How Corporate Venture Capital Firms Respond to Climate Change: Impacts on Ecological Innovation Outcomes

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KEYWORDS

Green patent

Climate change

Corporate Venture Capital

Environmental performance

Natural Resource Based View

ABSTRACT

In the scenario of combating climate change risks, the creation of disruptive technologies, through research and development, acquires a key role in contrasting the catastrophic effects predicted by the scientific community. This paper aims to understand whether and how corporate investors react to different types of climate change risk and opportunity exposure, through the in-house production of green patents. The sample consists of 87 U.S. corporate venture capital firms, with information spanning from 2001 to 2022. The results show that these players do react to general climate change exposure via green patent applications. The effect is even more powerful when climate change creates business opportunities for these companies. Conversely, an opposite effect is found on the number of non-green patent applications. Moreover, the analysis conducted using physical climate change exposure, allows us to capture a peculiar result. When it comes to dealing with short-term risk, the internal knowledge creation process takes a back seat, probably favouring investments in technologically advanced start-ups. The results of this paper, show how these firms can be an important player in the long-term battle against the consequences of climate change, providing eco-innovations necessary to lower our carbon footprint.

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PALAVRAS-CHAVE

Patente verde

Alterações climáticas

Capital de risco das empresas

Desempenho ambiental

Visão baseada nos recursos

RESUMO

No cenário de combate aos riscos das alterações climáticas, a criação de tecnologias disruptivas, através da investigação e desenvolvimento, adquire um papel fundamental para contrariar os efeitos catastróficos que a comunidade científica prevê. Este artigo tem como objetivo compreender se e como os investidores empresariais reagem aos diferentes tipos de exposição a riscos e oportunidades associados às alterações climáticas, através da produção interna de patentes verdes. A amostra é constituída por 87 empresas de capital de risco dos EUA, com informação de 2001 a 2022. Os resultados mostram que estes actores reagem efetivamente à exposição geral das alterações climáticas através de pedidos de patentes verdes. O efeito é ainda mais forte quando as alterações climáticas criam oportunidades de negócio para estas empresas. Por outro lado, verifica-se um efeito oposto no número de pedidos de patentes não ecológicas. Além disso, a análise efectuada através da exposição física às alterações climáticas permite-nos captar um resultado peculiar. Quando se trata de lidar com o risco a curto prazo, o processo interno de criação de conhecimento passa para segundo plano, favorecendo provavelmente os investimentos em empresas tecnologicamente avançadas em fase de arranque. Os resultados deste documento mostram como estas empresas podem ser um ator importante na luta contra as consequências das alterações climáticas, fornecendo inovações ecológicas necessárias para reduzir a nossa pegada de carbono.

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Contents

Introduction

"*The popular idea of cutting our emissions in half in 10 years only gives us a 50% chance of staying below 1.5°C, and the risk of setting off irreversible chain reactions beyond human control. These numbers also rely on my generation sucking hundreds of billions of tons of your CO_2 out of the air with technologies that barely exist*"[3]. This is how Greta Thunberg's speech at the 2019 UN Climate Action Summit starts, highlighting the urgency of actions to avoid the catastrophic effects of climate change predicted by the world's scientific community (Aalst, 2006). These words are a consequence of the idle attitudes of the world's nations and their ineffective agreements made years before. Indeed, on the 22nd of April 2016, 177 Nations signed an arrangement that went down in the history as Paris Agreement, according to which they committed to keep the temperature rise below 2° and - if possible - below 1.5° compared to pre-industrial levels. However, these objectives and the actions undertaken to comply with them seem inadequate nowadays to fight the increasingly evident effects of climate change (Clemencon, 2016; Nisbet et al., 2019). As stated in the World Economic Forum report, around $50 trillion by 2050 is supposed to be invested to finance the transition to a net-zero emission economy and avoid a disaster. The report poses evidence also of the necessity to develop disruptive technologies in such a field given that most of the emission abatement post-2030 will be obtained relying on eco-innovations not yet developed, such as hydrogen-based fuels and carbon capture and utilization solutions[4]. Therefore, the research and development activity of firms, with the production of climate change mitigation technologies, reflects a worldwide interest and has attracted the attention of a large number of scholars (Fang et al., 2022; Fawzy et al., 2020). Here there is the main purpose of this paper: shedding light on the potential triggers of the innovative outcomes, namely green patents, of CVC firms. This analysis can be crucial in understanding if such players can be considered or not as useful in this gruelling battle.

Corporate Venture Capital firms in this sense, play a pivotal role in their activities of patent production and investment in clean tech start-ups. CVC describes the common practice of firms creating supporting divisions aimed at obtaining non-controlling ownership stakes in start-ups with great potential. These investments are made with the ultimate objective of either resolving vulnerabilities or amplifying strengths (S. Ma, 2020). For instance, companies with low return on assets are more likely to start a CVC program to open up new market opportunities

[3] https://www.npr.org/2019/09/23/763452863/transcript-greta-thunbergs-speech-at-the-u-n-climate-action-summit

[4] https://www.marshmclennan.com/assets/Archive/Images/Files/Financing-the-Transition-to-a-Net-Zero-Future.pdf

and improve future revenues (Gbadji et al., 2011). Nevertheless, the primary use of this kind of vehicle is to acquire know-how and readily available technologies, quickly strengthening their innovation process (Chemmanur et al., 2014). Existing literature has explored the effects of climate change, such as greenhouse gas emissions and green investments, on these firms' financial performance, indicating positive impacts. Firms with better environmental performances do provide enhanced returns for their shareholders both in the short and in the long term (Benkraiem et al., 2023). However, there is a gap in understanding how these environmental shifts affect investment decisions and the production of green solutions by CVC firms. This study seeks to address this discrepancy by determining if CVC firms are capitalizing on these changes or not employing a new measure of climate change exposure. Recognizing the challenges in measuring climate change exposure at the firm level, (Sautner et al., 2023) developed a machine learning algorithm able to identify all relevant bigrams related to climate change exposure in earnings call transcripts. Subsequently, the relative frequency of these bigrams indicates the level of exposure across various dimensions, revealing potential risks or opportunities. Using data coming from reliable resources such as PatentScope, Orbis Intellectual Property, and Compustat we managed to create a final dataset with information about green innovation and climate change exposure of 87 CVCs from 2001 until 2021. An ad-hoc methodology, namely Poisson regression, was used to meet the characteristics of the count-dependent variable.

Although such a relationship has been partially analysed by (Sautner et al., 2023) in their preliminary economic applications, showing a positive impact of these exposures on green patents, this paper specifically solves two shortcomings in the literature. This is the first study analysing the effects of climate change on innovation outcomes within a sample of corporate investors, breaking the exposure into its main components with the aim of analysing companies' reactions to risks and opportunities arising from climate change. Second, differently from what has been done in the literature, this research aspires to analyse the impact of such triggers on the green innovation outcomes up to the second year after the exposure seeking to disentangle the long-lasting effects climate change seems to have on firms' investment decisions. The interest behind the research questions lies in the fact that, contrary to what is observed in the general case, these players can rely also on efficient venture capital investments to move forward in the knowledge acquisition process (Battisti et al., 2022). Our findings reveal that their patent generation activity positively responds to general and company-specific climate change exposure. The significant effect observed in the second year after the shock highlights the sustained influence this theme has on business decisions. Thus, contributing to the ongoing debate about the role of CVCs in fighting climate change through technological advancement achieved with the production of green patents (Rimmer, 2011). Indeed, the role and importance of developing Intellectual Property (IP) in such a struggle are discussed and it becomes clear that overcoming the terrible foreseen consequences requires a multifaceted approach involving the creation of green technologies by multiple actors (Grubb, 2004). This paper also contributes to the Natural Resource Based View (NRBV) theory, providing for the first time an analysis of the resources' triggers instead of focusing on the latter's impact on firms' financial outcomes. The resources available to a company may determine its future ability to create a competitive advantage, but the status and condition of this set may also reflect how the company has responded to external triggers over time. Additionally, the analysis conducted on the impact of the different climate change risk and opportunities exposure on the green innovation outcomes and the differences with the results obtained by (Sautner et al., 2023), suggests how these players might respond using a totally different vehicle such as venture capital investments to react quickly to these challenges. Indeed, the negative and persistent impact of physical climate change exposure on eco-innovation outcomes shown by our research emphasizes the inability of such a mechanism to address short-term environmental threats. These specific results, highlight the uniqueness of the sample under analysis and contribute to the limited set of articles examining the behaviours of CVC firms (Dushnitsky, 2008). Finally, given the demonstrated positive reaction of eco-friendly patent generation to business opportunities embedded in climate change, this paper contributes to the literature on green transition and may suggest specific policy interventions, such as subsidies to promote green R&D. Policymakers and their programs should prioritize sustained support to the development of numerous and diverse technologies rather than focusing on a single, unattainable solution (Mowery et al., 2010).

The reminder of this paper is organised as follows. In Section 1 an introduction about what venture capital is and who are the players involved is given. The subsequent Section 2 goes into detail on the main findings from the literature that are relevant to our study. In Section 3 we will deep dive into the process of sample selection, and we will better understand how the main variables are constructed. Descriptive statistics and key results are discussed in Section 4. In the last paragraph, some robustness checks to test the quality of our results are shown. At last, Section 5 draws a conclusion about the discussed topic and poses evidence on the limitations of our research.

1. What is Venture Capital

Considered as a branch of the private capital sector, venture capital is the activity of funding early-stage and high-growth companies. In exchange for the amount locked in, the investor will receive ownership shares of the investee, which will compensate for the huge hazard undertaken. This will determine a high-risk high-profit relationship. The aforementioned scheme is usually pursued by two different players: Independent Venture Capital, namely funds, or well-established firms under the name of Corporate Venture Capital. In a more general way, both IVC and CVC play a critical role in the development of our society by providing resources to firms that otherwise might find it difficult to raise funds. This condition is favoured by the huge halo of uncertainty around the figure of start-ups, which typically don't have stable revenues or tangible assets and usually have partially developed business ideas (Gompers & Lerner, 2001). Some of the most well-known companies, like Amazon, Google, and Apple, were once just new companies with ideas that would have been wasted if no one had believed in them.

1.1 Independent Venture Capital vs Corporate Venture Capital

To the Independent Venture Capital field belong funds, managed by General Partners (GPs), whose objective is to pool money from institutional investors, such as pension funds, as well as high-net-worth individuals (Limited Partners), to invest in promising start-ups according to a predefined investment strategy established in the limited partnership agreement. The final aim of these players is to profit from the potential success of the companies they are investing in. Originating from the common root of private equity funds, this kind of investment vehicle has become more and more appealing to the financially sophisticated public, responding to the urgency of diversification on one hand and potentially high returns on the other. With a finite lifespan, these funds seek to provide know-how and network to their start-ups assuring their prosperity. The consequent returns will then compensate the riskiness and the illiquidity of their investments. Examples of IVC are Battery in the U.S. and Blume in India.

