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Determinants of innovation in energy enterprises

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To Carolina, my steadfast companion on this journey, for inspiring me every single day.

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Contents

1 Introduction

This chapter presents the urgent need for sustainable energy practices in the context of global resource scarcity and environmental degradation and provides the basis for a detailed examination of the drivers of innovation in the European Union energy sector.

1.1 Motivation

Due to decades of resource scarcity and industrial expansion caused by population growth and expansion of the industrial sector, there is an urgent need for a shift to sustainable practices and reduced consumption. In the second half of the 20th century, it became clear that conventional models of development would mean a catastrophic future for the earth and humanity. Groundbreaking publications such as Rachel Carson's 1962 “Silent Spring” and the Club of Rome's 1972 report “The Limits to Growth” exposed the severe environmental impact of unbridled economic activity (Sklair, 2019).

The necessity for this transition was and still is driven by the exhaustion of non-renewable resources, extensive ecological degradation, unequal resource distribution and climate change which together have brought our planet to its ecological boundaries. In particular climate change, which is primarily caused by greenhouse gas (GHG) emissions from fossil fuels, has become a serious concern. The Intergovernmental Panel on Climate Change (IPCC) has regularly reported on the ongoing changes in climate patterns and their widespread impacts on ecological and human systems, underscoring the urgent need for significant action to mitigate these impacts, and the relevance of the 2015 Paris Agreement and the United Nations Sustainable Development Goals (IPCC, 2023).

According to the European Environment Agency (EEA), in 2022 the sector contributing the most to GHG emissions in the European Union (EU) is Energy Supply (as seen in Figure 1), representing approximately 27.5 percent of emissions.

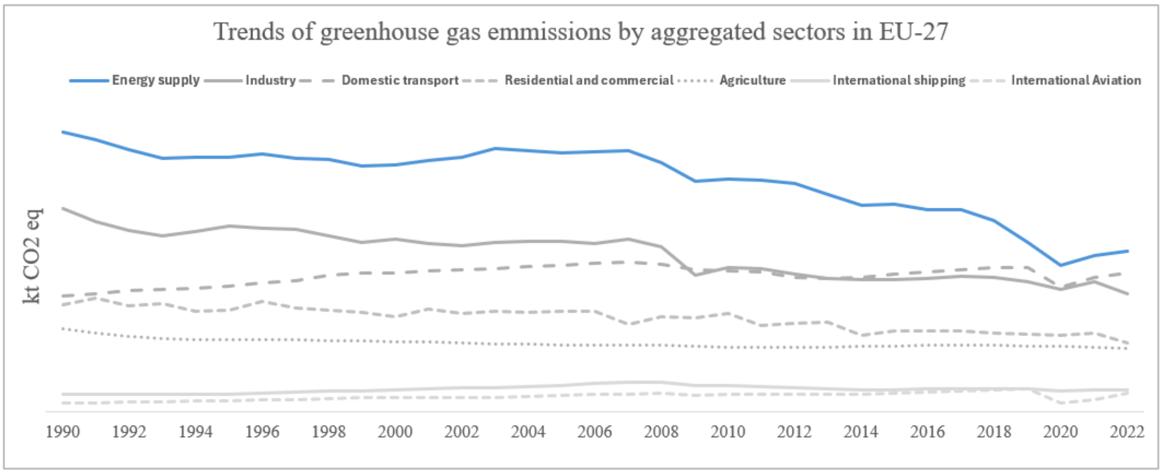

Figure 1. Analysis of the greenhouse gas emissions, per sector, from 1990 to 2022. Source: EEA, 2022

In addition, one-third of the EU's science areas are directly related to the energy sector given the urgency to drastically reduce fossil fuel usage (EEA, 2024).

Energy companies are thus at the forefront of this transition, being able to adapt to the future of energy consumption through eco-innovation, the development and implementation clean[1] technologies such as solar and wind energy, reducing greenhouse gas emissions, and aligning with the global climate goals.

1.2 Dissertation Contributions

Despite the widespread recognition that climate change is an urgent issue and that energy firms are key actors in this transition, the interplay between the energy sector's progress and the emergence and development of technological innovation is still understudied.

Studies such as those by Acemoglu et al. (2016) and Aghion et al. (2016), have emphasized the critical role of innovation, and consequently eco-innovation, in addressing climate changes, alongside the factors that drive such innovations, as discussed by Horbach (2016) and Acemoglu et al. (2023a). Research efforts have examined specific drivers of innovation, including employment (Horbach, 2010), subsidies (Lekavičius et al., 2020), diffusion (Fichter and Clausen, 2021), cooperations (Greco et al., 2017), oil prices (Carrilho-Nunes and Catalão-

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[1] Clean innovations in the context of energy firms relate to a range of technologies and practices designed to reduce environmental impact and promote sustainability. These can include the adoption of renewable energy sources such as solar, wind, and hydroelectric power; advancements in energy efficiency, battery storage solutions, the development of smart grid technologies and carbon capture and storage technologies.

Lopes, 2020), among others. Additionally, studies have concentrated on particular types of innovation (Rodríguez-Rebés et al., 2021), specific countries (Horbach, 2008) or individual sectors (Correia & Rua, 2016). For the energy sector, Nawrocki and Jonek-Kowalska (2023) studied innovation drivers in Polish energy companies, while Costa-Campi et al. (2019) conducted similar research for Spanish energy firms.

This research aims to bridge this gap, by focusing only on EU firms within the Energy Sector, leveraging micro-level data from the Community Innovation Survey (CIS), a well-established database for innovation research. The aim is to identify the innovation drivers that are most relevant for companies in this key sector that is at the forefront of the fight against climate change. In doing so, it seeks to understand these drivers in the context of the energy sector's unique challenges and compare them to the broader innovation drivers found relevant to the green transition across all sectors.

1.3 Dissertation Structure

This research follows the standard dissertation research structure, beginning with a literature review that examines the role of innovation in the energy transition and analyses key determinants. This is followed by the data characterization section, which details the data sources and methodology used for the empirical analysis. The research methodology section describes the econometric models applied, with a focus on the probit models estimating the probability of innovation activities within firms. The results section presents and interprets the results and links them to the previously established theoretical framework, the discussion theorizes on specific findings, and at the end conclusions, limitations, and future work proposals are presented.

2 Literature Review

In this literature review, the focus is on understanding the literature covering the key factors that make energy companies competitive in innovation in general and in eco-innovation in particular. To this end, the importance of innovation in the transition from dirty[2] to clean sources is analysed and the main drivers of this innovation are examined in more detail.

2.1 Role of Innovation in the Energy Transition

By now, there is a consensus that economic activities that emit greenhouse gases such as Carbon Dioxide (CO_2) contribute to climate change. To mitigate this impact, several milestones have been achieved, mainly the 2015 Paris Agreement (COP 21), the Glasgow Climate Pact, and the 13th goal of the United Nations Sustainable Development Goals (SDG) - take urgent action to combat climate change and its impacts -, all reuniting calls for action to combat it.

The EU also has goals targeting this topic, one is primarily focused on reducing greenhouse gas emissions and transitioning to renewable energy sources to combat climate change. Accordingly, the EU has set the target of reducing greenhouse gas emissions by at least 40 percent below 1990 levels by 2030 and aims for climate neutrality by 2050. This includes increasing the share of renewable energy in the final energy consumption to 27 percent and improving energy efficiency by 27 percent as part of its "Europe 2020" strategy. Interestingly, this goal includes advancing science and technology and was split into ten "science priority areas," with the energy sector accounting for one-third of them. This is primarily because, to mitigate the worst possible effects of climate change, fossil fuel consumption must be drastically reduced (EU Science Hub, 2023; European Commission, 2023).

For companies, how they can reduce pollution from these activities is through process optimization, process innovation, changing material usage, or ceasing production entirely. It is not difficult to predict that the latter option will not be preferred by companies as their main motivation is to generate profits. The option, therefore, is to redirect their economic activities towards less polluting ones using a key tool, innovation. For this reason, many authors see

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[2] Dirty innovations in the context of energy firms refer to a range of technologies and practices that prioritize increased production or cost-efficiency at the expense of environmental health and sustainability. These include the continued use or expansion of conventional fossil fuel technologies such as coal, oil, and natural gas extraction. Additionally, these innovations can include older or less efficient technologies that result in higher emissions of pollutants and greenhouse gases, contributing to environmental degradation and climate change.

innovation as the only way to maintain global economic growth while keeping it healthy and livable for future generations (Ion and Cristina, 2014).

Eco-innovation thus involves the development, implementation, or use of a product, service, production technique, organizational framework, or management or business strategy that is new to the company or end user. It is characterized by its ability to significantly reduce environmental hazards, pollution, and the adverse effects of resource use - including energy consumption - over its entire life cycle compared to relevant alternatives (Sezen & Çankaya, 2013).

Distinguishing between clean and dirty innovations in the context of energy companies is another important definition. On the one hand, clean innovations often regard renewable energy technologies, such as solar and wind power, because they minimize environmental impact and improve energy efficiency, and are frequently enhanced by advancements in energy storage and smart grids. On the other hand, dirty innovations in the energy industry usually concentrate on enhancing technologies related to fossil fuels, like improved coal combustion and effective techniques for extracting oil and gas. Despite their efficiency improvements, these innovations continue to contribute significantly to greenhouse gas emissions and environmental degradation, reflecting the sector's economic reliance on and dependence on fossil fuels.

