Does carbon capture & storage mitigate carbon premium? Evidence from patents

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November 1, 2025

Abstract

Motivated by recent evidence of a carbon risk premium (Bolton and Kacperczyc, 2021), we analyze firm-level patenting in Carbon Capture Utilization & Storage (CCUS) technologies and its impact on stock market performance from 2010 to 2022. Using zero-inflated Poisson regressions on patent and financial data and CO_2 emissions, we find CCUS patents respond to CO_2 emissions and climate policies. Moreover, although CCUS patents are negatively (positively) related with market-to-book (stock returns), we find that the effect turns if the firm is a high CO_2 emitter and environmental regulation is tighter. Our findings suggest that CCUS innovation reduces the carbon risk premium, benefiting firms with higher environmental risks.

Keywords: eco-innovation, carbon capture & storage, CCUS patents, green transition, climate risk, firm value, stock returns

JEL Codes: O31, Q55, G14

Acknowledgements: We would like to thank Carlo Cambini, Federico Caviggioli, Sandro Montresor, Joelle Noailly, Chiara Ravetti, Francesco Rentocchini, Giuseppe Scellato, Andrew A. Toole, and seminar participants at the IIOC, International Industrial and Organization Conference in Boston, CIES Seminar Series in Geneva, EMEI Seminar Series in Turin, UCLEI Summer School in Bologna, XXII SIEPI Annual Workshop in Bergamo for comments and suggestions. This manuscript is part of the project NODES, which has received funding from the MUR –M4C2 1.5 of PNRR funded by the European Union - NextGenerationEU (Grant agreement no. ECS00000036).

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1 Introduction

Carbon capture (usage) & storage is an umbrella term bringing together a wide range of different technologies, all contributing to a procedure that involves *"the capture of CO_2, generally from large point sources like power generation or industrial facilities that use either fossil fuels or biomass as fuel. If not being used on-site, the captured CO_2 is compressed and transported by pipeline, ship, rail or truck to be used in a range of applications, or injected into deep geological formations such as depleted oil and gas reservoirs or saline aquifers."* (IEA, 2023)[1]. CCUS technologies have roots dating back to the 1920's, when methods were developed to separate CO_2 from sealable methane in natural gas reservoirs. The concept of storing separated CO_2 underground was developed during 1950's, driven by the intuition that high-pressure CO_2 could enhance oil recovery (hereafter EOR) from reservoirs that had been only partially depleted by traditional extraction methods. Then, recently[1] with the introduction of new technologies - e.g. *Direct Air Capture and Storage* (DACCS), *Bio-Energy with Carbon Capture and Storage* (BECCS) and long-term storage -, CCUS innovation has started to be valued as a powerful tool to reduce CO_2 emissions (Bui et al., 2018)[22] and, consequently, also subsidised by governments[2]. However, to date, total capture capacity is still low, as the efficiency and scope of these new technologies are low compared to the high sunk costs of projects, raising doubts about whether CCUS can keep pace with expectations. In our technology overview, we highlight the peculiar nature

[1] In the European Union, the first EU CCUS directive (2009/31/EC), establishing a legal framework for storing CO_2 was issued in 2009.

[2] In the US, 136 projects received 13.5 billion USD for the period 2011-2026. In 2020, the UK government has allocated 1 billion £ with the Carbon Capture & Storage Infrastructure Fund (CIF) starting 2020 (Sovacool et al., 2024[89]). In the EU, projects are financed through the Innovation Fund, Horizon Europe and Connecting Europe Facility - Energy (CEF-E).

of CCUS innovation and discuss its pros and cons with respect to environmental issues as well as possible unintended consequences, such as bolstering the lock-in into carbon-intensive industries.

This paper studies what drives firms to innovate in CCUS technologies and how capital markets evaluate their efforts, using patents as a measure of innovation output.[3] In figure 1, our data show that in the last 30 years, the patenting trend has been flat until 2000, slowly increased until 2010 and then started to climb fast around 2015, when the first COP-21 made everybody aware of the climate risk, engaging also the finance industry in the fight against climate change (see Bolton and Kacperczyc, 2021)[14].

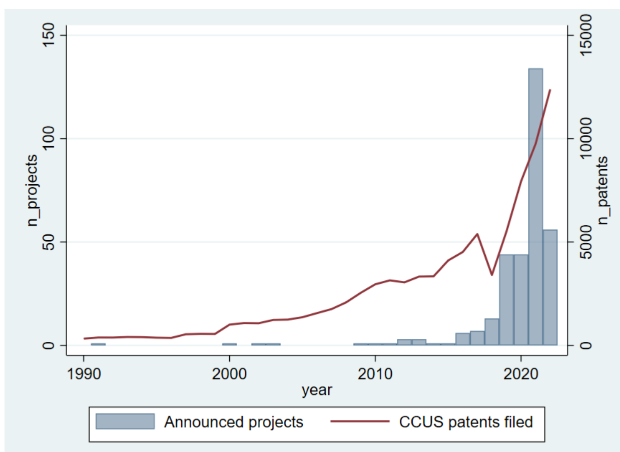

Figure 1: CCUS patents filed and announced CCUS projects by year globally (source: own data).

On the one hand, the acceleration in CCUS patenting may result from increasingly stringent environmental policies, which can provide incentives to innovate stronger than cost reductions (Della Longa et al., 2021[32]). On the other hand, firms in highly profitable and concentrated markets (such as the fossil fuel industry) that operate with stable and cost-

[3]Our study does not evaluate the environmental impact of CCUS project deployment. This still remains a debated subject, sitting among the hot topics discussed at the COP28 in Dubai (November 2023).

effective technologies may have little incentive to shift to novel and riskier innovations, as implied by Arrow's replacement effect (Arrow, 1962[6]). In this trade-off, CCUS innovations can be a unique opportunity for these firms to straddle the exploitation of their specific technological know-how and the pursue of a sustainable environmental transition. The pressure from financial markets can therefore combine with regulatory constraints to provide firms with powerful incentives to reduce their climate impact by innovating in environment-friendly technologies, as long as investors evaluate that they can internalize their benefits (Hart & Zingales, 2017)[50]. In fact, the intangible capital embedded in patents and projects that enhance the firm's social impact has been found to contribute to firm's market value (see Griliches, 1981[47] and Edmans, 2022[38]). CCUS innovations appear to join technological and social (climate-related) aspects, thus motivating our interest in their determinants and impact.

The empirical analysis uses a panel of worldwide firms tracked from 2010 to 2022. We identified CCUS patents based on WIPO specific IPC/CPC classification codes and downloaded, from Orbis-IP database, all patents in the CCUS sub-classes and in the higher hierarchical class to which CCUS patents belong. Information on the identity of the patenting firm then allowed us to match patent data with company financial data and CO_2 emissions from Orbis and Eikon-Refinitiv. Data on stock market returns, value and carbon emissions are available only for publicly listed firms, and we use a panel of publicly listed companies with at least a patent in CCUS or neighboring technologies to address two main research questions. First, we estimate what drives firms' decision to patent in CCUS (i.e., extensive margin) and how much they do it (i.e., intensive margin), focusing on the role of direct carbon emissions and environmental policy tightness. To measure the country regulatory pressure, we rely on the Environmental Policy Stringency index (EPS) computed by the OECD (Botta et al., 2014[18] and Kruse et al. 2022[59]), focusing on its sub-indices specifically related to decarbonization policies. EPS sub-indices can be viewed as credible demand-pull factors for firms' green transition strategies, and are often found to accelerate eco-innovation (Hassan & Rousselière, 2022[52]). To estimate firms' patenting activity, we employ the zero-inflated Poisson regression model, which conveniently deals with count patent data within a two-stage model, assuming two different zero-generating processes (see Noailly & Smeets, 2015[74], Briggs & Wade, 2014[19] for recent applications).

Second, we investigate the impact of firms' CCUS patents on their market value and stock returns, and whether the financial markets' response to CCUS patenting changes with their levels of CO_2 emissions and with tighter environmental regulation.[4] Empirically, we depart from the typical approach estimating the market value of patents (see Gambardella, 2013[45]) to obtain the firm-level private return of intangible assets (see Bosworth & Rogers, 2001[17]; Tovainen et al., 2002[92]; Thoma, 2021[91]) in that we follow the literature that models market value as a function of tangible and intangible (knowledge) assets, in our case CCUS patents (see Griliches, 1981[47], Hall, 1999[48] for a review, and Colombelli et al., 2020[30] for recent evidence). We extend this model by testing whether the effect of CCUS patents on market value depends on CO_2 emissions, i.e., on the firm's carbon-transition risk. We then turn to total stock returns, as recent evidence of a "carbon risk premium" requested by investors to high-emitting firms (see Bolton and Kacperczyc, 2021[14] and Bauer et al., 2022[8] among the others) is a plausible motivation to investigate if CCUS patent activity

[4]Arguably, this might suggest a strategic use of patenting in CCUS technologies to address changes of climate policy and pressure from environmentally motivated investors (see for example Yu et al., 2017[99].

might mitigate this risk, as a reward to firms' efforts to innovate in technologies that reduce CO_2 emissions. We thus differ from the finance literature investigating directly the presence of a carbon risk premium in that we search what can reduce it. Hence, evidence of a negative relationship of CCUS patents with expected stock returns would suggest that they reduce the carbon risk premium requested by the financial markets to invest in the patenting companies. Finally, because the stranded asset problem may particularly expose carbon-intensive firms to the "climate transition risk" (Byrd & Cooperman, 2018)[23], we also test whether the mitigating effect of CCUS patents is stronger for companies with higher CO_2 emissions.

Our findings may be summarized as follows. First, the decision of innovating in CCUS technologies is likelier the "browner" is the firm (i.e., the higher the level of its CO_2 emissions) and the tighter is the environmental regulation, while increases in patenting intensity are (weakly) related to "increases" in direct emissions. Second, patenting in CCUS technologies seems to be acknowledged by the stock market, particularly if the firm is a high CO_2 emitter. In fact, although CCUS patents appear negatively related to the firm's market value, the relationship turns positive when we account for the level of CO_2 emissions, suggesting that stock markets positively evaluate the CCUS innovation activity of firms with a negative environmental impact. Similarly, we find that CCUS patents are positively related with expected stock returns, suggesting that investors require a higher risk premium, possibly due to both the idiosyncratic climate-transition risk of firms engaging in CCUS technologies and the uncertain returns of research activity in this field. However, the risk premium reduces for firms with higher carbon emissions, showing that the stock market recognizes their effort to mitigate not only their climate impact but also the negative effect of the climate-transition risk on their profits. Based on our results, we can calculate quantitative effects from which we derive policy implications.

We contribute to the literature in several ways. First, our study is the first one, to the best of our knowledge, that analyses, at the firm-level, the determinants and the financial impact of patenting in a technology like CCUS, which is deemed by UNECE (2021) as essential to unlock the full potential of decarbonization and attain carbon neutrality. Second, we address the debate on the carbon risk premium by studying what may reduce it, and find that high-emitting firms may mitigate their climate-transition risk by innovating in CCUS technologies, which are embedded in their genetic heritage, hence, to some extent, less difficult and costly to deploy. Third, our finding that the direct market response to the innovation effort in this field is not outright positive suggests that CCUS innovation is not (yet) viewed as other green and high-tech innovations (see Doran & Ryan, 2012[36] and Colombelli et al., 2020[30] for green inventions and Feyzrakhmanova & Gurdgiev, 2016[42], and Bruneo et al., 2023[20] in pharmaceuticals and biotechnology). This is probably due to the climate-transition risk associated with many of the patenting firms engaged in the fossil fuel industries and to the uncertainty about the actual economic benefits. Fourth, our evidence nevertheless suggests that acknowledgment by the capital markets may provide the more polluting firms with economic incentives to eco-innovate that might be more effective, and less easy to elude, than environmental policy norms.

The remainder of the paper is organized as follows. Section 2 presents an overview of CCUS technologies. Section 3 presents the background literature for our study and derives the research questions. Section 4 describes the construction of the dataset, the main variables and the descriptive statistics. Section 5 presents the empirical strategies and results. Section 6 concludes. In the appendix, we present the IPC classification codes used to identify CCUS technologies, additional descriptive statistics and the correlation matrices, the derivation of the empirical models and the results of a battery of robustness checks.

2 A critical overview of CCUS technologies

CCUS patents are classified based on International and Cooperative Classification (IPC / CPC) codes. Mapping these codes to technological groups is a complex task that was addressed by the specialized literature.[5] For our purposes, we adhere to the segmentation outlined in the IPCC 2005 special report on Carbon Dioxide Capture and Storage[70], and to the subsequent adaptations by UNECE[90] and the Directorate-General for Climate Action of the European Commission[29].

This framework views CCUS as a four-step process: capture, transportation, storage and utilisation. The capture phase involves several systems, depending on how CO_2 is produced: post-combustion capture, pre-combustion capture, and oxy-fuel combustion capture are examples of available technologies. These systems employ advanced gas separation technologies, as reflected in the IPC / CPC codes. Transporting captured CO_2 can be done via pipelines, which, although costly, offer high capacity and long-distance capabilities. Water-borne transport is used for large-scale movements of CO_2 and other liquefied gases, while rail and road transport, though less common, are used for smaller capacities. Then, CO_2 is either utilized to produce economically valuable goods or long-term stored. Utilization of captured CO_2 can occur through mineralization, to incorporate CO_2 into concrete, chemical processes

[5] For an inventory of CCUS technology reserves, detailed technological insights, and specialized references, see Kang et al., 2021[56] who, applying a dynamic programming algorithm combined with topic modeling to patent data, identify twenty-seven key technology clusters and derive the main development paths for the CCUS patent market.

to produce synthetic fuels or fertilizers,or biological methods like biochar sequestration to enhance the quality of soil. The environmental impact of these uses differs, as mineralization into cement offers greater potential in terms of scale and sequestration duration, while chemical uses require smaller quantities and shorter sequestration time.

Finally, storage involves injecting high-pressure CO_2 into geological formations, such as deep aquifers and oil deposits. Aquifers, i.e., porous rock formations containing salty water beneath impermeable rock layers, can securely store CO_2 for long periods with minimal leakage risk. Another option is EOR, where CO_2 is injected into oil wells to extract remaining oil reserves. Although not universally adopted, EOR has been a common practice since the 1970s (Merchant, 2017[69]) among fossil fuel companies. This technique can be considered beneficial to the environment provided that the quantity of injected (and stored) CO_2 is higher than the sum of the amounts of CO_2 emitted during the extraction process and by the extracted oil.

However, recent CCUS technologies show great potential towards combating climate change. DACCS (*Direct Air Carbon Capture and Storage*), DOC (*Marine, or Direct Ocean Capture*), BECCS (*Bio-Energy Carbon Capture and Storage*), and Microalgae-based carbon sequestration represent carbon removal options that directly aim at sequestration of emissions from the atmosphere, the seawater or through bio-masses. Although many challenges, such as the need for further technological advancement and high operational costs, may still delay the deployment and scale-up of these technologies (Al Yafiee et al., 2024[3]), the main difference between point-source and carbon removal technologies lies in the environmental and economic implications their implementation has in the real world, particularly with regard to their impact on the diffusion of renewables and the phase-out of carbon-intensive assets.

