# The Impact of Corporate Climate Action on Financial Markets: Evidence from Climate-Related Patents*

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**Abstract**

We study the impact of climate-related patents on financial markets. We exploit the quasi-random assignment of patent examiners with different degrees of leniency as an exogenous shock in patent approvals to allow for causal interpretations. We find that firms with more lucky climate-related patents subsequently display higher positive cumulative abnormal stock returns and enjoy a lower cost of capital, compared with similarly innovative but unlucky firms. These results hold especially during periods of high attention towards climate change and for initial climate patent granting. Firms with more lucky climate-related patents also exhibit better environmental ratings and attract more responsible institutional investors. OLS regressions show that firms developing more climate-related technologies reduce more direct carbon emission intensity.

*Key words: climate-related patents, green patents, examiner leniency, climate change, implied cost of capital, ESG ratings, responsible investors, CO2 emissions.*

*JEL classification: G11, G23, G24, O34.*

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# I. Introduction

The corporate sector is by far the largest source of carbon dioxide (CO2) and other greenhouse gas emissions (CDP, 2017). Here referred to as carbon emissions, these likely constitute one of the leading cause of climate change (IPCC, 2022). Many companies have announced plans to cut carbon emissions, with more than two-third of S&P 500 companies having adopted such policies and about half having set specific targets to reduce emissions, according to Refinitiv.[1] Corporate climate action consists in planning, implementing and evaluating corporate policies aimed at reducing carbon emission, and has become a focal issue in the growing investor attention to environmental, social, and governance (ESG) objectives that puts companies under increasing pressure through shifting valuations and shareholder votes (Flammer, 2015; Krueger, Sautner, and Starks, 2020; Sauzet and Zerbib, 2022). Research on corporate climate action and firms' financial performance is rapidly growing, with one branch studying the link between corporate environmental performance and stock returns (Chava, 2014; In, Park, and Monk, 2019; Bolton and Kacperczyk, 2021; Pástor, Stambaugh, and Taylor, 2022; Hsu, Li, and Tsou, 2022) and another the interaction between ESG performance and institutional investors (Starks, Venkat, and Zhu, 2017; Gibson, Glossner, Krueger, Matos, and Steffen, 2020; Gibson Brandon, Krueger, and Mitali, 2020; Gibson Brandon, Krueger, and Schmidt, 2021).

There are two main empirical challenges when studying the impact of corporate climate action. The first challenge is the potential endogeneity in the association between corporate climate performance (usually measured by environmental ratings or carbon emissions) and financial market responses. As recently argued by Berg, Koelbel, Pavlova, and Rigobon (2021), numerous firm-level characteristics can correlate with both a firm's environmental rating and its future stock returns, resulting in an omitted variable bias. For example, firms with a better management team may be more likely to manage their environmental performance well, and at the same time, these firms may enjoy higher future returns (Gompers, Ishii, and Metrick, 2003).

The second challenge is related to measurement errors that could bias the analyses of the impact of corporate climate action on financial markets (Angrist and Krueger, 2001). Various papers have recently argued that ESG ratings display high levels of disagreement (Dimson, Marsh, and Staunton, 2020; Berg, Koelbel, and Rigobon, 2022; Gibson Brandon et al., 2021). The low level

[1] https://www.refinitiv.com/perspectives/future-of-investing-trading/are-sp-500-companies-prioritizing-environmental-sustainability/.

of correlation across ratings, including on the environmental dimension, suggests that such ratings are noisy measures of the underlying ESG performance of firms. For example, Berg et al. (2022) indicate that measurement issues contribute to more than half of the divergence in ESG ratings across the various providers. Berg, Fabisik, and Sautner (2020) argue that data providers' updates of historical ESG data might lead to closer associations with financial performance. Another reason why measuring ESG performance is difficult is that some firms manipulate their reporting, a practice known as greenwashing (Marquis, Toffel, and Zhou, 2016).[2] Because inaccuracies and attempts of manipulation in corporate reporting are hard to detect for ESG rating agencies, greenwashing might be one of the causes of divergence in ESG ratings and could lead to measurement errors.[3]

Our paper addresses these two challenges by looking at one important type of corporate climate action, namely innovation in climate change mitigation technologies. Such green innovation is expected to play a major role in reducing the social cost of the energy transition (Acemoglu, Aghion, Bursztyn, and Hemous, 2012; Acemoglu, Aghion, Barrage, and Hémous, 2020). Specifically, we look at patent grants, using the fact that the United States Patent and Trademark Office (USPTO) tags patents on climate change with a specific code, "Y02", as part of an international agreement. Climate-related patents deal for example with renewable energy generation, energy storage, energy savings, hydrogen technology, and carbon capture and storage.

Focusing on patents offers two main methodological advantages. First, the institutional details of the patent examination process allow us to exploit a quasi-random variation in patent approvals that offers a unique instrumental variable in the context of corporate climate policies, at the core of our empirical strategy. Second, the fact that patents are granted by an official third party (the USPTO) after rigorous scrutiny mitigates concerns about corporate greenwashing.