Corporate Venture Capital (CVC) refers to firms, that differently from the first players, pursue their own business and invest, usually with ad-hoc funds, in high-potential start-ups related or not to their own industry. These protagonists are generally quite different in terms of the purpose and organization of their investment. Indeed, is proven that CVCs do not only look at venture capital investments from a speculative point of view, but they aim to obtain tangible and intangible value-added benefits allowing them to acquire knowledge in a faster way than what could have been done internally (McNally, 1995). This kind of practice has become more and more popular in the last decade, leading the CVC to get an ever-larger slice of the whole VC sector. In particular, the amount of invested capital faced a rapid increase from a level of €50bn in 2012 to €147bn in 2017[5]. Examples of successful CVCs are Google Ventures in the United States and Samsung Ventures in Korea.

1.2 Stages of Investment

In understanding the peculiarity behind this field, we can identify four distinct stages of venture capital investments, each with its own characteristics.[6]

- ***Seed Stage***: This early-stage round aims to fund start-ups that are still developing their main idea and do not have any revenues yet. The amounts invested will be used by the company to test their prototype and create a business plan.
- ***Early Stage***: At this stage, these companies have already completed the testing phase with a final product as a result. Funds provided by venture capitalists will then be used to promote their product and obtain a share of the market they are in.
- ***Expansion Stage***: Start-ups in this phase have already created a well-established customer base but aim to get a larger slice of the industry with the help of investments and the know-how of venture capitalists.
- ***Late Stage***: Considered the final phase, companies at this stage are looking for help to either go public through an Initial Public Offering or to be acquired by a larger competitor.

2. Literature Review and Development of Hypotheses

2.1 Theoretical Framework

With the objective to explain the differences among firms' performance, a theory gone down in history as Resource Based View was developed. The main idea behind it is that the heterogeneous set of resources available to companies, and how well these are managed, is the main trigger of their different financial performances (Barney, 1991; Wernerfelt, 1984). Specifically, the scores they obtained on certain indicators namely, value, rareness, imitability, and substitutability will define the ability of these resources to generate sustainable and durable competitive advantage (Barney, 1991). This basket was later better analysed in its components, identifying four different types of resources: physical, organizational, human, and knowledge (Pereira & Bamel, 2021; Priem & Butler, 2001). Among them, knowledge represents the key

[5] https://www.bcg.com/publications/2018/how-best-corporate-venturers-keep-getting-better
[6] https://www.forbes.com/advisor/investing/venture-capital/

element in competitive advantage generation given its peculiar features such as appropriateness, aggregation, and transferability (Grant, 1996). However, this theory has been highly criticized given its lack of concern about environmental-related issues and its inability to explain the creation of competitive advantage in the context of environmental changes (Desarbo et al., 2005). This is one of the main reasons that led authors to develop the Natural Resource Based View theory which, based on the foundations of the RBV, takes into account the environmental pressures from several stakeholders such as governments, shareholders, and debtholders. In particular, this theory establishes how, differently from what was happening in the past, in order to achieve a strategic advantage firms need to look at sustainable and long-term horizon strategies instead of looking to short-term profitable ones that might cause environmental problems (Hart & Dowell, 2011). According to this framework, responsible management of a firm's resources can lead to long-lasting reputational and financial success despite sacrificing short-term results. In this research, we combine the Knowledge-Based View (KBV) and Legitimacy theory to better explain the role of eco-innovation in performance generation and its response to external triggers. According to (Grant, 1996), the availability of knowledge-based resources and their management is the primary driver for superior business performance. The intrinsic characteristics of the intellectual capital promote cost reduction and improvement of procedural efficiency, providing benefits to firms and their stakeholders. Additionally, the protection granted to these resources helps firms avoid imitation and ensures sustainable competitive advantage. In parallel, (Suchman, 1995) affirmed, in the development of the legitimacy theory, that firms need to revise and adapt their actions to socially accepted values in order to fulfil public expectations. The aforementioned approach leads organizations to gain legitimacy and external validation, securing the success of their business decisions (Deegan, 2002). In this scenario, ecological innovation obtained under the shape of green patents can help achieve such results, guaranteeing the development of environmentally friendly innovation on one side, improving the technological and procedural set-up, and responding to widespread social pressure and concerns about climate change, thereby obtaining reputational gains.

2.2 Relevant Findings

Within the theoretical context designed by the NRBV and its related theories, the impact of such resources on firms' outcomes was quietly explored. Among others, the relationship between environmental performance and the financial performance of corporate venture capital firms has seen exponential interest among academics through the years. This interest can be easily explained by the need to understand the effects of the increasing capital-intensive green investments made by corporations in tackling climate change. Green investment, as defined by (Eyraud et al., 2013), refers to any investment aimed at reducing greenhouse gas and air pollutant emissions while maintaining the production and consumption of non-energy goods. Here, two main branches of the literature can be identified. On one side, green innovation strategies can lead to a competitive advantage through the reduction in production costs and an increase in reputation which means improved financial performance (Banerjee, 2001). This outcome is also confirmed by (De Marchi, 2010), assessing that investment in such areas leads to a consolidation of the firm's competitive advantage. On top of this, additional works explained how investment in environmental practice leads firms to reach a double goal: environmental and economic better performances (Chariri et al., 2018; Guenster et al., 2011). Further research claims that the relationship between Corporate Social Performance (CSP) and Corporate Financial Performance (CFP) is U-shaped. A low level of commitment to social and environmental themes leads to better financial performance compared to a moderate level of CSP. Conversely, a high level of CSP is associated with the highest level of economic performance. This can be explained by the fact that these practices require investments that will produce benefits only in the long run, once these procedures are considered mature and authentic (M. Barnett & Salomon, 2011). This is the main reasoning behind the Stakeholder Influence Capacity (SIC) theory, consisting of the ability to enhance the relationship with stakeholders using corporate social responsibility activities, strengthening the firm's credibility to the public (M. L. Barnett, 2007). On the other side, the downward of this approach is promptly found. Indeed, different studies affirm how given that these investments are done under an obligation by governments, the capital invested is not allocated to profitable commercial projects leading, as a consequence, to worse financial performances (Ambec & Lanoie, 2008; Weche, 2018). In line with this idea, the concave relationship between carbon emissions and Tobin's q, as shown by (Misani & Pogutz, 2015), poses in evidence the importance of balance in a firm's decisions. In this specific case, an intermediate level of carbon emissions was associated with a higher level of Tobin's q, compared to extremely low and high levels of emissions. Furthermore, the efforts of these players in enhancing their green profile translate into worse business performance when considering industry analyst earnings per share forecasts in 1 and 5 years as a measure of a firm's financial performance (Cordeiro & Sarkis, 1997). In an attempt to explore this interaction, more ambiguous results were also found. Indeed, in the analysis of (King & Lenox, 2002) no statistically significant connection has been found between pollution reduction and financial gains.

Having analysed the controversial relationship between environmental and financial performance, we can now delve deeper into the former to better understand what lies behind it. What do firms need to do to obtain better environmental performance? Indeed, several different actions can be undertaken by these firms to reduce their environmental impact such as green patents creation or investments in clean tech startups. Supporting this thesis, numerous scholars tried to understand the impact of such firms' practices on their carbon footprint. In particular, the study of (Lee & Min, 2015), focused on analysing the behaviours of Japanese manufacturing firms in the period from 2001 to 2010, described how an increase in green research and development investment leads to a reduction in carbon emissions. Analogously, (Sagar & Holdren, 2002) argue that an increase in R&D improves the technological setup, reducing the environmental risks associated with energy production and consumption. Along with these findings (Battisti et al., 2022) showed, with the help of a longitudinal analysis on 100 American and European companies, how CVC programs have a positive impact on a firm's environmental and social outcomes. Moreover, environmental patents have proved to be a significant trigger not only for the creators but also for global advancement. The findings of (Esmaeilpour Moghadam & Karami, 2024) reveal indeed a positive and significant impact of investing in environmental-related patent generation in promoting sustainable energy production in the MENA region. In line with this evidence, (Mazzucato, 2013) showed how the sustainability transition is being promoted by incentivising investment in cleantech start-ups, where cleantech refers to products, services, or processes that create value using few or no non-renewable resources and generate significantly less waste than traditional alternatives (Pernick & Wilder, 2007).

Near pure financial performance reasoning, we need to be aware that a widespread feeling of responsibility is increasingly influencing investor in their investment activity. These players are indeed progressively favouring green investments and in particular those with a low carbon footprint, over environmentally harmful ones (Ceccarelli et al., 2023). In the natural experiment carried out on the U.S. mutual funds market, it was pointed out that investors do take into account non-monetary aspects in their portfolio allocation decisions. Mutual funds, labelled as sustainable faced $36 billion in net inflows more than low sustainable ones, even though the former did not outperform the latter in terms of returns (Hartzmark & Sussman, 2019). Along with this argument, the latest Morgan Stanley Sustainable Signals survey, made among 2820 active individual investors across the U.S., Europe, and Japan, showed that 77% of them consider crucial the sustainable investing sector. On top of this, more than half of the surveyed pool, namely 54%, was found to be planning an increase in funds invested in this field[7]. This highlights the pivotal role of green investment activities, such as green patenting, in firms' reputational improvement and their future ability to raise funds. A better understanding of its triggers might help us in seeking the real values behind these investment choices and figuring out if these players can be valuable or not in contrasting climate change-related issues. In our specific case, this research aims to understand whether CVCs respond through internal processes to some possible triggers of environmental changes. The peculiarity lies in the fact that these resources, namely green patents, are now seen as an outcome and not anymore, a trigger. Supporting our thesis, in their analysis conducted over 136 companies of the Fortune Global 500 ranking, (Kolk & Pinkse, 2005) found out that managers do respond to climate change through either innovation or compensatory approaches. The former has the objective to improve technologies and procedures available to a company in favour of green ones able to reduce greenhouse gas emissions. The latter focuses on compensating for environmental impacts through monetary strategies, such as the purchase of emission credits. Nevertheless, the structure of the response to climate change is firm specific and reflects the riskiness perceived. Moreover, when considering GHG emissions as a proxy for climate change, a positive and significant impact is found on green innovation outcomes. Higher levels of carbon dioxide emissions produced from gas and liquid fuels are associated with a greater number of climate change related patents. However, this effect is reversed when considering carbon dioxide emissions from solid fuel consumptions, such as in the case of coal (Su & Moaniba, 2017). Within the framework of our investigation this is much more interesting, as these players can achieve a similar result through VC investments, which have been shown to be more efficient than the slow internal value creation process (Battisti et al., 2022). Our paper relies on the findings of (Sautner et al., 2023) which allow us to overcome the main issue in this kind of analysis: how to estimate climate change exposure at a firm level. Indeed, the methodology of the above-mentioned authors, based on a machine learning approach, aims to disentangle the multifaceted impact that environmental changes have on a firm's business. The main challenge here was represented by the idea that climate change might lead to obstacles and issues for some companies while opportunities for others (Giglio et al., 2021). Given the development of these disaggregated measures, we can capture the behaviours of firms exposed to different environmental triggers.

