationship between trade activities and CO2 emissions in the top 10 carbon-emitting countries. The findings reveal a bidirectional Granger causal relationship between changes in GDP, exports, imports, renewable energy consumption, and environmental innovation with consumption-based carbon emissions. Specifically, variations in these economic and environmental factors Granger cause changes in TCO2 emissions, and conversely, changes in TCO2 emissions Granger cause shifts in EXP, REC, and EI. This implies that policies targeting economic growth, trade dynamics, renewable energy adoption, and environmental innovation can significantly impact consumption-based CO_2 emissions. Moreover, changes in TCO2 emissions also exert a causal influence on trade activities, renewable energy consumption, and environmental innovation. These findings carry substantial policy implications, suggesting that interventions aimed at addressing carbon emissions should consider the interconnectedness of economic activities, environmental practices, and trade dynamics within a country's context. Meanwhile Dritsaki [38] tests the Granger causation between various pairs of innovation, macroeconomic and environmental factors in the EU during the period 1990–2020 showing the presence of a unidirectional causal relationship between per capita CO_2 emissions and per capita energy consumption towards innovation.

Part IV

Analysis

7 Fixed effects regression on panel data

After having assembled the panel dataset like described in section 5 various analyses have been conducted utilizing the models explained in section 6, albeit with technical changes and adjustments that are going to be explained when relevant. The analysis begins with an investigation on how the acquisition of green patents impacts different environmental variables. Due to the panel nature of the dataset the choice of regression model falls between two valid alternatives : Fixed or Random effects (see section 6.1 for details). Intuitively the better alternative seems to be a Fixed Regression, as the nature of the omitted variables is likely to be correlated with the variables in the model and the main effects to estimate are the ones of variables that change through time, like the acquisition of a patent in a given year by a given firm. To better guide the choice an Hausman test (described in section 6.1.1 was performed, the results strongly rejects the null hypothesis that no endogeneity is present in the model, confirming the choice of a fixed effects model over a random one.

chi-Squared: 143.5 degrees of freedom: 15 p-Value: 4.67e-23

Table 8 contains the results of six experiments having the scope 1 equivalent CO2 emissions as dependent variable (chosen due to the abundance of information related to this variable in the dataset) and the two boolean explanatory variables *Developed* signaling if the firm has developed a green patent and *Acquired* signaling if the firm has obtained a green patent either by direct purchase or in a M&A. The explanatory variables have been lagged by one year in models (1)(2)(3)(4), by up to three years in model (5) and up to five years in model (6). Moreover, a series of control variables are introduced to limit the influence of confounding and other extraneous variables, these include the natural log of Revenues (*Revenue_ln*) to control for the size of firms, their ROA (*ROA*) used as a profitability measure, the ratio of PPE over Total Assets (*Tangibility*) as a tangibility index, and the ratio of R&D over Assets to account for a firm innovative activity (RnD_N). Model (1)(2) contain only entity effects and (3)(4)(5)(6) contain both entity and time fixed effects.

Overall, the relatively low R^2 values across the models suggest that the current set of independent variables may not fully capture all factors influencing emissions and energy usage. This implies the presence of unaccounted-for variables or complexities that warrant further exploration. However, the low p-values of the F-tests indicate that the models are statistically significant, providing confidence in the overall validity of the findings at conventional levels of significance.

Once the independent variables have been chosen Table 9 compares their impact on five different environmental variables : Scope 1 CO2 equivalent emissions, Scope 2 CO2 equivalent emissions, Scope 3 CO2 equivalent emissions, Total Energy Consumption and Total Waste Production. An in-depth explanation of each environmental variable can be found in Tab17 in the appendix.

Starting with the analysis of the control variables the size of a company exhibits a consistently significant and positive correlation with all five environmental indicators studied, confirming the intuitive conclusion that larger companies tend to have a greater impact across various environmental metrics. The negative coefficients observed for ROA indicate that companies with more efficient use of their assets generally exhibit lower emissions, waste production, and energy consumption. However, the lack of significance for scope 3 emissions might imply that even resource-efficient companies need to rely on brown and environmentally inefficient supply chains. Interestingly, the tangibility index doesn't appear to influence CO2 equivalent emissions, but shows an impact on waste production and energy consumption, while R&D intensity is associated with reductions in scope 2 emissions and energy consumption.

Moving to the effects of patent obtainment, only a weak correlation is found between the external acquisition of environmentally sound technologies and a reduction of scope one emissions with a three and four years lag. Acquisition also seems to increase scope 3 emissions with a five-year lag and diminish scope 2 with two years. Development is mostly significant with shorter lags of one or two years and its positive coefficients surprisingly suggest an increase in emissions, waste and energy usage rather than a