Our identification strategy exploits quasi-random shocks in the probability of patent approvals. The patent literature has demonstrated that some patent examiners are more lenient and grant patents more easily than other examiners in the same field of patent applications, for person-specific, idiosyncratic reasons (Cockburn, Kortum, and Stern, 2002). Moreover, in most USPTO technology art units, patent examiners are assigned to patent applications in a quasi-random fashion (Sampat

[2] Various companies have been accused of concealing negative information or exaggerating environmental benefits of their products or services, see, e.g., https://earth.org/greenwashing-companies-corporations.

[3] Berg et al. (2021) propose a method to attenuate the measurement error problem by instrumenting ESG ratings of a given agency with ratings of other agencies.

and Williams, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2020).[4] Combining these two facts, our exogenous variation relies on patent examiner "lotteries". As a result, the instrument allows us to separate patent grants from underlying technologies and only focus on the signaling (or information) effect of climate patent approvals due to a lucky draw of lenient examiners.[5]

We aim to explore the reaction of financial markets, of ESG-minded investors and of the ESG rating ecosystem to announcements of climate-related patent approvals. We also want to understand the real effects of patented climate-related innovation on companies' CO2 emissions. To conduct this analysis, we match the sample of climate patent applications with other firm-level data sources, notably the Refinitiv ESG database. The resulting panel allows us to compare two similar firms that submit the same number of climate patent applications, but are assigned to examiners with different leniency attitudes.

We instrument our main variable of interest, the number of newly issued climate-related patents of a firm in period $t$, with the average leniency of examiners who assess the company's applications. We add fixed effects to compare firms with the same number of applications and in the same art unit and year. We verify that climate patent applications are indeed more likely to be granted when assigned to more lenient examiners. For example, in the firm-year sample, a one standard deviation increase in the average leniency leads to around 1.8 more climate patents in a given year (this increase represents 10% of the mean and 50% of the median number of climate patents in a year). Moreover, we conduct a series of exogenous tests to check that our analysis is immune to recent concerns regarding our examiner's leniency instrument. We then use the predicted probability of additional climate patents as the explanatory variable in the second-stage regressions.

Our main results are as follows. Looking at realized stock returns, we find that companies that are granted climate-related patents by luck in the patent examiner "lottery" benefit from a significant cumulative abnormal return of about 10% over the next 12 months, which translates into an approximately 2% 12-month abnormal return per climate patent.[6] Such large abnormal returns could be generated by a permanent improvement in perceived corporate performance or risk, or be a financial market reaction to the information contained in the green patent approval. The second interpretation appears plausible in light of our subsequent findings on the effect of attention to

[4]Patent applications are assigned to art units of patent examiners by technological specialization. There are about 900 art units, so they are a rather granular subdivision of the patent examination process.

[5]A varying leniency is not inconsistent with a rigorous scrutiny: some examiners may grant more patents than others but still choose better technologies.

[6]There are often multiple patents during one time period.

climate change and on the changes in ESG-minded investors' stock holdings.

We consider the effect of changes in public attention to climate change, using a daily index of the coverage and negativity of climate topics in leading US newspapers (MCCC index of Ardia, Bluteau, Boudt, and Inghelbrecht, 2020). We find that abnormal returns after random shocks in patent approvals are substantially higher (around 20%) in top tercile periods of climate change attention. They are less than 8% and insignificant in periods of lower climate change attention. This result suggests that positive abnormal returns realized after lucky climate-related patent draws are related to climate change issues and not to a general tendency for financial markets to react positively to the granting of patents.

We document that the reaction is strongest for a firm's initial climate-related patents. We show that a firm belonging to the lowest tercile by stock of climate-related patents (corresponding to the first ten climate-related patents) enjoys a significant abnormal stock return of up to 20%, but the effect is no longer significant for firms with a larger climate patent stock. This finding is in line with the informational effect of startup patents uncovered by Farre-Mensa et al. (2020) who show that the first patent granted to an entrepreneurial company is critical to its future success, but not subsequently granted patents.

We also explore short-term abnormal returns following (random variations in) climate-related patent grants. We find that daily CARs around the patent announcement date are significant only when the patent is granted in a period of heightened (top-tercile) climate change attention. We find that cumulative daily CARs are increasing up to three days after these events, reaching an average level of 0.8%.

After analyzing realized returns, we turn to their counterparts, expected returns. We use implied cost of capital (ICC) to measure expected returns, and find that a one standard deviation increase in the number of newly issued climate patents leads to an approximately 0.9% drop in ICC over the subsequent 12 months. Thus, the positive abnormal returns are accompanied by a concomitant reduction in the ICC over roughly the same horizon. Importantly, further analysis confirms that the drop is most pronounced (and only consistently significant) when patents are granted during top-tercile periods of public attention to climate change. This finding is in line with the idea that the temporary change in ICC is mainly the effect of the financial market reaction, not an anticipation of any decrease in future risks that could reduce the cost of capital, such as risks concerning environmental litigation or controversies (Chava, 2014).