The evidence points to a preference for clean innovation in the stock market when comparing this classification of the firms' innovations with their valuation. Dechezleprêtre et al. (2021) claim that with each additional clean patent per million dollars of book value Tobin's Q[3] increases by 3.77 percent. In turn, dirty technologies have lower market valuations and can even have a negative effect on a company's market value. The market's preference for environmentally sustainable technologies is highlighted by this differential valuation, which is likely due to changing societal preferences, regulatory expectations, and the expectation of long-term financial gains from clean technology investments (Acemoglu et al., 2016; Kittner et al., 2017).

In addition, Pinkse et al. (2023) distinguished apart the four capabilities of innovation. First, the recombinative capability, meaning the ability to innovate by merging diverse

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[3] Tobin's Q is a financial ratio that compares a firm's market value to its book value, specifically the replacement cost of its assets. A higher Tobin's Q suggests the market values the company's assets more than their recorded book value, indicating positive investor expectations.

technological components; second, the collaborative capability, referring to the establishment of partnerships and engaging in open innovation with external entities; third, the integrative capability, ensuring the commercial viability of low-carbon technologies by aligning R&D efforts with market demands or, in other words, transforming niche low-carbon solutions into mainstream products; and finally, the socio-cognitive capabilities, which address the need for a paradigm shift in the perception of climate change and net-zero innovation among various stakeholders.

Technologies can in fact become cheaper than fossil fuels after sufficient advances, potentially lowering energy prices (Acemoglu et al. (2023)) as can observed from Figure 2, where solar photovoltaic, onshore, and offshore wind have become less expensive than fossil fuels, thus reaching grid parity. Also, intermediate sources like natural gas, which have a flexible supply and emit about 30 percent less CO_2 than oil and 50 percent less than coal per unit of energy, could be very important to advance this transition, although they are not clean energy sources. However, it is important to notice the impact of the shale gas[4] boom in this transition. Regarding this, Acemoglu et al. (2023) developed a model with three energy sources, coal, shale gas, and renewables, and showed that a shale gas boom is beneficial in the short run but can redirect innovation away from renewables.

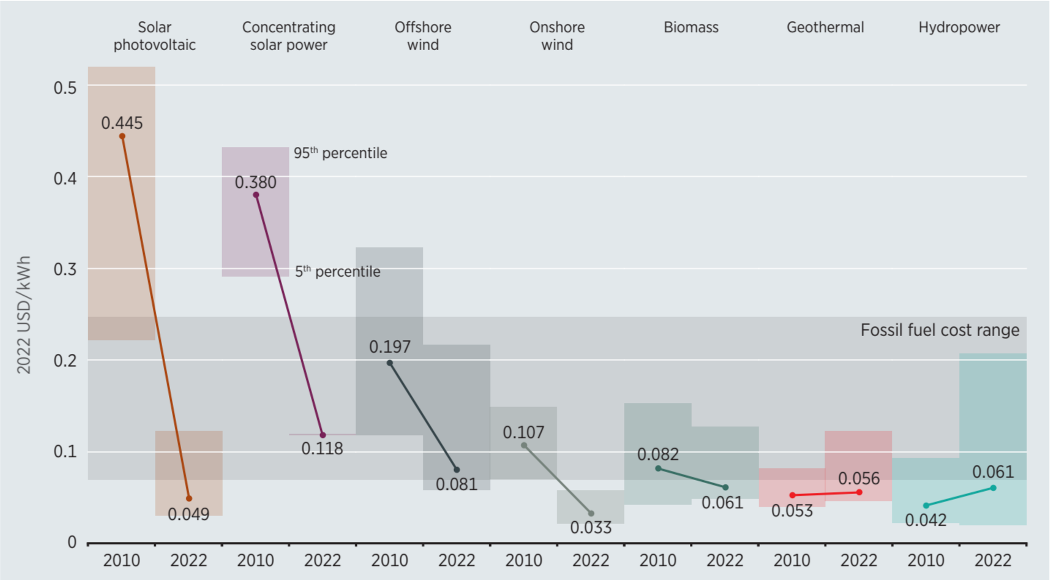

Figure 2: Global LCOE from newly commissioned utility-scale renewable technologies, 2010 and 2022. Source. Irena, 2023

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[4] The shale gas boom refers to the rapid increase in extraction and production of natural gas from shale formations due to advancements in hydraulic fracturing and horizontal drilling technologies, significantly impacting energy markets and sparking environmental concerns.

2.2 Main Determinants of Innovation

Barbieri et al. (2016), as well as He et al. (2018), divided drivers of eco-innovation into four groups: technology push, the technical capability for eco-innovation; stakeholder pull, which refers to the norms and demands that impact a firm's reputation and image by reflecting the ecological concerns among stakeholders and the broader society; policy push-pull, which directly relates to the importance of taxation and policies; and other firm-specific actors that reflect the firm’s willingness to pursue sustainability.

In addition, six factors that encourage EU businesses to adopt innovations that replace fossil fuel energy with renewable energy sources are high energy, water, or material costs, which is a factor that in the current war scenario in Ukraine, makes the chances of introducing eco-innovations high; environmental regulations; environmental taxes; government grants or subsidies; market demand for environmental innovations; and voluntary actions or initiatives for good environmental practice within a sector (Zastempowski, 2023).

2.2.1 Environmental policies and interventions

Policy intervention is essential to prevent environmental degradation by redirecting innovation from dirty to clean technologies, especially when sectors are highly substitutable[5]. Per the Porter Hypothesis (Porter and Linde, 1995), short-term regulatory measures, such as carbon taxes or research subsidies, could suffice to move technological advancement toward sustainability. The optimal environmental regulation should be a combination of an input tax, such as a carbon tax to control current emissions, and research subsidies or profit taxes to influence the direction of research (Acemoglu et al., 2023). Once clean technologies mature, further intervention may not be necessary, allowing environmental goals to be met without compromising long-term economic growth. This approach underscores the importance of timely action to minimize the environmental and economic impacts of delaying the shift towards “cleaner” alternatives.

Regarding the potential impact on the economic growth of policy interventions, Nordhaus (2007) considers that these limited and gradual interventions are necessary, with the eventuality

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[5] Highly substitutable sectors are industries or segments of the economy where products or services offered by different firms are viewed as nearly identical or easily replaceable by consumers, leading to minimal differentiation among competitors.

of slightly reducing long-run growth. Other calls are made for interventions that persist throughout time, for instance, Stern (2009), claims that despite the possibility of large financial costs, these interventions must be implemented permanently. However, there are the most extreme arguments, such as the one by Mauger (2023), where growth has to come to an end to achieve a sustainable planet (Acemoglu et al., 2012).

Additionally, a study conducted by Aghion et al. (2016) found that, after 15 years, clean innovation stocks will surpass dirty stocks with a 40 percent increase in fuel prices compared to the 2005 fuel price. Furthermore, estimates for public policy suggest that a 10 percent increase in fuel prices faced by a company is likely to result in a 10 percent increase in green patenting and a 5 percent decrease in fossil fuel patents (Carrilho-Nunes and Catalão-Lopes, 2024; Carrilho-Nunes and Catalão-Lopes, 2020). Also, it was concluded that an increase in the price of electricity for industrial use also prompts a rise in the patents connected with solar and wind energy study, as studied by Diaz Arias and van Beers (2013), and so the increase in crude oil price will be an essential driver of renewable energy innovation. Indeed, existing empirical evidence indicates that changes in the relative price of energy inputs have an important effect on the types of technologies that are developed and adopted. For example, Newell et al. (1999) demonstrated that while stable energy prices led to cost-reducing innovations in air conditioners, the oil price hikes shifted the focus to enhancing their energy efficiency.

Empirical research has demonstrated how important regulatory frameworks are to the advancement of eco-innovation. These rules frequently take the form of a regulatory “push/pull effect", in which it has been discovered that the development and uptake of new clean technologies are greatly aided by a balanced combination of demand-pull and technology-push policies. Furthermore, econometric data indicates that a policy mix that equally makes use of these tools tends to have more favorable effects on environmental innovation (Costantini et al., 2017; Veugelers, 2012).

Furthermore, these interventions' strategic and temporal planning is essential. One example is Acemoglu et al. (2012) who show that production processes can be successfully shifted toward sustainability by temporarily taxing clean inputs in place of dirty ones. But they also stress the need for prompt action because postponing the implementation of these regulations may make the shift to “cleaner” production more difficult and expensive. Furthermore, specifically for Eastern European countries, historical research emphasizes how heavily these rely on subsidies as a result of the high costs of switching to greener production technologies, highlighting the economic difficulties and dependencies that can affect the efficacy of policy in different regional contexts (Horbach, 2016).

Diffusion is described by Fichter and Clausen (2019) as the purchase, use, imitation, or adaptation of an innovation by a growing number of persons or organizations as adopters, allowing for the spreading of innovations across various sectors, impacting not just market dynamics but also the adoption of new technologies and practices. Most research on the topic of diffusion of environmental innovation is focused on the two more successful sectors, renewable energy and energy efficiency. By analysing the dissemination rate, the authors reported one of the highest rates for environmental product innovation and services in the internet and computing sector at almost 50 percent, followed by 32 percent for energy-efficiency products and services, and 26 percent in the renewable energies sector. Such results, highlight the relevance of targeting higher diffusion rates by deploying a policy mix, characterized by a more balanced use of demand-pull and technology-push instruments (Costantini et al., 2017). However, Lanjouw and Mody (1996) argued that the effect of policy interventions also depends heavily on the severity of the instrument, while soft instruments, such as information-based interventions, can be very helpful in accompanying hard interventions in a policy mix. Alone measures are far from sufficient.