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Variable	CO2Scope1_ln	CO2Scope1_ln	CO2Scope1_ln	CO2Scope1_ln	CO2Scope1_ln	CO2Scope1_ln
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS	PanelOLS	PanelOLS
No.Observations	7355	5752	5177	3304	3304	3304
Cov.Est.	Robust	Robust	Robust	Robust	Robust	Robust
R-squared	0.0624	0.0793	0.1171	0.1180	0.1186	0.1192
R-Squared(Within)	0.0624	0.0793	0.1012	0.0941	0.0946	0.0952
R-Squared(Between)	0.1932	0.2099	0.2774	0.2990	0.2998	0.2991
R-Squared(Overall)	0.1920	0.1997	0.2594	0.2928	0.2933	0.2925
F-statistic	143.79	107.42	118.19	62.090	37.415	26.826
P-value(F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
const	2.5347***	1.1469	-1.7727	-2.2198	-2.2362	-2.2527
	(2.6293)	(1.1046)	(-1.6028)	(-1.6215)	(-1.6317)	(-1.6379)
Revenue_ln	0.4540***	0.5180***	0.6419***	0.6545***	0.6551***	0.6560***
	(10.910)	(11.591)	(13.520)	(11.110)	(11.109)	(11.088)
ROA		-0.4776**	-0.7267***	-0.9306***	-0.9313***	-0.9364***
		(-2.1722)	(-3.1441)	(-3.5158)	(-3.5193)	(-3.5421)
Tangibility			0.0117**	0.0106	0.0104	0.0103
			(2.2903)	(1.1580)	(1.1420)	(1.1293)
RnD_Intensity				-0.0001	-0.0001	-0.0001
				(-0.5560)	(-0.5658)	(-0.5280)
Developed_t-1	0.0028	-0.0083	0.0009	0.0118	0.0124	0.0139
	(0.1308)	(-0.3958)	(0.0410)	(0.4115)	(0.4297)	(0.4784)
Acquired_t-1	0.0615	0.0279	0.0252	0.0712	0.0712	0.0703
	(1.6058)	(0.6870)	(0.5986)	(1.2983)	(1.2799)	(1.2606)
Developed_t-2					0.0230	0.0243
					(0.7566)	(0.7947)
Acquired_t-2					-0.0271	-0.0280
					(-0.6673)	(-0.6940)
Developed_t-3					0.0012	0.0027
					(0.0367)	(0.0818)
Acquired_t-3					-0.0605*	-0.0645*
					(-1.6682)	(-1.7748)
Developed_t-4						-0.0071
						(-0.2336)
Acquired_t-4						-0.0647*
						(-1.7750)
Developed_t-5						-0.0038
						(-0.1350)
Acquired_t-5						-0.0410
						(-0.8916)
Effects	Entity	Entity	Entity Time	Entity Time	Entity Time	Entity Time

Table 8: Comparison of multiple Fixed Effects models, complete dataset utilized, Scope 1 CO2 equivalent emissions chosen as dependent variable.

decrease. These results are fairly weak and are more aligned with the results drawn by Bolton, Kacperczyk and Wiedemann [14] that despite a steady rise in the share of green R&D, green innovation does not predict future reductions in carbon emissions whether in the short or medium term.

The previous models utilized the complete dataset of IPC Green patents transactions to investigate the relation between their obtainment and environmental variables. The following section performs the same fixed effects regression three more times with different subsets of the original database, taking into account only transactions of patents related to specific subgroups of green technologies as defined by the IPC Green categorization : "Pollution Control" (Tab. 10), "Carbon Capture and Storage" (Tab. 11) and "Alternative Energy" (Tab. 12). A breakdown of the technologies contained in each group can be found in table 18 in the appendix.

Pollution Control technologies include IPC categories like "Treatment of waste gases other than CO2", "Control of water pollution" or "Treatment of waste". One would expect this category of patents to heavily impact CO2 scope 1,2 and 3 equivalent emissions, but this doesn't seem to be the case for either development or acquisition. In contrast, Carbon Capture and Storage patents exhibit a significant reduction in scope 1 emissions after three and four years of their acquisition but fail to impact scope 2 and 3, their development is however correlated with a decrease in total waste production with a one and four years lag. Finally, the obtainment of alternative energy patents (that include categories of technologies like bio-fuels, solar, wind and geothermal energy) shows the most impact on its related environmental indicator, total energy usage, as both development and acquisition have significant and negative coefficients at different time frames.

These results provide tentative support for the hypothesis that firms strategically acquire or develop patents to address specific environmental challenges, particularly those related to energy usage. The significant impact of alternative energy patents on total energy consumption suggests that firms may actively seek out technologies to mitigate energy-related issues through patent acquisitions. However, the lack of substantial impact observed for pollution control patents underscores the importance of strong eco-

	Scope1	**Scope2**	**Scope3**	**Energy**	**Waste**
Dep.Variable	CO2Scope1_ln	CO2Scope2_ln	CO2Scope3_ln	EnergyTotal_ln	WasteTotal_ln
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS	PanelOLS
No.Observations	3304	3231	2033	3777	3527
Cov.Est.	Robust	Robust	Robust	Robust	Robust
R-squared	0.1192	0.1505	0.0183	0.0700	0.0981
R-Squared(Within)	0.0952	0.0782	0.0320	0.0704	0.1107
R-Squared(Between)	0.2991	0.4316	0.2178	0.3830	0.2912
R-Squared(Overall)	0.2925	0.4249	0.1981	0.3692	0.2803
F-statistic	26.826	34.320	2.2078	17.293	23.377
P-value(F-stat)	0.0000	0.0000	0.0060	0.0000	0.0000
const	-2.2527	-3.0322**	1.8611	0.4990	-4.6769***
	(-1.6379)	(-2.3838)	(0.4175)	(0.3349)	(-3.8476)
ROA	-0.9364***	-0.9193***	-1.0816	-1.0559***	-1.1176***
	(-3.5421)	(-3.2097)	(-0.9602)	(-3.3446)	(-3.7832)
RnD_Intensity	-0.0001	-0.0010***	0.0007	-0.0002	-0.0014***
	(-0.5280)	(-3.0352)	(0.7385)	(-0.6239)	(-3.9269)
Revenue_ln	0.6560***	0.6876***	0.5200***	0.6818***	0.7032***
	(11.088)	(12.576)	(2.7349)	(10.678)	(13.443)
Tangibility	0.0103	0.0123	-0.0212	0.0231*	0.0817***
	(1.1293)	(1.2274)	(-0.6579)	(1.8627)	(3.2297)
Developed_t-1	0.0139	0.0526*	0.3638**	0.0462	0.0662**
	(0.4784)	(1.8582)	(2.2362)	(1.2717)	(2.0049)
Acquired_t-1	0.0703	0.0141	-0.0985	-0.1101	0.0685
	(1.2606)	(0.2700)	(-0.3879)	(-1.5974)	(1.3945)
Developed_t-2	0.0243	0.0225	0.3160**	-0.0054	0.0651**
	(0.7947)	(0.7620)	(2.1290)	(-0.1371)	(2.0233)
Acquired_t-2	-0.0280	-0.1245*	-0.0930	-0.0334	0.0096
	(-0.6940)	(-1.7884)	(-0.3591)	(-0.7003)	(0.2378)
Developed_t-3	0.0027	-0.0299	-0.0396	-0.0074	0.0039
	(0.0818)	(-0.9148)	(-0.2794)	(-0.1739)	(0.1207)
Acquired_t-3	-0.0645*	-0.0121	-0.0509	-0.1333**	-0.0221
	(-1.7748)	(-0.3068)	(-0.1883)	(-2.1519)	(-0.4239)
Developed_t-4	-0.0071	-0.0304	-0.1005	-0.0278	-0.0954***
	(-0.2336)	(-1.1789)	(-0.6131)	(-0.7014)	(-3.0809)
Acquired_t-4	-0.0647*	-0.0358	0.2005	-0.0777	-0.0578
	(-1.7750)	(-0.7510)	(0.8509)	(-1.0623)	(-1.0503)
Developed_t-5	-0.0038	0.0327	-0.1101	0.0575	-0.0392
	(-0.1350)	(1.1660)	(-0.5970)	(1.5070)	(-1.1097)
Acquired_t-5	-0.0410	0.0130	0.5260**	-0.0080	-0.0351
	(-0.8916)	(0.2442)	(2.1455)	(-0.1404)	(-0.6550)
Effects	Entity Time	Entity Time	Entity Time	Entity Time	Entity Time