We are interested in understanding the driving forces behind the financial market reaction. We consider two non-exclusive channels: (1) institutional investors' demand-driven price pressure and (2) ESG rating agencies' response to climate patenting. Concerning the first channel, we document that institutional investors react favorably to the news of climate patent issuance. A one standard deviation increase in the number of patent grants leads to an increase of around 6% in total institutional ownership within one year, with institutional ownership monotonically rising throughout the first four quarters. The effect is only significant during periods of heightened attention to climate change. Next, we rank investors by their revealed preferences for environmental issues, using the value-weighted Refinitiv environmental score of their portfolio holdings as proposed by Gibson Brandon et al. (2020). We find that only institutions with an above-median environmental focus change their portfolio holdings after patent grants, and we find that they do so only in periods of heightened attention to climate change. We obtain the same finding when we dis-aggregate and look at fund-level changes in stock holdings. Thus, the strong response of institutional ownership is driven by ESG-minded institutional investors, during times when climate concerns are salient.

Concerning the second channel, we find that Refinitiv ESG, one of the leading ESG rating agencies, reacts favorably to exogenous shocks in climate-related patent grants, and adjusts ESG scores upwards. We obtain similar results if we instead use the S&P Global ESG scores.[7]

Our results on climate-related patents do not carry over to other green patents that are not related to climate change: when we apply the same methodology to these other green patents, we do not find any higher subsequent realized returns, lower expected returns, increased institutional investor holdings or higher ESG ratings. The contrast is striking and might be due to the fact that other green patents are not assigned a specific tag by the USPTO. It demonstrates the particular role of climate action in companies' interaction with financial markets about environmental issues. It confirms that our findings are not due to a general tendency of markets to react positively to lucky draws in the patent lottery, but are specific to climate-related innovation.

We then turn to real climate change mitigation effects of climate-related patents. We investigate whether firms with climate-related patents use these technologies to reduce their CO2 emissions. When we look at random variations in patent approvals (using again the 2SLS regressions set-

[7]Thus, our results do not seem to depend on issues related to the backwards updating of Refinitiv ESG data, see Berg et al. (2020). Relevant for this issue, our research design implies that only one of our results could potentially be affected by doubts about the reliability of updated Refinitiv ESG scores, namely the tests in Section 6.A. See the discussion there.

up), we find no significant effects of climate-related patent grant shocks on CO2 emissions or on total energy used. This is in line with the idea that firms that have been unlucky in the climate patent lottery still have access to new climate change mitigation technologies that are on average as effective as those of firms with lucky patent draws.

However, the more interesting question is about the real impact of the climate-related technologies that all of these firms are developing, i.e., of the underlying innovations that the inventors can use even if no patent protection is granted. We thus conduct OLS regressions of the effects of increased climate-related innovation (proxied by the number of climate-related patents). We find significant reductions in direct (Scope 1) emission intensity starting in year 3 after the climate-related patent application year, at the aggregate level and at the individual patent category for transportation, goods, and energy sectors. Thus, climate-related patents are associated with significant improvements in patent holders' carbon efficiency, but the effect appears to be slow and to be entirely linked to the underlying technology and not to it being granted patent protection.

Our paper contributes to three strands of literature. First, our work is closely related to a small but growing literature regarding green patents and technologies. Cohen, Gurun, and Nguyen (2021) document that listed firms in the energy sector contribute a lot to green patents but receive lower ESG ratings and are frequently excluded from investing scopes of ESG funds. Extending the analysis to non-listed firms, Dalla Fontana and Nanda (2022) show that climate patents granted to firms backed by Venture Capitalists represent a small share of climate patents but that these patents are more likely to cite fundamental science and to be subsequently cited. Andriosopoulos, Czarnowski, and Marshall (2022) compare green patents with other patents through event studies in the US and find no evidence that investors value green innovation. This result is at odd with the findings of Dechezleprêtre, Muckley, and Neelakantan (2019) on a global sample of clean and dirty patents. Gao and Li (2021) and Li, Neupane-Joshi, and Tan (2022) link green patents to firms' performance on toxic emissions and releases. Bolton, Kacperczyk, and Wiedemann (2022) focus on the determinants and emission impact of corporate green innovation. To the best of our knowledge, we are the first to exploit quasi-random assignments of lenient examiners to study the impact of climate patents. A further contribution is that we expand the analysis by expanding the original definition of climate patents from Haščič and Migotto (2015) by including two recently added subcategories of the Y02 tagging scheme, for climate innovation related to information and communication technology (tag Y02D) and to the production of goods (tag Y02P).