2.2.2 Path dependency

Path dependency, as discussed by Eitan and Hekkert (2023), Fouquet (2016), and Unruh (2009 and 2002), suggests that firms that have attained knowledge in the production of polluting products are more likely to continue to innovate in polluting patents. The contrary is also valid, firms that have historical skills in greener processes will accumulate more green patents and innovate in green technologies. This is why the concept of path dependency constitutes a barrier to the transition to clean energy. Therefore, given the current innovation panorama, there is a tendency to maintain a lock-in effect in dirty technologies and economies with high $C0_2$ emissions, even in the face of moderate carbon taxation or Research and Development (R&D) subsidies directed towards clean technologies. This situation underscores the necessity for more robust and heavier immediate actions to accelerate the clean energy transition. As the economy's knowledge base gradually shifts towards cleaner solutions, the intensity of these interventions could potentially be reduced in the future, aligning more closely with the evolving energy landscape whilst alleviating the previously hindered economic growth.

Member state priorities differ when it comes to harmonizing environmental policies within the EU due to national differences in energy intensities, sector structures, and environmental impacts. These conflicting priorities are frequently the result of technological lock-ins in pollution-intensive technologies, which complicate the transition to more sustainable innovation systems by generating large path dependencies (Cecere et al., 2015; Zeppini and van den Bergh, 2011). In such countries, environmental policy may be more important for the introduction and implementation of eco-innovations compared to countries that are already locked-in in environmental technologies. Furthermore, a nation's ability to create new environmentally conscious knowledge and infrastructure is just as important as its economic standing when it comes to making the switch from conventional, dirty technologies to “cleaner” alternatives. All of these things have an impact on a nation's capacity to abandon antiquated technology systems and adopt environmentally sound practices (Horbach, 2016).

2.2.3 Cooperation in the open approach

The topic of cooperation is very significant when assessing innovation between firms. When this is aligned with open approaches, it broads the possibilities of companies to achieve innovations and paradigm shifts. It is subdivided into four categories, open movement, open innovation, non-producer innovation, and business model innovation. These cooperations arise as a way to reinforce transparency and collaboration between entities that innovate, which supports more efficient research, reduce costs, and opens up new market opportunities. Indeed, cooperation, can take place between companies and customers, suppliers, competitors, universities, private or public R&D laboratories, and others. Together, these enable a transformative framework for modern businesses. Horbach (2016) argues that, compared to more established innovation fields, some eco-innovation areas are relatively new, such as electromobility and renewable energies. As a result, these areas rely more on outside information sources and fundamental research activities. Therefore, when it comes to eco-innovation, universities and other research institutions are important players. Local cooperation networks may concentrate especially on fostering eco-innovation since information flows appear to be especially crucial for emerging technologies (De Marchi, 2012; Ghisetti et al., 2015). However, Greco et al. (2017) pointed out that despite collaboration with other actors, especially universities, companies in the power and energy sector are still more interested in developing incremental and low-risk innovations.

The open movement expands access to information and increases transparency and participation in various sectors, while open innovation allows companies to overcome traditional R&D boundaries by integrating external ideas and technologies. When applying open innovation to for-profit companies, it is assumed that many, if not most, experts and innovation potential reside outside the company. However, this does not stop the company from investing in its internal research and development, as the scarcity of internal research and development resources can constrain an organization's ability to venture into new knowledge domains, as evidenced by its limited absorptive capacity (Cohen & Levinthal, 1990; Pihlajamaa et al., 2017).

Non-producer innovations allow end users to directly address specific needs, promoting user-driven solutions that are more likely to succeed because of their relevance and practicality. At the same time, business model innovations enable companies to quickly adapt to changing market demands and technologies and leverage collaborative and transparent practices to promote sustainability, efficiency, and competitive advantage. Pinkse et al. (2023) and Snihur and Zott (2020) defend that companies must abandon their current business models and come up with creative ideas that meet the demand of clients but also align with net zero emissions, which entails a significant amount of organizational de-learning by managers and staff, possibly having to readjust the company’s mission to meet both targets.

Together, these strategies promote a more inclusive, adaptive, and sustainable approach to business innovation and market presence (Dall-Orsoletta et al., 2022).

2.2.4 Firm size

Employment is influenced as well by a change in a company's behavior towards a sustainable goal, as noted by Horbach and Rennings (2013). For example, an innovation that allows for lower resource consumption for the same output will make the innovating firm's product more competitive as the price falls, leading to higher demand and an increase in employment. This can be used to justify the argument that innovative companies are characterized by significantly more dynamic employment development compared to non-innovative companies. With end-of-pipe technologies, however, this effect might not be as beneficial to the business as it would be with “cleaner” technologies. Despite this, when describing the effect of job creation by environmental innovation activities, some authors such as Horbach (2010), Pfeiffer and Rennings (2001), and Rennings and Zwick (2003) argue that the effect is not as relevant as some may consider. Despite this, for firms to conduct an internal change towards environmental innovation, firms should strive to attract employees with green skills. These workers are believed to be able to evaluate the cost and benefits of net-zero investments and promote them internally to directors. Despite this, it should be noted that attracting and retaining this specialized workforce that is as of now, limited could be a challenge in hard-to-abate sectors, such as the energy industry (Demirel and Kesidou, 2019; Stern and Valero, 2021).

Regarding number of employees, Hermansen (2011) used survey data on innovative activities of Danish firms to assess the relationship between firm size and innovation and discovered a U-shape effect, meaning that compared to medium-sized businesses, small and large businesses are more likely to engage in innovative activities. Axenbeck (2019) studied the effect of environmental innovations on firm profitability with respect to firm size and showed that small and medium-sized enterprises generally benefit more from these innovations than large enterprises.Andries and Stephan (2019) found that large firms benefit financially when environmental innovations are driven by regulation, whereas small firms benefit more from customer-driven environmental innovations.

2.2.5 Market demand

In addition, a model that demonstrated the areas in which the market size effect could be seen was conducted by Acemoglu et al. (2012), encouraging innovations in the direction of the larger demand where higher profits are possible. Following the same reasoning, the price effect was also noted, with innovations moving in the direction of the highest possible price. The laissez-faire equilibrium leads to an “environmental catastrophe” in which the quality of the environment falls below a critical threshold. Indeed, technological innovations in a concentrated market are more likely to be promoted by large companies with monopolistic power (Schumpeter, 1912). This is the well-known Schumpeterian hypothesis, which states that the main factors affecting innovation are market structure and company size. Lunn (1986) distinguished between process and product innovation after using the number of patents as a measure of inventive activity and found out that although there was no significant relationship between concentration[6] and product innovation, there was a statistically significant relationship between concentration and process innovation.

Related to this, exposure to prosocial attitudes and a market with strong competition also fosters clean innovation, where significant increases in these together can have the same impact as a large fuel-price increase (Aghion et al., 2020). Consumers can have a significant impact on business decisions in the energy sector, especially when they demand “cleaner” products. One important factor that stands out is the interaction between market structure, competition, and consumer preferences, which tends to have a pro-climate effect. Overall, Acemoglu et al. (2023) concluded that civil society action and knowledgeable consumers can in fact be strong catalysts to reroute corporate innovation toward environmentally friendly technologies.

2.2.6 Research and Development

R&D expenditures play a crucial role in driving innovation, particularly in the development of renewable energy technologies. Greco et al. (2017) specifically identify several challenges within the power and energy sector that necessitate substantial investments in R&D, such as enhancing the efficiency of solar photovoltaic systems, advancing energy storage methods, and addressing the decommissioning and cleanup of nuclear sites. These investments are significantly influenced by a variety of determinants, including technological availability, governmental policy interventions, such as subsidies, and fluctuations in market conditions, such as fuel prices.

Furthermore, an analysis of eco-innovation determinants in Eastern European countries by Horbach (2016) reveals significant disparities in R&D investments compared to Western Europe. The general level of R&D expenditure as a percentage of gross domestic product (GDP) in these countries is notably lower than the EU average (2,24 percent in 2022). This indicates a pronounced reliance on external knowledge sources, reflecting a lower development level, different environmental priorities, less environmental awareness among the population, and higher energy intensity within their economies (Eurostat, 2023).

If research and innovation systems are how technology is learned, it is expected to have far more widespread effects than just bringing down the price of a single technology (Criqui et

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[6] Concentration measures how much an industry is dominated by a few firms. High concentration means that a small number of firms hold a large market share, typically leading to reduced competition and potentially influencing innovation, pricing, and barriers to market entry.

al., 2015). This gives researchers even more reason to concentrate their efforts on examining how the energy sector's growth affects innovation and research systems collectively (Lekavičius et al., 2020). Lastly, the positive relationship between patents and technological development, as explored by Hidalgo and Molero (2009) and further supported by Kim and Brown (2019), demonstrates how governance processes that strengthen energy performance standards alongside consistent R&D investments can significantly enhance energy innovation. Lin and Chen (2019) also contribute to this understanding by showing that R&D expenditures and economic growth not only provide short-term benefits but also have long-term positive implications for renewable energy technological innovations, with electricity pricing affecting only the long-term patenting of these technologies.

Notably, the effect on innovation of R&D expenditures combined with company size was studied by Scherer (1965a, 1965b). The results showed that there is a proportional increase of innovations with the firm size until the firm becomes larger than the threshold level, which in 1955 was the equivalent of 500 million dollars in sales. Contrasting this, Shefer and Frenkel, (2005) and Morton and Nancy (1982) argued that R&D and its innovative potentially innovative output do not increase proportionately with firm size and that in more high-tech industries, the relationship was proved to be negative. Cohen et al. (1987) found an insignificant relationship between R&D intensity and firm size.