Hence, not surprisingly, given the complexity and diversity of CCUS technologies, whether they can be defined straightforwardly "green" is still an object of debate within the scientific community. While point-source technologies like E.O.R. and carbon removal options like DACCS and DOC are usually grouped under the CCUS umbrella, they differ significantly in terms of technology maturity (see Kang et al. 2021[56]), infrastructure needs and policy relevance. As long as these differences matter also beyond the standpoint of mitigation, the motivations behind investing and innovating along different pathways, i.e., whether to aim for genuine decarbonization objectives or to pursue asset-preserving strategies, are worth to be studied specifically.[6] Therefore, while CCUS may hold significant potential for contributing to the green transition (UNECE, 2021[90]; Nath et al., 2024[72]) by enabling sector-specific technological advancements in that direction, ensuring cost savings in meeting climate targets[7] (Budinis et al., 2018[21]), and as a component of a hydrogen production process[8], one has also to consider its drawbacks to give an unbiased assessment. First, some forms CCUS - especially when linked to E.O.R. or used by fossil fuel incumbents - may risk reinforcing *lock-in* investments in fossil fuel-related infrastructure typical of carbon intensive technological pathways, delaying energy transition and hindering progress of other green technologies (Vergragt et al., 2011[93]; Faber et al., 2025[39]). Second, to maximize its effectiveness, CCUS requires efficiency-enhancing innovation and substantial financial investments due to

[6] We thank one Reviewer for raising this point. Unfortunately, due to the technical difficulties that exist in disentangling technologies still in their infancy like NET in terms of patent codes' identification (see more on this issue in the data section and, for detailed analyses, Kang et al. 2021[56] and Kang et al. 2022[55]), to address this matter empirically is beyond the scope of our study.

[7] IPCC estimates a 138% increase in discounted transition costs (2015-2100) should CCUS be abandoned. `https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_summary-for-policymakers.pdf`

[8] for example, see the UK CCUS-Enabled Hydrogen Production Report `https://hydrogen-uk.org/wp-content/uploads/2023/09/HUK-CCUS-Enabled-Hydrogen-Production.pdf`

the high costs of project development[9]. Scaling projects to the hub level helps decrease costs related to CO_2 capture and raw material availability (for usage), and may thus make CCUS economically feasible for applications in several sectors (e.g., cement, see Monteiro et al., 2022[71]). Clearly, CCUS still faces various challenges, starting from a well-defined regulating framework, incentives for infrastructure efficiency (e.g., project hubs, transportation facilities, storage sites, etc.) and cost barriers (Nath et al., 2024[72]). Balancing the pros and cons of these issues implies serious policy and economic considerations beyond the scope of this paper. However, to enforce the green transition, industrial and energy policy should particularly promote "green" or net-negative emission CCUS technologies to mitigate potential environmental externalities[10].

Summarizing, our technology review has highlighted the controversial nature of CCUS and the difficulty to enlist it, unquestionably, as an eco-innovation. However, to the extent that the new generation of CCUS innovations are motivated by decarbonization policy and that firms in carbon-intensive industries that patent in this field may ultimately reduce their CO_2 emissions, in this paper we will treat it as (a peculiar type of) eco-innovation.

3 Related literature and research questions

The academic literature on CCUS technologies mainly covers techno-economic analyses, case-studies for industrial plants and cross-sectional patent landscapes, whereas the research questions of our study pertain to the field of economics. Thus, our conceptual framework builds upon two streams of the economic literature - the study of eco-innovations and the

[9]See Wang et al., 2021[94] for a study on survival rate of CCUS projects.
[10]See Rosa et al., 2021[85] for a study on water-footprint of CCUS technologies.

analysis of the impact of innovation (and in particular eco-innovations) on firms' performance in the financial markets.

3.1 Eco-innovations

Even though the definition of eco-innovation is not unique across the various studies, it is often referred to as the subset of innovations with a specific focus on the reduction of the adverse effects on the environment and a more efficient use of resources (Hojnik & Ruzzier, 2016)[54]. They typically include technological, product or process innovations as well as social or institutional innovations. In general, their positioning straddles innovation and environmental economics (Rennings, 2000)[84], leading to the well-known "double externality problem". Not only eco-innovations generate knowledge externalities in the stage of research and development, but they also produce environmental externalities at the time of adoption and diffusion. Hence, and also due to high risk and uncertainty, the private returns of R&D are lower than the social returns, making firms reluctant to invest in this kind of innovations. CCUS fits into this case, since private returns from its implementation are proportional both to the stringency of environmental policies such as carbon pricing or emission trading schemes (in the case of storage) and to the revenues generated from new products involving captured CO_2 (in the case of usage). Nevertheless, initial sunk costs for CO_2 capture are still too high, and carbon pricing is too low to make projects profitable in many cases (Budinis et al., 2018[21]), in spite of their potential environmental benefits. Hence, given the urgent need of solutions to face the climate risk, dedicated policies have to encourage firms to invest in eco-innovation. Indeed, a substantial literature has developed around the impact of environmental policy on eco-innovation. Yange et al. (2022)[98] use the number of green patents over local population levels as a measure of urban eco-innovation to show the positive effects of low-carbon city policies in China. Cainelli et al. (2020)[24] with a firm-level study exploiting the European Community Innovation Survey, find that the environmental policy has positive impact on innovations targeted to the circular economy.

The literature on the determinants of eco-innovation is also rich and dense, though not on CCUS. Many studies focus on the difference between traditional and green innovation, often finding that typical drivers such as (general) R&D expenditure and human capital are more effective in fostering traditional innovation than green one. Focusing on green innovation, the presence of quality management systems (See Cuerva et al., 2014)[31], the access to public funds and fiscal incentives (Cecere, Corrocher & Mancusi, 2020)[26], and public-private collaborations (Scarpellini et al., 2012)[86] were found to be significant determinants, while De Marchi (2012)[33] has shown that, within eco-innovation activities, cooperative R&D substitutes traditional internal R&D. Finally, it has been suggested that the development of eco-innovation is often sector-specific, and that its determinants are influenced by sectoral features (Galliano & Nadel, 2015)[44].[11] For example, Faria & Andersen (2017)[41] find that, in the automotive industry, green innovations tend to converge at sector-level and increase in intensity when they are complementary to existing innovations. These findings, though related to other fields of innovation, are particularly useful in defining a theoretical framework for studying CCUS technologies and their adaptability to environmental objectives to the extent that they are complementary to some of the fundamental technologies used in the core business of firms. Examples of such complementarity and adaptability is EOR for Oil

[11] See also Del Rio et al., 2010[34]

& Gas and CCS in the cement industry where the captured CO_2 is used as inert additive for concrete.

Eco-innovations are also studied for their impact on climate change and, specifically, on the levels of CO_2e emissions. The evidence is mixed. On the one hand, Puertas & Marti (2019)[83] (with a country-level analysis using patents and R&D innovation) and Lee & Min (2015)[60] (with a firm-level study focusing on green R&D) find that eco-innovations lead to an overall significant reduction of CO_2e emissions. On the other hand, Bolton, Kacperczyk and Wiederman (2023)[16], in a recent comprehensive study on a worldwide sample of firms tracked from 2005 to 2020do not find any significant effect of green innovation on direct and indirect corporate CO_2 emissions of the innovating firms.

Ultimately, the literature has also focused on the pressure exercised by high CO_2 emissions on companies' strategies, i.e., whether firms might be induced to invest in eco-innovation to leverage their commitment with the markets and mitigate environmental issues related to the carbon-transition risk of their activities. In this vein, Wang et al.(2020)[96], with a country-level analysis, find that the climate-related pressure exerted by CO_2 emissions increases the probability of eco-innovation (particularly green-technologies in specific fields, such as transportation), through the mediation of environmental regulation.

The above arguments and empirical findings pave the way for our first research question:

RQ 1a: *What drives the decision to patent in CCUS technologies?*

RQ 1b: *What is the role of environmental pressure related to the climate risk?*

We study these questions by investigating factors that affect heterogeneous firms' decision to patent in CCUS (extensive margin) and how much to innovate (intensive margin), i.e., how many patents, conditional on a positive patenting decision. We are not studying what triggers the decision to enter in the realm of CCUS technologies.

We approximate the environmental pressures with firm-level CO_2 emissions and with environmental regulation, as measured by country-level sub-indices of the Environmental Policy Stringency Index (EPS)[12]. The former suggests that CCUS patent intensity might be higher in companies in carbon-intensive sectors, which are more exposed to a stranded asset problem (Byrd & Cooperman, 2018)[23]. We are driven by the insights of the previous literature, whereby demand factors related to climate risk concernmay drive the decision to engage in eco-innovation, whereas considerations about cost saving, efficiency improvements and firm capabilities more likely affect patent intensity (Kesidou & Demirel, 2012)[58].

To the extent that environmental pressure also equates to greater climate risk, affecting the preferences of financial investors, also the public equity markets may end up requiring higher returns - i.e., a *carbon risk premium* - to high-emitting companies (Bolton & Kacperczyk, 2021)[14]. This is the issue we address in the following section.

3.2 Innovation and stock market performance

In general, patents are thought to bring value to the firm in that they assign exclusive property rights on a certain invention for a limited period of time (see Griliches, 1981[47], Bloom & van Reenen, 2002[11], Hall et al., 2005[49]). Their private returns have often been estimated in terms of discounted patent rents (see Pakes et al., 1984[75] and, more recently,

[12] In particular, we employ the sub-indices relative to Carbon taxation, Emission Trading Schemes and R&D public subsidies. If it were possible to examine the effect of these policies on point-source and net emission technologies separately, one could expect that R&D public subsidies and other forms of governmental incentives to technical advancements (should) significantly explain an increase in patents in the field of carbon removal.

Bessen, 2009[10]). This approach, however, estimates the market value of patents, rather than whether patents contribute to firms' market value. Therefore, to model the impact of CCUS patents on the firms' financial performance we refer to another branch of the innovation literature (see Hall, 1999[48] for a review), which was set off by the seminal work by Griliches (1981)[47], who ultimately finds that the market value of companies is positively related to the value of their knowledge assets. Since then, this framework has been largely adopted by studies investigating the impact of R&D investment and patents on firm market value. Whether research efforts positively affect market value by reducing uncertainty about the firm's prospects (Nemlioglu & Mallick, 2020)[73] is an example of the recent directions taken by this literature. Colombelli et al. (2020)[30] has adapted this framework to green innovation, finding that green patenting positively affects firm's market value as measured by the market to book ratio. We follow their approach and describe the estimating model in more detail in the empirical design section.

The impact of environment-related issues on firms' stock market performance has also been modeled in the framework of expected stock returns and their relationship with carbon risk of *green* and *brown* companies[13]. As already discussed, the increasing engagement of investors in climate-friendly issues (Bolton and Kacperczyk, 2023)[15] is expected to combine with climate policies to incentivize risk-taker companies to overcome the competition asymmetries implied by high-cost investments - thanks to a dynamic view of the economic cycle that will eventually ensure a competitive advantage to companies active in environmental innovation (see Porter & Van Der Linde, 1995[82] and Porter, 1991[81]). In a context of

[13]See Bauer et al., 2022[8], who study the relative equity pricing of more vs. less climate-friendly companies; and Gorgen et al. 2020[46], who compare the stock returns of brown and green firms to construct a carbon risk factor

climate change where shareholders grow more socially responsible, maximization of shareholder welfare - rather than wealth - becomes the objective of utility-maximizing investors, laying the ground for environment-friendly investments (Hart & Zingales, 2017)[50].

In this paper, we refer to the concept of "carbon premium", which Bolton & Kacperczyk (2021)[14] introduce and empirically find in a cross-section of US-stock returns, as the higher premium requested by the equity market to invest in firms with a higher level of CO_2 emissions. The literature that studies the relationship between intangible assets and stock returns typically assumes that discounted future value of R&D might not be fully incorporated by investors due to its inherent riskiness and uncertainty. To the extent that R&D intensity is associated with increased volatility (Chan, Lakonishok & Sougiannis, 2001)[27] higher returns (i.e., a higher cost of of capital) will be required by the market, especially when the firm is financially constrained (Li, 2011)[62].

When introducing patents or R&D expenditures in this framework, results generally hold, as both patents and R&D intensity are found positively associated with higher and more volatile returns (Mazzucato & Tancioni, 2008)[68]. In particular, Pástor & Veronesi (2006)[78] argue that, during "technological revolutions", novel technologies - such as railroads in the 1800s and internet in the late 1990s - imply higher uncertainty about the expected future productivity and profits of innovating firms, thus raising their discount rate and their returns. This framework fits the current situation, as firms race to achieve the most efficient green technology in order to face increasing environmental constraints in a context of radical social and economic change (hence surrounded by systematic uncertainty). However, the debate on this topic is still open. On the one hand, Andriosopoulos et al. (2022)[4], with an event study on the announcement effect of new green patents made by the USPTO in US, have found that they have no significant impact on market value, also for companies active in carbon-intensive sectors. On the other hand, Leippold & Yu (2023)[61], with a portfolio simulation analysis, found that green patents have a negative impact on annual realized returns, although their realized profits are found to be higher than expected in response to market shocks which generate higher environmental pressure, confirming that green patents confer greater protection against climate risk. We thus differ from this literature that investigates directly the presence of a carbon risk premium in that we estimate the whether CCUS patent activity can reduce it.

In the end, the literature reveals that the uncertainty related to the market's response to eco-innovation comes from different, possibly opposite sources. On the one hand, higher risk due to R&D and climate policy uncertainty (which raise the risk premium), on the other hand, mitigation of the firm's transition risk when the new technology is pro-environment (which lowers the risk premium). This contrast, with an uncertain net effect, properly fits the case of firms patenting in CCUS, as the financial markets signal their trust (or mistrust) by requesting firms a lower (or a higher) premium. We contribute by providing empirical evidence on which effect prevails.

The above literature motivates our second research question:

Research question 2: *Do capital markets respond to CCUS patenting, and does the response change with firms' "browness"?*

4 Sample construction, Data, and Descriptive statistics

4.1 Patent data

To construct the dataset we extracted CCUS patents from Orbis-IP (Intellectual Property), the Bureau van Dijk's platform dedicated to intellectual property data, using CCUS-specific codes by the International and Cooperative Patent Classifications (IPC/CPC) selected by WIPO.[14] We identified CCUS patents based on the selection of codes available in the IPC green inventory for carbon capture and storage patents,[15] to which we added the CPC codes in the Y02C[16] and Y02P[17] sub-classes for carbon capture, sequestration or disposal of greenhouse gases, because these were missing in the IPC green inventory.[18]

Then, we retrieved patents also from the higher hierarchical IPC/CPC class so as to enable the comparison between firms patenting in CCUS technologies and firms that have not filed CCUS patents but still do research in a neighbouring technological area. We define this set as CCUS-neighbouring technologies.[19] Appendix A reports the codes and brief

[14]WIPO classification comprises classes, sub-classes, groups and sub-groups. See Figure 2 In Appendix A.

[15]The IPC green inventory provide sub-group-level codes for CCUS technologies. See `https://www.wipo.int/classifications/ipc/green-inventory/home`

[16]`https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y02C.html`

[17]`https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y02P.html`

[18]As remarked in Section 2, distinguishing, and separately analyzing, newer carbon removal technologies (negative emission, or NET) based on patent codes classification appears, for the time being, still quite complex. Kang et al. (2022)[55] note that NET development is still at the beginning, and propose a methodology to identify patents (and patent families) pertaining to these fields. So far, however, the identification of these technologies has not yet been translated into a standard patent classification that we can use to construct a database appropriate for our empirical analyses. Although the analysis of the determinants and the implications of these technologies is of great interest, our empirical approach implies that we rely on a patent classification that allows us to address our research questions within a firm-level approach.

[19]Specifically, we add patents featuring at least one IPC/CPC code relative to the same sub-classes (level 3) that include CCUS technologies. By comprising these additional patents (and firms) in the dataset, in the empirical analysis, we can contrast firms with CCUS patents and firms with similar scientific know-how

descriptions of the groups that altogether define CCUS technologies (Table 11) and of the sub-classes used to identify neighbouring technologies (Table 12). As we downloaded patents throughout the world, to ensure cross-country comparability we only included patents filed within WIPO, EPO, USPTO, Japan and China national offices[20] to avoid double counting of patents filed both at a national and regional office. We focused on priority patent filings to capture firms' commitment to innovative activity (rather than its success).[21] Then, we matched patent data with accounting and financial data for firms identified through Orbis identification number.

To control for possible involvement of firms in other environmental innovation, we include a "green" patents variable, downloaded from Orbis IP and identified as "green" based on the ENV-tech classification by OECD (see Haščiči & Migotto, 2015 [51]).[22] To avoid double counting, we subtracted the number of CCUS green patents from the count of green patents for each firm and year and, for reasons of computational capacity, we included the "green patents" control only since year 2010. We then built a binary variable to denote firms that filed at least one green (non-CCUS) patent in every year of the period 2010-2022.

that did not file CCUS patents, not only firm with higher and lower CCUS patenting activity. We thank one Reviewer for suggesting this strategy.