Table 9: Comparison of multiple Fixed Effects models, , complete dataset utilized,

nomic incentives tied to environmental issues. Unlike energy-related concerns, where the cost of electricity serves as a significant economic driver, pollution control lacks comparable economic incentives that might push firms to invest in developing or acquiring related environmental innovations.

Pollution Management Patents					
	Scope1	**Scope2**	**Scope3**	**Energy**	**Waste**
Dep.Variable	CO2Scope1_ln	CO2Scope2_ln	CO2Scope3_ln	EnergyTotal_ln	WasteTotal_ln
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS	PanelOLS
No.Observations	1858	1824	1186	2186	2009
Cov.Est.	Robust	Robust	Robust	Robust	Robust
R-squared	0.1382	0.1987	0.0146	0.1271	0.1742
R-Squared(Within)	0.0910	0.1373	0.0280	0.1239	0.1980
R-Squared(Between)	0.3264	0.4619	0.2407	0.4636	0.2447
R-Squared(Overall)	0.3259	0.4236	0.2257	0.4478	0.2732
F-statistic	17.758	26.931	1.0122	19.400	25.777
P-value(F-stat)	0.0000	0.0000	0.4382	0.0000	0.0000
const	-1.8461	-6.4278***	0.2429	-1.1387	-8.0534***
	(-1.2506)	(-4.2003)	(0.0379)	(-0.7249)	(-5.6508)
ROA	-0.4134	-1.0090**	-1.6420	-0.5683	-0.9049**
	(-1.2179)	(-2.4516)	(-1.1369)	(-1.5632)	(-2.5533)
RnD_Intensity	-0.0009**	-0.0013***	4.648e-05	-0.0020***	-0.0020***
	(-2.0238)	(-2.8555)	(0.0219)	(-2.6402)	(-3.9762)
Revenue_ln	0.6414***	0.8340***	0.6080**	0.7579***	0.8541***
	(10.284)	(12.887)	(2.2578)	(11.425)	(14.091)
Tangibility	0.0776***	0.0800***	0.0315	0.1027***	0.0793***
	(5.3898)	(4.0562)	(0.4219)	(4.8667)	(3.2950)
Developed_t-1	-0.0059	0.0366	0.1397	-0.0286	-0.0021
	(-0.1789)	(1.3152)	(0.8705)	(-0.7308)	(-0.0621)
Acquired_t-1	0.0734	0.0206	-0.1558	-0.0134	0.1385**
	(1.1080)	(0.2792)	(-0.4294)	(-0.1835)	(2.1113)
Developed_t-2	0.0166	0.0101	0.0749	-0.0507	0.0489
	(0.4745)	(0.3716)	(0.5093)	(-1.0584)	(1.3958)
Acquired_t-2	-0.0224	-0.1615*	-0.1034	-0.0154	0.0217
	(-0.3755)	(-1.7065)	(-0.2664)	(-0.2404)	(0.3960)
Developed_t-3	-0.0269	-0.0345	-0.2044	-0.0193	-0.0182
	(-0.7796)	(-1.0296)	(-1.2778)	(-0.3981)	(-0.5239)
Acquired_t-3	-0.0220	0.0022	-0.3548	-0.1188	-0.0735
	(-0.4147)	(0.0408)	(-0.8661)	(-1.3731)	(-1.0621)
Developed_t-4	-0.0370	-0.0068	0.0510	-0.0333	-0.0955***
	(-1.1807)	(-0.2395)	(0.3168)	(-0.7188)	(-2.7731)
Acquired_t-4	-0.0012	-0.0284	-0.0150	0.0669	-0.0957
	(-0.0213)	(-0.4353)	(-0.0431)	(0.8824)	(-1.2297)
Developed_t-5	-0.0392	0.0152	0.0166	0.0584	-0.0366
	(-1.0409)	(0.4727)	(0.0959)	(1.2502)	(-0.8994)
Acquired_t-5	0.0170	0.0366	0.4540	0.0409	-0.0342
	(0.2649)	(0.5296)	(1.5576)	(0.5809)	(-0.4912)
Effects	Entity	Entity	Entity	Entity	Entity
	Time	Time	Time	Time	Time