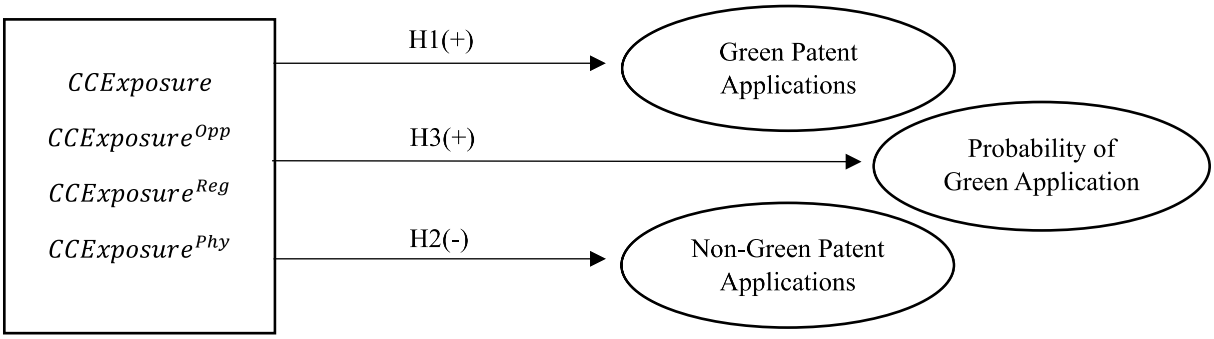
[7] https://www.morningstar.com/sustainable-investing/more-than-50-individuals-say-theyll-boost-sustainable-investments-this-year

Hypothesis 1. *Climate change exposure, in all its facets, has a positive and significant impact on the number of green patents applications in the subsequent two years.*

Hypothesis 2. *Climate change exposure, in all its facets, has a negative and significant impact on the number of non-green patents applications in the subsequent two years.*

Hypothesis 3. *Climate change exposure, in all its facets, has a positive and significant impact on the likelihood of applying for a green patent in the subsequent two years.*

Figure 1: Graphical representation of the research hypotheses.



3. Data and Methodology

3.1 Sample Selection

To obtain the final sample, we retrieved from the Refinitiv Eikon Screener the last forty years of venture capital deals. From this, we extracted all the Corporate Venture Capital firms, headquartered in North America, that completed at least one deal during the time frame under consideration. The choice of focusing the investigation on U.S. firms is not accidental but determined by the pivotal role played by these players in the VC market as claimed by (Hege et al., 2008). At this stage, we extracted 202 firms. Subsequently, using the PATENTSCOPE database provided by the World Intellectual Property Organization, we retrieved data about green patent applications made by the above-mentioned firms. These were identified using the Cooperative Patent Classification criteria, according to which we included all the patent applications with an embedded CPC code of Y02. This designation is indeed assigned to all "*technologies or applications for mitigation or adaptation against climate change*"[8]. Under this classification all technologies with the aim of either preventing the emission of greenhouse gases, according to the Paris Agreement and Kyoto Protocol, or attempting to reduce the effects of climate change in general are prescribed. Orbis Intellectual Property, a database of Bureau van Dijk, was instead used to recover data on the number of total applications made by these CVC firms. Accounting information needed to create control variables was extracted from the Compustat database.

Finally, we matched the list of North American CVC firms with a database compiled by Sautner et al., containing firm-level climate change exposure information for over 10,000 companies across 34 countries, to come up with a final dataset of 87 firms spanning from 2001 to the end of 2022, with a total of 1,741 firm-year observations.

3.2 Dependent Variables

Throughout this working paper, we will focus our attention on three different dependent variables. Indeed, aiming to address the above-mentioned hypothesis, we will initially consider green and non-green patent applications. Later, we will introduce a dummy variable that takes the value 1 if, in that year, the company applied for a patent with a CPC code of Y02, and 0 otherwise. Finally, we will shift our focus to a relative variable, defined as the ratio between the total number of green applications and the total number of patent applications, along with a Winsorized variant of the original count measures, to assess the robustness of the main results.

[8] https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html#Y02

3.3 Independent Variables

With the main objective of identifying the different levels of climate change exposure, (Sautner et al., 2023) created a machine learning methodology able to identify in the transcripts of the earning conference call the keywords related to different semantic fields. This urgency comes from the difficulty in assessing how individual firms might be influenced by climate change (Giglio et al., 2021) given that this exposure shows up in several different facets. It is indeed true that, while climate change poses risks and obstacles for some companies with a significant environmental impact, it can provide growth opportunities for others. Renewable energy or electric vehicles are just some of the industries that have been facing in the last years an increase in demand, and as a result, a rise in their profits. The authors came up with measures of the relative frequency of these words, capturing multi-dimensional exposure, defined as:

- $CCExposure$; measured as the relative frequency of the number of bigrams related to climate change that appear in earnings conference calls.
- $CCExposure^{Opp}$; measured as the relative frequency of the number of bigrams related to climate change opportunities that appear in earnings conference calls.
- $CCExposure^{Reg}$; measured as the relative frequency of the number of bigrams that capture regulatory shocks related to climate change that appear in earnings conference calls.
- $CCExposure^{Phy}$; measured as the relative frequency of the number of bigrams that capture physical shocks related to climate change that appear in earnings conference calls.

The first variable includes bigrams related to both the opportunity-related and risk-related semantic fields, such as “renewable energy” or “air pollution”, to play the role of a general climate change exposure variable. The second variable consider instead words that capture opportunities coming from climate change, “wind power” and “solar energy” are an example. Bigrams belonging to the third variable relate to regulatory interventions as in the case of “carbon tax”. As regards the last variable, this encompasses word pairs linked to physical climate change such as “ice control” and “wind speed”. This measure aims to consider the exposure of those firms to actual environmental effects of climate change.

As suggested by the authors, we apply a peculiar logarithmic transformation to these variables in the form of $\log(1 + CCExposure^{x})$. This transformation addresses two main problems. Firstly, these measures are significantly right skewed, with a consistent number of observations having very small values, which can lead to biased results in regression models. Secondly, since most of the time the value of these measures is exactly zero, we add one to avoid losing observations and to retain important information.

3.4 Control Variables

Using the Global Company Key (gvkey), we retrieved financial accounting data to construct a set of control variables. Firm size is taken into account by considering the logarithm of total assets $log\, AT$, while the financial structure is measured by the ratio between total liabilities and total assets $\frac{LT}{AT}$. Basic Earning Power $\frac{EBIT}{AT}$, defined as EBIT over total assets, captures the earning ability of a company before taxation and interest. More specific control variables are added, such as Research & Development intensity $\frac{XRD}{AT}$ and tangibility $\frac{PPENT}{AT}$. The former is defined as the ratio of Research & Development expenses to total assets, while the latter is defined as the ratio of PPE expenses to total assets. Additionally, firm-fixed effects $\sum Firm_i$ and year-fixed effects $\sum Year_t$ are included to control for any additional differences in firms' characteristics and macroeconomic context changes during the time frame under consideration.

3.5 Statistical Methodology

Throughout the analysis, we will change the methodological approach to meet the characteristics of our dependent variables and address the three different hypotheses. In the beginning, we will rely on a Poisson regression to account for two main aspects of the green and non-green applications variables: the count variable measuring the number of applications made during the year and the right-skewed distribution with most observations lying at small values. In this specification, robust standard error for the parameter estimates are considered as suggested by (Cameron & Trivedi, 2010).

H1:

$$
\begin{aligned}
GreenAppl_{i,t+j} &\\
= \exp\Big(&\alpha + \beta_0\, log\big(1 + CCExposure_{i,t}^{x}\big) + \beta_1 FirmSize_{i,t} + \beta_2 DebtRatio_{i,t} \\
&+ \beta_3 CashRatio_{i,t} + \beta_4 PPEintensity_{i,t} + \beta_5 BEP_{i,t} + \beta_6 R\&Dintensity_{i,t} \\
&+ \sum Firm_i + \sum Year_t + \epsilon_{i,t+j}\Big) \qquad ; \qquad j \in \{1,2\}
\end{aligned}
$$

H2:

$$
\begin{aligned}
& NonGreenAppl_{i,t+j} \\
& \quad = \exp\Big(\alpha + \beta_0\, log\big(1 + CCExposure_{i,t}^{x}\big) + \beta_1 FirmSize_{i,t} + \beta_2 DebtRatio_{i,t} \\
& \quad + \beta_3 CashRatio_{i,t} + \beta_4 PPEintensity_{i,t} + \beta_5 BEP_{i,t} + \beta_6 R\&Dintensity_{i,t} \\
& \quad + \sum Firm_i + \sum Year_t + \epsilon_{i,t+j}\Big) \qquad ; \qquad j \in \{1,2\}
\end{aligned}
$$

Then, a logit regression is used to deal with the dummy dependent variable and obtain estimates of the effects of climate change exposure on the probability of applying for a green patent. This model allows us to overcome a strict assumption made in traditional models, which forces the relationship between the dichotomous dependent variable and the independent variables to be linear.

H3:

$$
p\big(GreenOrNot_{t+j} = 1 \big| X_t\big) = \frac{1}{1 + e^{-(z_t)}} \leftrightarrow\; logit\big(p_{t+j}\big) = \log\left(\frac{p_{t+j}}{1 - p_{t+j}}\right) = z_t \;\; ; \; j \in \{1,2\}
$$

Where $z_t = \alpha + \beta_0\, log\big(1 + CCExposure_{i,t}^{x}\big) + \beta_1 FirmSize_{i,t} + \beta_2 DebtRatio_{i,t} + \beta_3 CashRatio_{i,t} + \beta_4 PPEintensity_{i,t} + \beta_5 BEP_{i,t} + \beta_6 R\&Dintensity_{i,t} + \sum Industry_i + \sum Year_t$

In the end, a panel regression is applied to analyse the impact on the green ratio. Here, given that the approach relies on a normal distribution of the variables of interest we applied a logarithmic transformation in the form of log $(1 + GreenRatio)$. This is done to normalize the distribution, avoiding biased estimates of the coefficients, and keep important information in the common case of a green ratio equal to zero. Notice that we use lagged independent variables to consider both statistical and logical aspects of the relationships among our variables. First, we expect the effects of climate change on firms' outcomes to show up with some delay given that the process of patent generation is not immediate and takes time. Second, examining the effect of climate change exposure on green outcomes at $t + 1$ and $t + 2$ allows us to limit endogeneity issues and ensure consistent results by preventing a spurious relationship.