In line with the findings of Acs et al. (1994), small businesses can create innovative products with comparatively little financial investment because they can take advantage of the knowledge already in existence from university research and R&D from large corporations. That is, when there are significant R&D spillover effects, innovation can be fostered. Against this backdrop, Ugur et al. (2020) concluded that R&D spillovers tend to have lower productivity effects and lower statistical significance compared to in-house R&D and that own R&D is necessary to build absorptive capacity and secure profits from external knowledge effects.

3 Data Characterization

This chapter outlines the Community Innovation Survey (CIS), the dataset used in this analysis. It further details the variables analysed and provides a preliminary analysis, emphasizing the trends of each variable in understanding innovation dynamics within European energy firms.

3.1 Community Innovation Survey

The CIS serves as a crucial source of information on innovation within the European enterprise sector. Initiated in 1992, the survey operates on a biennial data collection cycle. Each iteration of data collected is referred to as a wave, with the 2018 CIS representing the most recent wave available for all surveyed countries. A wave in this context denotes the complete set of data collected during one iteration of the survey, encompassing responses from numerous firms about their innovation activities within a specified timeframe. For example, the 2018 wave's data refers to the period from 2016 to 2018. The participants are companies from the European Union, EFTA countries, and EU candidate countries, which answer anonymously and must have more than ten employees. The survey follows the Oslo Manual that ensures uniformity and comparability of data across the different countries, covering several key definitions such as innovative firms, product innovations, process innovations, and more recently broadening their scope to capture non-technical forms of innovation and social and service innovations. In the CIS, innovation can be characterized in different profiles, varying from new-to-market innovations to non-innovators, enabling a better comparison between innovation behaviours, and the role of each company in the development process. Improvements in data quality and relevance were introduced in CIS 2018, where the aim was to make the questionnaire more inclusive for non-innovators by avoiding selective filtering based on the innovative status of the company, thus allowing comparisons between innovative companies and non-innovative companies that are more valuable for policy and research (Eurostat, 2023).

Several previous studies have analysed innovation drivers through CIS such as Horbach (2016), concerning eastern European countries, Zastempowski (2023) for a specific year and Frenz and Ietto-Gillies (2009) for a specific country, to name a few. The data is highly relevant for policymakers and researchers as it provides insights that inform national and EU-level innovation policies, such as the European Innovation Scoreboard.

In this dissertation, we considered three waves of the European CIS (2014, 2016 and 2018). The countries considered were Bulgaria, Germany, Greece, Spain, Hungary, Norway, Portugal and Slovakia.[7] The data set is cross-sectional, meaning that there is no tracking for the same firm in different years.[8] Since the goal of our work is to analyse innovation for energy firms, the NACE code used was the 35 which corresponds to the sector of electricity, gas, steam and air conditioning supply, and the data set has 703 observations.

3.2 Variables Description

To examine the impact of innovation determinants discussed in previous research, this study structures its analysis around several key variables derived from survey questions. The analysis initially focuses on dependent variables, which assess whether a company has engaged in any innovation, and then categorizes the type of innovation into product-only innovation, process-only innovation, both product and process innovation, and whether the company has sought to protect its innovations through intellectual property rights.

The classification of company innovation is initially determined by a binary variable that identifies whether any innovation—product, process, or both—has occurred, assigning a value of 1 for innovation presence and 0 for its absence. Subsequently, more specific binary variables are introduced to detail the type of innovation. One variable marks a value of 1 if the company exclusively innovated in products and 0 in all other cases, including those without any innovation. Another variable similarly identifies companies that only innovated in processes, also marked 0 for non-innovators and those involved in other types of innovation. Lastly, a variable is used to identify dual innovators, assigning a value of 1 to companies that introduced both product and process innovations and 0 to all others, including those that innovated in only one type or in none.

Furthermore, the binary variable for intellectual property reflects whether a company has sought to protect its innovations through patents, utility models, industrial designs, trademarks,

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[7] The countries excluded from the analysis due to low response rates across the three waves were the Czech Republic, Spain, and Romania. Additionally, there were no Belgian companies that participated in all three waves, resulting in Belgium's absence from the study.

[8] Cross-sectional data refers to information collected from multiple subjects (such as individuals, groups, or entities) at a single point in time. This type of data snapshot is used to examine a phenomenon across a sample at one moment, rather than looking at changes over time.

trade secrets, or copyrights, marked as 1 if any of these protective measures were taken, and 0 if none were employed. This enables an analysis of the factors driving innovations that the firm deemed valuable enough for protection.

For the independent variables, public funding is assessed by whether a company received any form of public funding. This includes support from the European Union, national governments, or local and regional authorities. It is coded as 1 if the company received funding, and 0 otherwise. This variable serves as a proxy for subsidies and policy incentives that encourage firms to invest in innovative activities, such as the EU Horizon 2020 program (Nordhaus, 2007; Acemoglu et al., 2023b; Horbach, 2016; European Comission, 2023b).

Cooperation is measured by being marked with the value 1 if the company engaged in cooperation, such as with other enterprises within or outside its enterprise group, suppliers, clients, competitors, research institutes, consultants, laboratories or universities, 0 if none of these happened (Frenz & Ietto-Gillies, 2009). The effect captured here is the open movement, specifically open collaboration, that allows pooling innovation capability between different entities (Horbach, 2016; De Marchi, 2012; Ghisetti et al., 2015).

The logarithm of the turnover of the company is performed, as a measure of the company performance, also present in the study of Horbach and Rennings (2013).

Regarding the firm’s workforce, the indicator of the number of employees represents the size of the firm in line with Horbach (2016), distinguishing between companies that have 250 or more employees, having a value of 1, and the companies that have below 250 employees, getting the value of 0. To evaluate the effect of the education level of employees, the indicator gets the value of 1 if more than 25 percent of employees have a tertiary degree, 0 otherwise, a common variable for this assessment, also used by Horbach and Rennings (2013). The 25 percent threshold was chosen because it is the closest possible value to the average level of employees with a higher education in EU Member States, which was 31.8 percent in 2022 (Eurostat, 2022).

Our analysis also includes country dummy variables for Bulgaria, Germany, Hungary, Norway, Portugal, Slovakia (with Greece being the omitted variable serving as base). Finally, the wave dummies of 2018, 2016 taking the value 1 if it corresponds to the selected year, 0 otherwise, with the omitted wave of 2014 being the base variable.

3.3 Descriptive Statistics

In this section, we describe the sample to gain a better understanding of the data that will be used in the models and to perform a preliminary analysis in order to signal potential trends or effects that will be examined in more detail in Section 5.

Since the dependent variables used are directed towards the innovations of firms, the distribution of this behaviour and the type of innovation should be analysed. To better understand this metric, Figure 3 shows that most innovation is in processes, which is consistent with the activity sector examined. Most energy firms focus their efforts on process optimization to achieve greater resource efficiency and energy efficiency. Dual innovation in products and processes accounts for the second-largest share of innovations, at 37 percent, followed by product-only innovators, who account for 16 percent of all innovations, which include many of the most recent technological advancements in solar panels, wind turbines, smart grids, electric vehicle charging stations, and carbon capture and storage, to mention a few other areas.

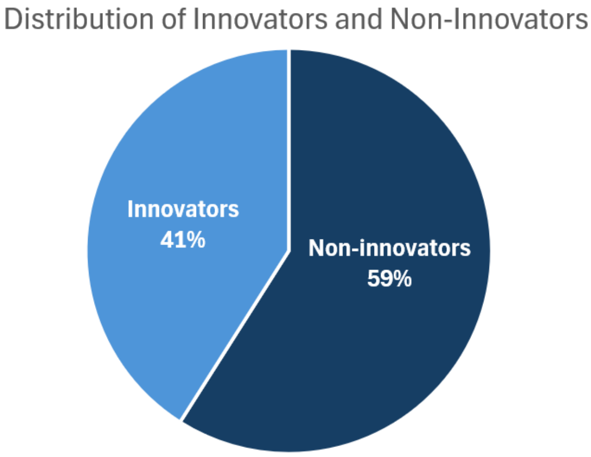

Figure 3. Percentage of firms that innovated and did not innovate during the time period considered.

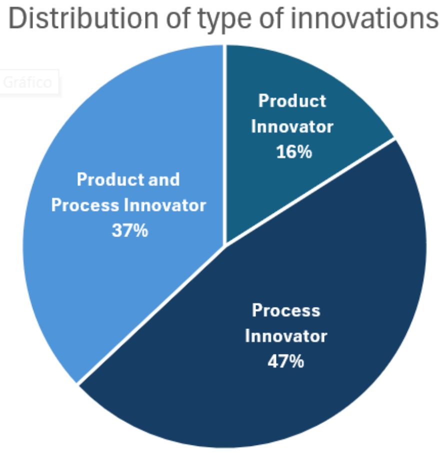

Figure 4. Percentage of the type of innovations.

Given the significant role subsidies play in fostering innovation, Figure 5 highlights the primary sources of public funding, with the EU and Central Government providing the majority of these funds. While definitive conclusions regarding the impact of these funding programs on innovation cannot be drawn from this section alone, a preliminary comparison between the proportion of innovative firms that received funding and those that did not reveals a notable discrepancy. Specifically, firms that received funding demonstrated a 41 percent higher incidence of innovation compared to their unfunded counterparts (Figure 6). This observation underscores the importance of further analysis and suggests the potential positive effects of these funding initiatives on firm-level innovation.