Table 10: Comparison of multiple Fixed Effects models, "Pollution Control" Patents

Carbon Capture and Storage Patents					
	Scope1	**Scope2**	**Scope3**	**Energy**	**Waste**
Dep.Variable	CO2Scope1_ln	CO2Scope2_ln	CO2Scope3_ln	EnergyTotal_ln	WasteTotal_ln
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS	PanelOLS
No.Observations	3304	3231	2033	3777	3527
Cov.Est.	Robust	Robust	Robust	Robust	Robust
R-squared	0.1209	0.1487	0.0144	0.0680	0.0961
R-Squared(Within)	0.0990	0.0772	0.0216	0.0685	0.1084
R-Squared(Between)	0.2941	0.4300	0.1926	0.3826	0.2886
R-Squared(Overall)	0.2876	0.4238	0.1732	0.3695	0.2790
F-statistic	27.277	33.826	1.7280	16.762	22.871
P-value(F-stat)	0.0000	0.0000	0.0445	0.0000	0.0000
const	-2.1606	-2.9894**	2.0367	0.5133	-4.6400***
	(-1.5699)	(-2.3578)	(0.4560)	(0.3451)	(-3.8016)
ROA	-0.9546***	-0.9188***	-1.3378	-1.0333***	-1.1186***
	(-3.5962)	(-3.1960)	(-1.1780)	(-3.2775)	(-3.7860)
RnD_Intensity	-0.0001	-0.0010***	0.0006	-0.0002	-0.0013***
	(-0.4894)	(-2.9541)	(0.6800)	(-0.6278)	(-3.8722)
Revenue_ln	0.6526***	0.6858***	0.5198***	0.6810***	0.7016***
	(11.025)	(12.576)	(2.7260)	(10.671)	(13.353)
Tangibility	0.0105	0.0119	-0.0176	0.0232*	0.0819***
	(1.1473)	(1.1965)	(-0.5261)	(1.8462)	(3.2192)
Developed_t-1	0.0386	0.0758	0.0667	0.0391	0.0942**
	(0.8934)	(1.5126)	(0.2402)	(0.9386)	(2.1923)
Acquired_t-1	0.0259	0.0160	-0.2045	-0.0098	0.0474
	(0.5551)	(0.2071)	(-0.5782)	(-0.1419)	(0.5343)
Developed_t-2	-0.0713	-0.0062	0.0536	-0.0191	-0.0004
	(-1.5903)	(-0.1405)	(0.2165)	(-0.4373)	(-0.0090)
Acquired_t-2	0.0115	0.0612	-0.5473	-0.0039	0.1103
	(0.2622)	(0.9977)	(-1.4188)	(-0.0614)	(1.4662)
Developed_t-3	-0.0595	-0.0313	-0.1020	-0.0012	-0.0623
	(-1.4232)	(-0.6457)	(-0.4552)	(-0.0246)	(-1.4540)
Acquired_t-3	-0.1067*	-0.0410	-0.4284	-0.0501	0.1277
	(-1.8118)	(-0.4999)	(-0.8427)	(-0.6950)	(1.6093)
Developed_t-4	-0.0846	-0.0265	-0.3406	-0.0142	-0.1043**
	(-1.5486)	(-0.5108)	(-1.3188)	(-0.2855)	(-2.4487)
Acquired_t-4	-0.1360**	-0.1174	0.2987	-0.1177*	0.1169
	(-2.5557)	(-1.3050)	(0.5900)	(-1.7808)	(1.2056)
Developed_t-5	0.0365	0.0458	-0.4656	0.0847	0.0048
	(0.6314)	(1.0139)	(-1.3812)	(1.4743)	(0.0982)
Acquired_t-5	-0.0451	-0.0670	0.3043	-0.0165	0.0141
	(-0.6092)	(-0.5563)	(0.6175)	(-0.1841)	(0.1371)
Effects	Entity Time	Entity Time	Entity Time	Entity Time	Entity Time

Table 11: Comparison of multiple Fixed Effects models, "Carbon Capture and Storage" Patents