Second, our paper closely relates to recent work investigating corporate environmental performance and financial market responses. Bolton and Kacperczyk (2021) find that absolute carbon emissions were positively associated with realized abnormal returns over the period 2005-2017. Focusing on revenue-adjusted emissions, In et al. (2019) find that firms with low relative emissions experienced positive abnormal return over the period 2010-2015.[8] Pástor et al. (2022) have documented lower expected returns but larger realized returns for "green stocks" compared to "brown stocks", measured by environmental MSCI ESG Ratings, between 2012 and 2020, a period with increasing climate change concerns and flows to sustainable investments. Hsu et al. (2022) find that toxic emission intensity is positively associated with realized abnormal returns over the period from 1992 to 2018. Chava (2014) finds that firms with better environmental performance enjoy a lower cost of capital. We complement this literature by establishing a causal link between corporate climate action and various financial market as well as real outcomes.

Finally, our paper is also related to the literature on corporate innovation and stock returns. For example, Kogan, Papanikolaou, Seru, and Stoffman (2017) leverage market responses to the news of patent approval from the USPTO to measure the private value of technologies for companies and link their measure to resource allocation across firms as well as macroeconomic growth. Cohen, Diether, and Malloy (2013) show that stock market valuations do not appropriately reflect past innovation successes. Hirshleifer, Hsu, and Li (2013, 2018) document higher long-term cumulative abnormal returns for firms with higher innovation efficiency and originality, respectively. Fitzgerald, Balsmeier, Fleming, and Manso (2021) recently discover that exploitative innovation strategies allow firms to enjoy higher abnormal returns. In our paper, we find positive short-term as well as long-term abnormal returns after lucky grants of climate-related patents.

The rest of the paper proceeds as follows. Section II describes the data and summary statistics, and Section III develops our key identification strategy. Section IV provides our main results on financial market reactions, and Section V offers evidence on the underlying driving forces. Section VI presents further results on the real effects of climate patents, and Section VII concludes.

[8] Other recent work includes Aswani, Raghunandan, and Rajgopal (2022)

# II. Data and Sample Construction

## A. Climate Patents Data

We construct our dataset of climate-related patent applications based on the USPTO Patent Examination Research Dataset (PatEx) as the primary data source, limiting the sample to US-based publicly listed corporations. For comparison, we also construct a dataset of other green patent applications. Patent application and examination data became available in the wake of the 2000 American Inventors Protection Act (AIPA), which requires the USPTO to publish most US patent applications no later than 18 months after the first filing date of a patent application, starting in late 2000. From PatEx, we extract the patent application number, patent number, filing date, decision date, the examiner who assesses the focal patent application, and the examiner's technology art unit for each US utility patent application.[9] Next, we define the decision date of a patent application as the grant date if the application is finally granted. For rejected patents, we use the date of final rejection (CTFR) or non-final rejection (CTNF) as the decision date.[10]

PatEx does not provide any information about the owner of each patent application (the assignee), nor on Cooperative Patent Classification (CPC) codes. To complete the dataset with information on these missing items, we obtain assignee's information from the USPTO Patent Assignment database, matching PatEx with the application numbers and only using employee-to-employer assignments with a single assignee. We obtain each application's CPC codes from PatentsView.

After getting assignee information, we match each assignee of a patent application to the CRSP/Compustat listed firms, applying the matching concordance provided by Arora, Belenzon, and Sheer (2021).[11] Since the concordance only covers granted patents, we expand the matched

[9] In the USPTO system, patents on mechanical, electronic, and chemical technologies are generally called "utility patents" (Graham, Marco, and Miller, 2018). As is customary, we exclude provisional, PCT (Patent Cooperation Treaty), reissue, and re-examination applications from our analysis.

[10] The last non-final rejection date of a patent is used when there is no final rejection date and the patent is not granted. 45% of rejected patents have only non-final rejection date. This means that applicants fail to respond to the non-final rejection letter within three months.

[11] We use the concordance provided by Arora et al. (2021) instead of the one by Kogan et al. (2017) for two reasons. First, Arora et al. (2021) include not only patents of listed corporations but also those filed by private subsidiaries of listed corporations. This helps us identify patents filed by subsidiaries and ultimately owned by a public corporate parent. Second, they consider various name changes of public firms in their (patent assignee)–(firm name) fuzzy matching. Kogan et al. (2017) follows a matching concordance of the NBER Patent Project, and the NBER Patent Database does not conduct this dynamic name matching. As argued by Arora et al. (2021), their matching significantly improves the original matching offered by the

sample by applying the same matching procedure to failed/rejected patent applications. For example, an assignee named "ABBOTT LAB" matches to a listed corporation with PERMNO = 20482 from 2001 to 2014. Then, if the same assignee "ABBOTT LAB" had a rejected patent application in 2013, it should also be matched to PERMNO = 20482.[12] Finally, we obtain a sample of 1,316,275 patent applications by US-listed corporations from 2001 to 2020, with a granting ratio equal to 72%.[13] Appendix B provides details about the matching procedure.