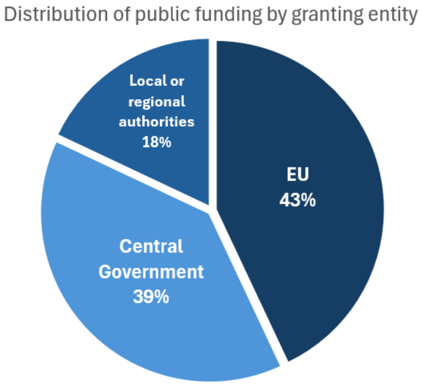

Figure 5. The sources of public funding granted to companies.

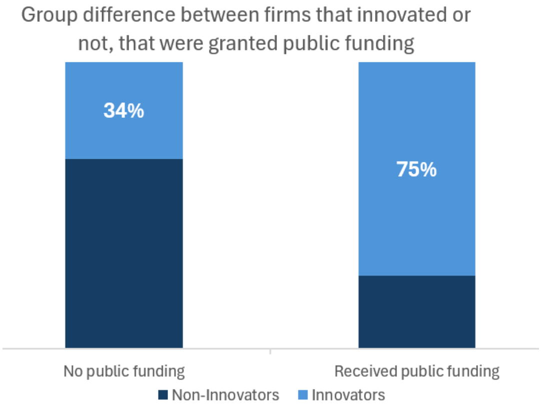

Figure 6. Comparison between companies that innovated and companies that did not, divided by being or not granted public.

Cooperation between entities is another frequently discussed determinant of innovation in the literature. Figure 7 shows that 31 percent of firms engaged in cooperative agreements, while the remainder did not. An analysis of the frequency of cooperation types in Figure 8 reveals that suppliers are the most common partners, which may stem from the role of suppliers in providing essential components and advanced materials for the development of new energy technologies. These are followed by consultants, commercial labs, and private research institutions, withing the enterprise group, clients, universities, the government, and competitors.

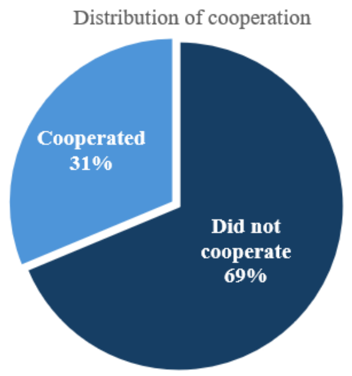

Figure 7. Percentage of companies that incurred in innovations and the companies that did not.

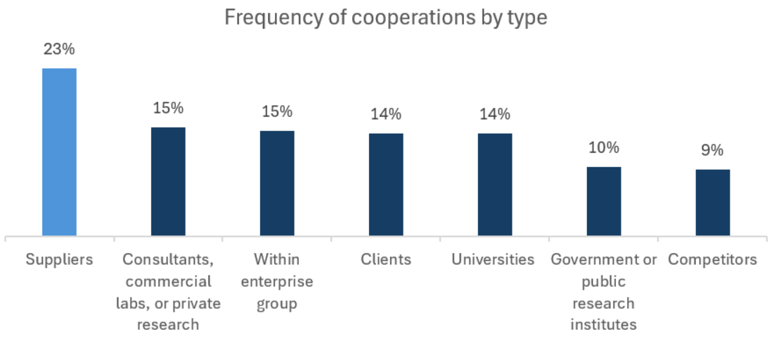

Figure 8. The percentage of each type of cooperations incurred by firms.

Transitioning to workforce dynamics, Figure 9 delineates the disparities in innovative behaviour between smaller companies, which have fewer than 250 employees, and larger companies with 250 or more employees.

Echoing the trends observed in Figure 6 regarding public funding and observing Figure 9, larger companies exhibit a 25 percent higher incidence of innovation compared to their smaller counterparts, suggesting that workforce size may significantly influence innovation output. Additionally, regarding educational attainment as shown in Figure 10, the proportion of innovative firms among those with at least one quarter of their workforce possessing tertiary education actually decreased. This observation warrants further analysis to draw definitive conclusions about the impact of educational level on innovation.

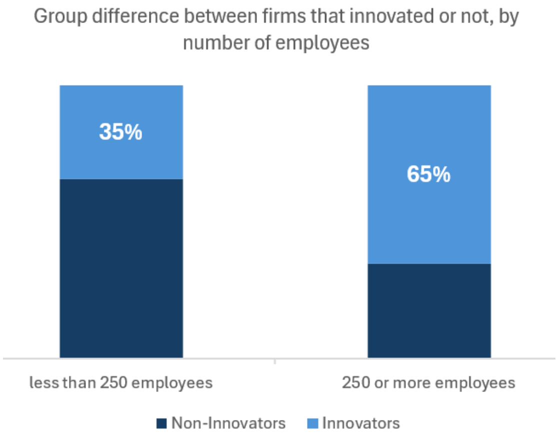

Figure 9. Comparison between companies that innovated and companies that did not, divided by having less than 250 employees, or 250 or more.

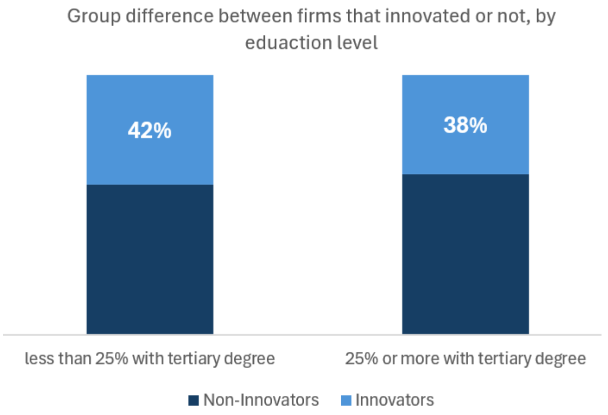

Figure 10. Comparison between companies that innovated and companies that did not, divided by having less than 25 percent of employees with a tertiary degree, or 25 percent or more.

Table 1 provides an overview of the descriptive statistics of the variables, including number of observations, standard deviation, mean, maximum, and minimum. In addition to previous analyses in this chapter, the distribution of innovation types within the dataset reveals that 6.4 percent of firms are product-only innovators, 19.1 percent are process-only innovators, and 11.6 percent are dual innovators. Regarding intellectual property, 11.6 percent of companies pursued protection for their innovations. For financial support, 16.8 percent of firms received public funding. By using the exponential of the average logarithm of turnover, the calculated average turnover for firms is approximately 200 million euros. On average, firms spend about 1.5 percent of their turnover on innovation. From a human capital perspective, 33.7 percent of firms have over 25 percent of their workforce holding a tertiary degree, and 20.1 percent of firms employ more than 250 people.

Table 1. Descriptive Statistics

Variable	Observations	Mean	Std. Dev	Min	Max
Innovator	703	0.407	0.492	0	1
Product only innovator	703	0.064	0.245	0	1
Process only innovator	703	0.191	0.393	0	1
Product and process innovator	703	0.152	0.359	0	1
Protected innovation	696	0.116	0.321	0	1
Public funded	703	0.168	0.374	0	1
Cooperated	703	0.313	0.464	0	1
Turnover logarithm	703	16.827	2.212	11.280	22.738
Innovation expenditure (share of turnover)	703	1.459	10.399	0	187.163
University degree[9]	703	0.337	0.473	0	1
Company size[10]	703	0.201	0.401	0	1

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[9] Measuring if the company has 25 percent or more employees with tertiary degree.

[10] Measuring if the company has 250 or more employees working for the company.

4 Research Methodology

With the variables chosen as measures of possible firm’ effects on innovation, we proceed with our empirical analysis applying econometric methods. The estimated marginal effects are read according to the *ceteris paribus* concept, whereby when comparing the effect of an independent variable such as the firm's performance on a dependent variable that measures whether the firm is innovative or not, it is essential to take into account all other remaining variables constant to ensure that the effect of the other independent variables in the model does not influence the effect being studied on firm performance. In this study, the probit model is used to estimate these effects since it allows to estimate the effect of several independent variables on a binary dependent variable, assuming a non-linear relationship between each other.

4.1 Probit Model for Binary Response

The probit model is commonly used in the literature for models with a binary dependent variable, meaning that this variable can only take two values, 1 or 0. When dealing with such variable, the goal is to assess the probability of the response represented by Equation 4.1, using k independent variables.

$$P(y=1|x) = P(y=1|\, x_1, x_{2,} \ldots . x_k). \qquad (4.1)$$

Such binary variables can have a simple application and interpretation through the Linear Probability Model, but the relationship between the dependent and independent variables is assumed to be linear, which makes it not suitable for many cases. Not only the second unit’s increase effect is assumed to be the same as the first but there is also the potential to predict probabilities outside the 0 to 1 range, the second major drawback of this model.

Unlike the Linear Probability Model, there are models that assume a non-linear relationship, such as the Probit Model or the Logit Model. The choice between these, comes down to preference (Pinzon, (2016)) since the results do not significantly differ and so in this instance, the probit model was chosen.