	Alternative Energy Patents				
	Scope1	**Scope2**	**Scope3**	**Energy**	**Waste**
Dep.Variable	CO2Scope1_ln	CO2Scope2_ln	CO2Scope3_ln	EnergyTotal_ln	WasteTotal_ln
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS	PanelOLS
No.Observations	1750	1712	1152	2041	1927
Cov.Est.	Robust	Robust	Robust	Robust	Robust
R-squared	0.0971	0.1533	0.0299	0.0775	0.1126
R-Squared(Within)	0.0522	0.0772	0.0361	0.0678	0.1177
R-Squared(Between)	0.3463	0.4627	0.2491	0.4812	0.2241
R-Squared(Overall)	0.3457	0.4545	0.2350	0.4365	0.2500
F-statistic	11.309	18.617	2.0629	10.498	15.003
P-value(F-stat)	0.0000	0.0000	0.0117	0.0000	0.0000
const	-1.1855	-2.4534	1.2215	-0.4360	-4.4218**
	(-0.7362)	(-1.6402)	(0.1785)	(-0.2348)	(-2.4800)
ROA	-0.5961*	-1.1984***	1.1294	-0.9965**	-0.1029
	(-1.8092)	(-3.1088)	(0.7410)	(-2.1098)	(-0.3040)
RnD_Intensity	-0.0006**	-0.0010**	-0.0009	-0.0013**	-0.0006*
	(-2.0782)	(-2.4037)	(-0.5578)	(-2.3764)	(-1.8710)
Revenue_ln	0.6134***	0.6666***	0.5625*	0.7303***	0.6999***
	(9.0257)	(10.528)	(1.9596)	(9.3226)	(9.2305)
Tangibility	0.0815***	0.0601***	0.0191	0.0993***	0.0135
	(4.4043)	(2.9199)	(0.2005)	(3.6484)	(0.5752)
Developed_t-1	-0.0128	0.0101	0.3231*	-0.0082	-0.0008
	(-0.3259)	(0.3372)	(1.9074)	(-0.1849)	(-0.0227)
Acquired_t-1	0.0348	-0.0160	-0.0561	-0.2703**	0.0198
	(0.4482)	(-0.3069)	(-0.1505)	(-2.2922)	(0.2842)
Developed_t-2	0.0221	0.0188	0.3534**	-0.0823	0.0341
	(0.5822)	(0.6058)	(1.9873)	(-1.5091)	(0.8960)
Acquired_t-2	-0.0621	-0.1626*	-0.2696	-0.0862	-0.0822
	(-1.1255)	(-1.9017)	(-0.7058)	(-1.0256)	(-1.3085)
Developed_t-3	-0.0234	0.0063	-0.2033	-0.0640	-0.0085
	(-0.6075)	(0.2029)	(-1.1818)	(-1.3580)	(-0.2335)
Acquired_t-3	-0.0187	0.0166	0.2791	-0.1757**	0.0115
	(-0.3725)	(0.3441)	(0.6692)	(-2.5350)	(0.1497)
Developed_t-4	-0.0188	-0.0210	-0.0800	-0.1053**	-0.0937**
	(-0.5411)	(-0.7109)	(-0.4745)	(-2.1271)	(-2.4933)
Acquired_t-4	-0.0458	0.0134	0.5889*	-0.2124*	-0.0367
	(-0.8520)	(0.2223)	(1.7325)	(-1.7523)	(-0.4978)
Developed_t-5	-0.0198	-0.0289	-0.0160	0.0327	-0.0648
	(-0.5305)	(-0.8465)	(-0.0980)	(0.5997)	(-1.5326)
Acquired_t-5	-0.0836	0.0017	0.9257***	-0.1400	-0.1077
	(-1.3891)	(0.0209)	(3.3111)	(-1.3942)	(-1.0621)
Effects	Entity	Entity	Entity	Entity	Entity
	Time	Time	Time	Time	Time

Table 12: Comparison of multiple Fixed Effects models, "Alternative Energy" Patents

8 Bivariate Probit Regression

After examining the impact of green patents on environmental performance, we shift our focus to investigate the reverse relationship, addressing our third research question: *Does a firm's environmental performance influence its decision to acquire a green patent?* For this purpose the employed model is a Bivariate Probit (refer to section 6.2 for detailed information on this regression type). In this model, we consider two dependent binary variables: *"Patent_Acquired"*, which takes the value 1 if a company acquires a green patent in a given year through M&A activity or direct purchase, and 0 otherwise; and *"Patent_Developed"* which takes the value 1 if the company independently develops a green patent and 0 otherwise. The dataset has been enriched with annual firm-country data with the Environmental Policy Stringency Index (*ESP_Stringency*), a country-specific internationally-comparable metric of environmental policy rigor provided by the OECD. Stringency reflects the extent to which environmental policies impose explicit or implicit costs on polluting or environmentally harmful behavior, incorporating a mix of market-based instruments like GHG taxes and CO2 trading scheme prices, non-market-based instruments, and technological support. Additionally, industry groups categorized by NACE level 1 codes are included. Following Hoffmann [60] to ensure comparability across firms and reducing biases in inter-company comparisons, each firm's green performance variables have been standardized by dividing them by total Assets, obtaining emissions intensities. The same has been applied to Research and Development expenditures.

The results, as summarized in Table 13, yield valuable insights into the determinants of firms' acquisition and development of green patents. Let's start by analyzing the control variables. The size of an entity, evaluated by the natural log of its revenues (*Revenue_ln*), seems to influence positively both the acquisition and development of green patents, suggesting a propensity for larger firms to engage more actively in green innovation endeavors. This trend may be attributable to the greater financial resources and organizational capacity of larger entities to invest in sustainable research and development initiatives.

Return on Assets (*ROA*) shows a negative relationship with patent development but isn't significant on Acquisitions. Companies with higher levels of profitability may prioritize short-term financial gains over long-term sustainability objectives and therefore don't engage in green innovation.

Unexpectedly higher levels of research and development intensity (*RnD_Intensity*) have a significant and negative coefficient for both types of patent obtainment. A similar result is obtained by Przychodzen [96] when studying the relation of R&D over sales on the Ratio of green patents developed by a firm. As suggested by Lee and Min [73] the more firms engage in brown R&D the less likey they are to engage in green research. Since green R&D is still a niche activity, higher amounts of total R&D might underlie higher amounts of brown R&D, leading to a decrease in green patents obtainment.

The significant increase in patent obtainment observed within the Information and Communication sector (NACE sector J) underscores the sector-specific dynamics influencing green innovation. Similarly, the Manufacturing sector (Sector C) exerts a significant influence on patent development, highlighting distinct patterns of green technology adoption across industries.

Interestingly the strictness of environmental policies in a given firm's country, measured via the Environmental Stringency Index (*EPS_Index*) positively influences the development of patents. As highlighted by Martinez [80] this result is in line with the Porter hypothesis, indicating that environmental regulations can have a positive influence on the decisions that companies adopt in relation to innovation.

Moving to the environmental variables the intensity of CO2 Scope 1 equivalent Emissions has a significant and positive impact on green patents development but doesn't on acquisitions, while Scope 3 are significant for acquisitions but not for development. Firms with higher direct emissions may be more inclined to invest in the development of green technologies to mitigate their environmental impact. Conversely, since Scope 3 emissions mostly account for the environmental performance of a business's supply chain, it's possible that firms with "brow" supply chains need to rely on strategic acquisition of green technologies due to a lack of resources to self-develop them. Lastly, total waste production intensity (*WasteTotal_N*) seems to impact negatively on the development of green technologies.