[20]We have chosen to include patents filed by China, a major innovator in CCUS technologies, even though the quality of their data has been sometimes argued by researchers in this area. Indeed, patent quality is not the focus of our analysis, as much as it is the innovation effort strategy that patenting firms communicate to the financial markets.

[21]Priority year was used whenever available, and the filing year was employed when the latter was missing.

[22]This classification has been extensively used in the green innovation literature to identify environmental-friendly technologies (see Fusillo, 2023[43] as an example).

4.2 Firm data

Based on information about patent applicants, we identified firms that patented at least one CCUS innovation (*CCUS firms*) and firms patenting in neighbouring technology during the period 2000-2022, tracking them over time (in order to ultimately construct a firm panel dataset). This time frame allows us to cover the potential evolution of firms' patent strategy in a period when the worldwide sensitivity to climate risks was rapidly growing, and at the same time to exclude companies that had not been active in this field for quite a long period. The panel data consists of publicly listed firms because the research questions addressed by this study require stock market data (market value and total stock returns) and carbon emission data, which are consistently collected from Eikon-Refinitiv only for quoted firms.

For each company, the number of patents was counted and summed by year. However, some companies are affiliated or subsidiaries of a large corporation. To control for the corporate strategy in the development of CCUS technologies (research and innovation paths, production synergies and infra-group financing), we added up the patents of firms belonging to the same corporate group or GUO, i.e., Orbis IP's "global ultimate owner", while keeping all other accounting and financial variables at the GUO (i.e. corporate) level (see Benassi et al., 2021)[9]. For companies not affiliated to groups there is a one-to-one correspondence between patent and accounting/financial data.

From Orbis database we retrieved the balance sheet data, the market-to-book ratio (as a proxy of the Tobin's q) and the information on the firm's geographic location and industry NAICS codes. From Eikon-Refinitiv database, we collected the annual total stock returns and carbon emissions (Scope 1 CO_2 emissions), which we use as a proxy of the external pressure on the firm to reduce its environmental impact.[23] We then matched the firm data in the Orbis and Eikon databases by using the company ISIN code.

Table 1 reports the average CCUS patent filings per GICS sector and the corresponding average level of Scope 1 CO_2 emissions. The level of carbon emissions is higher in Utilities, Energy, Materials while Energy, Consumer discretionary and Materials are the top patenting sectors.

Table 1: CCUS Patents and CO_2 Emissions per Firm-Year by GICS Code (own data)

GICS Code	CCUS Patents (Mean)	CO_2 Emissions (Mean)
Energy	6.56	18,200,000
Materials	1.83	7,569,314
Industrials	1.23	369,616
Consumer Discretionary	2.69	614,135
Consumer Staples	0.07	1,104,146
Health Care	0.22	1,132,234
Information Technology	1.04	298,230
Communication Services	0.72	278,247
Utilities	0.77	29,200,000
$N firms$	259	259
Total	2.03	6,150,744

To further account for the external pressure to reduce the climate impact, we draw on the *Environmental Policy Stringency index* (Botta et al., 2014[18] and Kruse et al., 2022[59]) based on different policy indicators at the country level.[24] To address policy interventions specifically related to decarbonization policies, we single out the following sub-indices: *CO_2 Tax*, *CO_2 ETS*, *Diesel tax*, *Low Carbon R&D subsidies*, *Technology support policies.*

[23] CO_2 emissions are classified as Scope 1 (direct emission from production), Scope 2 (indirect emission from consuming purchased heat and electricity) and Scope 3 emissions (indirect emissions from logistics, sale and disposal of sold products). Given the large number of missing values for Scope 2 and 3 emissions, we use Scope 1 emission. Since also Scope1 data report several (around 2%) missing values, we decided to linearly interpolate the missing values in between non-missing years so as to maintain, as much as possible, the integrity of the distributions over time.

[24] The index is calculated by the OECD and covers market- and non-market based policy instruments and technology support policies (e.g., public R&D expenditure).

The final dataset includes 408 firms, of which 259 patented at least one CCUS innovation in the sample period. Total CCUS patents filed in the sample period amounts to 5,937. The starting date of the panel data used in the econometric analyses is 2010 because the information on green patenting is available only from 2010. Table 2 and Table 3 report the distribution by country of origin and by GICS sector of the publicly listed firms in the panel data we use in the empirical analyses, highlighting *CCUS firms* i.e., those with at least one CCUS patents.

Table 2: *Firms distribution by (top 10) country*

Country	Total	CCUS firms
US	112	54
JP	106	100
DE	36	20
GB	36	18
FR	33	16
SE	14	5
FI	11	7
IE	8	6
NO	8	4
CH	7	7
Other	37	22
Firms	408	259

Table 3: *Firms distribution by GICS sector*

Sector	Total	CCUS firms
Communication Services	2	2
Consumer Discretionary	41	28
Consumer Staples	11	2
Energy	32	26
Health Care	43	12
Industrials	139	86
Information Technology	5	4
Materials	109	85
Utilities	25	14
Firms	408	259

As shown by Table 3, firms with at least one CCUS patent are quite distributed among GICS sectors, although 48.3% of the companies operate in Energy, Utilities and Materials, which include many carbon-intensive industries.

4.3 Variables and descriptive statistics

In this section, we present the variables used in the analyses and the descriptive statistics.[25] We compute the descriptive statistics over the period 2010-2022 for the full estimation sample. Table 4 describes the innovation and environmental variables, Table 5 presents the firm-level economic and financial variables, Table 6, compares the innovation variables of companies with high (above-median) and low (below-median) levels of carbon emissions. In Appendix B, we report the Correlation matrix and in Table 14, the mean differences for the sub-samples of firm with and without CCUS patents (i.e., those in the neighbouring technology field as per IPC/CPC codes).

In Table 4, the main variable we use to describe CCUS patenting is *CCUS_pat*, the firm-year number of CCUS patents while *CCUS_dummy* is the binary variable denoting whether the firm i has filed 1 or more CCUS patents in year t. We also computed the stock of patents (*CCUS_Stock*) , the R&D stock (*R&D_Stock*) and the stock of (non-CCUS) green patents (*Green_stock*), assuming an annual growth rate of knowledge capital of 8% and a depreciation rate of 15%, in line with relevant literature (e.g., Colombelli et al., 2020[30]).

To estimate the firm market value model, the innovation variables are normalized by fixed assets (*R&D_stock/Fix. Assets*) or R&D expenditure (CCUS and green total patents respectively *CCUS/R&D_stock*, *Green/R&D_Stock*). The patent stock, available on Orbis platform, is normalized by total assets to account for size distortions, and transformed in logarithms (*ln_norm_Pat_Stock*). Similarly, R&D is divided by total assets (*R&D_int*), whereas carbon emissions were transformed into logarithms.

[25] All variables are winsorized at 1% and 99% levels, as a standard practice to reduce the effect of possible outliers in the data derived by Orbis.

Table 4: *Innovation variables and carbon emissions*

Variable	N	Mean	SD	p50	p90	p99
CCUS_pat	3,153	1.535	7.674	0	3	24
CCUS_dummy	3,153	.2533	.4361	0	1	1
CCUS_Stock	3,153	8.786	40.64	0	19.52	134.14
CCUS/R&D_Stock	3,137	5.53e-06	.0000239	0	.0000104	.000108
Green_pat	3,153	182.47	391.3	48	486	1715
Green_dummy	3,153	.8233	.3814	1	1	1
Green_stock	2,897	1,108.83	2,324.38	301.95	2,996.38	9,946.19
Green/R&D_Stock	2,885	.00078	.003058	.0001699	.0016368	.008916
ln_norm_Pat_Stock	3,153	.0009371	.001405	.000483	.002271	.007407
R&D_int	3,153	.0294	.03999	.01899	.06761	.1766
R&D_stock/Fix. Assets	2,031	.9547	1.9186	.4736	2.2466	8.4629
ln_Scope1	3,153	13.0460	2.6885	12.8479	16.8162	18.6918
ln_Scope2	3.044	12.712	1.918	12.852	15.084	16.249
ln_Scope3	2,223	14.261	3.341	14.72	18.64	20.17
Policy_PCA	3,153	1.557	1.055	1.482	3.052	3.640
_TAXCO2	3,153	1.340	1.939	1	6	6
_RD_SUB	3,153	3.768	1.421	3	6	6
_TRADESCH_CO2	3,153	1.203	.9993	1	3	3
Sample	All firms					

Table 5 describes the firm-level variables. To measure firm size we use the (log of) total assets (*ln_Tot_Assets*). The yearly growth of revenues (*Rev_growth*) is included to capture the short-term firm growth while the market-to-book ratio (*TobinsQ*) accounts for growth and profitability prospects as valued by the equity market. The return on asset (*ROA*) - the ratio between net income over total assets - measures accounting profitability. In order reduce the noise over the long panel period, we use the three-year moving average of ROA (*ROA_3y_MA*). We apply the same transformation to revenue growth (*Rev_growth_rate_3y_MA*). To capture the volatility of profitability, we calculated the three-year moving standard deviation of ROA (*ROA_3y_sd*). *Leverage*, the ratio of long term debt to total liability, accounts for firm indebtedness and financial structure. Finally, capital intensity, a proxy for asset tangibility (*Cap_Intensity*) is the ratio of total assets to the number of employees and labour productivity (*Lab_Productivity*) is revenues by employee. Finally, the annual total returns (*Tot_Ret*) are sourced from the Eikon Refinitiv platform and *Tot_Ret_sd* is the three-year standard deviation of returns that we use as a proxy of firm risk.

Table 5: *Firm-level control variables*

Variable	N	Mean	SD	p50	p90	p99
ROA_3y_MA	3,140	.0446	.0505	.0427	.1021	.1916
Cap_Intensity	3,153	1065.18	1752.07	584.89	2198.87	10315.69
ln_Tot_Assets	3,153	16.576	1.27	16.63	18.36	18.36
Leverage	3,153	.1917	.1230	.1781	.3399	.5847
Rev_growth_rate_3y_MA	3,121	.0347	.1696	.0228	.1341	.4777
Rev_growth_rate	2,972	.0487	.448	.01072	.2081	.7912
Lab_Productivity	3,142	589.78	588.46	394.83	1062.88	3180.383
ROA_3y_sd	3,118	.0187	.0266	.011	.0403	.120
TobinsQ	2,982	.999	.992	.701	2.019	5.255
Tot_Ret	2,868	12.08	35.852	9.13	53.016	124.66
Tot_Ret_sd	2,611	29.54	23.345	24.233	52.657	121.90
Sample	All firms					

Finally, in Table 6, we test whether the CCUS patent intensity of firms with high (above the median) and low (below median) *scope1* carbon emissions significantly differs, and we find that firms with a higher climate impact are significantly more active in CCUS and green patenting.

Table 6: *Mean differences between high- and low-carbon emitting firms (T-tests)*

CCUS firms	$\mu_{\text{above}} - \mu_{\text{below}}$	μ_{above}	μ_{below}	*tstat*	*N*
CCUS_pat	1.77	2.43	0.66	6.54***	3,153
Green_pat	162.24	264.95	102.71	11.89***	3,153
R&D_int	-0.0202	0.019	0.039	-14.61***	3,153

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Empirical strategy and results

5.1 Determinants of CCUS innovation

5.1.1 Empirical strategy

When we ask what determines the intensity of patenting, we implicitly exclude firms that, having a technological and scientific know-how that neighbors that of CCUS do not file a patent in the specific CCUS field. This approach might generate a sample-selection bias where the factors driving the patenting decision - for example unobservable specialization costs - may also affect the intensity of their research effort but are not accounted for. Therefore, our dataset includes companies that innovate in the broader CPC/IPC technological field (i.e., the higher hierarchical class) that contains the CCUS group of patents as a subset. Precisely, we add firms that filed patents featuring at least one IPC/CPC code relative to the same sub-classes (level 3) that include CCUS technologies, as shown in Figure 2 in Appendix A.

Our assumption on the innovating behavior is that every year companies face two sequential decisions: 1) whether or not to file a CCUS patent (extensive innovation margin); 2) how much to invest in CCUS innovation, i.e., how many patents to file, conditional on the positive patenting decision (intensive margin). To address this problem empirically, we use the Zero-inflated Poisson (ZIP) regression model (see Noailly & Smeets, 2015)[74], which conveniently combines the process that governs the realization of the binary outcome (patents vs. non-patent) with the process explaining the realization of the number of patents filed conditional on patenting. The ZIP model is based on the assumption that a zero patent outcome is the realization of two different processes. The "structural" zeroes are realized when the firm decides not to file a patent in a given year (say because the expected profits from innovation minus the costs of patent application do not exceed the innovation investment), and are modeled by a probit regression. The "standard" zeroes occur when the firm does not file a patent in that year due to some exogenous factors (e.g., the innovation has not yet reached the required TRL - technology readiness level, or the R&D efforts were unsuccessful), and are modeled by a Poisson regression.[26] Since the dataset includes both CCUS patenting firms and firms patenting in neighboring technologies, we assume that all sampled firms can decide, every given year, whether to file for a patent (we use the priority year to capture the year of filing decision) and we can discriminate between firms deciding not to patent in a given year and firms that failed to do so.

To model CCUS patenting behavior and capture cross-firm heterogeneity, we rely on a large set of firm-level variables such as size, profitability (ROA) and its variability, revenue growth, financial leverage and capital intensity. The patent stock and the normalized R&D expenditure account for the firm's innovation capacity. Moreover, in line with the literature

[26]The zero-inflated Poisson model resembles the Heckman selection model but has less restrictive normality assumptions, does not require an exclusion restriction in the second step and can deal with count data (without logarithmic transformations) that better fit our firm-level patent data. Moreover, the zero-inflated model does not censor observations in the second step but, assuming two latent groups (an Always-0 Group and a Not Always-0 Group), it proceed in three steps: it models membership in the latent groups, then it models counts for those in the Not-Always 0 group, and ultimately it computes observed probabilities as a mixture of the probabilities of the two groups (Long & Freese, 2014[64]). See Appendix C for a derivation of the model.

on eco-innovation, we include labor productivity as a proxy of human capital, and a dummy denoting that the firm has also green patents (other than CCUS patents), to control for past activity and experience in the green knowledge sector. We lag all variables one year to reduce concerns about reverse causality.

As CCUS patents appear specifically intertwined to climate risk problems related to CO_2 emissions and to the bad reputation of high polluting firms, two natural drivers of CCUS innovation are *Scope1* CO_2 emissions (lagged one, two, and three years)[27] and environmental regulation. In the first step, when estimating the extensive margin (i.e., membership in the latent groups), we include lags of CO_2 emissions in levels because the patenting decision is more likely driven by the magnitude and continuity of the environmental riskiness of the firm. To proxy for the country-level regulatory policy, we add three sub-indices of the *Environmental stringency index* (OECD) specifically addressing carbon emission issues, such as *CO_2 tax*, *Emission Trading Schemes* and *Low carbon R&D subsidies*, which are likely to motivate CCUS innovation. In the second step, when estimating patent intensity (intensive margin), we enter the three lags of CO_2 emissions as first-differences to capture the shot-term incentives that may drive the intensity of the patenting process.

Because the cumulated knowledge stock cannot be considered strictly exogenous, we rely on the pre-sample mean estimator by Blundell (1995)[13], which accounts for firm fixed effects by the pre-sample mean of the dependent variable.[28] Therefore, we add the mean of CCUS

[27]We lag carbon emissions not only to address reverse causality concerns, but also to account for the fact that research activity needs time to reach the results that allow firms to file a patent. We stop at t-3 to avoid losing too many observations. Moreover, in our last specification, we test the joint significance of the three lags to investigate the dynamics of the process, controlling for the full trend of CO_2 emissions.