So, to analyse the model in a linear way so that it is possible to infer on the effect of one variable, ceteris paribus, on the outcome success or failure, in this work, a latent variable is used. This variable, presented in Equation 4.2, is a linear combination of the independent variables and is not directly observed, but is assumed to underlie the observed binary outcome.

$$y^* = \beta_0 + x\beta + e. \tag{4.2}$$

Where,

$$Y = \begin{cases} 1, if\ y^* > 0 \\ 0,\ otherwise \end{cases} \tag{4.3}$$

This latent variable is then used on the cumulative distribution function of the standard normal distribution denoted by Φ, which assumes that the error term is normally distributed with average of 0 and standard error of 1. This function ensures that all predicted probabilities are within the range of 0 to 1, and is described in Equation 4.4.

$$\Phi(z) \equiv \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{t^2}{2}} dt. \tag{4.4}$$

This function is then used in the Maximum Likelihood Estimation (MLE) equation, observed in Equation 4.5, with *i* observations and *k* variables, to compute the total likelihood of observing the entire data set given the independent variable’s parameters, where β is a vector containing all coefficients associated with the independent variables that are predicting the outcome.

$$L(\beta) = \prod_{i:Y_i=1} (\Phi(\beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki})) \prod_{i:Y_i=0} \left(1 - \Phi(\beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki})\right). \tag{4.5}$$

For mathematical convenience and computational stability, the logarithm is applied to equation 4.5, and the following Equation 4.6 is obtained.

$$logL(\beta) = log \sum_{i:Y_i=1} \big(\Phi(\,\beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki})\big) + log \sum_{i:Y_i=0} \big(1 - \Phi(\,\beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki})\big). \qquad (4.6)$$

The beta coefficients are then adjusted through iterative optimization algorithms that aim to maximize this log-likelihood. Each iteration updates the parameter estimates to increase the log-likelihood, refining the model's fit to the data based on how well the predicted probabilities match the observed binary outcomes. The resulting probability of the event occurring is represented in Equation 4.7.

$$\mathrm{y} = \Phi(\,\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k). \qquad (4.7)$$

Post-model fitting, it is important to look at how one can read the coefficients in the Probit Model regression. Since it involves a non-linear transformation using the cumulative distribution function of the standard normal distribution, the coefficients do not directly translate to the change in probability of the outcome variable y being 1. So, by using Equation 4.8 one can capture the marginal effect of the x_k on the probability y, for observation 1.

$$ME = \frac{\partial y}{\partial x_1} = \beta_1 \Phi(\,\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k). \qquad (4.8)$$

The Average Marginal Effect for each independent variable is then obtained by averaging these individual effects across all observations, expressed in Equation 4.9.

$$AME_i = \frac{1}{n} = \sum_i \beta_k ME_i. \qquad (4.9)$$

5 Results

5.1 Probability of Innovating

The approach used to build the models in Table 2 is a stepwise regression, where each variable is added one at a time, to understand if there were changes in significance of variables from one model to another. Due to the lack of a clear hierarchy of innovation drivers in the literature, the variable selection in the stepwise regression model was systematically organized.

It began with variables influenced by external entities, specifically public funding and cooperation. Next, the logarithm of turnover, a variable reflecting the companies' market context. The analysis then progressed to firm-specific variables, starting with expenditure on innovations, to directly measure financial commitment to innovation activities, which was followed by the two workforce-related variables, tertiary degree and number of employees. Before delving into the marginal effects of each variable, it is thus possible to see that with the three first variables, public funding, cooperation and the logarithm of the turnover, when the following variable was added, the marginal effect of the variable already being measured decline showing that the added variable had an effect on the probability of the firm innovating that was being measured by the variable that was already in the model.

Now, from Table 2, observing the marginal effects of Model 7, one can infer on the effects of the variables, on the probability of firms innovating. A firm getting access to public funding, either by the EU, national or local authorities, increases its probability of innovating, on average, by 23.4 percentage points, significant at the one percent level. For a firm that co-operated with other public or private businesses, universities, government or clients, it is 20.7 percentage points more likely that on average, this firm will innovate compared to companies who did not cooperate.

As a control for market demand for the company’s products, the logarithm of the turnover, showed that if a firm increases its turnover by 1 percent, it has now a higher probability of innovating of, on average, 0.049 percentage points.

Regarding expenditures in innovation, for a 10 percent significance level, a company that increases its spending by 1 percentage point as share of turnover will have, on average, a higher possibility of innovation by 1.1 percentage points.

For variables such as university degree, which accounts for firms where a quarter or more of employees hold a tertiary degree, and company size, defined by having more than 250 employees, the impact on the likelihood of firm innovation was not statistically significant, and thus no conclusions can be drawn.

*Table 2. Marginal effects from a probit model (robust standard errors in parentheses). The dependent variable measures if the company innovated or not. All regressions include year dummies, and the last model includes country dummies; significant at * significant at 10 percent, **significant at 5 percent, and *** significant at 1 percent.*

Innovator	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7$^{\text{Note}}$
Public funded	0.381^{***}	0.249^{***}	0.250^{***}	0.246^{***}	0.239^{***}	0.241^{***}	0.234^{***}
	(0.045)	(0.049)	(0.048)	(0.049)	(0.049)	(0.039)	(0.039)
Cooperated		0.358^{***}	0.301^{***}	0.298^{***}	0.296^{***}	0.216^{***}	0.207^{***}
		(0.039)	(0.042)	(0.042)	(0.042)	(0.031)	(0.031)
log(Turnover)			0.031^{***}	0.032^{***}	0.026^{***}	0.048^{***}	0.049^{***}
			(0.007)	(0.008)	(0.009)	(0.009)	(0.009)
Innovation Expenditure (share of turnover)				0.001	0.001	0.000	0.011^{*}
				(0.001)	(0.001)	(0.001)	(0.005)
University degree					-0.014	-0.051	-0.048
					(0.033)	(0.032)	(0.031)
Company size					0.069	-0.009	-0.012
					(0.049)	(0.045)	(0.045)
Wave Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	No	No	No	No	Yes	Yes
Pseudo R-squared	0.145	0.234	0.251	0.251	0.254	0.355	0.361
Log likelihood	-406.386	-364.064	-355.853	-355.695	-354.438	-306.525	-303.262
N	703	703	703	703	703	703	703

Note: Model 7 includes an interaction between companies that received public funding, and their expenditure on innovation in order to assess if the impact of these expenditures on the probability of the firm innovating becomes significant when the company has already received public funding. The coefficient of this interaction does not appear on Table 2. due to the fact the coefficients displayed are average marginal effects, and so this coefficient is shown in Table 6, in the appendix, in the probit model before calculating the marginal effects.

Model 7 includes an interaction between public funding and innovation expenditure to determine if the likelihood of a firm innovating is significantly influenced when it has received public funding. This model aims to uncover whether public subsidies enhance the effectiveness of firms' investments in innovation, since the significance of this measure highly contrasted with the literature. The coefficient for this interaction, however, is not presented in Table 2 because that table lists average marginal effects. Consequently, to provide a focused analysis of this interaction, Table 3 displays the marginal effect of increasing innovation expenditures as a share of turnover, computed separately for firms receiving public funding or not.[11]

Table 3. Marginal effects of the interaction shown in Table 2 of the probit of model 7, between companies being granted public funding and their expenditure in innovation as share of turnover.

Innovator	Model 7
Public Funding=0 #Expenditure Innovation	0.014**
	(0.007)
Public Funding=1 #Expenditure Innovation	-0.002
	(0.002)
N	703

For companies that did not receive public support, an increase in innovation spending by 1 percent correspondingly raised their likelihood of innovating by an average of 1.4 percentage points. In contrast, for companies that received public funding, an increase in expenditure on innovation does not have a statistically significant impact on their probability of innovating.

One possible explanation may relate to the nature and constraints of the funding itself. Public funding is often allocated with specific criteria and for predefined projects, which might limit a firm's flexibility to explore beyond the agreed-upon activities. These funds could be tied to technological areas or types of innovation that are deemed important by policymakers rather than by market-driven needs. As a result, while the funding ensures that certain innovative activities are pursued, it might not necessarily increase the overall likelihood of innovation beyond these boundaries. Furthermore, public funding can sometimes lead to a dependency effect, where firms become reliant on external financial support and reduce their internal investments in R&D. This could inadvertently dampen the intrinsic innovative capabilities or motivations within the company. In contrast, firms without public funding may feel more

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[11] The probit model’s coefficients used for computing the marginal effects in Tables 2 and 3 are displayed in Table 6 in the Appendix, where the coefficient of the interaction is shown, and thus it is possible to assess that the difference between the effect measured for both groups in Table 3. By looking at the coefficient of the interaction in the probit model, which is -0.061 and significant at a 5 percent level, one can infer that the effect between the two groups is in fact different, or in other words, that the interaction is statistically significative.

pressure to innovate to compete and survive in the market, leading to a more significant impact of increased innovation spending on their likelihood of innovating. These privately funded initiatives might also be more aligned with market needs and immediate business objectives, potentially leading to more directly observable innovative outcomes.

5.2 Probability of Innovating in Each Type of Innovation

Observing the two models in Table 4, after analysing Table 2, allows for a clear view on the differences between the effect of innovation' drivers for different types of innovation, *ceteris paribus*. The first model contrasts companies that have exclusively engaged in either product innovation or process innovation, highlighting the differences between these singular focus areas. The dependent variable is assigned a value of 1 if the company innovated only in product, and 0 if it only innovated in process. The second model examines firms that are dual innovators, those that have participated in both product and process innovations assigning them a value of 1 and compares them to companies that have committed solely to one type of innovation, being assigned a value of 0. This section strategically excludes non-innovators to sharpen the focus on the comparative effects among these specific groups of innovating companies.

Regarding the obtaining of public funding, the only significant result was for product and process innovators which for a 5 percent significance level, are 12.4 percentage points more likely, on average, to introduce innovations if they get access to this capital, compared to companies that only produce one type of innovation.

For cooperation, if firms innovate in both types of innovations, their chance of introducing innovations rises by 16.2 percentage points on average, compared to companies that only innovate in one type. No conclusions are drawn from the analysis of the logarithm of the turnover of the firm and for the difference in the number of employees, since there were no statistically significant marginal effects.