Dependent Variable	Patent_Acquired				Patent_Developed			
	Estimate	Std. Error	z value	Pr(>|z|)	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-1.121e+01	2.189e+03	-0.005	0.99591	-1.427e+01	2.057e+03	-0.007	0.99447
CO2Scope1_Intensity	1.599e-01	1.783e-01	0.897	0.36989	1.665e-01	6.224e-02	2.675	0.00746***
CO2Scope2_Intensity	4.095e-01	4.248e-01	0.964	0.33499	-1.273e-01	2.847e-01	-0.447	0.65471
CO2Scope3_Intensity	1.864e-02	5.862e-03	3.179	0.00148***	-6.977e-03	6.548e-03	-1.066	0.28665
EnergyTotal_Intensity	-6.873e-03	1.173e-02	-0.586	0.55790	5.530e-03	4.837e-03	1.143	0.25287
WasteTotal_Intensity	-1.594e-02	6.441e-02	-0.248	0.80448	-1.050e-01	4.917e-02	-2.136	0.03265**
ROA	-8.646e-03	9.646e-02	-0.090	0.92857	-1.050e-01	4.917e-02	-2.136	0.03265**
Revenue_ln	2.340e-01	7.509e-02	3.117	0.00183***	3.210e-01	4.080e-02	7.868	3.60e-15***
RnD_Intensity	-3.226e-03	1.582e-03	-2.039	0.04147**	-6.014e-03	8.122e-04	-7.404	1.32e-13***
EPS_Index	-1.032e-01	1.263e-01	-0.817	0.41399	1.553e-01	7.509e-02	2.068	0.03869**
Sector C	4.219e-01	3.526e-01	1.197	0.23143	5.591e-01	2.007e-01	2.786	0.00534***
Sector D	-5.561e+00	8.192e+03	-0.001	0.99946	-4.190e-01	4.807e-01	-0.872	0.38340
Sector F	3.061e-01	5.526e-01	0.554	0.57965	1.193e-02	2.932e-01	0.041	0.96754
Sector G	-4.527e+00	8.192e+03	-0.001	0.99956	1.508e-01	5.760e-01	0.262	0.79350
Sector H	-5.673e+00	8.192e+03	-0.001	0.99945	-9.946e-02	9.332e-01	-0.107	0.91512
Sector J	1.249e+00	4.379e-01	2.853	0.00434***	1.624e+00	3.261e-01	4.980	6.37e-07***
Sector K	-4.238e+00	8.192e+03	-0.001	0.99959	3.240e-01	6.177e-01	0.525	0.59990
Sector M	-4.578e+00	8.192e+03	-0.001	0.99955	-5.165e+00	4.196e+03	-0.001	0.99902
Year Effect	Yes				Yes			
Industry x Year	No				No			

n = 1143 theta = 0.31(0.1,0.453) tau = 0.201(0.0639,0.299)

Observed information matrix is positive definite

Table 13: Bivariate Probit, *, **, *** refers to significance at the 10, 5, and 1% level respectively

9 Dumitrescu–Hurlin Test for Granger causality in a panel dataset

Our last research question seeks to verify the presence of causal linkages between the obtainment of green patents and a change in environmental performances, or vice versa. To test this hypothesis a Dumitrescu-Hurlin Granger causality test, discussed in section 6.3, is employed. Following the approach of Ali [3], a series of pairwise tests have been conducted on each of the five green indicators intensity and the same two methods of patent obtainment (Either Development or Acquisition) utilized in previous sections. It must be stressed that Dumitrescu's test null hypothesis is the absence of causality for all individuals in the panel, and rejecting H0 does not exclude noncausality for some individuals.

Starting from table 14, the null hypothesis that a change in a given environmental variable intensity does not Granger cause a change in patent development for all entities in our dataset is rejected for all variables excluding CO2 scope 2 intensity. Conversely, the null hypothesis is accepted when testing the Granger causality of patent obtainment over a change in all environmental variables but CO2 Scope 2. Based on these findings, it appears that changes in most environmental variables may influence the development of patents related to environmental innovation. However, the reverse causality, where patent obtainment drives changes in environmental indicators, is less evident, except in the case of Scope 2 intensity. This suggests that firms may be more reactive to changes in their environmental performance when it comes to pursuing green patents, rather than actively seeking patents as a means to drive environmental improvements, as shown by previous models.

On the other hand in table 15 CO2 Scope 1 and CO2 Scope 3 intensity show signs of bidirectional causality, meaning that the external acquisition of green patents is both Granger caused, and Granger causes, a change in those environmental indicators. The null hypothesis of no Granger causation is also rejected for Scope 2 over Patent Acquisition and for Patent Acquisition over Energy intensity. These models confirm the different roles of patent development and patent acquisition, where the former seems to be triggered as a response to environmental performances but doesn't seem to change their trajectory, while the latter causes a change in green indicators but isn't caused by them.