[28]As highlighted by Blundell et al. (2002)[13], in count data models with individual specific constants, the Poisson maximum likelihood estimator is inconsistent for the parameters of interest if the regressors are predetermined, hence not strictly exogenous.

patenting in the period 2000-2011 as a proxy of the time-invariant cross-firm heterogeneity in innovation capacity, and a binary variable denoting if the firm has patented in the pre-sample period (see also, for recent applications, Noailly & Smeets, 2015[74] and Majo & van Soest, 2011[65]).

As a robustness check, we estimate the same specifications using the Zero-Inflated Negative Binomial model (ZINB). Furthermore, we estimate the intensity of patenting using a standard Poisson count data model using the sub-sample of firms that have filed at least one CCUS patent in the period. The results are in Appendix E.1.

5.1.2 Results

In Tables 7 and 8 , we report the results of the ZIP regressions augmented with the pre-sample mean estimator. Recall that in the ZIP model, the extensive margin in Table 7 estimates the probability that firm i files a CCUS patent in year t, while the "intensive" margin in Table 8 estimates how many patent firm i files in year t conditional on the patenting decision.[29].

[29] Note that in the extensive margin the standard ZIP model predicts the probability to have a zero outcome (i.e., probability *not* to patent). For the readers' convenience, we inverted the signs of the coefficients in Table 7.

Table 7: *ZIP - Extensive margin*

1st-step **Probit regression**				
	(1)	(2)	(3)	(4)
CCUS_pat=1	t-1	t-2	t-3	L_all
ln_Scope1_{t-1}	0.146***			0.148
	(0.001)			(0.255)
ln_Scope1_{t-2}		0.141***		-0.0672
		(0.002)		(0.722)
ln_Scope1_{t-3}			0.139***	0.0665
			(0.003)	(0.554)
$\_TRADESCH\_CO2_{t-1}$	-0.156**	-0.140*	-0.166**	-0.167**
	(0.030)	(0.051)	(0.022)	(0.021)
$\_TAXCO2_{t-1}$	0.0665*	0.0567	0.0748*	0.0763*
	(0.095)	(0.163)	(0.068)	(0.062)
$\_RD\_SUB_{t-1}$	-0.0538	-0.0489	-0.0491	-0.0515
	(0.306)	(0.335)	(0.339)	(0.321)
$Green\_dummy_{t-1}$	1.180***	1.157***	1.166***	1.158***
	(0.000)	(0.000)	(0.000)	(0.000)
$ln\_norm\_Pat\_Stock_{t-1}$	-6.908	-16.93	-17.80	-13.02
	(0.904)	(0.674)	(0.664)	(0.754)
$Rev\_growth\_rate\_3y\_MA_{t-1}$	1.517**	1.799**	2.006**	1.937**
	(0.037)	(0.035)	(0.020)	(0.025)
$Leverage_{t-1}$	-1.775***	-1.394**	-1.213*	-1.217*
	(0.005)	(0.035)	(0.075)	(0.075)
$ln\_Tot\_Assets_{t-1}$	-0.0841	-0.106	-0.0900	-0.0975
	(0.260)	(0.171)	(0.259)	(0.224)
$R\&D\_int_{t-1}$	-5.298*	-4.307	-4.379	-4.037
	(0.054)	(0.137)	(0.137)	(0.164)
$Cap\_Intensity_{t-1}$	-0.000141	-0.000152	-0.000141	-0.000145
	(0.271)	(0.158)	(0.190)	(0.172)
$Lab\_Productivity_{t-1}$	-4.59e-06	5.81e-05	8.34e-05	8.45e-05
	(0.983)	(0.749)	(0.645)	(0.645)
$ROA\_3y\_MA_{t-1}$	-0.173	-0.265	-0.589	-0.602
	(0.891)	(0.844)	(0.670)	(0.663)
pre_sample_ccus	0.471**	0.477***	0.468***	0.462***
	(0.012)	(0.000)	(0.000)	(0.000)
pre_sample_ccus_dummy	0.306	0.356**	0.433**	0.437**
	(0.132)	(0.043)	(0.013)	(0.013)
H0: t-1 t-2 t-3 = 0				10.43***
Observations	2,877	2,755	2,630	2,630
Year FE	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes
N_clust	395	377	360	360

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: *ZIP - Intensive Margin*

2nd-step **Poisson regression**				
	(1)	(2)	(3)	(4)
CCUS_pat_count	D1	$D1_{t-1}$	D_{t-2}	D_all
D.ln_Scope1	0.199			-0.0294
	(0.165)			(0.882)
$D.ln\_Scope1_{t-1}$		0.0641		-0.194
		(0.489)		(0.292)
$D.ln\_Scope1_{t-2}$			0.201**	0.318***
			(0.012)	(0.005)
$Green\_dummy_{t-1}$	-0.375	-0.292	-0.385	-0.383
	(0.269)	(0.312)	(0.204)	(0.198)
$ln\_norm\_Pat\_Stock_{t-1}$	136.1***	146.9***	160.1***	160.7***
	(0.005)	(0.002)	(0.001)	(0.001)
$Rev\_growth\_rate\_3y\_MA_{t-1}$	-2.261***	-2.555***	-2.782***	-2.774***
	(0.000)	(0.001)	(0.000)	(0.000)
$Leverage_{t-1}$	-1.839**	-2.490***	-2.501***	-2.496***
	(0.034)	(0.003)	(0.003)	(0.003)
$ln\_Tot\_Assets_{t-1}$	0.108	0.149*	0.142*	0.143*
	(0.196)	(0.070)	(0.085)	(0.082)
$R\&D\_int_{t-1}$	-0.612	-4.442	-4.583	-4.876
	(0.914)	(0.429)	(0.415)	(0.382)
$Cap\_Intensity_{t-1}$	-0.000373**	-0.000340**	-0.000319***	-0.000322***
	(0.020)	(0.013)	(0.007)	(0.007)
$Lab\_Productivity_{t-1}$	0.000694**	0.000584***	0.000546***	0.000543***
	(0.013)	(0.008)	(0.005)	(0.006)
$ROA\_3y\_MA_{t-1}$	-3.470**	-3.125**	-3.295**	-3.260**
	(0.041)	(0.045)	(0.027)	(0.030)
pre_sample_ccus	0.0738***	0.0734***	0.0733***	0.0732***
	(0.000)	(0.000)	(0.000)	(0.000)
pre_sample_ccus_dummy	1.309***	1.183***	1.140***	1.138***
	(0.000)	(0.000)	(0.000)	(0.000)
H0: D1 LD1 LD2 = 0				8.85**
Observations	2,877	2,755	2,630	2,630
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N_clust	395	377	360	360

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Starting from the extensive margin, we find that the amount of (log) emissions (ln_Scope1_{t-1}) is a significant (and positive) predictor of the decision to innovate in the CCUS sector. The evidence holds when we test, separately, three lags of the variable, to account for a delay in the patenting response. When we include all three lags in Column (4), we find no significant evidence, but the F-test at the bottom of the table tells us that the three coefficients are jointly significant. To confirm the relevance of environmental pressure in the extensive margin, we find that the decision to patent is positively related to carbon pricing ($\_TAXCO2_{t-1}$) and negatively related to the tightness of Emission Trading Schemes ($\_TRADESCH\_CO2_{t-1}$).

Although this latter result seems counterintuitive, we must consider that ETS schemes do not provide, to date, for direct remuneration of negative emissions, thereby reducing the incentives to invest in these technologies[30]. Finally, we find that the coefficient on Low Carbon R&D subsidies ($\_RD\_SUB_{t-1}$) is insignificant.

Results in Table 7 also show that having previously filed patents in green technologies (*Green_dummy*) positively affects the probability of filing CCUS patents, while the coefficient on the generic patent stock is insignificant. These results suggests the decision to innovate in CCUS is driven by the urgency to address a "dirty" environmental profile as well as by firm-specific innovation capacity and experience in green technologies. Turning to the other control variables, we find that the probability of CCUS patenting is higher for high-growth firms ($Rev\_growth\_rate\_3y\_MA_{t-1}$), less levered ($Leverage_{t-1}$) and smaller companies ($ln\_Tot\_Assets_{t-1}$). Perhaps surprisingly, R&D intensity ($R\&D\_int_{t-1}$) is negatively related to the decision to innovate in CCUS (but the coefficient is significant only once). The finding of insignificant, ambiguous - even negative - relationships between general R&D expenditure and eco-innovation has already been addressed by the literature. For example, it has been argued that technological capability is only one of the drivers of eco-innovation, and that the higher complexity of the other determinants may dilute its relationship with cyclical R&D expenditures[31]. Furthermore, as suggested by (Wang & Hagedoorn, 2014)[95] this result may also depend on the delayed effect of research investment and the readiness of

[30] ETS policies are diversified across countries; for instance, from 2018, the US tax credit has been ruled by the 45Q scheme for Carbon Sequestration `https://www.iea.org/policies/4986-section-45q-credit-for-carbon-oxide-sequestration` that provides compensations between $50 and $85 dollars per ton of sequestrated industrial emissions in the form of tax credits (hence incentivizing mostly high-revenue firms, `https://www.mckinsey.com/industries/oil-and-gas/our-insights/scaling-the-ccus-industry-to-achieve-net-zero-emissions`. Conversely, the EU ETS does not compensate negative emissions at all yet.

[31] See Diaz-Garcìa et al., 2015[35] for review and discussion of past results.

innovation to become a patent. Finally, the probability to file CCUS innovations seems to increase if the firm has previously patented in the same field (*pre_sample_CCUS_dummy*) and the greater the patenting intensity in the pre-sample period (*pre_sample_CCUS*). This is indicative of a "specialization effect", in line with well-established evidence that technological innovation is a path-dependent activity (in the evolutionary economics tradition, see the seminal contributions of Patel & Pavitt, 1997[79] and Dosi & Nelson, 2010[37]; more recently, with reference to green innovation, see also Aghion et al., 2019)[2].

In Table 8, the dependent variable is the number of CCUS patents filed by the firm in a year. When we look at the relationship between patent filings and the growth in carbon emissions (*D.ln_Scope1*), we find that only the coefficient in Columns (3) is statistically significant, suggesting a medium-term incentive to file more patents is in place (i.e., between t-2 and t-3) when the company is active in CCUS technology. The evidence holds in Column (4), where we test the joint significance of the three lagged differences, as shown at the bottom of the table. Interestingly, green patenting is negatively signed (though insignificant), potentially indicating a substitution effect when firms have to allocate specific R&D resources to different, and costly, projects. In contrast with the extensive margin, now patent stock ($ln\_norm\_Pat\_Stock_{t-1}$) enters with a positive sign suggesting that patent intensity eventually depends on the experience and continuity of the firm's innovative effort in general while the positive and significant coefficients on the pre-sample mean and dummy show that sector-specific technological specialization is also crucial.

Turning to the other control variables, we find that larger companies ($ln\_Tot\_Assets_{t-1}$) that grow less ($Rev\_growth\_rate\_3y\_MA_{t-1}$) appear to file more CCUS patents. Moreover, the intensity of CCUS patenting is positively associated to labor productivity ($Lab\_Productivity_{t-1}$)

and negatively related to profitability ($ROA\_3y\_MA_{t-1}$). Finally, we find that patent intensity is higher in less levered (i.e., more capitalized) companies, suggesting that these firms have to rely more on the equity market, not only because they are innovative, hence riskier, but also due to their double externality problem. The different pattern of results between intensive and extensive margins supports our choice to design our research question as a two-step process. Hence, if the choice to innovate appears to be mainly driven by environmental, policy, and technological factors, patent intensity is eventually constrained by cost efficiency and financial constraints related to a double externality problem.

To summarize, our empirical analysis shows that firms patenting in CCUS technologies have technological know-how and experience in the field of eco-innovation and, more importantly, that they respond both to environmental policies and to their sector-specific climate risk, as shown by results on CO_2 emissions. Our findings suggest that CCUS can be assimilated to other eco-innovations, as also implied by the evidence that the decision to patent and the intensity of patent activity are explained by different drivers (Kesidou et al., 2012)[58]. These results hold to an array of robustness tests. First, due to high persistence of carbon emissions, we used emission intensity (computed as the ratio of emissions to sales) instead of the log of the total amount. Second, because the different structure of the lagged emissions implies that we estimate our models on (slightly) different samples, we estimate all regressions with the most restricted sample (i.e., t-3) in Column (4), N=1526. Third, we re-estimate the intensive margin regressions using the Pseudo Poisson Maximum Likelihood (PPML) estimator[32] as an alternative to the ZIP model. Fourth, we estimate

[32] See Silva et al., 2006[88] and 2011[87]

all regressions with zero-inflated negative binomial regressions.[33]. Results of the robustness tests in Appendix E.1 confirm the evidence above.

5.2 CCUS patenting and stock market performance

Our second research question addresses the impact of firm's CCUS patent intensity on their performance in the stock market. The underlying issue is whether financial markets are willing (or capable) to acknowledge and reward these technologies, thereby embracing a wider range of objectives from shareholder value to shareholder welfare (Hart and Zingales, 2017)[50], from investors and governments' climate concerns, as tighter environmental policies may jeopardize firms' profitability. This would provide a significant incentive to innovate in CCUS technologies in addition to environmental policies. To this purpose, we estimate, first, the relationship between CCUS patents and firm value and then their relationship with total stock returns. As our data includes not only firms with a CCUS patenting activity, but also those with patents in a neighboring research area (see Section 4 and Appendix A), our analysis contrasts both companies with more or less CCUS patents and firms with and without CCUS patents.

5.2.1 CCUS patenting and firm value

Our empirical model draws on a recent contribution by Colombelli et al. (2020)[30], who estimate the impact of the generation of environmental (green) technologies inventions (proxied by patents) on firm market value for a panel of European countries, and find that firm market value is positively related to green patents. Following Griliches (1981)[47], Hall

[33] We thank one referee for suggesting us to perform this analysis.

(1999)[48] and Hall et al. (2005)[49], we also model the firm's market value as a function of a combination between tangible and intangible assets, as in equation (1):

$$V_{it} = b_t(A_{it} + \gamma K_{it})^{\sigma} \tag{1}$$

where V_{it} is the market value of firm i at time t, A_{it} is the value of tangible assets, K_{it} denotes the firm's knowledge, i.e., intangible assets, and the parameter σ allows for non-constant returns to scale. Approximating intangible assets by the number of (CCUS and Green) patent stocks and by the R&D stock, and lagging one year to control for potential reverse causality, our baseline specification becomes (see Appendix D for the derivation of the estimating model):

$$log\, Q_{it} = log\, b_t + \gamma_1 \frac{R\&D\_stock_{it-1}}{A_{it-1}} + \gamma_2 \frac{CCUS\_stock_{it-1}}{R\&D\_stock_{it-1}} + \gamma_3 \frac{Green\_stock_{it-1}}{R\&D\_stock_{it-1}} + \beta Controls_{it-1} + \epsilon_{it} \tag{2}$$

Where $logQ_{it-1}$ is the logarithm of the Tobin's Q, the R&D to tangible assets ratio captures the firm's commitment to generate new knowledge, $\frac{CCS\_stock_{it-1}}{R\&D\_stock_{it-1}}$ measures the actual patenting yield of the specific CCUS technology, i.e., our variable of interest, and $\frac{Green\_stock_{it-1}}{R\&D\_stock_{it-1}}$ is its counterpart with green (non-CCUS) technologies, that we enter as a control variable.[34] ϵ_{it} is the random stochastic error with zero mean. Both are lagged one year to account for a delay in the response of average stock returns[35]. We then add the one-year lag of *scope 1* CO_2 emis-

[34] To build the R&D, CCUS and green patent stocks, we used the perpetual inventory method, assuming a depreciation rate of 15% (see also Hall, 1999[48]).