The final step is to identify green patents, including climate-related and other green patents, among these 1,316,275 applications. We employ the method developed by the OECD (Haščič and Migotto, 2015) and used by Cohen et al. (2021). It relies on patent classifications in the International Patent Classification (IPC) as well as on the CPC codes jointly adopted by the USPTO and the European Patent Office (EPO). In 2010, USPTO and EPO announced to the United Nations Framework Convention on Climate Change the creation of a new tag in their joint CPC scheme that specifically identifies climate-related technologies, a new tag called "Y02". Originally the "Y02" tag was limited to climate change mitigation in energy production (Y02E), but it was quickly expanded to three additional categories: transportation (Y02T), building (Y02B), and capture, storage or disposal of greenhouse gases (Y02C).[14] These tags were applied to all new patent grants from 2012 onward, and later back-filled to older patents.[15] We keep track of a recent expansion in the "Y02" tagging scheme and include two new categories that were added to the scheme in 2019: climate mitigation in information and communication technologies (Y02D) and in the production and processing of goods (Y02P).[16] Thus, we identify climate-related patents as patents tagged with one of the following "Y02" categories: Y02B (Building), Y02D (Digital), Y02E (Energy), YO2P (Goods), and Y02T (Transportation).[17]

We classify a patent application as "other green patent" if at least one of its CPC codes falls

NBER.

[12]When the same assignee matches to more than one PERMNO in the same year, we use location information (state, city, and ZIP code) to manually check the matching.

[13]Our granting ratio is slightly higher compared with the one indicated by Farre-Mensa et al. (2020). This is probably due to the fact that larger and publicly listed firms are more likely to be successful with their patent applications than the startups studied by Farre-Mensa et al. (2020).

[14]Dalla Fontana and Nanda (2022) validate the fact that Y02 patents are indeed climate patents by applying a text-based analysis to their titles.

[15]Climate-related patents may reduce $CO_2$ emissions within the boundaries of the firm using them (Scope 1), at its energy suppliers (Scope 2), or within its supply chain, upstream and downstream (Scope 3).

[16]See https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html for details.

[17]We exclude Y02C ($CO_2$ capture and storage) and Y02W (wastewater treatment) patents from our main analyses since the number of patents in these groups is very small. Our results hold if we include these patents in our sample.

in the set related to green patents as defined by Haščič and Migotto (2015) but it is not tagged with the "Y02" label. The OECD defines three categories of other green patents: patents for environmental management technologies, water-related adaptation technologies, and bio-diversity protection technologies (Haščič and Migotto, 2015).

Table I, Panel A provides summary statistics for our sample of green patent applications. In total, there are 86,363 green patent applications (about 5% of the patents in our dataset) with a 73% granting rate. Panel A also provides statistics for climate-related and other (non climate-related) green patent applications separately. Climate-related patents have a lower granting rate on average and a longer time window from application to decision dates.

Table I, Panel B tabulates the top five FF-48 industries with the largest number of climate-related and other green patent applications, separately. The energy sector contributes a lot to green patents as highlighted in Cohen et al. (2021).[18] Panel C shows that firms obtain on average 22.72 (5.26) patent decisions in each year (month) with such decisions.

In Figure 1, Panel A, we plot the annual number of patent applications for the five Y02 subcategories thst we consider.[19] The number of climate-related patents granted has been quickly growing in recent years, as shown in Figure 1, Panel B. Consistently with Table I, Panel A, the transportation sector shows the most climate-related patents, followed by the energy and IT sectors.

## B. *Data about ESG ratings, Institutional Ownership, and Stock Returns*

We collect ESG data from the Refinitiv ESG database and use the Environmental Score (*envrnscore*), an industry-adjusted and percentile ranking score, as our primary metric for firm-level environmental performance. The coverage of Refinitiv ESG is S&P 500 + NASDAQ 100 during 2003 – 2009, and later it expands to Russell 1000 in 2010, and Russell 3000 in 2017.[20] Refinitiv

[18] Several factors explain why our data slightly differ from Cohen et al. (2021): (i) we focus on application data, containing both issued and rejected patents; (ii) we cover a different time period; (iii) we follow the recent expansion of CPC Y02 scheme and include the new subcategories Y02D and Y02P.

[19] Panel A of Figure 1 plots our sample by application year and shows a sharp decrease in patent applications at the end of the sample period due to the classical truncation bias that is well-known in the patent literature (Lerner and Seru, 2021): this bias reflects the fact that most applications filed between 2018 and 2020 have typically not yet received decisions at the time of our analysis. Our paper is largely immune to this truncation bias since we use the patent *decision year*, and not the *application year* to construct patent variables in all regressions.

[20] Our return results do not depend on this step-wise extension of coverage. In the Online Appendix, we reproduce our tests using the Russell 1000 index sample and find similar results. The Russell 3000 index gives inconclusive results. Our interpretation is that the attention to corporate climate actions and specifically

splits the Environmental Score into three sub-scores (pillars): emissions, resource consumption, and innovation. The scores for all three pillars are also percentile-ranked. We obtain data on the direct (Scope 1) CO2 equivalent emissions from Refinitiv.