X	X Does NOT Granger-Causes Patent Development	Patent Development Does NOT Granger-Cause X
CO2Scope1 Intensity	Reject the null hypothesis (Ztilde = 5.3567, p-value = 8.474e-08)	Accept the null hypothesis (Ztilde = -0.33233, p-value = 0.7396)
CO2Scope2 Intensity	Accept the null hypothesis (Ztilde = 0.16163, p-value = 0.8716)	Reject the null hypothesis (Ztilde = 4.3628, p-value = 1.284e-05)
CO2Scope3 Intensity	Reject the null hypothesis (Ztilde = 8123049, p-value = 2.2e-16)	Accept the null hypothesis (Ztilde = 0.53115, p-value = 0.5953)
EnergyTotal Intensity	Reject the null hypothesis (Ztilde = 4.9288, p-value = 8.274e-07)	Accept the null hypothesis (Ztilde = -0.030122, p-value = 0.976)
WasteTotal Intensity	Reject the null hypothesis (Ztilde = 28.911, p-value <2.2e-16)	Accept the null hypothesis (Ztilde = 0.66596, p-value = 0.5054)

alternative hypothesis: Granger causality for at least one individual

Table 14: Dumitrescu - Hurlin Granger (not) Causality test for patent development

X	X Does NOT Granger-Causes Patent Acquisition	Patent Acquisition Does NOT Granger-Cause X
CO2Scope1 Intensity	Reject the null hypothesis (Ztilde = 5.5047, p-value = 3.698e-08)	Reject the null hypothesis (Ztilde = 2.0342, p-value = 0.04193)
CO2Scope2 Intensity	Reject the null hypothesis (Ztilde = 4.6657, p-value = 3.076e-06)	Accept the null hypothesis (Ztilde = -0.52077, p-value = 0.6025)
CO2Scope3 Intensity	Reject the null hypothesis (Ztilde = 16.712, p-value <2.2e-16)	Reject the null hypothesis (2.4607, p-value = 0.01387)
EnergyTotal Intensity	Accept the null hypothesis (Ztilde = -0.20023, p-value = 0.8413)	Reject the null hypothesis (Ztilde = 1.9553, p-value = 0.05054)
WasteTotal Intensity	Accept the null hypothesis (Ztilde = -1.2742, p-value = 0.2026)	Accept the null hypothesis (Ztilde = 0.31459, p-value = 0.7531)

alternative hypothesis: Granger causality for at least one individual

Table 15: Dumitrescu - Hurlin Granger (not) Causality test for patent acquisition

Part V

Conclusions

The main purpose of this thesis was to dive into the complex realm of environmental literature, particularly focusing on the practical results of environmental innovation on green performances within corporate settings. Our first model findings underscore the nuanced impact of green patent acquisition on environmental performance. The direct development of green patents shows little to no association with environmental outcomes, meaning that these technological advancements have not materialized in lower pollution within a five-year lag, and are instead associated with a slight increase in emissions and waste production the year after development. On the other hand, the external acquisition of green patents seems to have a somewhat positive impact on green performances. Upon closer examination of specific technologies, such as those related to alternative energy, a tangible impact is observed with both acquisition methods, coinciding with a decrease in energy consumption. Nevertheless, it is important to note that the observed decrease in energy consumption may be driven by cost-efficiency strategies rather than sustainability efforts.

Furthermore, our bivariate probit regression unveils an intriguing connection between the stringency of environmental policy instruments and patent development. We find that more stringent policies, which increase the costs associated with environmentally harmful behavior, are linked with heightened patent development. However, this correlation does not extend to patent acquisitions. Notably, the significant association between external patent acquisition and scope 3 emissions implies that firms with brown supply chains may face challenges in developing green patents internally, necessitating reliance on external acquisitions. On the other hand, for patent development, higher scope 1 emissions increase the probability of development within a firm, while firms with greater waste intensity exhibit a decreased likelihood of green patent development.

Finally, our Granger causality analysis offers insights into the dynamic relationship between patent obtainment and environmental performance. It suggests that firms have a reactive approach to direct environmental innovation, as they pursue patent development in response to a change in green performance. However, these developed patents seem to have a minimal influence in green indicators, a result that corroborates the finding of our first model. On the contrary, green patents acquired externally influence environmental performance.

These conclusions underscore the intricate interplay between environmental innovation, corporate behavior, and ecological outcomes. As discussed in Part II, an important focus of EI literature is finding the moderating effects shaping the relationship between green technological advancement and firm's results. This thesis finds that different methods of patent obtainment could lead to different results and might be triggered by different circumstances. Environmental performances, particularly when influenced by policies imposing costs on polluting behavior, appear to motivate firms to pursue direct environmental innovation via patent development. However, this thesis finds the outcome of such innovation efforts scarce, as the development of green patents only results in positive environmental outcomes when those benefits emerge as a byproduct of economic efficiencies, as in the case of energy consumption. On the other hand, patents acquired via purchase or as part of M&A deals, are successful in effecting emissions and energy usage but the acquisition itself is not driven by policy stringency or green variables other than emissions.

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A Appendix

Name	**Description**
Assets (Dollars)	The company's actual value normalized to reflect the I/B/E/S default currency and corporate actions (e.g. stock splits). Current Assets are any asset reasonably expected to be sold, consumed, or exhausted through the normal operations of a business within the current fiscal year or operating cycle (whichever period is longer). Typical current assets include cash, cash equivalents, short-term investments, accounts receivable, stock inventory and the portion of prepaid liabilities which will be paid within a year.
COGS (Dollars)	The company's actual value normalized to reflect the I/B/E/S default currency and corporate actions (e.g. stock splits). Cost Of Goods Sold are the direct costs attributable to the production of the goods sold by a company.
Employees (Number)	Represents the number of full-time employees and full-time equivalents of part-time/temporary employees, as reported, as of the fiscal period end date.
Revenue (Dollars)	Represents revenue from all of a company's operating activities after deducting any sales adjustments and their equivalents.
R&D (Dollars)	The company's actual value normalized to reflect the I/B/E/S default currency and corporate actions (e.g. stock splits). R&D Expense are Research and Development expenses incurred for a given period.
ROA	The company's actual value normalized to reflect the I/B/E/S default currency and corporate actions (e.g. stock splits). Return On Assets is a profitability ratio and as such gauges the return on investment of a company. Specifically, ROA measures a company's operating efficiency regardless of its financial structure (in particular, without regard to the degree of leverage a company uses) and is calculated by dividing a company's net income prior to financing costs by total assets.
Tangibility	Ratio of Property Palant and Equipment value over total Assets