[35] Notably, in our robustness analysis we address the possibility that a distortion may arise when the lag between the actual application and the disclosure of the news to the public is longer than one year, e.g., 18 or 24 months. Since we have no access to information about the disclosure date of each patent, to deal with this potential time inconsistency we re-estimate our models by applying both (i) a two-year lag to all patent variables (ii) a mix between the one and two-year lag to accommodate a (more plausible) 18 month

sions and its interaction with CCUS patent intensity to investigate not only how the stock market responds to CCUS (and green) patenting, but also whether it responds differently to patents filed by companies with higher levels of carbon emissions, i.e., higher climate risk. Indeed, climate concerns may irk not only the sensitivity of environment-friendly investors but also of profit-motivated shareholders who dread the backlash of a costly conversion of the production process.

We add a large set of control variables that includes firm size, financial leverage, accounting profitability (3-year average and standard deviation), revenue growth, labour productivity, and capital intensity. To control for external regulatory pressure, we use 5 sub-indices of the OECD Environmental Policy Stringency (EPS) specifically related to carbon emission problems.[36]. For conciseness, we insert a data reduction of these indices obtained with Principal Component Analysis, named *Policy-PCA*.[37] This variable, being influenced by domestic policy is also expected to capture idiosyncratic industry-related factors. The final estimating model then becomes:

$$\begin{aligned} log\,Q_{it} = log\,b_t + \gamma_1 \frac{R\&D\_stock_{it-1}}{A_{it-1}} + \gamma_2 \frac{CCUS\_stock_{it-1}}{R\&D\_stock_{it-1}} + \gamma_3 \frac{Green\_stock_{it-1}}{R\&D\_stock_{it-1}} \\ + \gamma_4 \log scope1_{it-1} + \beta X_{it-1} + \upsilon_s + \nu_t + \tau_c + \epsilon_{it} \end{aligned} \tag{3}$$

Column (1) includes industry, year, and country fixed effects, while estimates in Columns

time period. In particular, assuming that patent filings were uniformly distributed during the year, we could identify the yearly count of disclosed patents as the sum of the patents filed in the first half of the previous year (*t-1*) plus the filings in the second half of the year before (*t-2*). Results are in Appendix D, Table 22.

[36] *CO_2 Tax*, *CO_2 ETS*, *Low Carbon R&D subsidies*, *Technology support policies*, *Diesel tax*.

[37] We use the concise Policy-PCA measure to keep the interpretation of the results manageable, since this variable enters both linearly and interactedly with carbon emissions.

(2), (3) and (4) account for firm and year fixed effect estimates. Robust standard errors are clustered at the firm level. Table 9 reports the results.

Table 9: *Market performance: Tobin's Q*

ln_Q	(1)	(2)	(3)	(4)
$CCUS/R\&D\_stock_{t-1}$	202.9	1.912	-2,780**	-2,988**
	(0.810)	(0.996)	(0.037)	(0.024)
$Green/R\&D\_stock_{t-1}$	-4.831	3.825	3.318	27.84
	(0.321)	(0.236)	(0.257)	(0.199)
ln_Scope1_{t-1}	-0.0761***	0.0124	0.0116	0.0130
	(0.000)	(0.553)	(0.582)	(0.536)
$ln\_Scope1_{t-1}\#CCUS/R\&D\_stock_{t-1}$			234.1**	252.9**
			(0.040)	(0.029)
$ln\_Scope1_{t-1}\#Green/R\&D\_stock_{t-1}$				-1.908
				(0.268)
$R\&D\_stock/Fixed\ Ass._{t-1}$	0.0207**	-0.00581	-0.00584	-0.00574
	(0.040)	(0.600)	(0.599)	(0.605)
$ln\_Tot\_Assets_{t-1}$	-0.0795***	-0.169***	-0.169***	-0.169***
	(0.005)	(0.007)	(0.007)	(0.008)
$Leverage_{t-1}$	-0.682***	-0.312	-0.317	-0.312
	(0.006)	(0.201)	(0.193)	(0.202)
$Cap\_Intensity_{t-1}$	8.59e-06	-7.49e-05*	-7.63e-05*	-7.76e-05*
	(0.428)	(0.079)	(0.072)	(0.066)
$ROA\_3y\_MA_{t-1}$	7.659***	4.940***	4.926***	4.916***
	(0.000)	(0.000)	(0.000)	(0.000)
$Policy\_pca_{t-1}$	0.0843***	0.0707***	0.0725***	0.0724***
	(0.002)	(0.005)	(0.004)	(0.004)
$ROA\_3y\_sd_{t-1}$	0.810	-0.744	-0.752	-0.754
	(0.529)	(0.536)	(0.530)	(0.529)
Observations	2,546	2,546	2,546	2,546
Year FE	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes
r2_a	0.672	0.257	0.257	0.257
Number of firm_id	349	349	349	349

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Column (1) and (2) the same model is presented without and with firm fixed effects for comparability. In both columns, we find no direct association between firm value and CCUS patenting ($CCUS/R\&D\_stock_{t-1}$), nor with green patenting ($Green/R\&D\_stock_{t-1}$) or with R&D intensity ($R\&D\_stock/Fixed\ Ass._{t-1}$).[38] CO_2 emissions (ln_Scope1_{t-1}) enters with

[38] An interesting evidence comes from Faria et al. (2022)[40] who find a negative impact of green patents on market value in a sample of firms in oil-related sectors.

a negative and significant coefficient at a cross-sectional level, in line with the idea that the stock market penalizes firms with heavier climate impact (see, for example, Matsumura et al., 2014[67] or Perdichizzi et al., 2024[80]), but the variable turns insignificant in the FE models.[39] The environmental policy variable, *Policy-PCA*, is positive and significant in all columns, suggesting that in countries where environmental policy is tighter, the stock market anticipates that "brown" companies are prompted to adjust sooner to greener technologies. This finding is consistent with evidence by Choi & Luo (2021)[28] that the impact of firm-level emissions on market-value is negative and worse in countries with tighter environmental policies. Finally, turning to control variables, we find that firm value is positively related to accounting profitability ($ROA\_3y\_sd_{t-1}$), and negatively correlated with firm leverage ($Leverage_{t-1}$) and size ($ln\_Tot\_Assets_{t-1}$).

Results become more informative in Columns (3)-(4), where we test whether the lack of significance of the relationship between CCUS patents and firm value may depend on a non-linearity, i.e., that the impact of patents may change depending on its level of "browness". When we add the interaction between CCUS patents and carbon emissions, results show that CCUS patents enter with a negative coefficient, but the interactive term is positive and significant. This suggests that CCUS patenting does affect the firm's market value positively, but only if the company is a high carbon emitter, hence more subject to the climate-transition risk and to the need to convert, urgently, to less polluting technologies. More specifically, we can calculate that, based on estimates in column 4, the negative effect of CCUS patenting on the market-to-book ratio turns positive at a level of *ln_Scope1* emissions equal to 11.77,

[39]This is likely due to persistence, i.e., low variability in absolute terms over time of the emission variable in levels.

and that the number of firms exceeding the turning point is quite large, i.e., 261 out of 408 companies benefit from CCUS patenting in terms of market value.

Interestingly, we find no such significant effect with broadly-defined *green* patents, which suggests that the stock market seems to value positively firms with higher climate risk when they direct their research efforts towards environment-friendly, but sector-specific, technologies.

5.2.2 CCUS patenting and stock returns

We now focus on total stock returns to investigate if CCUS patenting may mitigate the so-called "carbon risk premium", i.e., the higher expected returns required by investors for holding stocks of brown companies that face, more than others, the climate-transition risk (Bauer et al. 2022)[8]. In this literature, a relevant contribution is by Bolton and Kacperczyk (2021)[14] who, within the traditional efficient capital markets theory, estimate the effect of carbon emissions on stock returns using panel regressions rather than standard portfolio methods (see, among the others, Pástor et al., 2021[77], and Bauer et al., 2022[8]). In this paper, we follow their estimating approach, but depart from their research question, in that we investigate the relationship between (annual) stock returns and CCUS patents. In fact, our interest is for the market response to companies' efforts to reduce their firm-specific climate risk. To the extent that many CCUS patenting firms in our dataset operate in high carbon-intensive industries, they are subject to a stronger environmental pressure that can reduce their market value. In this context, patenting in fields such as CCUS could be a safe strategy to mitigate their carbon risk, and we expect that it should reduce the stock market premium.

In our analysis, the stock returns of firm i in year t are regressed on the number of CCUS patents, the log of direct carbon emissions, a vector of control variables and *Policy-PCA* our summary measure of environmental stringency policies related to decarbonization issues:

$$\begin{aligned} Tot\_Ret_{it} = \beta_0 + \beta_1 CCS\_patents_{it-1} + \beta_2 logscope1_{it-1} \\ + \beta_3 EPS_{it-1} + \gamma Controls_{it-1} + \mu_i + \lambda_t + \epsilon_{it} \end{aligned} \tag{4}$$

Table 10 reports the results of panel regressions that include a large set of firm-level variables typical in the financial literature estimating stock returns regressions. The log of total asset ($ln\_Tot\_Assets_{t-1}$) is a measure of firm size, the Tobin's Q ($TobinsQ_{t-1}$) is a proxy of growth prospect, the standard deviation of the stock returns ($Tot\_Ret\_sd_{t-1}$) measures the company's risk, and the level (ROA_{t-1}) and 3-year standard deviation ($ROA\_3y\_sd_{t-1}$) of the return on assets measure profitability and its volatility while the financial leverage controls for the capital structure. In addition, given our focus on research activity, we include a *Green dummy* to denote if the firm has filed a green patent in year *t-1*, the normalized R&D expenditures ($R\&D\_int_{t-1}$), and the capital-labour intensity ($Cap\_Intensity_{t-1}$) and labour productivity ($Lab\_Productivity_{t-1}$) to control for the production function. Finally, all estimated models include firm, and year fixed effects interacted with GICS sectors to account for time varying industry-specific technological trends and different exposure to climate concerns (see, for example, Pástor et al., 2022[76]) and control for additional unobserved firm level variables. ϵ_{it} is the error term. All RHS variables are lagged one year and robust standard errors are clustered by firm. Also with stock returns regressions we test the robustness of our results to a longer delay between the patent filing and the announcement to the market. Results are in Appendix E.2, Table 26.

Table 10: *Market performance: Stock returns*

Tot_Ret	(1)	(2)	(3)	(4)
CCUS_pat$_{t-1}$	-0.200	2.017**	1.986*	4.537**
	(0.320)	(0.046)	(0.057)	(0.016)
Green_pat$_{t-1}$	9.61e-05	-2.23e-06	0.00466	0.000906
	(0.984)	(1.000)	(0.908)	(0.982)
ln_Scope1$_{t-1}$	-0.583	-0.499	-0.469	-0.369
	(0.635)	(0.685)	(0.710)	(0.771)
ln_Scope1$_{t-1}$#CCUS_pat$_{t-1}$		-0.148**	-0.146**	-0.272***
		(0.019)	(0.024)	(0.008)
ln_Scope1$_{t-1}$#Green_pat$_{t-1}$			-0.000327	-8.27e-05
			(0.905)	(0.976)
Policy_pca$_{t-1}$	-5.026***	-5.085***	-5.088***	-4.658***
	(0.002)	(0.001)	(0.001)	(0.004)
Policy_pca$_{t-1}$ #CCUS_pat$_{t-1}$				-0.325*
				(0.051)
TobinsQ$_{t-1}$	-8.251***	-8.334***	-8.349***	-8.305***
	(0.009)	(0.009)	(0.009)	(0.009)
R&D_int$_{t-1}$	280.5**	282.4**	282.4**	282.5**
	(0.014)	(0.014)	(0.014)	(0.014)
ln_Tot_Assets$_{t-1}$	-8.532*	-8.417*	-8.438*	-8.313*
	(0.051)	(0.053)	(0.054)	(0.057)
Leverage$_{t-1}$	10.90	10.85	10.83	10.53
	(0.581)	(0.583)	(0.584)	(0.593)
Cap_Intensity$_{t-1}$	0.000669	0.000653	0.000655	0.000693
	(0.611)	(0.621)	(0.621)	(0.602)
ROA$_{t-1}$	-43.05	-42.65	-42.68	-42.38
	(0.327)	(0.332)	(0.332)	(0.335)
Tot_Ret_sd$_{t-1}$	0.554***	0.554***	0.554***	0.554***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA_3y_sd$_{t-1}$	-39.61	-39.53	-39.59	-38.78
	(0.400)	(0.401)	(0.401)	(0.410)
Lab_Productivity$_{t-1}$	-0.00120	-0.00107	-0.00108	-0.00112
	(0.834)	(0.853)	(0.852)	(0.845)
Observations	2,587	2,587	2,587	2,587
Number of firm_id	347	347	347	347
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes
Year X GICS FE	Yes	Yes	Yes	Yes
r2_a	0.263	0.263	0.263	0.263

Robust pval in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Results in Column (1) show that CCUS patents have no significant impact on total returns, neither have green patenting and direct carbon emissions. However, in Columns (2)-(4), when we allow for non-linearity in the relationship between CCUS patents and carbon emissions, the CCUS coefficient turns positive and significant while the interaction enters with a negative and significant coefficient.[40] This evidence suggests that, CCUS patents *per se*, are associated with higher stock returns, i.e., raise the premium requested by the market to invest in these companies, partly due to their implicit connection with climate risk and partly due to the (usual) high uncertainty and costs associated with patent activity.

However, the negative and significant interaction with CO_2 emissions tells us that, for high emitters, CCUS patents reduce the carbon risk premium. Considering the forward-looking nature of the stock market, this suggests that innovating in CCUS technologies is viewed as promising enough to lower, in perspective, the pressure by regulators and environmentally-friendly investors on companies in most polluting sectors.

In Column (3), we add the interaction between green patents and carbon emissions, but neither the linear term nor the interaction are significant, while the evidence on CCUS patents still holds. Finally, in Column (4), we focus on the impact of environmental policy by interacting Policy-PCA with CCUS patents, and find that the mitigation effect of CCUS patents is stronger in countries where environmental policies are tighter, which suggests that capital markets, though globalized, take into due account also the local stance of environmental policy.[41]

Using our results in Table 10, we can calculate quantitative effects of the impact of CCUS patenting and derive some policy implications. So, in Col. (3), the positive effect of

[40]This finding is consistent with the negative sign on CCUS patents and positive coefficient on the multiplicative term in the previous Tobin's regressions

[41]Interestingly, this result allows some speculations with regard to a possible different market response to CCUS patenting. While the mitigation of the carbon premium for high emitting companies (see columns (2), (3), (4)) might suggest an incentive to lock-in into carbon-intensive technological pathways, the result that the mitigating effect is significantly larger where climate policy is tighter (column (4)) might suggest that the market rewards high-emitters not for innovation efforts in CCUS technologies that would lock them in in carbon intensive activities, but for investing in alternative, carbon removal options. These speculations suggest that further, more specific, analysis is required to disentangle the complex nature of CCUS technologies and its new technological pathways.

CCUS patents on total returns turns negative (thus reducing the risk premium) at a value of *ln_Scope1* emissions of 13.63, and the number of firms surpassing the turning point is 162 out of 408. If we use the coefficients in Col. (4), where we also account for the effect of environmental policy (via the interaction with Policy-PCA), the turning point is at 14.91 and 95 are the firms that will see a reduction in their risk premium (hence a lower cost of equity) thanks to their patenting activity. With a simple exercise of comparative statics, we find that if Policy-PCA went to zero - i.e., no environmental constraints at all - the number of firms benefiting from their CCUS patenting would fall to 35 while, should policy become most stringent, this number would jump to 221. Turning to control variables, we find that stock returns are positively related with their variability and negatively related with the market-to-book ratio in line with the literature (e.g., Bolton and Kacperczyk, 2021[14]). Moreover, R&D intensity enters with a positive and significant coefficient, reflecting investors' concern about high uncertainty and risk related to both the standard research activity and the CCUS technology-specific risks.[42]

Overall, our finding are in line with the risk framework described by Angelo & Johnston (2023)[5], whereby firms' innovative skills are correlated to lower future returns as a consequence of the compensation of the related risk. However, our results add further insights by showing that the pattern of the perceived risk is not constant across firms but depends on their environmental profile and on how strongly innovation is needed for an improvement, in other words on how tight the climate policy is.