4. Results

4.1 Descriptive Statistics and Correlations

Table 1 presents summary statistics of the whole set of variables that we are going to use. This includes dependent, independent, and control variables for the three different specifications. The 87 CVC firms present an average (median) number of green patent applications of 39.49 (5) per year. Consideration about the magnitude of these numbers can be done by comparing them to the average (median) of the total number of applications which amounts to 2599.24 (1104). The considerably high skewness of these variables respectively 6.82 and 2.81 highlights the importance of using methodologies that account for this characteristic in order to avoid biased results and wrong conclusions. It is evident how the Winsorization methodology shrunk the original distribution of the two main count variables, reducing the impact of extreme values. The maximum green applications decreased from an initial level of 1503 to 661, and the non-green ones from 27453 to 20117. This resulted in a lower kurtosis, from 65.30 to 20.35 and 12.53 to 8.73, respectively. Summary statistics of the four main independent variables provide evidence of how firms are much more exposed to the general and opportunity climate change variables. In fact, the log transformation of the general climate change exposure and the opportunity exposure are on average 0.48 and 0.17 respectively. Conversely, given the low averages and standard deviations, they are less likely to face regulatory and physical climate change exposure. This can be explained by the fact that regulatory changes and physical catastrophes are much less frequent and, as a result, less discussed in earnings calls.

Additionally, Table 2 presents pairwise correlations among the above-mentioned variables. This, measured as $\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) / \sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\ \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ can be crucial in a preliminary analysis since it can show rough relationships between variables. In general, all the different specifications of patent applications are positively correlated among them. Higher number of total patent applications are associated, as expected, to higher number of green ones. More considerations can be done on the main variables of interest. Specifically, with a correlation coefficient of 0.37 between $\log(1 + CCExposure)$ and $GreenAppl$ we can conclude that companies that are more exposed to the climate change argument are likely to have a higher number of green patent applications. As expected, when considering the opportunity extent of such exposure the correlation coefficient becomes higher settling at a level of 0.41. Additional analysis con be conducted on the control variables. In particular, we can see how bigger firms, measured in terms of logarithm of total assets, tend to have a higher number of patent applications regardless of the type. This is clearly intuitive given that larger firms are expected to have more resources to invest in such projects. Furthermore, an additional aspect to consider is the positive and significant correlation between $DebtRatio$ and $GreenAppl$ which at a level of 0.11 shows how a higher debt level favours the production of this type of capital-intensive patent. Similar insights are obtained looking at the relationship between $PPEintensity$ and $GreenAppl$ variables.

4.2 Preliminary Analysis

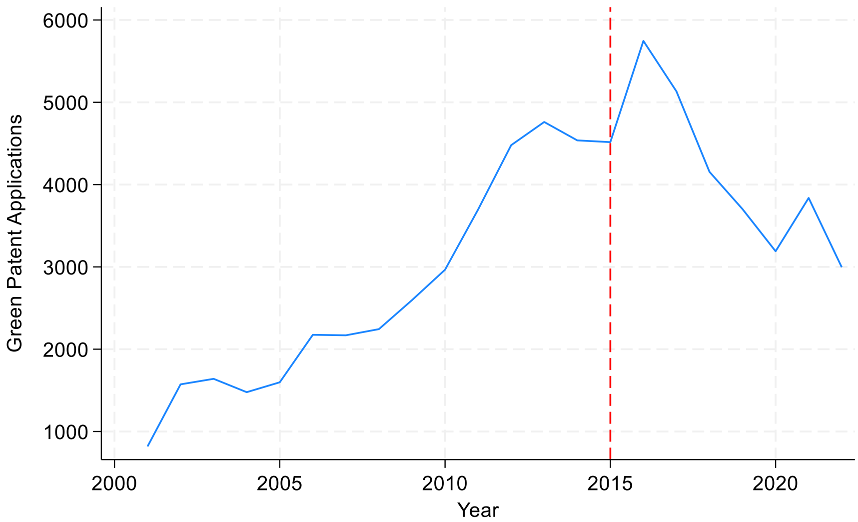
The first analysis that can be done to grasp the idea behind the key independent variable under consideration, namely climate change exposure, is ordering firms according to it. In the table below, we extracted the top two and bottom two firms in terms of their exposure. General Electric and Exelon Corp, with an average level throughout the years of 16.16 and 10.33 respectively, are the two firms with the highest levels. Abbott Laboratories and Biogen Inc, the least exposed, score 0.13 and 0.11 on average. These results are consistent with the expectations. The formers have both businesses dealing with energy providing, which is the most sensitive sector to climate change due to its environmental impact and central role in energy transition discussions. On the opposite side, the latter two firms are in the pharmaceutical and healthcare sectors, which have a lower impact on climate-related issues.

Table 3: Firms' average climate change exposure ranking.

	Firm Name	$CCExposure$ ($\times$ $\mathbf{10^3}$)
1.	General Electric Co	16.16
2.	Exelon Corp	10.33
…	…	…
86.	Abbott Laboratories	0.13
87.	Biogen Inc	0.11

Before going into a detailed analysis of the effects of climate change exposure on the green outcomes of the firms, we need to take a look at the trend of the original dependent variables over the years. Graph 1 shows the evolutions of the total number of green patent applications generated by the full sample of companies for each year. As we can see, starting in the early 2000s, there was a significant increase in the total number of applications, reaching its peak shortly after 2015. This date is not random, but it was a crucial mark on the calendar of climate change effects fighting. Indeed, the cooperation of the global leaders at the UN Climate Change Conference also known as COP21, reached a crucial milestone with the historic Paris Agreement adopted on the 12th December of 2015. The said agreement set long-term objectives to counteract the devastating effects of climate change, such as holding the global temperature increase to 2°C above pre-industrial levels. These objectives are accompanied by financial support to developing countries to limit their emissions, as well as periodic updates on the progress made by the participants in aligning with these goals[9]. As a consequence, this agreement highlighted the urgency to increase the attention to the subject, bringing firms to increase their investment in generating original solutions able to address the problem. However, after an initial booming phase, where firms probably experienced a fear of missing out, there was a drop in the number of applications returning to sustainable levels.

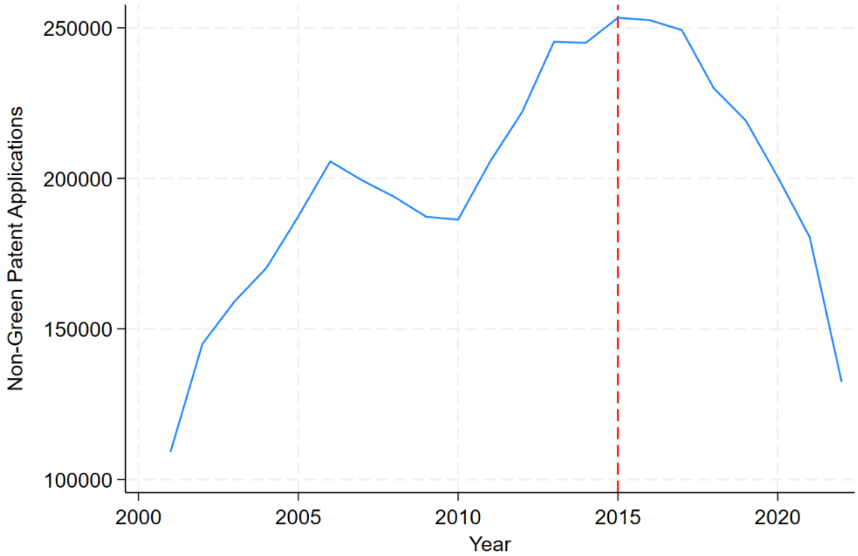
Graph 1: Evolution of green patenting activity, in the sample under analysis, between 2001 and 2022.



Conversely, the Paris Agreement of 2015 seems to have negatively affected the pattern of non-green patent applications. Clearly, the upward trend in the said variable was inverted right after the arrangement settlement reaching very low levels similar to the ones obtained in the early 2000s. This result can be easily explained by the fact that the accord posed more attention to the transition requiring consistent investments by the companies in reaching the set goals. Therefore, the capital-intensive patenting activity might have been overshadowed by the investments in environmentally friendly technologies already tested and ready to use or by its green counterpart.

[9] https://www.un.org/en/climatechange/paris-agreement

Graph 2: Evolution of non-green patenting activity, in the sample under analysis, between 2001 and 2022.



4.2 H1: Climate Change Exposure Effects on Green Patent Applications

When assessing the effect of different specifications of climate change exposure on green patent applications, we face a variety of results. To have a better understanding, we will analyse the impact of the four different climate change factors against our dependent variable separately. Notice that in this context, given the Poisson regression model used in the analysis, we can interpret the influence in terms of percentage change in the dependent variable given a one standard deviation increase in the independent. Indeed, this economic effect is measured as $(e^{\beta \times STD} - 1) \times 100$, where STD is the standard deviation of the independent variable and β is the regression coefficient associated to it.

Looking at Table 4 we can investigate the effect of the main climate change measure on the number of green patent applications. One standard deviation increases in the $CCExposure$ variable leads to a 10.73% increase in the number of green patent applications in the subsequent year when controlling for a set of firms' characteristics and adding Firm and Year Fixed Effects. This impact, as described in Table 5, is still positive and significant in the second year even though it has a lower magnitude. One standard deviation increase in the $CCExposure$ at time t leads to a 8.63% increase in the number of green patent applications in $t + 2$. The outcome of this analysis confirms that green patents creation is one of the vehicles adopted to address environmental issues, as suggested by (Kolk & Pinkse, 2005). More specifically, these results highlight and ensure that the relationship between climate change and the response of firms through internal green knowledge creation is positive and significant. Our approach stands next to, and supports, the research of (Su & Moaniba, 2017), who previously found, using carbon emissions from solid fuel and gas consumption as a proxy for climate change, that Y02 technology production is positively affected by the worsening of environmental conditions.

Tables 6 and 7 present the results of the regression analysis using the $CCExposure^{Opp}$ as the independent variable, showing how this effect is more pronounced when dealing with opportunities deriving from climate change. One standard deviation increase in the exposure at time t leads to a 8.54% and 9.80% increase in the number of green patent applications in the subsequent first and second year respectively, when controlling for firms' characteristics, Firm and Year Fixed effects. Accounting for the lower variability of this second independent variable, we can see how its effect has a greater magnitude, highlighting the mechanism according to which firms are more willing to react when the climate change factor represents an opportunity for their businesses. This reinforces the analysis conducted by (R. Ma et al., 2023), which concludes that firms experiencing higher exposure to opportunities arising from climate change increase their amount of investment. Our research confirms that this effect is still present in a corporate investor's environment, where funds are allocated to support the research and development activities necessary for patent generation. Conversely, we do not find any statistically significant relationship between the change in the regulatory exposure of the said firms on their green outcomes in either of the two following years as shown by Tables 8 and 9.