When assessing the level of education of employees, the impact on the probability of innovating of having more than one quarter of employees with a tertiary degree is greater by 18.6 percentage points, on average, for companies that innovate only in product, compared to those that only innovate in process. For firms that are dual innovators, the chance of introducing an innovation is higher on average by 11.8 percent compared to one-type innovators.

*Table 4. Marginal effects from a two probit models (robust standard errors in parentheses). The first measures product innovation (Model 1), with the base outcome being innovating only in processes; and the second model, measuring the firms that innovated in product and process innovation in the same CIS wave, the base outcome is innovating in only one type. All regressions include year dummies and country dummies; * significant at 10 percent, **significant at 5 percent, and *** significant at 1 percent.*

Type of Innovator	(1) Product only and process only	(2) Product and Process
Public funded	0.010	0.124^{**}
	(0.076)	(0.059)
Cooperated	0.057	0.162^{***}
	(0.066)	(0.054)
Log(Turnover)	-0.025	-0.001
	(0.021)	(0.017)
Innovation Expenditure (share of turnover)	-0.007	0.002
	(0.006)	(0.003)
University degree	0.186^{***}	0.118^{**}
	(0.070)	(0.059)
Company size	0.029	0.119
	(0.095)	(0.076)
Wave Dummies	Yes	Yes
Country Dummies	Yes	Yes
Pseudo R-squared	0.137	0.234
Log likelihood	-87.140	-158.764
N	179	286

5.3 Analysis of Findings

The first finding on the probit model estimating the probability of firms being innovators or not is that firms getting access to public funding are more likely to innovate, by a significant percentage, which is in line with the literature that claims that research subsidies are one of the main drivers of innovation for energy firms, and that it allows for a direction shift of innovations, toward “cleaner” technologies (Porter and Linde, 1995; Acemoglu et al., 2023b; Horbach, 2016). When analysing this effect for different types of innovation, the impact of receiving public funding, or in other words, subsidies, is higher for companies that innovate in product and processes, compared to one-type innovators. The study by IRENA (2018) confirms this, with energy companies relying heavily on product and process innovations, specifically because now they must answer to the penetration of renewable energy and empowerment of consumers through digitalization that requires significantly more flexibility in the system to guarantee the supply and correspond to the new energy and environment goals. It is important to mention the study of Wiesenthal et al. (2012), where public funding is believed to be insufficient to increase innovation levels in energy firms to the point where they are able to overcome these challenges.

Concerning cooperation, the results were also in line with several studies regarding the open movement and specifically open collaboration, such as Greco et al. (2017), De Marchi (2012) and Ghisetti et al. (2015), mentioning that these partnerships enable companies to achieve innovations, especially if the areas where the innovations are taking place are new, and thus more information sources are needed. Richter (2013) confirms the conclusion that cooperations between dual-innovative firms have a higher innovation potential compared to one-type innovators where these external R&D strategies, aligned with internal R&D and acquisition of machinery strategies is the way that energy firms can improve their business model innovation to meet the four goals of companies in this sector, product and process innovation, reducing environmental impacts and meet regulatory requirements. Daim et al. (2013) and Sanyal and Cohen (2009) studies are also in line with the effect concluded and add that the benefit of these cooperations is not only to share information in a complex sector but also as a risk-sharing strategy, where firms can undertake different projects with the same amount of resources but using collaborations for hedging against uncertainty.

The turnover was also a significant determinant for innovation, as a proxy for customer demand for the company’s product, also used by Horbach and Rennings (2013). Although the measure does not distinguish between dirty and clean innovations and considering that the turnover of energy firms is directly related to the type of energy that the firm is selling, the will of the customer to buy only clean energy can influence the firm innovating in that direction. The literature considers customer demand as a main determinant of innovation, specifically for eco-innovations, where this effect is sometimes considered to be stronger (Kammerer, 2009; Prokop et al., 2019; Horbach et al., 2012). Despite this, one could argue that, for instance, a company that increases its turnover has more flexibility to risk investing in new innovations, and thus eventually develops more innovation output, especially in a heavily machine-dependent industry such as the power and energy sector where high capital is a necessity. On the other hand, a company whose turnover is solid and positive may indicate that it has already established its market presence, and the goal can either be to innovate, for instance, in the supply chain or to halt the innovation process until it is needed again. Baporikar (2015) argues that there are two scenarios, the first being that the culture of innovation is best sustained when there is a balance between uncertainty and fear in the market and therefore there should be some budget for developing experiments when there is a downturn in the market, only to stimulate the innovation process again when the market is rising. The second scenario states that companies only produce significant innovation achievements when they are in a crisis.

For level of education, measuring if a firm that has a quarter or more of the company's employees with a tertiary degree, and company size, measuring if the company has more than 250 employees, the impact on the probability of the firm innovating probability was not statistically significant. This result follows some of the literature findings but contradicts others. For education level, in fact, EBRD (2014) reported also that the effect on innovation as not significant and the reasoning is that the ratios of education capture the quantity and not the quality. The same can be applied to the number of employees of the company, which also captures the quantity and not the innovative quality, capacity, or capability. This creates a barrier to assessing this result, especially when qualified workers are considered crucial and lacking in the energy industry (Demirel and Kesidou, 2019; Stern and Valero, 2021). Several studies have thus, found that the effect is not significant (Horbach, 2010; Pfeiffer and Rennings, 2001; and Rennings and Zwick, (2003), while others found significant results, but in opposite directions, such as Hermansen (2011), Axenbeck (2019) and Andries and Stephan (2019).

5.4 Robustness Analysis

To evaluate the robustness of the findings presented in the previous chapter, a robustness analysis was conducted. This analysis aims to analyse the innovation process from a different approach by differentiating between the act of innovating, previously assessed, and the effectiveness or value of the innovation. Specifically, this assessment focuses on the dependent variable intellectual property, which gauges whether a company sought to secure protection for its innovation through intellectual property rights. This decision often reflects a firm's assessment of an innovation's potential impact or quality, suggesting a strategic investment in innovations that offer considerable competitive advantages or market potential. While this approach sets aside innovations that may be important for sustainability but not directly profitable, it remains a relevant measure for examining how the importance of certain drivers might shift when focusing on innovations perceived as valuable enough to protect.

Intellectual property rights play a dual role in innovation ecosystems. In a traditional closed innovation model, these rights serve to exclude competitors, securing a firm's market position. Conversely, in open innovation frameworks, intellectual property helps balance the interests of various stakeholders, allowing for recognition and compensation to the innovators while facilitating broader, more efficient, and sustainable industry practices through cooperative engagement (UNECE, 2012).

This robustness check allows for an analysis that distinguishes between general innovations and those deemed protection-worthy. Incorporating intellectual property rights as a variable helps assess whether the protective strategies companies adopt for their innovations are related to different motivational drivers compared to general innovation activities, thus offering a more nuanced understanding of the innovation landscape. It also helps in exploring the broader discourse on intellectual property's role in fostering cooperation within the open innovation movement, particularly in sectors like energy where efficiency and resource management are crucial.

Table 4 presents an analysis with intellectual property as the dependent variable and its results using the same independent variables employed in the previous analysis. Initially, the marginal effects estimated, which represent the impact on the probability of a firm seeking protection for its innovations, decreased to less than half compared to the previously measured probability of the firm engaging in any innovation. This outcome is expected as the likelihood of a firm incurring costs to protect innovations perceived as valuable is typically lower than that of developing innovations in general. This supports the hypothesis that using intellectual property as a measure offers a more precise approach to assessing innovation.

*Table 5. Marginal effects from a probit model (robust standard errors in parentheses). The dependent variable measures if the company searched to protect its innovation. All regressions include year dummies, and the last model includes country dummies; significant at * significant at 10 percent, **significant at 5 percent, and *** significant at 1 percent.*

Protected innovation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Public funded	0.194^{***}	0.119^{***}	0.106^{***}	0.104^{***}	0.106^{***}	0.092^{***}
	(0.044)	(0.039)	(0.037)	(0.037)	(0.038)	(0.027)
Cooperated		0.156^{***}	0.102^{***}	0.100^{***}	0.101^{***}	0.097^{***}
		(0.031)	(0.030)	(0.030)	(0.030)	(0.024)
Log(Turnover)			0.026^{***}	0.027^{***}	0.024^{***}	0.021^{***}
			(0.005)	(0.005)	(0.006)	(0.006)
Innovation Expenditure (share of turnover)				0.000	0.000	0.000
				(0.001)	(0.001)	(0.001)
University degree					0.047^{*}	0.057^{**}
					(0.024)	(0.025)
Company size					0.016	0.018
					(0.032)	(0.031)
Wave Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	No	No	No	No	Yes
Pseudo R-squared	0.069	0.132	0.185	0.185	0.192	0.209
Log likelihood	-232.953	-217.361	-204.107	-204.012	-202.163	-197.931
N	696	696	696	696	696	696

Furthermore, the variables that were previously identified as significant drivers of innovation in energy firms continued to be significant in this analysis. This suggests that these drivers apply to all types of innovations, not only those deemed unworthy of protection, thus contributing to the robustness of the previous findings. The variable measuring innovation spending did not show statistical significance. Nonetheless, this probit model revealed two intriguing results.