[42]To further explore the propensity of firms with very high emissions to invest in these technologies, we re-estimated column (4) of Table 10, accounting for a quadratic effect of carbon emissions, but we found that the coefficients are insignificant, both linearly and interactedly with CCUS patents. Then we also tested whether the firm's investment in R&D may vary with CO_2 emissions, i.e. increase (or decrease) with the brownness of the company. We found no evidence of such non-linear effect, but all other results remain unchanged. We thank one Reviewer for suggesting these further in-depth analyses.

6 Conclusion

This paper studies the factors influencing firms' decisions to innovate in Carbon Capture and Storage (CCUS) technologies and the impact of CCUS patenting on their performance in the stock market. Although CCUS is often viewed as key to decarbonization, we highlight that it comprises a wide range of very different technologies, from E.O.R. to D.A.C.C., so that the debate is still open about whether it can be defined straightforwardly "green". An overview of the data reveals that many firms patenting in CCUS belong to carbon-intensive industries and that CCUS patenting has increased starting from the year 2000, in particular from 2010. By leveraging on firm-level data on CCUS, green and generic patent activity, carbon emissions, and financial performance, we identify key determinants as well as implications for both firms and policymakers.

Our results show that higher levels of carbon emissions are positively related to both the probability and the intensity of patenting CCUS innovations. Moreover, we find strong evidence of path dependency in CCUS innovation: firms with prior patents in CCUS technologies are more likely to continue innovating in this field. The tightness of environmental policy at the country level positively affects the decision to patent CCUS innovations. Altogether, these results suggest that environmental pressure, as captured by both the firm-specific climate risk and the country-level climate policy, acts as a significant driver of CCUS innovation.

When we turn to financial performance, our analysis shows that CCUS patents are positively valued by the stock market when the patenting firm is a high carbon emitter. These companies experience a reduction of the carbon risk premium, which suggests that investors recognize and reward efforts to improve their (poor) environmental performance in a risk-mitigating perspective. When we calculate the quantitative effects of CCUS patenting, we find that the stance of the local environmental policy is crucial in determining the magnitude of the impact, i.e., the number of firms that, thanks to their patent activity in CCUS, benefit from a reduction of the risk premium. Interestingly, we find no evidence of a significant similar effect for green patents on market value and total return, suggesting that investors perceive a sector-specific eco-innovation like CCUS as a more credible commitment for these firms.

This study contributes to the literature on the impact of intangibles on firms' performance in the capital market. Our findings are in line with the literature showing that eco-innovation positively affects firm's market performance subject to tight environmental pressure, provided the costs of shifting from traditional to eco-innovation are small. This may be the case with CCUS, which adapts sector-specific technologies to the goals of the green transition and opens a practical gateway strategy for *brown* companies that aim to signal their commitment to sustainability.

Our research is subject to a number of limitations. For reasons of data availability it was not possible to have a longer observation period, nor could we access to technology-specific R&D data and to the disclosure date of patent filings. A longer time span, disaggregated R&D data and a more exact timing would allow us more insights on the dynamics between firm signaling and market response. Furthermore, it is important to add that the analysis of the impact of these technologies on the environment, e.g. the amount of CO_2 emissions at the firm-level, was out of the scope of our study; nevertheless, this part of the story is crucial for policymakers to evaluate appropriate strategies, and is part of our future agenda along with a more thorough and meticulous patent analysis that disentangles *green* and *non-green* CCUS patents.

In conclusion, our study highlights the critical, and complementary, role of environmental policy and stock market incentives in fostering CCUS innovation, clearly indicating that a significant response - both by firms and investors - exists for solutions that build on knowledge available at industry level that can be adapted to green purposes, despite the high costs of research and project development. Hence, policymakers could design strategies that not only regulate emissions but also actively promote eco-innovations that take into account the potential of matching between sectoral specificity and suitable technologies, ensuring a sustainable transition to a low-carbon economy.

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Appendices

A IPC/CPC classification

In the literature, patent retrieval may follow three main approaches, that is a search based on keywords, (see Kaushal et al., 2021) [57], on technology-specific codes (see Camara et al., 2016)[25] or on a combination of keywords and codes (see Liu et al.,2021)[63]. Each method has its pros and cons: while searching keywords and codes could deliver more precise results, many technologies not directly showing the right combination might be overlooked. Figure 2 shows the structure of IPC/CPC codes that we followed to retrieve our CCUS patent data.[43].

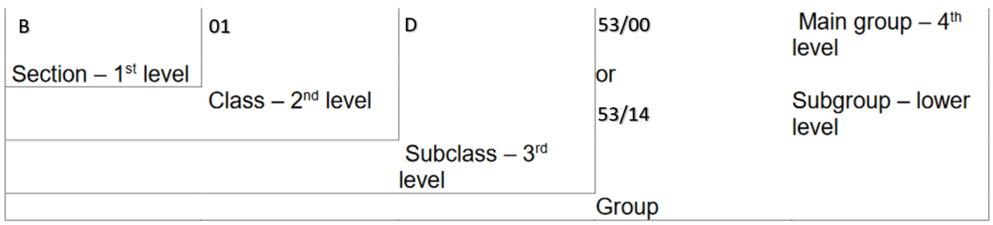

Figure 2: WIPO code classification

Due to the hierarchical nature of WIPO categorization, some patents could be difficult to isolate under single subgroups in relation to the type of technology they represent and the use it is made of each of them[97]. By the same token, a search solely based on title and abstracts is likely to leave out patents which are directly linked to the knowledge chain that is the object of the study. Eventually, we decided to run a search based on technology-specific codes, which should allow us to include all the patents that are, either completely or in part, ascribed to CCUS technologies. Specifically, our research query covered each patent (available on Orbis IP database) that contained, among its list of IPC/CPC codes, at least one code relative to the sub-class to which CCUS technologies belong to; then, we proceeded to isolate strictly CCUS patents based on technology-specific codes as provided and categorized by WIPO (the so-called sub-groups).

Table (12) reports the codes and brief definitions of the sub-classes we used to identify *CCUS neighbouring technologies*, while table (11) reports the IPC/CPC sub-groups codes used by WIPO to identify *CCUS technologies*.

[43]Figure 2 shows the nested ordering of IPC/CPC categories with an example code from the actual CCUS sample (*B01D53/14*, corresponding to *gas separation by absorption*). The full lists are in tables 12 and 11)

Table 11: IPC/CPC WIPO groups of *CCUS technologies*

Code	description
B01D53/14	by absorption
B01D53/22	by diffusion
B01D53/62	Carbon oxides
B65G5/00	Storing fluids in natural or artificial cavities or chambers in the earth
E21F17/16	Modification of mine passages or chambers for storage purposes, especially for liquids or gases
C01B31/20	Carbon dioxide
C01B32/50	
E21B41/00	Equipment or details not covered by groups E21B15/00 - E21B40/00
E21B43/16	Enhanced recovery methods for obtaining hydrocarbons
F25J3/02	by rectification, i.e. by continuous interchange of heat and material between a vapour stream and a liquid stream
Y02P40/18	Carbon capture and storage [CCS]
Y02P10/122	by capturing or storing CO_2
Y02P90/70	Combining sequestration of CO_2 and exploitation of hydrocarbons by injecting CO_2 or carbonated water in oil wells
Y02C20/40	Capture or disposal of CO_2
Y02A50/20	Air quality improvement or preservation, e.g. vehicle emission control or emission reduction by using catalytic converters

Table 12: IPC/CPC WIPO sub-classes used to identify *CCUS neighbouring* technologies

Code	description
B01D	separation
E21F	safety devices, transport, filling-up, rescue, ventilation, or drainage in or of mines or tunnels
C01B	non-metallic elements; compounds thereof
E21B	earth or rock drilling; obtaining oil, gas, water, soluble or meltable materials or a slurry of minerals from wells
B65G	transport or storage devices, e.g., conveyors for loading or tipping, shop conveyor systems or pneumatic tube conveyors
F25J	liquefaction, solidification, or separation of gases or gaseous mixtures by pressure and cold treatment
Y02P	climate change mitigation technologies in the production or processing of goods
Y02A	technologies for adaptation to climate change
Y02C	capture, storage, sequestration or disposal of greenhouse gases

B Correlation matrix and sample mean differences

The following table shows the correlation matrix (table 13) for the variables used in the empirical analyses.

Table 13: *Correlation Matrix*

	CCUS_pat	Green_pat	Pat_stock	ln_Scope1	EPS	TradeSchCO2	Taxdiesel	TAXCO2	RD_SUB	TechSup	ROA3yMA	ROA_sd	ROA_3y_sd	Rev_gr	Rev_gr3y_MA	Cap_int	Leverage	Prod.	Size	Tot_Ret	TobinsQ	R&D_norm
CCUS_pat	1																					
Green_pat	0.437***	1																				
Pat_stock	0.271***	0.595***	1																			
ln_Scope1	0.120***	0.119***	0.0336	1																		
EPS	0.102***	0.111***	0.0779***	-0.0682***	1																	
TradeSchCO2	-0.0947***	-0.203***	-0.144***	-0.108***	0.0612**	1																
TaxDiesel	0.0104	-0.0264	-0.0405*	-0.0458*	0.546***	0.491***	1															
TAXCO2	-0.00250	-0.100***	-0.0840***	-0.103***	0.466***	0.329***	0.489***	1														
_RD_SUB	0.0796***	0.107***	0.0954***	-0.0317 0	.636***	-0.249***	0.0314	0.253***	1													
TechSup	0.152***	0.239***	0.170***	0.0589**	0.745***	-0.357***	0.127***	0.0290	0.724***	1												
ROA3yMA	-0.0563**	-0.0207	-0.0789***	-0.178***	-0.175***	0.102***	-0.0513**	0.0293	-0.214***	-0.238***	1											
ROA_sd	-0.120***	-0.129***	-0.0452*	-0.225***	-0.173***	0.171***	-0.0495*	0.0723***	-0.134***	-0.258***	-0.00836	1										
ROA_3y_sd	-0.0563**	-0.0831***	0.00124	-0.0771***	-0.123***	0.153***	-0.0143	-0.00788	-0.121***	-0.163***	-0.136***	0.512***	1									
Rev_gr	-0.0310	-0.00214	-0.0386*	-0.0610**	-0.0422*	0.0328	-0.0111	0.0254	-0.0158	-0.0634**	0.118***	0.153***	0.108***	1								
Rev_gr3y_MA	-0.0591**	-0.0530**	-0.0875***	-0.103***	-0.0830***	0.0973***	0.000907	0.0384	-0.0465*	-0.117***	0.142***	0.266***	0.0667***	0.514***	1							
Cap_int	-0.0275	-0.108***	-0.111***	0.245***	-0.140***	-0.0594**	-0.131***	-0.0754***	-0.0364	-0.0784***	-0.0463*	0.0875***	0.0492*	0.0276	0.0741***	1						
Leverage	-0.0294	-0.125***	-0.0841***	0.316***	-0.155***	0.0562**	-0.0899***	-0.0676***	-0.0941***	-0.154***	-0.208***	-0.0162	0.0465*	-0.0468*	-0.0220	0.181***	1					
Prod.	-0.00547	-0.0646***	-0.137***	0.339***	-0.121***	-0.106***	-0.159***	-0.0504*	0.0231	-0.0334	0.0266	0.0785***	0.0473*	0.0888***	0.0933***	0.704***	0.127***	1				
Size	0.125***	0.212***	0.336***	0.606***	-0.0280	-0.0755***	-0.0284	-0.0858***	-0.0220	0.0629**	-0.0628**	-0.257***	-0.139***	-0.0238	-0.0817***	0.227***	0.149***	0.220***	1			
Tot_Ret	-0.00799	-0.0135	-0.0308	-0.0622**	0.00260	0.0110	-0.0202	0.0259	0.00386	0.00631	0.0823***	0.0956***	-0.0130	-0.0294	0.0386*	-0.0198	0.00627	-0.0342	-0.0686***	1		
TobinsQ	-0.0931***	-0.0891***	-0.0973***	-0.454***	-0.172***	0.138***	-0.0785***	0.0424*	-0.174***	-0.277***	0.548***	0.358***	0.165***	0.217***	0.219***	-0.0751***	-0.198***	-0.0804***	-0.326***	0.0510**	1	
R&D_norm	-0.0354	0.0809***	0.206***	-0.375***	-0.130***	-0.00610	-0.127***	-0.107***	-0.0505*	-0.0877***	0.131***	0.284***	0.219***	0.120***	0.136***	-0.111***	-0.179***	-0.134***	-0.189***	0.0351	0.533***	1

Estimation sample

* p < 0.05, ** p < 0.01, *** p < 0.001

Table 14: *Mean differences between CCUS and CCUS neighbouring firms (T-tests)*

CCUS firms	μ_{CCUS}	$\mu_{\text{CCUS\_neighb}}$	$\mu_{\text{CCUS}} - \mu_{\text{CCUS\_neighb}}$	t	N
CCUS_pat	2.253	0	2.253	7.75***	3,153
Green_pat	253.09	31.32	221.76	15.3***	3,153
ln_Scope1	13.58	11.91	1.67	16.9***	3,153
norm_Pat_Stock	.0011	.00068	.00037	7.04***	3,153
R&D_int.	.025	.0384	-.0132	-8.75***	3,153
Tot_Ass.	16.79	16.11	.676	14.4***	3,153
ROA_3y_MA	.0413	.0518	-.0105	-5.46***	3,140
Tot_Ret	12.18	11.85	.321	0.219	2,868
ln_Q	-.504	-.0558	-.448	-13.32***	2,982
Leverage	.185	.207	-.0219	-4.68***	3,153
Cap_Int	1047.78	1102.42	-54.64	-.81	3,153
Lab_Prod	635.77	490.27	145.5	6.48***	3,142

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Zero-inflated poisson model

The extensive margin process is modeled by a probit model with the following form:

$$Pr(Pat_{it} = 0|\mu_{it}) = 1 - \Phi(log\mu_{it}) \tag{5}$$

where

$$\Phi(log\mu_{it}) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{log\mu_{it}} e^{-\frac{t^2}{2}} dt \tag{6}$$

and

$$\mu_{it} = \exp\left(\beta_0 + \beta_1 \log scope1_{it-1} + \beta_2 envstr_{it-1} + \gamma X_{it-1} + \upsilon_s + \nu_t + \eta_i\right) \tag{7}$$

The main explanatory variable we use to model CCUS patenting behavior is the lagged *scope 1 emissions* both in levels and in differences. We include the vector X_{it-1} containing a set of control variables at firm-level (ROA, revenue growth, log of total assets, leverage, capital intensity, stock of general patents, normalized R&D expenditure). υ_s, ν_t and η_i are sets of sector, year and firm fixed effects proxied by the Blundell pre-sample mean estimator (Blundell et al., 1995)[13].

Once the decision is made by the firm, the following step is modeled by a log-linear Poisson regression, typically suitable for count data (see Hausman et al., 1984)[53]. The Poisson regression has the following form:

$$E(Pat_{it}|X_{it}, \upsilon_s, \nu_t, \tau_c, \eta_i) = \lambda_{it} \tag{8}$$

such that

$$\lambda_{it} = \exp\left(\beta_0 + \beta_1 \log scope1_{it-1} + \gamma X_{it-1} + \upsilon_s + \nu_t + \eta_i + \tau_t\right) \tag{9}$$

Note that $\mu_{it} \neq \lambda_{it}$, i.e., the probit specification adds environmental stringency index as a further country-level control to determine the probability of market entry. Furthermore, all probit models feature the lagged scope 1 emissions and not the differences. For reasons of (lack of) convergence, it was not possible to include country-level fixed effects in the estimation of the extensive margin, though they were included in the intensive margin (τ_t). It follows that the conditional mean of the model will be:

$$E(Pat_{it}|X_{it}, \upsilon_s, \nu_t, \tau_c, \eta_i) = \Phi(log\mu_{it}) \times \lambda_{it} \tag{10}$$

Table 15 reports descriptive statistics of the CCUS patents' pre-sample mean (Blundell et al., 1995[12]; 2002[13]) and of the binary variable in the used sample.