An intriguing result is instead found when analysing the effect of physical climate change exposure. As we can see from Tables 10 and 11 an increase in the $CCExposure^{Phy}$ leads to a decrease in the subsequent years in the number of green applications. More precisely, one standard deviation increase in physical exposure leads to a decrease of 4.58% and 4.92% in the following first and second years, respectively. This result can be counterintuitive at first glance, but it is not. As previously discussed, green patenting aiming to address climate change requires investments and takes time to generate results. This means that, when CVC firms are facing physical exposure to climate change, cannot rely on green patenting in order to tackle their carbon risk in the short term. They will instead use several different methodologies like an equity participation in disruptive clean tech start-ups or investments in well-known climate change addressing technology able to facilitate their transition (Mazzucato, 2013). This means that the capital-intensive mechanism of green patenting will be shadowed leading to a reduction in these applications in the short term. This result is indeed different from the one obtained by (Sautner et al., 2023) in their analysis conducted among a general population of firms. In that circumstance, an increase in this kind of exposure had a positive but no significant impact on the number of green patents applications made in the subsequent year. This highlights the peculiarity of the subsample under analysis and how important the additional VC investment strategy is for CVC firms. In particular, this might help them in the process of knowledge acquisition, allowing for an immediate response to urgencies generated by environmental changes. However, in doing so, they need to allocate resources efficiently, sometimes at the expense of green patenting activities.

4.3 H2: Climate Change Exposure Effects on Non-Green Patent Applications

With the intention of analysing the effect of all the different facets of climate change exposure on the non-green patent applications, we generated a new variable, which is the difference between the total number of applications made in a year and the green ones. Table 12 presents the results of the four Poisson regression models, that differ in terms of the main independent variable. What is clear from it is that, regardless of the branch of belonging, an increase in climate change exposure leads to a decrease in the number of non-green applications made in the next year. Effects are indeed negative and statistically significant for all the said variables except for the opportunity extent. A one standard deviation increase in the log-transformed climate change exposure results in a decrease in non-green patent applications by 4.91% in general, 3.47% in regulatory contexts, and 2.17% in physical contexts. The effect, by taking into account the variance of the variables, is higher when firms are facing physical exposure with respect to a regulatory exposure whose impact is itself greater than the general exposure variable. This outcome is in line with our expectations: an increase in climate change exposure leads firms to react by investing either in green patenting or climate-related start-ups, reducing the amount of resources available to spend on non-green patenting. According to Table 13, no statistically significant effect is found in the second year following the exposure, indicating that these variables are merely short-term triggers and do not influence firms' investment decisions in the long run. This validates and builds upon previous literature findings, which indicate that firms respond to general climate change exposure by reducing the number of non-green patents (Sautner et al., 2023). In addition, our analysis demonstrates that in a corporate investor environment, this effect is even larger when considering regulatory and physical impacts, providing evidence for the idea according to which CVC firms are willing to shift their attention to green practices able to improve reputation and build competitive advantage.

4.3 H3: Climate Change Exposure Effects on the Probability of Green Patent Application

In order to test the third hypothesis an additional variable was created. This consists of a dummy variable taking value 1 if the company applied for a green patent and 0 otherwise. Dealing with such kind of variable using the usual regression models is not anymore possible so we used a different approach known as logistic regression. Indeed, the S-shaped curve lying behind this methodology better fits the characteristics of the dichotomous dependent variable, avoiding predictions going out of its domain as it might happen with linear regression. On top of this, to avoid perfect predictability and ensure a reasonable number of observations we included industry-fixed effects instead of firm-fixed effects. The former was obtained considering the two-digit NAICS code, able to identify the industry the firms belong. Moreover, due to the model's exponential nature, the marginal effect on odds can be computed in the same way as for Poisson regression.

Looking at Table 14, given the positive and significant coefficient for the general climate change exposure variable, we can affirm that an increase in the exposure of a CVC firm to the general climate change argument leads to a greater likelihood of generating a green patent in the subsequent year. More in detail, one standard deviation increase in the general tagging of climate change exposure results in a 59.37% increase in the odds of applying for a green patent in the subsequent year. In year $t + 2$ this effect is still positive and significant even though with a lower magnitude. Table 15 shows how one standard deviation increase in the above-mentioned exposure leads to a 38.62% increase in the odds of applying for a patent with a CPC code of Y02 in the subsequent second year. This highlights again the long-lasting nature of such exposure, resulting in a short and medium-term response of the affected companies. Tables 16 and 17 show that this impact is even higher when considering the opportunities coming from climate change. One standard deviation rise in the climate change opportunity exposure leads to a 99.30% and 93.75% increase in the odds of applying for a green patent in the subsequent first and second year after the exposure. Consistent with the previous specifications, no significant impact is instead found when considering the regulatory and physical exposure variables.

Under this new configuration, which considers a different statistical methodology and an additional dependent variable specification, conclusions drawn above still hold. Firms' specific exposure to general climate change themes does increase the likelihood of applying for eco-friendly patents in the subsequent two years, as also suggested by the literature.

Additionally, for the first time, the effects of additional risks and opportunities arising from this topic are studied in this environment, highlighting the crucial role of the latter as a trigger for eco-innovation advancement.

4.4 Robustness Checks

4.4.1 Linear Panel Regression Analysis

To test the validity of the results obtained in the previous sections, we consider another dependent variable, defined as the ratio of the number of green patent applications to the total number of applications filed in a year. The impact of climate change exposure on this relative measure will then be analysed using a new estimation technique, a linear panel regression. This approach will help us to assess two main assumptions of our model: the Poisson regression may not be a good methodology to capture the effects of such variables; the absolute dependent variable may lead to biased estimates that are the result of the intrinsic characteristics of the firms. Before going into the detailed analysis, we need to understand what are the results that we expect, to confirm the validity of our methodology. As an example, considering the general climate change exposure measure, an increase in this variable should lead to a rise in the ratio at $t + 1$, as it has a positive effect on green applications and a negative, though smaller, effect on non-green applications. This ideally results in an increase in the numerator as well as in the denominator, albeit at a slower pace, resulting in a final increase in the ratio. Following similar reasoning, we expect an increase in the ratio for all the other variables except for the physical exposure where we anticipate a slightly positive effect, but closer to zero.

Table 22 shows the results, confirming our foreseen outcomes. An increase of 1% in the general tagging climate change exposure led to a 1.09% increase in the ratio in the subsequent year. This impact is of higher magnitude in the case of climate-related opportunities exposure where a 1% increase leads to a 1.30% rise in the ratio. Along the same lines, an increase of 1% in the regulatory exposure led to a 1.25% increase in the green ratio. Finally, the effect of the physical exposure appears to be statistically insignificant, confirming our expectations. Similarly, Table 23 analyses the impact of the climate change exposure variables on the green ratio at time $t + 2$ and confirms the insights previously discussed. An increase of 1% in the broader climate change exposure has an effect of an increase in the ratio of 1.13% in the second year after the exposure. This effect jumps to 1.29% and 2.17% when considering the impact of the opportunity and regulatory extents respectively. In line with previous findings, no significant impact is found on the ratio using physical climate change exposure.

4.4.2 Winsoritazion Approach

To assess the validity of our results, an additional robustness check is provided, with the aim of evaluating whether the outcomes obtained previously are driven by the presence of outliers in our data. Specifically, a Winsorization approach, consisting of replacing extreme values with less extreme ones, to limit the impact of the above-mentioned outliers, is proposed. Given the nature of our data, the Winsorization of the two main independent variables, namely $GreenAppl$ and $NotGreenAppl$, is suggested. This approach will directly affect observations lying at the left and right tails of the distribution, replacing values below the 2^{nd} percentile and above the 98^{th} percentile, with threshold values themselves. This process is applied each year with the objective of limiting the effect of extreme values while still capturing the trend of such variables.

Table 24 presents the results of the four different Poisson regressions using the Winsorized green patent applications variable, both in year $t + 1$ and $t + 2$. Consistent with the original analysis, general climate change exposure has a significant and positive impact on the number of green patent applications made in the subsequent two years. One standard deviation increase in the independent variable leads to 11.72% and 8.95% growth in the number of applications made in year $t + 1$ and $t + 2$, respectively. Intuitively, this effect is of greater magnitude when considering the opportunity extent exposure. Indeed, accounting for the lower variability of this variable, the increase in the dependent variable reaches 13.96% and 15.95%, assuming an equal standard deviation as in the case of the general climate change exposure variable. Conversely, a one standard deviation increase in the physical exposure extent at time t leads to a reduction in the number of green patent applications of 3.97% and 4.48% at time $t + 1$ and $t + 2$, respectively. No significant relationship was found using the regulatory climate change exposure variable. Table 25 provides similar insights, this time using the Winsorized non-green patent applications variable as the dependent variable in the regression models to test the robustness of hypothesis 2. General climate change exposure, as well as the regulatory and physical extents, has a negative and significant impact on the number of non-green patent applications. A one standard deviation increase in these independent variables leads to a reduction in dependent variable of 4.25%, 4.43% and 2.34% in $t + 1$, respectively. The whole set of climate change exposure variables does not have a significant impact on this kind of applications two year after the exposure, confirming the previously discussed insights.

5. Conclusions and Limitations

Throughout our analysis we learnt how, according to the Natural Resource Based View, the set of sustainable practices and resources available to the firms define the possibility to create a long-term competitive advantage. Within this framework, we understood the crucial role of green patenting not only for the generating firms but also for the society as a whole, which can rely on these brilliant technologies with the aim of mitigating the devastating consequences of climate change.

Given this background, our research aimed to address whether and how peculiar players known as corporate venture capital firms, react to different facets of climate change exposure through green patent generation. Different from what has been done in literature our specific sample selection, is in charge of understanding if CVCs use the internal knowledge creation process even though they have an alternative vehicle known as venture capital investment. In particular, the latter, in the form of equity participation in potential disruptive start-ups in the field of ecological innovation, has been proven to be more efficient than the slow research and development activity (Battisti et al., 2022). At this stage, we became aware of the difficulties faced in determining firm-level climate change exposure, given that it might generate opportunities for some and threats for some others. To overcome this issue, we draw upon the findings of (Sautner et al., 2023) who created an innovative multilevel climate change exposure. Based on a machine learning approach, the authors were able to find from the transcripts of the earnings conference calls any bigrams related to four different semantic fields: general climate change, opportunities, regulation, and physical effects. The final measure was then computed as a ratio of the word pairs belonging to each field against the whole set of bigrams appearing in the conference.