We merge our climate patents data with the Refinitiv ESG and CRSP-Compustat firm-level data. The resulting merged data set yields a baseline sample that requires that each observation receives at least one climate patent decision from USPTO (either granted or rejected) in the year of that observation. Similarly, we construct a firm-quarter and a firm-month sample by aggregating climate patents at the quarterly and monthly levels. Table I, Panel C provides summary statistics. In our final matched sample, there are 419 unique firms receiving 56,150 decisions about their climate-related patent applications. The average number of patent applications in the firm-year (firm-month) sample is 22.7 (5.2), with 16.7 (3.9) granted.[21] Since both the number of patent applications and granted patents are highly skewed, we take the natural logarithm of these two variables ($ln(1+x)$) in all subsequent regression analyses. All variable definitions are in Appendix A.

We get institutional investors' stock holdings data from the Refinitiv 13F Database. Following Gibson Brandon et al. (2020), we calculate each institution's quarterly portfolio Environmental Score as the value-weighted average (Refinitiv) Environmental Score of its holding portfolio in that quarter.[22] In each quarter, we sort all institutions by their portfolio Environmental Score to get a measure of their revealed preferences for environmental issues. We obtain monthly stock returns and share outstanding data from CRSP (we only use stocks with share codes equal to 10 or 11 in our main analysis) and data for the Fama-French 5-factor model (Fama and French, 2015) from Kenneth French's Data Library.[23]

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to the climate patent signal is stronger for larger firms because they have alarger role to play in mitigating climate change.

[21]The average number of years in which a firm has at least one climate patent is 5.93. The average number of months in a given year in which a firm has climate patents is 3.97.

[22]We use firm-level Environmental Scores lagged by one year.

[23]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

# III. Identification Strategy

## A. Background about Patent Examination

We begin with a brief institutional background on patent applications and examinations.[24] Examinations and processing of utility patents involve two steps: (i) the USPTO first attaches a set of technology classes (USPC or CPC codes) to each application, and assigns the application to a specific technological art unit (there are about 900 art units in total) according to the technology classes; (ii) each application is then "docketed" (assigned) by an art unit supervisor to an individual patent examiner for assessing and examination.

Our exogenous variation lies in the second step of the examination. Lemley and Sampat (2012), Sampat and Williams (2019), and Farre-Mensa et al. (2020) argue that the matching of each application to an examiner is quasi-random within each art unit, in the sense that no observable variable, that could affect our variables of interest, can predict the examiner to whom an application is assigned. For example, in some art units, applications are randomly assigned according to the last two digits of the application number, while in others, they are simply assigned based on the busyness of examiners. Furthermore, examiners vary in their propensity to approve applications, a time-invariant personal characteristic that we call leniency. Following Cockburn et al. (2002), we define examiners with high and low propensity as lenient and strict examiners, respectively. We then use the quasi-random assignment of examiners with varying levels of leniency as a source of exogenous variation in green patent approvals. As discussed in Farre-Mensa et al. (2020), getting a patent from a lenient examiner is like winning a "patent lottery". It allows us to isolate a potential signaling or information effect of green patents from the impact of the underlying invention.

The next critical element in our identification strategy is the timeline of the patent examination process. There are three key steps in the process: the application, the reception of the first action letter, and the final decision (granting or rejection). Three key dates are associated with these three steps. The first date is when the patent applicant files an application to the USPTO (application date). The second date is when the first action letter is sent (first action letter's date).[25] Typically, only at this point does the applicant learn the identity of the assigned examiner. The third date is when the patent is granted or when the application is rejected (final decision date).

[24] More details can be found in Graham et al. (2018).

[25] About 87% of first action letters contain a non-final rejection decision, asking the patent applicant to revise the patent claims and descriptions.

In our paper, the empirical strategy is to identify the effect of exogenous climate patent grants on a firm's financial and operating performance. As a result, we need to specify an event window and define when the effect possibly begins. We use the third date, i.e., the financial decision date, as our starting point for identifying our signaling effects.[26]

## B. *Identification: Average Leniency of Patents Examiners*

In this section, we formally introduce our main identification strategy. We implement the random leniency assignment used by Sampat and Williams (2019) and Farre-Mensa et al. (2020) in a firm-time period sample, where the time period can be a year, a quarter, or a month.[27] We illustrate our regression design for the firm-year case. We aggregate the patent applications sample into a firm-year panel (using each application's final decision year) and merge it with our Refinitiv ESG dataset. We conduct a two-stage least-squares (2SLS) regression analysis with the following first stage:

$$Num\_Climate\_Pats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t}, \tag{1}$$

where we instrument $Num\_Climate\_Pats\_Granted_{i,t}$, the number of climate patents granted by USPTO and issued to Firm $i$ in Year $t$, using $Avr\_Leniency_{i,t}$, the average relative leniency of examiners who assess Firm $i$'s patent applications. In other words, this leniency instrument is constructed using the set of patent applications for which the firm receives decisions from USPTO in year $t$. We implement a so-called leave-one-out method in calculating $Avr\_Leniency_{i,t}$. More specifically,