Pre-sample	N	Mean	SD	Min	p25	p50	p75	p99	Max
CCUS mean	2,616	1.093113	3.195215	0	0	.0833333	.75	14.58333	38.75
CCUS dummy	2,616	.5940367	.4911714	0	0	1	1	1	1

Table 15: *Pre-sample mean and associated dummy variable for CCUS patenting*

To complement and support the empirical strategy described above, we explore the differences between the two sub-periods (pre-sample means). The following tables thus show the results from testing the mean differences of the main explanatory variables used in the paper. In particular, Tables 16 and 17 respectively test the mean differences between sample period (2010-2022) and pre-sample period explanatory variables by groups that did (CCUS_pre_sample_dummy=1) and did not (CCUS_pre_sample_dummy=0) patent any CCUS innovation in the pre-sample period.

Table 16: *Sample variables and past CCUS innovation groups (T-tests)*

Full	$\mu_{\text{CCUS\_d=1}} - \mu_{\text{CCUS\_d=0}}$	$\mu_{\text{CCUS\_d=1}}$	$\mu_{\text{CCUS\_d=0}}$	*tstat*	*N*
CCUS_Pat	2.685	2.757	0.072	8.238***	2,852
Green_Pat	209.3	239.41	30.10	15.78***	2,852
R&D_int	-.009	.0256	.0346	-5.896***	2,825
ln_Scope1	1.56	13.624	12.064	15.318***	2,766
ln_Tot_Ass.	.642	16.84	16.19	13.56***	2,852
Lab. Prod.	203.66	664.75	461.08	8.95***	2,845
Cap_Int.	204.35	1139.9	935.54	3.27**	2,845
ROA	-0.002	0.047	0.049	0.772	2,852

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: *Pre-sample variables past and CCUS innovation groups (T-tests)*

Full	$\mu_{\text{CCUS\_d=1}} - \mu_{\text{CCUS\_d=0}}$	$\mu_{\text{CCUS\_d=1}}$	$\mu_{\text{CCUS\_d=0}}$	*tstat*	*N*
R&D_int	-.0423	.0276	.0699	-18.63***	12,409
ln_Scope1	1.276	13.89	12.62	10.96***	1,951
ln_Tot_Ass.	2.808	14.23	11.42	71.52***	33,599
Lab. Prod.	172.72	510.77	338.05	21.21***	16,458
Cap_Int.	247.9	831.01	583.11	6.53***	27,011
ROA	0.048	0.0066	-.0415	2.29*	22,863

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

T-statistics indeed confirm that a significant difference between firms from the two groups is present both pre- and post-2011, thus empirically justifying the implementation of the estimator to control for unobserved firm-level heterogeneity impact on CCUS patenting.

D Market-to-book model

As anticipated in the relevant section, we draw from Griliches (1981)[47], Hall (1999)[48] and Hall et al. (2005)[49]. Herein we show the step-by-step derivation of the model, which sees the firm's market value as a function of a combination of tangible and intangible assets, as in equation (10):

$$V_{it} = b_t(A_{it} + \gamma K_{it})^{\sigma} \tag{11}$$

where V_{it} is the market value of firm i at time t, A_{it} is the value of tangible assets, K_{it} denotes the firm's knowledge, i.e., intangible assets, and the parameter σ allows for non-constant returns to scale. By dividing each term by A_{it}, applying logarithms on both sides and allowing $\sigma = 1$, we can rearrange as in (11):

$$log\, Q_{it} = log\, V_{it} - log\, A_{it} = log\, b_t + log\,(1 + \gamma \frac{K_{it}}{A_{it}}) \tag{12}$$

Where $logQ_{it}$ denotes the logarithm of the Tobin's Q. As in the original formulation of the model, γ represents the shadow value of knowledge assets relative to the value of tangible assets. Following Hall et al. (2005)[49], from equation (12), we modify the model by replacing K_{it} with consistent measures of the knowledge assets, that is R&D and the stock of (CCUS and Green) patents divided by the stock of R&D (all lagged to allow for time-consistency). The underlying idea is to "capture the knowledge-creation process as a continuum going from R&D to patents, which involves the sequential revelation of information about the value to the firm of the innovation generated along the way" (Hall et al. (2005) p.24 [49]):

$$log\, Q_{it} = log\, b_t + log\,(1 + \gamma_1 \frac{R\&D\_stock_{it-1}}{A_{it-1}} + \gamma_2 \frac{CCUS\_stock_{it-1}}{R\&D\_stock_{it-1}} + \gamma_3 \frac{Green\_stock_{it-1}}{R\&D\_stock_{it-1}}) + \epsilon_{it} \tag{13}$$

The ratio of R&D to tangible assets informs about the commitment of the firm to generate new knowledge in each period, while $\frac{CCUS\_stock_{it}}{R\&D\_stock_{it}}$ adds the actual patenting yield of the specific CCUS technology. ϵ_{it} represents the random stochastic error with zero mean. Finally, applying the approximation $log(1+x) = x$, valid for small enough x, we can rewrite (13) as:

$$log\, Q_{it} = log\, b_t + \gamma_1 \frac{R\&D\_stock_{it-1}}{A_{it-1}} + \gamma_2 \frac{CCUS\_stock_{it-1}}{R\&D\_stock_{it-1}} + \gamma_3 \frac{Green\_stock_{it-1}}{R\&D\_stock_{it-1}} + \epsilon_{it} \tag{14}$$

Finally we augment the model with scope 1 emissions in log, the usual firm-level control variables such as size, profitability, productivity, indebtedness, capital intensity (vector X_{it-1}), and year (ν_t), country (τ_t) and sector (υ_s) fixed effects. The resulting baseline model is the following:

$$\log Q_{it} = \log b_t + \gamma_1 \frac{R\&D\_stock_{it-1}}{A_{it-1}} + \gamma_2 \frac{CCUS\_stock_{it-1}}{R\&D\_stock_{it-1}} + \gamma_3 \frac{Green\_stock_{it-1}}{R\&D\_stock_{it-1}} + \gamma_4 \log scope1_{it-1} + \beta X_{it-1} + \upsilon_s + \nu_t + \tau_c + \epsilon_{it} \tag{15}$$

We can estimate equation (15) with OLS.

E Robustness analysis

E.1 Determinants of CCUS patenting

In this section we present a battery of robustness tests on the the results of the ZIP models.

Firstly, we deal with the issue of the size of the sample when using different lags of the carbon emission variable. Tables 18 and 19 report the results of the ZIP models when we use the sample restricted to keep the number of observations constant across the three specifications (i.e., considering N from column (4)).

Table 18: *ZIP - Extensive margin*

1st-step **Probit regression**				
	(1)	(2)	(3)	(4)
CCUS_pat=1	L1	L2	L3	L_all
L._TAXCO2	0.0719*	0.0711*	0.0748*	0.0763*
	(0.082)	(0.084)	(0.068)	(0.062)
L._RD_SUB	-0.0498	-0.0483	-0.0491	-0.0515
	(0.343)	(0.351)	(0.339)	(0.321)
L._TRADESCH_CO2	-0.166**	-0.164**	-0.166**	-0.167**
	(0.022)	(0.023)	(0.022)	(0.021)
L.Cap_Intensity	-0.000161	-0.000161	-0.000141	-0.000145
	(0.130)	(0.127)	(0.190)	(0.172)
L.ln_Tot_Assets	-0.0947	-0.0894	-0.0900	-0.0975
	(0.224)	(0.255)	(0.259)	(0.224)
L.Rev_growth_3y_mean	1.737**	1.812**	2.006**	1.937**
	(0.049)	(0.040)	(0.020)	(0.025)
L.Lab_Productivity	9.57e-05	9.63e-05	8.34e-05	8.45e-05
	(0.614)	(0.602)	(0.645)	(0.645)
L.ROA_3y_mean	-0.461	-0.487	-0.589	-0.602
	(0.739)	(0.724)	(0.670)	(0.663)
L.Leverage	-1.154*	-1.160*	-1.213*	-1.217*
	(0.085)	(0.084)	(0.075)	(0.075)
L.R&D_int	-4.360	-4.432	-4.379	-4.037
	(0.125)	(0.121)	(0.137)	(0.164)
L.Green_dummy	1.136***	1.141***	1.166***	1.158***
	(0.000)	(0.000)	(0.000)	(0.000)
L.ln_norm_Pat_Stock	-8.507	-12.06	-17.80	-13.02
	(0.846)	(0.775)	(0.664)	(0.754)
L.ln_Scope1	0.145***			0.148
	(0.001)			(0.255)
L2.ln_Scope1		0.140***		-0.0672
		(0.003)		(0.722)
L3.ln_Scope1			0.139***	0.0665
			(0.003)	(0.554)
pre_sample_CCUS	0.455***	0.460***	0.468***	0.462***
	(0.000)	(0.000)	(0.000)	(0.000)
pre_sample_CCUS_dummy	0.447**	0.443**	0.433**	0.437**
	(0.012)	(0.012)	(0.013)	(0.013)
Year FE	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes
H0: L1 L2 L3 = 0				10.43***

Robust pval in parentheses - SE clustered firm-level
*** p<0.01, ** p<0.05, * p<0.1

Table 19: *ZIP - Intensive Margin*

2nd-step **Poisson regression**				
	(1)	(2)	(3)	(4)
CCUS_pat_count	D1	LD1	LD2	d_all
L.Cap_Intensity	-0.000307**	-0.000308***	-0.000319***	-0.000322***
	(0.010)	(0.010)	(0.007)	(0.007)
L.ln_Tot_Assets	0.142*	0.142*	0.142*	0.143*
	(0.088)	(0.088)	(0.085)	(0.082)
L.Rev_growth_3y_mean	-2.441***	-2.511***	-2.782***	-2.774***
	(0.001)	(0.001)	(0.000)	(0.000)
L.Lab_Productivity	0.000523**	0.000529***	0.000546***	0.000543***
	(0.010)	(0.008)	(0.005)	(0.006)
L.ROA_3y_mean	-3.263**	-3.269**	-3.295**	-3.260**
	(0.037)	(0.034)	(0.027)	(0.030)
L.Leverage	-2.625***	-2.596***	-2.501***	-2.496***
	(0.002)	(0.002)	(0.003)	(0.003)
L.R&D_int	-4.164	-4.175	-4.583	-4.876
	(0.461)	(0.459)	(0.415)	(0.382)
L.Green_dummy	-0.300	-0.313	-0.385	-0.383
	(0.305)	(0.296)	(0.204)	(0.198)
L.ln_norm_Pat_Stock	145.6***	148.6***	160.1***	160.7***
	(0.002)	(0.002)	(0.001)	(0.001)
D1.ln_Scope1	0.0182			-0.0294
	(0.881)			(0.882)
LD1.ln_Scope1		0.0766		-0.194
		(0.401)		(0.292)
LD2.ln_Scope1			0.201**	0.318***
			(0.012)	(0.005)
pre_sample_CCUS	0.0730***	0.0731***	0.0733***	0.0732***
	(0.000)	(0.000)	(0.000)	(0.000)
pre_sample_CCUS_dummy	1.127***	1.131***	1.140***	1.138***
	(0.002)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
H0: D1 LD1 LD2 = 0				8.85**
chi2	450.44***	454.22***	459.37***	466.37***
Log pseudolikelihood	-2642.95	-2642.99	-2636.1	-2631.37
Observations	2,630	2,630	2,630	2,630
Number of firm_id	344	344	344	344

Robust pval in parentheses - SE clustered firm-level
*** p<0.01, ** p<0.05, * p<0.1

Second, we test our results using carbon emission intensity instead of the log of the amount of emissions. Again the evidence is consistent with our previous results. In Tables 20 and 21, the ZIP models use the alternative measure of emission intensity, computed as:

$$\frac{ln\_Scope_{it-1}}{sales_{it-1}}$$

.

Table 20: *ZIP - Extensive margin*

1st-step				
Probit regression				
	(1)	(2)	(3)	(4)
CCUS_pat=1	L1	L2	L3	L_all
L._TAXCO2	0.0529	0.0444	0.0602	-
	(0.170)	(0.263)	(0.129)	-
L._RD_SUB	-0.0460	-0.0431	-0.0431	-
	(0.361)	(0.385)	(0.387)	-
L._TRADESCH_CO2	-0.142**	-0.131*	-0.158**	-
	(0.045)	(0.070)	(0.026)	-
L.Cap_Intensity	-0.000172	-0.000179*	-0.000175*	-
	(0.145)	(0.090)	(0.090)	-
L.ln_Tot_Assets	0.0664	0.0396	0.0570	-
	(0.269)	(0.525)	(0.361)	-
L.Rev_growth_3y_mean	1.243*	1.409*	1.516*	-
	(0.063)	(0.070)	(0.057)	-
L.Lab_Productivity	8.99e-05	0.000146	0.000168	-
	(0.650)	(0.408)	(0.337)	-
L.ROA_3y_mean	-0.354	-0.387	-0.707	-
	(0.779)	(0.773)	(0.607)	-
L.Leverage	-1.647***	-1.278*	-1.090	-
	(0.009)	(0.053)	(0.104)	-
L.R&D_int	-6.304**	-5.379*	-5.569*	-
	(0.022)	(0.059)	(0.053)	-
L.Green_dummy	1.243***	1.215***	1.205***	-
	(0.000)	(0.000)	(0.000)	-
L.ln_norm_Pat_Stock	-10.20	-17.87	-16.91	-
	(0.832)	(0.658)	(0.684)	-
L.GHG_Int.	0.197*			-
	(0.089)			-
L2.GHG_Int.		0.171		-
		(0.135)		-
L3.GHG_Int.			0.131	-
			(0.226)	-
pre_sample_CCUS	-0.485***	-0.483***	-0.470***	-
	(0.002)	(0.000)	(0.000)	-
pre_sample_CCUS_dummy	-0.297	-0.355**	-0.437**	-
	(0.130)	(0.047)	(0.013)	-
Year FE	Yes	Yes	Yes	
GICS FE	Yes	Yes	Yes	

Robust pval in parentheses - SE clustered firm-level
*** p<0.01, ** p<0.05, * p<0.1

Table 21: *ZIP - Intensive Margin*

2nd-step				
Poisson regression				
	(1)	(2)	(3)	(4)
CCUS_pat_count	D1	LD1	LD2	d_all
L.Cap_Intensity	-0.000374**	-0.000340**	-0.000317***	-
	(0.020)	(0.013)	(0.008)	-
L.ln_Tot_Assets	0.108	0.149*	0.142*	-
	(0.190)	(0.068)	(0.083)	-
L.Rev_growth_3y_mean	-2.229***	-2.498***	-2.707***	-
	(0.001)	(0.001)	(0.000)	-
L.Lab_Productivity	0.000696**	0.000583***	0.000541***	-
	(0.011)	(0.008)	(0.006)	-
L.ROA_3y_mean	-3.472**	-3.154**	-3.338**	-
	(0.039)	(0.043)	(0.025)	-
L.Leverage	-1.863**	-2.524***	-2.535***	-
	(0.032)	(0.003)	(0.002)	-
L.R&D_int	-0.596	-4.447	-4.565	-
	(0.915)	(0.427)	(0.415)	-
L.Green_dummy	-0.383	-0.298	-0.390	-
	(0.254)	(0.301)	(0.198)	-
L.ln_norm_Pat_Stock	136.6***	147.0***	159.8***	-
	(0.004)	(0.002)	(0.001)	-
D1.ln_Scope1 0.195			-	
	(0.176)			-
LD1.ln_Scope1		0.0539		-
		(0.562)		-
LD2.ln_Scope1			0.191**	-
			(0.018)	-
pre_sample_CCUS	0.0739***	0.0735***	0.0734***	-
	(0.000)	(0.000)	(0.000)	-
pre_sample_CCUS_dummy	1.322***	1.197***	1.152***	-
	(0.000)	(0.000)	(0.000)	-
Year FE	Yes	Yes	Yes	
Country FE	Yes	Yes	Yes	
Observations	2,877	2,755	2,630	-
Number of firm_id	395	377	360	-

Robust pval in parentheses - SE clustered firm-level
*** p<0.01, ** p<0.05, * p<0.1

Note that estimates for column (4) are not available as the convergence for this specification was not achieved. This is a common phenomenon in non-linear models as the Zero-inflated Poisson.