The results of our analysis highlight how corporate venture capital firms do react to climate change exposure adjusting the composition of their patent portfolio. In particular, we saw how regardless of the field of climate change exposure in consideration, these players react by reducing the number of patent applications not related to the environmental subject in the following year. Distinctive results are instead found when considering the green patent applications as the dependent variable. Specifically, when these firms are dealing with the general climate change exposure, they react by increasing the number of applications for climate change mitigation patents, both in the first and in the second year after the exposure. As expected, this effect is even higher, when considering an increase in the opportunity exposure to climate change. This means that, when this “issue” poses business opportunities, as observed in the electric car industry, these firms try to increase their competitive advantage by generating more and more green patents. Conversely, the effect seems to be insignificant for an increase in the regulatory exposure while negative and significant for an increase in the physical exposure. This outcome, which is different from what has been found by (Sautner et al., 2023) in their economic application, reflects the nature of such players. In particular, these exposures coming from changes in the regulation or in natural disasters due to climate change, require an immediate answer which cannot be obtained through the slow process of patenting generation. Indeed, such firms can rely on what distinguishes them, which is the possibility of investing in clean tech start-ups with the final objective of capturing their knowledge and showing stakeholders how much they care about these issues. The analysis conducted on the probabilities provides consistent results. An increase in the general climate change exposure raises the odds of applying for a green patent in the subsequent first and second years. The magnitude of such an effect is even higher considering the opportunity exposure. No significant impact on such probabilities is found, considering the regulatory and physical exposure, which confirms the hypothesis made before. With a clearer picture, we can finally provide an answer to the question made in the beginning: Corporate Venture Capital firms are crucial players in the long-term battle against climate change. They represent an important value-added, given their reaction to these changes by creating innovation. This is indeed a subject not to be underestimated, given that only through technological advancements we might have a possibility to survive.

Despite the important and innovative contribution of this research to the ongoing debate about CVC investment decisions in reaction to climate change triggers, it is not exempt from limitations. First, the sample over which the analysis is conducted is made of only U.S. firms. This was justified by the majoritarian role played by these firms in the VC context compared to the EU correspondents. Nevertheless, this may be the subject of an extensive analysis which may or may not confirm the results obtained from this research. Second, the limited sample size due to information disclosure problems, could be enlarged through company-specific analyses thus improving the robustness of our results. Finally, while this paper takes into consideration the number of applications made by those firms, it fails to consider the quality of the patent generated. This might have been captured by the number of times these patents have been cited in related applications, highlighting the importance of such findings on the value creation over time.

APPENDIX

Table 1: Summary statistics for all the dependent, independent and control variables used in the research.

	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
GreenAppl	39.49	5.00	112.73	0.00	1503.00	6.82	65.30
GreenAppl_w	34.67	5.00	77.99	0.00	661.00	3.84	20.35
TotalAppl	2599.24	1104.00	3936.02	4.00	27912.00	2.81	12.44
NotGreenAppl	2559.07	1094.00	3878.36	4.00	27453.00	2.83	12.53
NotGreenAppl_w	2481.13	1094.00	3542.69	7.00	20117.00	2.36	8.73
GreenOrNot	0.72	1.00	0.45	0.00	1.00	-0.99	1.98
GreenRatio	0.02	0.00	0.03	0.00	0.43	4.73	40.47
$\log(1 + CCExposure)$	0.48	0.31	0.51	0.00	3.49	2.37	9.88
$\log(1 + CCExposure^{opp})$	0.17	0.06	0.34	0.00	2.77	3.62	18.51
$\log(1 + CCExposure^{reg})$	0.04	0.00	0.14	0.00	1.54	5.11	35.51
$\log(1 + CCExposure^{ph})$	0.01	0.00	0.05	0.00	0.89	11.35	160.33
Size	9.93	10.09	1.67	4.43	13.22	-0.51	2.98
DebtRatio	0.57	0.56	0.23	0.07	1.95	0.49	4.31
CashRatio	0.12	0.09	0.11	0.00	0.85	2.02	9.13
PPEIntensity	0.21	0.14	0.18	0.00	0.86	1.33	4.01
BEP	0.10	0.10	0.08	-0.69	0.37	-0.93	10.08
R&DIntensity	0.08	0.06	0.08	0.00	0.64	2.40	13.02

Table 2: Pairwise correlations among the whole set of variables (dependent, independent and control) used in the research.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) GreenAppl	1.00																
(2) GreenAppl_w	0.89*	1.00															
(3) TotalAppl	0.52*	0.63*	1.00														
(4) NotGreenAppl	0.50*	0.61*	1.00*	1.00													
(5) NotGreenAppl_w	0.50*	0.61*	0.98*	0.98*	1.00												
(6) GreenOrNot	0.22*	0.28*	0.31*	0.31*	0.33*	1.00											
(7) GreenRatio	0.47*	0.40*	0.00	-0.01	-0.01	0.32*	1.00										
(8) $\log(1 + CCExposure)$	0.37*	0.26*	0.05	0.04	0.05	0.09*	0.33*	1.00									
(9) $\log(1 + CCExposure^{opp})$	0.41*	0.26*	0.09*	0.08*	0.09*	0.07*	0.29*	0.89*	1.00								
(10) $\log(1 + CCExposure^{reg})$	0.22*	0.13*	-0.02	-0.03	-0.03	0.00	0.24*	0.69*	0.61*	1.00							
(11) $\log(1 + CCExposure^{ph})$	0.14*	0.15*	0.05*	0.04	0.05*	0.06*	0.10*	0.21*	0.12*	0.17*	1.00						
(12) Size	0.11*	0.20*	0.33*	0.34*	0.36*	0.29*	0.07*	0.10*	0.07*	0.14*	0.05*	1.00					
(13) DebtRatio	0.06*	0.05*	-0.04	-0.05	-0.04	0.07*	0.09*	0.08*	0.07*	0.07*	0.06*	0.27*	1.00				
(14) CashRatio	-0.11*	-0.09*	-0.07*	-0.07*	-0.08*	-0.09*	-0.08*	-0.21*	-0.18*	-0.17*	-0.02	-0.49*	-0.08*	1.00			
(15) PPEIntensity	0.24*	0.15*	-0.02	-0.03	-0.01	0.10*	0.29*	0.40*	0.35*	0.40*	0.04	0.28*	0.09*	-0.33*	1.00		
(16) BEP	0.00	0.04	0.20*	0.21*	0.21*	0.08*	-0.07*	-0.05*	-0.06*	-0.06*	0.01	0.18*	-0.21*	-0.09*	-0.04	1.00	
(17) R&DIntensity	-0.11*	-0.11*	-0.07*	-0.07*	-0.09*	-0.18*	-0.17*	-0.23*	-0.15*	-0.20*	-0.07*	-0.54*	-0.09*	0.58*	-0.33*	-0.20*	1.00

** $p<0.01$*

Table 4: Poisson regression of the number of green patent applications at t+1 against the general climate change exposure variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+1}$	(2) $GreenAppl_{i,t+1}$	(3) $GreenAppl_{i,t+1}$
$\log(1 + \mathrm{CCExposure}_{i,t})$,	1.0514***	0.3257***	0.1992**
	(0.0867)	(0.0969)	(0.0824)
$FirmSize_{i,t}$,		0.5510***	0.4713***
		(0.0375)	(0.0646)
$DebtRatio_{i,t}$,		-0.2259	-0.1159
		(0.3357)	(0.2383)
$CashRatio_{i,t}$,		1.7581***	-0.1511
		(0.5361)	(0.3527)
$PPEintensity_{i,t}$,		-1.1210***	-0.4416
		(0.3218)	(0.4670)
$BasicEarningPower_{i,t}$,		1.7566***	2.0403***
		(0.5884)	(0.5171)
$R\&Dintensity_{i,t}$,		0.6055	0.0770
		(0.8701)	(1.1817)
Constant	2.9888***	-2.3483***	-1.4941**
	(0.0830)	(0.4277)	(0.7185)
Pseudo R^2	0.23	0.23	0.84
Observations	1,649	1,360	1,360
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic effect, %	71.28	18.14	10.73

Table 5: Poisson regression of the number of green patent applications at t+2 against the general climate change exposure variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+2}$	(2) $GreenAppl_{i,t+2}$	(3) $GreenAppl_{i,t+2}$
$\log(1 + \mathrm{CCExposure}_{i,t})$,	1.1109***	0.4456***	0.1617*
	(0.0815)	(0.1085)	(0.0870)
$FirmSize_{i,t}$,		0.5508***	0.3549***
		(0.0372)	(0.0703)
$DebtRatio_{i,t}$,		-0.3129	0.0629
		(0.3632)	(0.2430)
$CashRatio_{i,t}$,		1.5028***	-0.5446
		(0.5266)	(0.4023)
$PPEintensity_{i,t}$,		-1.2542***	-0.1684
		(0.3244)	(0.5476)
$BasicEarningPower_{i,t}$,		2.1778***	2.2850***
		(0.6381)	(0.5739)
$R\&Dintensity_{i,t}$,		0.9685	1.2103
		(0.9200)	(1.2137)
Constant	2.9962***	-2.3311***	-0.6469
	(0.0811)	(0.4551)	(0.7690)
Pseudo R^2	0.24	0.23	0.85
Observations	1,560	1,290	1,290
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic Effect, %	76.58	25.62	8.63

Table 6: Poisson regression of the number of green patent applications at t+1 against the climate change exposure opportunities variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+1}$	(2) $GreenAppl_{i,t+1}$	(3) $GreenAppl_{i,t+1}$
$\log(1 + \text{CCExposureOpp}_{i,t})$,	1.3406***	0.2718*	0.2423**
	(0.1118)	(0.1640)	(0.1113)
$FirmSize_{i,t}$,		0.5449***	0.4617***
		(0.0375)	(0.0654)
$DebtRatio_{i,t}$,		-0.1627	-0.0869
		(0.3349)	(0.2366)
$CashRatio_{i,t}$,		1.8069***	-0.1894
		(0.5265)	(0.3538)
$PPEintensity_{i,t}$,		-0.8845***	-0.3948
		(0.3058)	(0.4516)
$BasicEarningPower_{i,t}$,		1.7396***	2.0505***
		(0.5819)	(0.5232)
$R\&Dintensity_{i,t}$,		0.2651	-0.0409
		(0.8610)	(1.1804)
Constant	3.3001***	-2.2362***	-1.4008*
	(0.0633)	(0.4285)	(0.7263)
Pseudo R^2	0.22	0.22	0.84
Observations	1,649	1,360	1,360
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic Effect, %	57.35	9.63	8.54