$$Avr\_Leniency_{i,t} = \frac{1}{N_P} \sum_{p \in P_{i,t}} \left( \frac{Num\_Pat\_Granted_{e,p} - I(Granted)_p}{Num\_Pat\_Examined_{e,p} - 1} - \frac{Num\_Pat\_Granted_{a,p} - I(Granted)_p}{Num\_Pat\_Examined_{a,p} - 1} \right), \tag{2}$$

where $N_P$ is the number of patent applications filed by Firm $i$ receiving final decisions in Year $t$; $P_{i,t}$ is the set of these patents applications. The subscript $e, p$ denotes the examiner $e$ who examines Firm $i$'s patent application $p$. $\frac{Num\_Pat\_Granted_{e,p} - I(Granted)_p}{Num\_Pat\_Examined_{e,p} - 1}$ is examiner $e$'s all-time granting ratio in her career in USPTO, excluding Firm $i$'s focal application $p$, the one out in the leave-one-out

[26] Since our empirical design focuses on signaling effects, it is most convincing to use the final decision date which is the date when the signal about a patent approval is typically made public. By contrast, Farre-Mensa et al. (2020) employ the date of receiving the first action letter.

[27] This approach is also employed by Gaule (2018) and Melero, Palomeras, and Wehrheim (2020).

method.[28] The same method applies in calculating the average granting ratio of the art unit to which the application is assigned and to which examiner $e$ belongs, $\frac{Num\_Pat\_Granted_{a,p} - I(Granted)_p}{Num\_Pat\_Examined_{a,p} - 1}$. Hence, our leniency measure is a relative leniency measure within an art unit.

We calculate an examiner's leniency considering her past and future evaluated applications. We include her future granting trajectory and not only her past granting history for two reasons. First, the leniency measure calculated from both past and future applications tracks an examiner's time-invariant characteristics, which are more likely to be exogenous. Furthermore, it helps reduce concerns that firms conduct examiner's shopping from past examination records (Barber and Diestre, 2022), as the results of future applications are not observable. Importantly, our main results are robust if we only use past applications to calculate leniency, as we document in the Online Appendix.

We add high-dimensional fixed effects (F.E.), including Industry × Year F.E. ($\nu_{j,t}$) and Art Unit × Year F.E. ($\iota_{a,t}$).[29] Importantly, we add a set of fixed effects for each annual number of patent applications filed by individual firms and receiving results in Year $t$ ($\tau_{app}$). By including the fixed effects ($\tau_{app}$) that control for the patent application propensity of firms, we make sure to compare firms with the same number of climate patent applications in a given firm-time period observation.[30] Among pairs of firms with identical patent application numbers in a given firm-time period observation, some are luckier than others and get a higher number of patents approved because of a lucky draw of relatively lenient patent examiners.

Table II, Panel A shows the estimates of our first stage. In all three samples (Firm-Year, Firm-Quarter and Firm-Month), the coefficients of $Avr\_Leniency$ are all positive and highly significant. Furthermore, the very high F-test statistics indicate that there is likely no concern about weak instruments in our identification approach. The coefficients are also economically significant. For example, in the firm-year sample, a one standard deviation increase in the average leniency leads to a number of additional climate-related patent applications being approved by USPTO for a firm

[28] When we calculate an examiner's granting ratio, we use all patent applications, including both green and non-green patent applications. We require each examiner to examine at least ten applications in the dataset.

[29] In the Art Unit × Year F.E., if the firm has patents examined by several art units, we select the art unit that is the mode of all art units of patent applications in each firm-year observation, i.e., the most frequent art unit.

[30] If we did not include this F.E., annual patent numbers could drive results since we analyze the combined effect of all patent applications within each firm-time period observation.

in a single year of 1.79 ($= 1.127 \times (1 + 16.7) \times 0.09$).[31] This number approximately corresponds to 10% of the mean number of patents per year and 50% of the median.

## C. Validity of our Instrument

Three potential issues might jeopardize the validity of our identification. First, Righi and Simcoe (2019) find evidence of technological specialization across patent examiners within art units and argue that examiner's leniency can be correlated with unobserved technological heterogeneity, which might also be correlated with dependent variables in the second stage. In our case, it would imply that firm-level stock returns, institutional investors' holdings and ESG scores might correlate with the unobserved technological heterogeneity of climate patents. This issue, however, is not a major concern for us because financial market participants, institutional investors and ESG rating agencies are not technology experts and are most likely unable to discriminate between technology categories that are more granular than art units. We control for technology classes in a rather fine grid by including the art unit $\times$ year F.E. in all 2SLS regressions, so that remaining technology heterogeneity could only arise within each art unit $\times$ year.