Table 16: Description of utilized financial variables

Name	**Description**
CO2Scope1 (Tonnes)	Direct of CO2 and CO2 equivalents emission in tonnes. Direct emissions from sources that are owned or controlled by the company (scope 1 emissions). Following gases are relevant : carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCS), perfluorinated compound (PFCS), sulfur hexafluoride (SF6), nitrogen trifluoride (NF3).Follows green house gas (GHG) protocol for all our emission classifications by type.
CO2Scope2 (Tonnes)	Indirect of CO2 and CO2 equivalents emission in tonnes. Indirect emissions from consumption of purchased electricity, heat or steam which occur at the facility where electricity, steam or heat is generated (scope 2 emissions). Same gasses and protocols as scope 1 are followed.
CO2Scope3 (Tonnes)	Total CO2 and CO2 Scope Three equivalent emission in tonnes. Scope 3 includes emissions from contractor-owned vehicles, employee business travel (by rail or air), waste disposal, outsourced activities. Emissions from product use by customers, emission from the production of purchased materials, emissions from electricity purchased for resale. Same gases as scope1 are relevant. Same gasses and protocols as scope 1 are followed.
TotalEnergy (Megajules)	Total direct and indirect energy consumption in gigajoules. The total amount of energy that has been consumed within the boundaries of the company's operations. Total energy use = total direct energy consumption + indirect energy consumption. Purchased energy and produced energy are included in total energy use. For utilities, transmission/ grid loss as part of its business activities is considered as total energy consumed and data not to consider electricity produced to answer energy use (utility company produce to sell). For utilities, raw materials such as coal, gas or nuclear used in the production of energy are not considered under 'total energy use'.
TotalWaste (Tonnes)	Total amount of waste produced in tonnes. Total waste = non-hazardous waste + hazardous waste. Only solid waste is taken into consideration, exceptionally if liquid waste reported in 'ton' then we do the summation to derive total including liquid waste. For sector like mining, oil & gas, waste generation like tailings, waste rock, coal and fly ash, etc are also considered.
EPS index	The OECD Environmental Policy Stringency Index (EPS) is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour. It covers 28 countries.

Table 17: Description of utilized environmental variables

ALTERNATIVE ENERGY	Bio-fuels	Solid fuels
		Liquid fuels
		Biogas
		From genetically engineered organisms
	Harnessing energy from manmade waste	Agricultural waste
		Gasification
		Chemical waste
		Industrial waste
		Hospital waste
		Landfill gas
		Municipal waste
	Hydro energy	Water-power plants
		Machines or engines for liquids
		Regulating, controlling or safety means of machines or engines
		Propulsion of marine vessels using energy derived from water movement
	Wind energy	Structural association of electric generator with mechanical driving motor
		Structural aspects of wind turbines
		Propulsion of vehicles using wind power
		Propulsion of marine vessels by wind-powered motors
	Solar energy	Photovoltaics (PV)
		Use of solar heat
		Hybrid solar thermal-PV systems
		Propulsion of vehicles using solar power
		Producing mechanical power from solar energy
		Roof covering aspects of energy collecting devices
		Steam generation using solar heat
		Refrigeration or heat pump systems using solar energy
		Use of solar energy for drying materials or objects
		Solar concentrators
		Solar ponds
	Geothermal energy	Use of geothermal heat
		Production of mechanical power from geothermal energy
	Using waste heat	To produce mechanical energy
		Of combustion engines
		Of steam engine plants
		Of gas-turbine plants
		As source of energy for refrigeration plants
		For treatment of water, waste water or sewage
		Recovery of waste heat in paper production
		For steam generation by exploitation of the heat content of hot heat carriers
		Recuperation of heat energy from waste incineration
		Energy recovery in air conditioning
		Arrangements for using waste heat from furnaces, kilns, ovens or retorts
		Regenerative heat-exchange apparatus
		Of gasification plants
	Storage of electrical energy	
	Power supply circuitry	With power saving modes
	Measurement of electricity consumption	
	Storage of thermal energy	
	Low energy lighting	Electroluminescent light sources (e.g. LEDs, OLEDs, PLEDs)
	Recovering mechanical energy	Chargeable mechanical accumulators in vehicles
POLLUTION CONTROL	Waste disposal	
	Treatment of waste	Disinfection or sterilisation
		Treatment of hazardous or toxic waste
		Treating radioactively contaminated material
		Refuse separation
		Reclamation of contaminated soil
		Mechanical treatment of waste paper
	Consuming waste by combustion	
	Reuse of waste materials	Use of rubber waste in footwear
		Manufacture of articles from waste metal particles
		Production of hydraulic cements from waste materials
		Use of waste materials as fillers for mortars, concrete
		Production of fertilisers from waste or refuse
		Recovery or working-up of waste materials
		Recovery of plastics materials from waste
	Air quality management	Treatment of waste gases
		Separating dispersed particles from gases or vapours
		Use of additives in fuels or fires to reduce smoke or facilitate soot removal
		Arrangements of devices for treating smoke or fumes from combustion apparatus
		Dust-laying or dust-absorbing materials
		Pollution alarms
	Control of water pollution	Treating waste-water or sewage
		Materials for treating liquid pollutants
		Removing pollutants from open water
		Plumbing installations for waste water
		Management of sewage
CARBON CAPTURE AND STORAGE	Carbon Capture	
	Carbon Storage	
	Carbon General	

Table 18: Brakedown of IPC subcategories that make up the technology groups utilized in the fixed effects models. Source : IPC

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