Table 7: Poisson regression of the number of green patent applications at t+2 against the climate change exposure opportunities variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+2}$	(2) $GreenAppl_{i,t+2}$	(3) $GreenAppl_{i,t+2}$
$\log(\text{CCExposureOpp}_{i,t})$,	1.4683***	0.5243***	0.2766**
	(0.1016)	(0.1705)	(0.1249)
$FirmSize_{i,t}$,		0.5407***	0.3492***
		(0.0371)	(0.0706)
$DebtRatio_{i,t}$,		-0.2515	0.1111
		(0.3640)	(0.2441)
$CashRatio_{i,t}$,		1.5577***	-0.5657
		(0.5175)	(0.3997)
$PPEintensity_{i,t}$,,		-0.9631***	-0.1977
		(0.3066)	(0.5333)
$BasicEarningPower_{i,t}$,		2.1990***	2.3173***
		(0.6242)	(0.5685)
$R\&Dintensity_{i,t}$,		0.6078	1.1955
		(0.9078)	(1.2112)
Constant	3.3029***	-2.1771***	-0.5891
	(0.0638)	(0.4530)	(0.7728)
Pseudo R^2	0.24	0.23	0.85
Observations	1,560	1,290	1,290
Firm Fixed Effect	NO	NO	NO
Year Fixed Effect	NO	NO	NO
Economic Effect, %	64.29	19.40	9.80

Table 8: Poisson regression of the number of green patent applications at t+1 against the climate change regulatory exposure variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+1}$	(2) $GreenAppl_{i,t+1}$	(3) $GreenAppl_{i,t+1}$
$\log(1 + \mathrm{CCExposureReg}_{i,t})$,	2.0283***	-0.1518	0.2281
	(0.3505)	(0.3743)	(0.2532)
$FirmSize_{i,t}$,		0.5500***	0.4635***
		(0.0371)	(0.0659)
$DebtRatio_{i,t}$,		-0.1267	-0.1404
		(0.3319)	(0.2403)
$CashRatio_{i,t}$,		1.8437***	-0.2111
		(0.5236)	(0.3546)
$PPEintensity_{i,t}$,,		-0.8120**	-0.1646
		(0.3260)	(0.4820)
$BasicEarningPower_{i,t}$,		1.6981***	2.0714***
		(0.5827)	(0.5275)
$R\&Dintensity_{i,t}$,		0.1006	-0.1069
		(0.8774)	(1.1818)
Constant	3.5542***	-2.2657***	-1.4646**
	(0.0633)	(0.4303)	(0.7302)
Pseudo R^2	0.07	0.22	0.84
Observations	1,649	1,360	1,360
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic Effect, %	31.85	-2.05	3.16

Table 9: Poisson regression of the number of green patent applications at t+2 against the climate change regulatory exposure variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+2}$	(2) $GreenAppl_{i,t+2}$	(3) $GreenAppl_{i,t+2}$
$\log(1 + \mathrm{CCExposureReg}_{i,t})$,	2.3934***	-0.2814	-0.0128
	(0.3833)	(0.5432)	(0.3239)
$FirmSize_{i,t}$,		0.5460***	0.3497***
		(0.0369)	(0.0710)
$DebtRatio_{i,t}$,		-0.1773	0.0371
		(0.3575)	(0.2527)
$CashRatio_{i,t}$,		1.6469***	-0.5817
		(0.5116)	(0.4055)
$PPEintensity_{i,t}$,		-0.8466**	0.0584
		(0.3320)	(0.5667)
$BasicEarningPower_{i,t}$,		2.1292***	2.3334***
		(0.6265)	(0.5748)
$R\&Dintensity_{i,t}$,		0.3026	1.0449
		(0.9312)	(1.2317)
Constant	3.5689***	-2.1969***	-0.6320
	(0.0645)	(0.4584)	(0.7763)
Pseudo R^2	0.08	0.22	0.85
Observations	1,560	1,290	1,290
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic Effect, %	38.58	-3.76	-0.17

Table 10: Poisson regression of the number of green patent applications at t+1 against the climate change physical exposure variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+1}$	(2) $GreenAppl_{i,t+1}$	(3) $GreenAppl_{i,t+1}$
$\log(1 + \mathrm{CCExposurePhy}_{i,t})$,	2.5995***	0.9739***	-0.9010***
	(0.3725)	(0.3172)	(0.2661)
$FirmSize_{i,t}$,		0.5501***	0.4540***
		(0.0373)	(0.0655)
$DebtRatio_{i,t}$,,		-0.1545	-0.2374
		(0.3355)	(0.2409)
$CashRatio_{i,t}$,		1.7870***	-0.1378
		(0.5275)	(0.3620)
$PPEintensity_{i,t}$,,		-0.8435***	-0.3024
		(0.3060)	(0.4841)
$BasicEarningPower_{i,t}$,,		1.6819***	2.1449***
		(0.5811)	(0.5218)
$R\&Dintensity_{i,t}$,		0.2595	0.0316
		(0.8633)	(1.1923)
Constant	3.6627***	-2.2605***	-1.2979*
	(0.0691)	(0.4319)	(0.7221)
Pseudo R^2	0.02	0.22	0.84
Observations	1,649	1,360	1,360
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic Effect, %	14.49	5.20	-4.58

Table 11: Poisson regression of the number of green patent applications at t+2 against the climate change physical exposure variable measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenAppl_{i,t+2}$	(2) $GreenAppl_{i,t+2}$	(3) $GreenAppl_{i,t+2}$
$\log(1 + \mathrm{CCExposurePhy}_{i,t})$,	2.4864***	0.7118***	-0.9680***
	(0.3895)	(0.2723)	(0.2842)
$FirmSize_{i,t}$,		0.5462***	0.3440***
		(0.0370)	(0.0708)
$DebtRatio_{i,t}$,,		-0.1945	-0.0463
		(0.3603)	(0.2542)
$CashRatio_{i,t}$,		1.6007***	-0.5222
		(0.5118)	(0.4145)
$PPEintensity_{i,t}$,,		-0.8970***	-0.0829
		(0.3054)	(0.5672)
$BasicEarningPower_{i,t}$,,		2.1194***	2.4336***
		(0.6259)	(0.5735)
$R\&Dintensity_{i,t}$,		0.4444	1.1908
		(0.9116)	(1.2298)
Constant	3.6860***	-2.1943***	-0.5066
	(0.0715)	(0.4596)	(0.7735)
Pseudo R^2	0.02	0.22	0.85
Observations	1,560	1,290	1,290
Firm Fixed Effect	NO	NO	YES
Year Fixed Effect	NO	NO	YES
Economic Effect, %	13.82	3.78	-4.92

Table 12: Poisson regression of the number of non-green patent applications at time t+1 against the four climate change exposure variables measured at time t. A set of variables (firm size, debt ratio, cash ratio, PPE intensity, BEP, R&D intensity) measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $NonGreenAppl_{t+1}$	(2) $NonGreenAppl_{t+1}$	(3) $NonGreenAppl_{t+1}$	(4) $NonGreenAppl_{t+1}$
$\log(1 + \text{CCExposure}_{i,t})$,	-0.0983**			
	(0.0498)			
$\log(1 + \text{CCExposureOpp}_{i,t})$,		-0.0476		
		(0.0634)		
$\log(1 + \text{CCExposureReg}_{i,t})$,			-0.2588*	
			(0.1523)	
$\log(1 + \text{CCExposurePhy}_{i,t})$,				-0.4211**
				(0.1881)
Constant	4.0431***	4.0316***	4.0507***	4.0510***
	(0.3449)	(0.3440)	(0.3448)	(0.3430)
Pseudo R^2	0.93	0.93	0.93	0.93
Observations	1,348	1,348	1,348	1,348
Control Variables	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Economic Effect, %	-4.91	-1.60	-3.47	-2.17

Table 13: Poisson regression of the number of non-green patent applications at time t+2 against the four climate change exposure variables measured at time t. A set of variables (firm size, debt ratio, cash ratio, PPE intensity, BEP, R&D intensity) measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $NonGreenAppl_{i,t+2}$	(2) $NonGreenAppl_{i,t+2}$	(3) $NonGreenAppl_{i,t+2}$	(4) $NonGreenAppl_{i,t+2}$
$\log(1 + \text{CCExposure}_{i,t})$,	-0.0708			
	(0.0528)			
$\log(1 + \text{CCExposureOpp}_{i,t})$,		-0.0351		
		(0.0685)		
$\log(1 + \text{CCExposureReg}_{i,t})$,			-0.2759	
			(0.2049)	
$\log(1 + \text{CCExposurePhy}_{i,t})$,				-0.3120
				(0.2187)
Constant	4.6337***	4.6291***	4.6374***	4.6458***
	(0.3779)	(0.3767)	(0.3768)	(0.3757)
Pseudo R^2	0.94	0.94	0.94	0.94
Observations	1,279	1,279	1,279	1,279
Control Variables	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Economic Effect, %	-3.56	-1.18	-3.69	-1.61

Table 14: Logit regression of the dummy variable that takes the value 1 if, in t+1 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the general climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+1}$
$\log(1 + \mathrm{CCExposure}_{i,t})$,	0.9106***
	(0.2662)
$FirmSize_{i,t}$,	0.7394***
	(0.0728)
$DebtRatio_{i,t}$,,,	0.6627*
	(0.3518)
$CashRatio_{i,t}$,	1.6477*
	(0.8411)
$PPEintensity_{i,t}$,,,	0.7726
	(0.8182)
$BasicEarningPower_{i,t}$,,,	1.3240
	(0.9662)
$R\&Dintensity_{i,t}$,,	2.5621**
	(1.2731)
Constant	-6.3363***
	(1.1644)
Pseudo R^2	0.23
Observations	1,329
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	59,37

Table 15: Logit regression of the dummy variable that takes the value 1 if, in t+2 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the general climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+2}$
$\log(1 + \mathrm{CCExposure}_{i,t})$,	0.6380**
	(0.2677)
$FirmSize_{i,t}$,	0.7130***
	(0.0734)
$DebtRatio_{i,t}$,	0.7324**
	(0.3532)
$CashRatio_{i,t}$,	1.7023**
	(0.8339)
$PPEintensity_{i,t}$,	0.6990
	(0.8257)
$BasicEarningPower_{i,t}$,	1.4234
	(0.9458)
$R\&Dintensity_{i,t}$,	2.4539*
	(1.2979)
Constant	-5.6541***
	(1.1689)
Pseudo R^2	0,22
Observations	1,260
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	38.62