In Table 2, when considering the dependent variable of public funding, it was the most influential driver of innovation among firms, with cooperation ranking second. However, Table 5 presents a reversal of this trend. When considering innovations deemed worthy of protection, cooperation emerges as slightly more impactful, demonstrating an average increase of 9.7 percent in the probability of a firm pursuing protection for its innovations, compared to 9.2 percent for public funding, *ceteris paribus*. This helps to infer on the literature finding that intellectual property is positively correlated with cooperation. It is important to note that both these variables are binary, whereas the variable representing the logarithm of turnover is continuous, reflecting the effect of a 1 percent increase. This distinction makes direct comparisons between the impacts of these variables on probabilities challenging. Nevertheless, the data suggest that when focusing exclusively on more significant or valuable innovations, the role of cooperation becomes more pronounced. This underscores the value of investing in cooperative initiatives and participating in the open innovation movement.

The second finding concerns the variable education level. Previously, this measure did not yield a statistically significant result. However, the current analysis indicates that having at least one quarter of employees with a tertiary degree increases the probability of a firm engaging in protection-worthy innovations by 5.7 percent, at a significance level of 5 percent. This result prompts a discussion on the influence of educational attainment within the workforce, particularly suggesting that higher education levels may be more important in scenarios where innovations are inherently more complex, thereby demanding greater innovative capacity and quality.

6 Discussion

The results of the dissertation allow to elaborate more into the specific drivers of innovation in energy firms. Several existing studies have focused on innovation, particularly eco-innovation, offering benchmarks to compare with the energy sector. As anticipated, many of the drivers identified are indeed common to both, as eco-innovation literature, though not exclusively focused on energy firms, highlights areas where such innovations significantly contribute to environmental transition, areas that are central to the innovations within energy firms.

The importance of granting public funding is a key element in this process. The analysis indicates that public funding is indeed more impactful than a company's R&D expenditure. This finding suggests that the method of distributing these funds warrants further discussion. One hypothesis is that companies with prior innovation experience are more adept at securing additional funding. If funds are allocated based on a company's assessment, entities providing the capital are likely to prioritize firms that have demonstrated innovation capabilities and flexibility in both product and process innovation. This approach underscores the importance of carefully considering the recipients of public funding and reveals potential inefficiencies in broad, horizontal funding distribution. The low impact of R&D expenditure may also suggest that the effectiveness of innovation spending could be more contingent on how it is directed and managed rather than merely its volume.

Cooperation, which is frequently highlighted in the literature, supports the hypothesis that complex sectors like energy need to mitigate the risks associated with innovation by partnering with entities such as suppliers. Companies should integrate these strategies into their processes, moving beyond the competitive barriers that hinder idea sharing. By partnering with the right entities, firms can achieve sustainable growth.

Turnover, as an indicator of market demand, also provides a basis for interesting discussions. The positive correlation could suggest that market demand for a company's product drives its willingness to innovate further. However, once a company has achieved a competitive product that customers seek, it is not typical for it to continue heavily investing in innovation. One possibility is that high turnover is the result of previous successful innovation, placing the company in a comfortable position where the primary challenge is not to gain market share but to maintain it. This means ensuring that new innovations are not missed. Consequently, as turnover grows, the share allocated to innovation may also increase, enhancing the likelihood of another successful innovation output. Additionally, this can be related to the quality of the workforce. Increased turnover could enable a company to hire specialized talent in innovation, particularly considering the literature's findings that employees with green skills are in short supply and offer a significant competitive advantage. This is especially relevant given that a higher level of education was a significant factor when evaluating innovation worth protecting.

Furthermore, the concept of path dependency described in the literature, although not measured in the models, could be relevant here. It is widely discussed that companies that have innovated in dirty technologies face substantial barriers when shifting their innovation efforts towards clean technologies. However, a company with high turnover due to dirty innovations might have the necessary capital and workforce to invest in clean innovations, without disregarding the costs associated with switching focus areas.

7 Conclusions, Limitations and Future Work

This chapter synthesizes the findings of the study on innovation drivers within the EU energy sector, evaluates the limitations of the current research, and proposes directions for future research.

7.1 Conclusions

The necessity for a sustainable transition is widely acknowledged, with energy companies at the forefront being the most impactful sector on greenhouse gas emissions within the EU. This dissertation fills a gap in the existing literature by focusing on the interplay between technological innovation and sector progress. It analyses European Union energy firms, using micro-level data from the last three waves (2014, 2016, and 2018) of the Community Innovation Survey (CIS) and applies probit models to identify the key innovation drivers within this sector. Public funding has emerged as a significant catalyst for innovation within energy firms, especially in facilitating shifts towards cleaner technologies and enhancing product and process innovations. This aligns with the broader academic perspective that recognizes subsidies as driving forces to innovation in the energy sector. Public funding not only boosts the overall likelihood of innovation but also exerts a more pronounced impact on companies that engage in both product and process innovations, adapting to the increasing integration of renewable energy and digital technologies. However, challenges persist, as some studies suggest that current levels of public funding may still be inadequate for firms to fully surmount technological and market barriers. This analysis suggests that the effectiveness of public funding often surpasses individual R&D expenditures, likely due to the size of this subsidies and to being strategically allocated to firms with established innovation tracks thus raising questions about the efficiency of broad, non-targeted funding approaches and emphasizing the need for distributions strategies that maximize innovation output in the energy sector.

Cooperation is increasingly recognized as a critical strategy for fostering innovation, particularly in the complex and highly regulated energy sector. Open collaboration, involving external partnerships with other innovative firms, significantly enhances a company's ability to innovate, especially in areas that are new and thus require diverse sources of information and expertise. Such cooperative efforts not only enable firms to access a wider pool of knowledge but also serve as an effective risk-sharing mechanism. By collaborating with suppliers and other partners, energy companies can not only share the inherent risks of innovation projects but also integrate and leverage external R&D alongside their internal efforts.

Turnover, used as a proxy for market demand, has also been identified as a significant determinant of innovation, particularly in the energy sector. Higher turnover encourages firms to invest in new innovations, particularly eco-innovations, responding to consumer preferences for clean energy. Conversely, a solid turnover could also reflect a company's established market presence, leading to less emphasis on continual innovation unless necessary to maintain competitiveness or to address supply chain improvements. This dynamic suggests that while turnover can drive innovation by providing the necessary resources and market validation, the direction and intensity of innovation efforts may vary based on the company's current market status and strategic priorities.

The variables of workforce, representing a firm's percentage of employees with a tertiary degree and whether a company has more than 250 employees, respectively, did not show a statistically significant impact on a firm's innovation probability. This aligns with certain academic perspectives that suggest these measures may reflect quantity rather than the quality or innovative capacity of the workforce. Similarly, the size of the company, as indicated by employee count, does not necessarily correlate with innovation capability. This result highlights the complexity of using straightforward educational or size metrics as indicators of innovation, particularly in sectors like energy where the quality and specific skills of employees are critical yet scarce. These findings echo the mixed results in the literature, where some studies report no significant effects and others report contradictory outcomes.

7.2 Limitations and Future Work

Considering the findings and inherent limitations of the study, it contributes to future research by offering proposals that deepen understanding and build upon the existing literature. Future studies might benefit from utilizing a database that better analyses sectors predominantly innovating through services, which the Community Innovation Survey (CIS) does not adequately cover. Since the data is cross-sectional, it did not allow to measure lagged effects by controlling for the same firm in different years. To broaden the amount of data used, including more waves when they are published would also be beneficial.

Some variables did not measure as directly the desired effect. In workforce, there could be a better distinction between the number of employees of a company and a clearer measure for the quality of education of workers rather than quantity. For financial support, the amount of public funding and not just if it was granted or not would allow for a more complex assessment.

One could also perform a study specifically on emerging innovators, classified in the European innovation scoreboard, and compare the results with a study on the strong innovators.

Additionally, employing the specific module for eco-innovation within the CIS could provide a clearer insight into the innovation determinants for energy firms that more directly impact the environmental transition.

To gain a more comprehensive understanding of innovation across the EU, one could include more countries in the study, particularly since the countries considered strong innovators by the European Commission do not participate in this survey. Future research could also explore using the turnover variable specifically for eco-products to test the significance of this driver in the energy transition. Furthermore, a more detailed analysis comparing the effects of public versus private funding, and examining the leverage of funding amounts, could yield interesting results, while specifically studying the process of granting these fundings.

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9 Appendix

*Table 6. Probit model (robust standard errors in parentheses). The dependent variable measures if the company innovated or not. All regressions include year dummies, and the last model includes country dummies; significant at * significant at 10 percent, **significant at 5 percent, and *** significant at 1 percent.*

Innovator	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Public funded	1.090***	0.779***	0.804***	0.790***	0.769***	0.978***	1.048***
	(0.142)	(0.151)	(0.154)	(0.156)	(0.157)	(0.167)	(0.170)
Cooperated		1.059***	0.917***	0.910***	0.905***	0.873***	0.849***
		(0.117)	(0.123)	(0.124)	(0.124)	(0.136)	(0.137)
log(Turnover)			0.109***	0.112***	0.090***	0.194***	0.201***
			(0.027)	(0.028)	(0.032)	(0.037)	(0.038)
Innovation Expenditure (share of turnover)				0.003	0.002	0.001	0.056*
				(0.005)	(0.005)	(0.005)	(0.029)
University degree					-0.051	-0.206	-0.196
					(0.117)	(0.128)	(0.129)
Company size					0.234	-0.036	-0.048
					(0.161)	(0.182)	(0.183)
Public funded=1 # Innovation Expenditure (share of turnover)							-0.061** (0.029)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	No	No	No	No	Yes	Yes
Pseudo R-squared	0.145	0.234	0.251	0.251	0.254	0.355	0.361
Log likelihood	-406.386	-364.064	-355.853	-355.695	-354.438	-306.525	-303.262
N	703	703	703	703	703	703	703

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