Third, we use a more standard count data model, i.e., the pseudo-maximum likelihood Poisson regression (Silva et al., 2011[87] and Silva et al., 2006[88]) on the sample firms that patent strictly defined CCUS patents. This estimator is robust to excessive zeroes (Martinez-zarzoso, 2013[66]) and is adequate to deal with count-data dependent variables. Results in Table 22 are consistent with the previous evidence from the intensive margin.

Table 22: *Poisson pseudo-maximum likelihood estimation*

	(1)	(2)	(3)	(4)
CCS_pat	D1	D2	D3	D_all
_TAXCO2_yr	0.0442	0.0387	0.0364	0.0368
	(0.401)	(0.462)	(0.493)	(0.486)
_RD_SUB_yr	-0.287***	-0.177*	-0.107	-0.108
	(0.008)	(0.062)	(0.286)	(0.279)
_TRADESCH_CO2_yr	-0.173*	-0.0484	0.00562	0.00717
	(0.094)	(0.578)	(0.950)	(0.935)
pre_sample_ccs	0.105***	0.119***	0.119***	0.118***
	(0.000)	(0.000)	(0.000)	(0.000)
pre_sample_dummy_ccs	1.262***	1.095***	1.219***	1.218***
	(0.000)	(0.000)	(0.000)	(0.000)
green_dummy_yr	0.718	0.717	0.677	0.686
	(0.173)	(0.142)	(0.177)	(0.169)
cap_empw_yr	-0.000247***	-0.000313***	-0.000327***	-0.000325***
	(0.003)	(0.000)	(0.000)	(0.000)
ln_tot_liab_w_yr	0.321***	0.381***	0.382***	0.381***
	(0.000)	(0.000)	(0.000)	(0.000)
norm_rd_neww_yr	-1.502	-1.957	-2.432	-2.608
	(0.435)	(0.342)	(0.258)	(0.229)
rev_g_3y_meanw_yr	-2.293***	-2.341***	-2.442***	-2.467***
	(0.000)	(0.000)	(0.000)	(0.000)
prod_lw_yr	0.000525***	0.000517***	0.000543***	0.000540***
	(0.000)	(0.000)	(0.000)	(0.000)
ln_norm_pat_stock_yr	199.6***	197.6***	206.3***	208.1***
	(0.000)	(0.000)	(0.000)	(0.000)
roa_3y_meanw_yr	-4.177***	-3.145***	-3.125***	-3.129***
	(0.000)	(0.000)	(0.001)	(0.001)
leveragew_yr	-2.257***	-2.580***	-2.582***	-2.555***
	(0.000)	(0.000)	(0.000)	(0.000)
ln_scope1_new_d_yr1	0.215			-0.142
	(0.122)			(0.292)
ln_scope1_new_d_yr2		0.0656		-0.0168
		(0.330)		(0.874)
ln_scope1_new_d_yr3			0.132*	0.188**
			(0.076)	(0.039)
Observations	1,991	1,918	1,838	1,838
Year FE	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
chi2	729.6	895.2	868.4	883.0

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Fourth, we use the zero-inflated negative binomial (ZINB) regression model instead of the Zero-inflated Poisson to estimate the determinants of CCUS patenting. Since the estimation process did not reach convergence neither when we use the three separate EPS sub-indices for environmental policy nor when we use the principal component reduction - *Policy-PCA*, we used the EPS OECD aggregate index as a proxy for the stance of environmental regulation. Results in Table 23 and 24 confirm our previous evidence and the role of both lagged CO_2 emissions and climate policy stringency.

Table 23: *ZINB - Extensive margin*

1st-step Probit regression				
	(1)	(2)	(3)	(4)
CCUS_pat = 0	L1	L2	L3	L_all
L.ln_scope1	-0.190***			-0.228
	(0.001)			(0.182)
L2.ln_scope1		-0.196***		0.147
		(0.001)		(0.599)
L3.ln_scope1			-0.192***	-0.120
			(0.002)	(0.447)
L.EPS	-0.357*	-0.364*	-0.398*	-0.390*
	(0.059)	(0.062)	(0.063)	(0.057)
L.Green_Dummy	-0.990***	-0.996***	-0.970***	-0.961***
	(0.002)	(0.001)	(0.001)	(0.001)
L.ln_norm_Pat_Stock	51.52	64.97	59.75	55.53
	(0.375)	(0.268)	(0.320)	(0.335)
L.Rev_growth_3y_mean	-1.655	-1.910	-1.788	-1.707
	(0.170)	(0.147)	(0.208)	(0.222)
L.Leverage	0.820	0.528	-0.116	-0.137
	(0.462)	(0.632)	(0.920)	(0.903)
L.ln_Tot_Assets	0.115	0.150	0.136	0.147
	(0.342)	(0.207)	(0.244)	(0.198)
L.Norm_R&D	6.072*	5.365	5.502	5.250
	(0.088)	(0.138)	(0.129)	(0.133)
L.Cap_Intensity	0.000271	0.000292	0.000295	0.000292
	(0.118)	(0.107)	(0.179)	(0.148)
L.Lab_Productivity	-8.75e-05	-0.000158	-0.000241	-0.000226
	(0.840)	(0.734)	(0.683)	(0.676)
L.ROA_3y_mean	0.226	0.410	-0.0590	-0.336
	(0.930)	(0.870)	(0.981)	(0.899)
pre_sample_ccus	-0.922***	-0.908***	-0.933***	-0.897***
	(0.000)	(0.000)	(0.002)	(0.002)
pre_sample_dummy_ccus	-0.245	-0.257	-0.348	-0.379
	(0.371)	(0.346)	(0.237)	(0.186)
Observations	2,764	2,647	2,526	2,526
Year FE	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes
N_clust	378	360	344	344

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: *ZINB - Intensive Margin*

2nd-step Negative binomial regression				
	(1)	(2)	(3)	(4)
CCUS_pat	D1	LD1	LD2	D_all
D1.ln_Scope1	0.124			0.190
	(0.302)			(0.425)
LD1.ln_Scope1		0.108		-0.321
		(0.239)		(0.154)
LD2.ln_Scope1			0.209**	0.299*
			(0.017)	(0.050)
L.Green_Dummy	0.525	0.497	0.430	0.438
	(0.113)	(0.113)	(0.176)	(0.171)
L.ln_norm_Pat_Stock	132.5**	140.9**	150.0***	143.7***
	(0.018)	(0.013)	(0.005)	(0.009)
L.Rev_growth_3y_mean	-2.043***	-2.037***	-2.029***	-1.984***
	(0.003)	(0.004)	(0.004)	(0.003)
L.Leverage	-1.869*	-2.100**	-2.305**	-2.372**
	(0.079)	(0.040)	(0.022)	(0.016)
L.ln_Tot_Assets	0.0908	0.106	0.103	0.105
	(0.417)	(0.317)	(0.343)	(0.321)
L.Norm_R&D	0.0262	-1.507	-1.793	-1.560
	(0.996)	(0.800)	(0.767)	(0.792)
L.Lab_Productivity	0.000451*	0.000419	0.000411	0.000413
	(0.092)	(0.106)	(0.152)	(0.134)
L.Cap_Intensity	-0.000196	-0.000187	-0.000190	-0.000195
	(0.154)	(0.169)	(0.206)	(0.188)
L.ROA_3y_mean	-1.774	-1.750	-2.350	-2.510
	(0.407)	(0.394)	(0.248)	(0.244)
pre_sample_ccus	0.123***	0.121***	0.120***	0.119***
	(0.002)	(0.002)	(0.002)	(0.002)
pre_sample_dummy_ccus	0.948**	0.950**	0.922*	0.901*
	(0.027)	(0.029)	(0.050)	(0.053)
Observations	2,764	2,647	2,526	2,526
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N_clust	378	360	344	344

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Fifth, to check if some of the control variable may drive the results, we have rerun the regressions in Columns (1) of Table 7 (Extensive margin) and Column (1) of Table 8 (Intensive margin) dropping, gradually and then altogether, the significant control variables, i.e., the 3-year MA of revenue growth, the green dummy, the patent stock and the leverage. Comfortingly, both L.ln_Scope1 and L.EPS keep their signs and significance as in the original tables. We also repeated the experiment with the specification that includes all three lagged levels (and differences) of CO_2 emissions (Column (4)). We found that the previous evidence holds (we do not report the results for reasons of space, but they are available on request.

Sixth, in the ZIP regressions, we dropped the pre-sample mean and the pre-sample dummy, and included the lagged CCUS patent variable to look for evidence of path dependence. We found that (i) the lagged dependent variable has the expected positive sign and is statistically significant, (ii) the CO_2 emissions keep their signs and significance, confirming the previous evidence. Results are available on request.[44]

E.2 Impact of CCUS patents on market value and stock returns - The timing of patent publication

As a general rule, in the major patent offices a period of 18 months is set before publishing the application of a new patent. Nonetheless, there are many exceptions: for example, following an explicit request by the applicant, the public disclosure of the application can be anticipated; or, when the claimed priority date is antecedent to the application filing date, the 18 month period is set to start from the prior rather than the latter, *de facto* reducing the delay; similarly, divisional patents (i.e., patents adding relevant concepts to prior applications having the same subject-matter to fulfill grant requisites) are publicly disclosed right after application in the case the parent application is already public[45]. These and other exceptions make the exact date of disclosure quite complex to identify, and the specialized literature studying the phenomenon of early disclosure has found that the time period can be smaller than full 18 months (see Baruffaldi & Simeth, 2020[7]), and, in any case, not greater. In the body of this paper, all our specifications consider a lag of 1 year in response that covers up to 12 of the 18 months for the delay in publication. As a robustness check, however, we check for the possible distortion generated by a different timing when the publication of patent applications is further delayed.

First, we present models considering a full two-year lag (*2-year*) in publication; hence, assuming that all patent disclosed in year t were filed in year *t-2*:

$$CCUS\_disclosed_t = CCUS\_pat_{t-2} \qquad Green\_disclosed_t = Green\_pat_{t-2} \tag{16}$$

[44] We thank the Reviewers for suggesting these additional robustness checks.

[45] see for instance EPO publishing rules (https://www.epo.org/en/service-support/faq/searching-patents/european-patent-register-and-federated-register/european-2) and AIPA USPTO rules (https://www.uspto.gov/web/offices/pac/mpep/s1120.html).

Second, we assume a uniform distribution of publications during the year (i.e., equal probability to file a patent before and after June) and we decompose the total yearly applications between patents filed before June and after June every year (*Mixed-lag*). In this setting, we consider the 18-months rule and we assume that patents filed before June in year t are disclosed in the following year *t+1* and the ones filed after June of year t are disclosed in the second following year *t+2*:

$$CCUS\_disclosed_t = \frac{CCUS\_pat_{t-1} + CCUS\_pat_{t-2}}{2} \quad Green\_disclosed_t = \frac{Green\_pat_{t-1} + Green\_pat_{t-2}}{2} \tag{17}$$

In this way we think we can better take into account the possible heterogeneous disclosure bias. Following in table 25 we show results for the regressions on market-to-book value[46]. The stocks of patents have been computed accordingly to the assumptions introduced above. Comfortingly, the robustness analysis confirms our previous results.

[46]Note that in models (5)-(6) we lose some observations due to how the variable is constructed: no count for green patents is available for year before 2010, hence the green patent stock is computed starting in 2011.

Table 25: *Market performance: Tobin's Q*

ln_Q	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patent var	2-year	2-year	2-year	2-year	Mixed-lag	Mixed-lag	Mixed-lag	Mixed-lag
L2.CCUS/L.R&D_stock	245.4	35.70	-3,051*	-3,205**				
	(0.803)	(0.921)	(0.050)	(0.041)				
L2.Green/L.R&D_stock	-5.755	2.888	2.420	24.69				
	(0.279)	(0.364)	(0.409)	(0.365)				
L.ln_Scope1#L2.CCUS/L.R&D_stock			258.4*	271.5**				
			(0.052)	(0.045)				
L.ln_Scope1#L2.Green/L.R&D_stock				-1.725				
				(0.418)				
L.ln_Scope1	-0.0761***	0.0117	0.0112	0.0122	-0.0743***	0.0158	0.0145	0.0159
	(0.000)	(0.578)	(0.595)	(0.563)	(0.000)	(0.457)	(0.496)	(0.456)
L.Policy_pca	0.0843***	0.0713***	0.0726***	0.0725***	0.107***	0.0962***	0.0984***	0.0988***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
L.CCUS/R&D_stock_mix					-334.9	-256.3	-6,821**	-7,303**
					(0.827)	(0.694)	(0.034)	(0.021)
L.Green/R&D_stock_mix					-2.388	2.511	1.328	35.64
					(0.647)	(0.370)	(0.607)	(0.331)
L.ln_Scope1#L.CCUS/R&D_stock_mix							546.9**	578.7**
							(0.045)	(0.030)
L.ln_Scope1#L.Green/R&D_stock_mix								-2.628
								(0.349)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,546	2,546	2,546	2,546	2,313	2,313	2,313	2,313
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.672	0.256	0.257	0.263	0.256	0.215	0.216	0.216
Number of firm_id	349	349	349	349	346	346	346	346

Robust pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 26 shows the same analysis applied to total returns. We find that, the results with patents lagged for two years are not informative, but those with a 18-month delay structure, in Columns (5)-(8), confirm our evidence.

Table 26: *Market performance: Total returns*

Tot_Ret	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	2-year	2-year	2-year	2-year	Mixed-lag	Mixed-lag	Mixed-lag	Mixed-lag
L2.CCUS_pat	-0.498*	1.494	1.494	2.068				
	(0.057)	(0.303)	(0.329)	(0.333)				
L2.Green_pat	-0.00347	-0.00344	-0.00347	-0.00422				
	(0.595)	(0.596)	(0.937)	(0.923)				
L.ln_Scope1#L2.CCUS_pat		-0.144	-0.144	-0.169				
		(0.163)	(0.183)	(0.199)				
L.ln_Scope1#L2.Green_pat			1.62e-06	4.75e-05				
			(1.000)	(0.987)				
L.Policy_pca#L2.CCUS_pat				-0.0929				
				(0.637)				
L.Policy_pca	-5.645***	-5.673***	-5.673***	-5.535***	-5.607***	-5.764***	-5.763***	-5.669***
	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)	(0.006)	(0.006)	(0.009)
L.ln_Scope1	0.689	0.762	0.762	0.776	0.697	1.003	0.902	0.917
	(0.579)	(0.540)	(0.557)	(0.550)	(0.574)	(0.424)	(0.487)	(0.482)
L.CCUS_pat_mix					-0.533*	6.304***	6.568**	7.016**
					(0.064)	(0.008)	(0.010)	(0.022)
L.Green_pat_mix					-0.00753	-0.00630	-0.0224	-0.0228
					(0.394)	(0.472)	(0.667)	(0.662)
L.ln_Scope1#L.CCUS_pat_mix						-0.514***	-0.533***	-0.552***
						(0.004)	(0.005)	(0.008)
L.ln_Scope1#L.Green_pat_mix							0.00115	0.00117
							(0.745)	(0.739)
L.Policy_pca#L.CCUS_pat_mix								-0.0708
								(0.744)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,223	2,223	2,223	2,223	2,223	2,223	2,223	2,223
Number of firm_id	332	332	332	332	332	332	332	332
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GICS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X GICS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.254	0.254	0.254	0.253	0.254	0.255	0.255	0.254

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As a further robustness check, we estimate the Tobin's q models lagging Green_Pat/R&D and R&D_Stock/Fixed Asset two years instead of one to match the lag structure in the ZIP analysis and to mitigate possible endogeneity concerns. Comfortingly, we find that the new results (available on request) confirm previous evidence. We thank one Reviewer for this suggestion.