Table 16: Logit regression of the dummy variable that takes the value 1 if, in t+1 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the opportunity climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+1}$
$\log(1 + \text{CCExposureOpp}_{i,t})$,	2.0396***
	(0.4888)
$FirmSize_{i,t}$,	0.7424***
	(0.0733)
$DebtRatio_{i,t}$,	0.7004**
	(0.3536)
$CashRatio_{i,t}$,	1.7357**
	(0.8390)
$PPEintensity_{i,t}$,	0.8661
	(0.8136)
$BasicEarningPower_{i,t}$,	1.2226
	(0.9936)
$R\&Dintensity_{i,t}$,	2.2679*
	(1.2663)
Constant	-6.2096***
	(1.1411)
Pseudo R^2	0.24
Observations	1,329
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	99.30

Table 17: Logit regression of the dummy variable that takes the value 1 if, in t+2 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the opportunity climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+2}$
$\log(1 + \text{CCExposureOpp}_{i,t})$,	1.9560***
	(0.5139)
$FirmSize_{i,t}$,	0.7294***
	(0.0742)
$DebtRatio_{i,t}$,	0.7852**
	(0.3536)
$CashRatio_{i,t}$,	1.8506**
	(0.8336)
$PPEintensity_{i,t}$,	0.7199
	(0.8202)
$BasicEarningPower_{i,t}$,	1.2796
	(0.9531)
$R\&Dintensity_{i,t}$,	2.3159*
	(1.2935)
Constant	-5.6913***
	(1.1533)
Pseudo R^2	0.23
Observations	1,260
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	93.75

Table 18: Logit regression of the dummy variable that takes the value 1 if, in t+1 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the regulatory climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+1}$
$\log(1+\ \mathrm{CCExposureReg}_{\mathrm{i,t}})$,	1.1908
	(1.4478)
$FirmSize_{i,t}$,	0.7103***
	(0.0720)
$DebtRatio_{i,t}$,	0.6225*
	(0.3493)
$CashRatio_{i,t}$,	1.3934*
	(0.8323)
$PPEintensity_{i,t}$,	1.0363
	(0.8220)
$BasicEarningPower_{i,t}$,	1.4214
	(0.9786)
$R\&Dintensity_{i,t}$,	2.1358*
	(1.2459)
Constant	-5.9374***
	(1.1574)
Pseudo R^2	0.23
Observations	1,329
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	17.63

Table 19: Logit regression of the dummy variable that takes the value 1 if, in t+2 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the regulatory climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+2}$
$\log(1+\ \mathrm{CCExposureReg}_{\mathrm{i,t}})$,	1.5423
	(1.8222)
$FirmSize_{i,t}$,	0.6939***
	(0.0728)
$DebtRatio_{i,t}$,	0.7269**
	(0.3538)
$CashRatio_{i,t}$,	1.4942*
	(0.8343)
$PPEintensity_{i,t}$,	0.8165
	(0.8236)
$BasicEarningPower_{i,t}$,	1.5430
	(0.9624)
$R\&Dintensity_{i,t}$,	2.2444*
	(1.2800)
Constant	-5.4198***
	(1.1493)
Pseudo R^2	0.22
Observations	1,260
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	23.40

Table 20: Logit regression of the dummy variable that takes the value 1 if, in t+1 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the physical climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+1}$
$\log(1+\text{CCExposurePhy}_{i,t})$,	3.9629
	(3.8386)
$FirmSize_{i,t}$,	0.7095***
	(0.0713)
$DebtRatio_{i,t}$,	0.5927*
	(0.3502)
$CashRatio_{i,t}$,	1.4496*
	(0.8355)
$PPEintensity_{i,t}$,	1.1266
	(0.8299)
$BasicEarningPower_{i,t}$,	1.4283
	(0.9752)
$R\&Dintensity_{i,t}$,	2.0493*
	(1.2194)
Constant	-5.8432***
	(1.1251)
Pseudo R^2	0.23
Observations	1,329
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	22.92

Table 21: Logit regression of the dummy variable that takes the value 1 if, in t+2 year, the company applied for a patent with a CPC code of Y02, and 0 otherwise against the physical climate change exposure variables measured at time t. A set of variables measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $GreenOrNot_{i,t+2}$
$\log(1+\text{CCExposurePhy}_{i,t})$,	5.4172
	(5.6192)
$FirmSize_{i,t}$,	0.6928***
	(0.0721)
$DebtRatio_{i,t}$,	0.6947**
	(0.3542)
$CashRatio_{i,t}$,	1.5508*
	(0.8382)
$PPEintensity_{i,t}$,	0.9239
	(0.8376)
$BasicEarningPower_{i,t}$,	1.5828
	(0.9662)
$R\&Dintensity_{i,t}$,	2.1713*
	(1.2577)
Constant	-5.3271***
	(1.1452)
Pseudo R^2	0.22
Observations	1,260
Industry Fixed Effect	YES
Year Fixed Effect	YES
Marginal Effect, %	32.58

Table 22: Panel regression of the logarithmic transformation of the ratio between the green patent applications and total number of applications made in year t+1 against the four different climate change exposure variables measured at time t. A set of variables (firm size, debt ratio, cash ratio, PPE intensity, BEP, R&D intensity) measured at time t are also added to control for different firms' characteristics. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $\log(1 + GreenRatio_{i,t+1})$	(2) $\log(1 + GreenRatio_{i,t+1})$	(3) $\log(1 + GreenRatio_{i,t+1})$	(4) $\log(1 + GreenRatio_{i,t+1})$
$\log(1 + \text{CCExposure}_{i,t})$,	0.0109***			
	(0.0018)			
$\log(1 + \text{CCExposureOpp}_{i,t})$,		0.0130***		
		(0.0026)		
$\log(1 + \text{CCExposureReg}_{i,t})$,			0.0125*	
			(0.0064)	
$\log(1 + \text{CCExposurePhy}_{i,t})$,				0.0078
				(0.0134)
Constant	0.0018	0.0027	0.0030	0.0051
	(0.0126)	(0.0126)	(0.0128)	(0.0127)
Observations	1,348	1,348	1,348	1,348
R-squared	0.5688	0.5652	0.5580	0.5568
Control Variables	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES

Table 23: Panel regression of the logarithmic transformation of the ratio between the green patent applications and total number of applications made in year t+2 against the four different climate change exposure variables measured at time t. A set of variables (firm size, debt ratio, cash ratio, PPE intensity, BEP, R&D intensity) measured at time t are also added to control for different firms' characteristics. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) $\log(1 + GreenRatio_{i,t+2})$	(2) $\log(1 + GreenRatio_{i,t+2})$	(3) $\log(1 + GreenRatio_{i,t+2})$	(4) $\log(1 + GreenRatio_{i,t+2})$
$\log(1 + \text{CCExposure}_{i,t})$,	0.0113***			
	(0.0020)			
$\log(1 + \text{CCExposureOpp}_{i,t})$,		0.0129***		
		(0.0029)		
$\log(1 + \text{CCExposureReg}_{i,t})$,			0.0217***	
			(0.0078)	
$\log(1 + \text{CCExposurePhy}_{i,t})$,				0.0118
				(0.0135)
Constant	-0.0073	-0.0074	-0.0079	-0.0057
	(0.0128)	(0.0129)	(0.0130)	(0.0130)
Observations	1,279	1,279	1,279	1,279
R-squared	0.5734	0.5687	0.5642	0.5616
Control Variables	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES

Table 24: Poisson regression of the winsorized green patent applications variable at time t+1 and t+2 against the four climate change exposure variables measured at time t. A set of variables (firm size, debt ratio, cash ratio, PPE intensity, BEP, R&D intensity) measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$GreenAppl_{i,t+1}$	$GreenAppl_{i,t+1}$	$GreenAppl_{i,t+1}$	$GreenAppl_{i,t+1}$	$GreenAppl_{i,t+2}$	$GreenAppl_{i,t+2}$	$GreenAppl_{i,t+2}$	$GreenAppl_{i,t+2}$
$\log(1 + \text{CCExposure}_{i,t})$,	0.2165***				0.1674*			
	(0.0796)				(0.0860)			
$\log(1 + \text{CCExposureOpp}_{i,t})$,		0.2553**				0.2892**		
		(0.1080)				(0.1227)		
$\log(1 + \text{CCExposureReg}_{i,t})$,			0.2710				0.0723	
			(0.2400)				(0.3038)	
$\log(1 + \text{CCExposurePhy}_{i,t})$,				-0.7788***				-0.8810***
				(0.2332)				(0.2641)
Constant	-1.4644**	-1.3632*	-1.4392**	-1.2801*	-0.6039	-0.5443	-0.6007	-0.4802
	(0.7182)	(0.7263)	(0.7310)	(0.7241)	(0.7690)	(0.7732)	(0.7774)	(0.7749)
Pseudo R^2	0.84	0.84	0.84	0.84	0.85	0.85	0.85	0.85
Observations	1,360	1,360	1,360	1,360	1,290	1,290	1,290	1,290
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Economic Effect, %	11.72	9.02	3.76	-3.97	8.95	10.27	0.99	-4.48

Table 25: Poisson regression of the winsorized non-green patent applications variable at time t+1 and t+2 against the four climate change exposure variables measured at time t. A set of variables (firm size, debt ratio, cash ratio, PPE intensity, BEP, R&D intensity) measured at time t are also added to control for different firms' characteristics. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$NGAppl_{t+1}$	$NGAppl_{t+1}$	$NGAppl_{t+1}$	$NGAppl_{t+1}$	$NGAppl_{t+2}$	$NGAppl_{t+2}$	$NGAppl_{t+2}$	$NGAppl_{t+2}$
$\log(1 + \text{CCExposure}_{i,t})$,	-0.0849*				-0.0725			
	(0.0499)				(0.0527)			
$\log(1 + \text{CCExposureOpp}_{i,t})$,		-0.0285				-0.0149		
		(0.0639)				(0.0696)		
$\log(1 + \text{CCExposureReg}_{i,t})$,			-0.3326*				-0.2518	
			(0.1763)				(0.2044)	
$\log(1 + \text{CCExposurePhy}_{i,t})$,				-0.4543**				-0.3288
				(0.1850)				(0.2195)
Constant	4.2518***	4.2437***	4.2672***	4.2627***	4.7295***	4.7266***	4.7342***	4.7431***
	(0.3388)	(0.3375)	(0.3383)	(0.3359)	(0.3635)	(0.3626)	(0.3629)	(0.3611)
Pseudo R^2	0.93	0.93	0.93	0.93	0.94	0.93	0.93	0.93
Observations	1,348	1,348	1,348	1,348	1,279	1,279	1,279	1,279
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Economic Effect, %	-4.25	-0.96	-4.43	-2.34	-3.64	-0.50	-3.37	-1.70

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