Second, Righi and Simcoe (2019) claim that a patent applicant's identity (i.e., the name of an assignee) may have an impact on the application's assignment, either directly or indirectly, due to its technological expertise (see page 140 in their paper). In other words, the same assignee (a firm) may always be assigned to the same examiners. To mitigate this endogeneity concern, we conduct a series of placebo tests in Table II Panel B. We regress the firm-year leniency measure on various firm characteristics measured in the previous year, as well as on the average examiner's leniency in the previous year. We do not find these ex-ante measures to be related to our instrument (except for firm size that is only weakly positively correlated with examiner's leniency; we thus control for firm size in our second-stage regression). Column (7) of Table II Panel B shows that past average leniency does not predict current one. Thus, Our analysis does not suffer from the endogeneity

[31] Since the dependent variable, $Num\_Climate\_Pats\_Granted$, is defined using a $ln(1+x)$ transformation, the following calculation is needed to obtain the marginal effect: $\frac{\partial ln(1+Num\_Pat)}{\partial Avr\_Leniency} = \delta = \frac{\partial ln(1+Num\_Pat)}{\partial Num\_Pat} \times \frac{\partial Num\_Pat}{\partial Avr\_Leniency} = \frac{1}{1+Num\_Pat} \times \frac{\partial Num\_Pat}{\partial Avr\_Leniency}$. We thus get $\frac{\partial Num\_Pat}{\partial Avr\_Leniency} = (1 + Num\_Pat) \times \delta$. We evaluate the marginal effect at the point where $Num\_Green\_Pats$ equals its average of 16.7 (see Table I Panel C) to calculate $\frac{\partial Num\_Pat}{\partial Avr\_Leniency}$. Finally, we multiply it with one standard deviation of $Avr\_Leniency$, which is 0.09 (see Table I Panel C), to find the 1.79 estimated impact. We redo the same calculation in the firm-month sample and find an increase in patents of 0.47 in every firm-month after a one standard deviation increase in the average leniency. This is consistent with our estimate in the firm-year sample because there are on average around 4 months per year in which a firm has at least one climate patent.

issue raised Righi and Simcoe (2019).

Third, Barber and Diestre (2022) recently document that because patent citations influence assignments of USPTO examiners, at least some firms use citations strategically to influence the decision on examiner assignments, a practice known as "examiner shopping". There are two reasons why this concern might be less relevant in our context. First, our choice to use past and future reviewed applications by a specific examiner when we construct our instrument (calculating leniency of each examiner) partially alleviates the issue of examiner shopping as future outcomes of applications are not observable. Second, the firms with the strongest incentive to engage into examiner shopping should be the firms with the worst environmental performance since they will arguably get the biggest boost from signaling climate virtue to the market by ways of climate-related patents. However, we find no evidence in support of this idea, as we show in Column (1) of Table II Panel B. We provide additional validity tests for our instrument in the Online Appendix.

# IV. Results on Financial Market Reactions

This section analyzes how random variations in climate-related patent approvals (due to luck in the examiner lottery) affect firms' valuation by financial markets. We explore the hypothesis that climate patent grants send a positive and credible signal about a firm's engagement in corporate climate action to market participants. Throughout, we conduct 2SLS regressions that exploit examiners' leniency differences. To investigate how firm value is affected, we consider realized returns (CARs), expected returns (implied cost of capital), and short-term announcement returns.

## A. *Climate-Related Patents and Stock Returns*

Many recent studies have documented large and significant realized abnormal returns for "green stocks" relative to "brown stocks", including In et al. (2019), Pástor et al. (2022), and Berg et al. (2021).[32] These studies, however, are exposed to two major drawbacks. First, as argued in Berg et al. (2021), numerous firm-level characteristics might be correlated with both a firm's environmental rating and its future returns, therefore resulting in a possible omitted variable bias that prevents any causal interpretation. For instance, firms with a better management team are more

[32] In contrast, Bolton and Kacperczyk (2021) find that carbon emissions are positively associated with abnormal returns.

likely to manage environmental issues well and, at the same time, to enjoy higher future realized returns.

Second, previous papers typically measure "greeness" and "brownness" of stocks using ESG ratings that have several limitations. For example, large disagreements exist between ratings, even those issued by the largest ESG rating agencies (Gibson Brandon et al., 2021). Also, ESG ratings rely to a large extent on unverifiable or ambiguous information.[33] Considering these shortcomings, we propose a new method for studying the relationship between a firm's environmental performance and stock returns (both short-term and long-term) using our patent leniency instrument.

We run the following 2SLS regression on our panel of firm-month observations:[34]

$$CAR[t : t + k]_{t,s} = \alpha \widehat{Num\_Climate\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \qquad (3)$$

In Equation (3), $t$ denotes month, and $s$ denotes firm (stock). The dependent variable is the cumulative abnormal return (CAR) starting from the month of green patent application results (from period $t$ to $t + k$), where $k$ ranges in 1 to 18. We define monthly abnormal returns as the alpha in the Fama-French 5-factor model (Fama and French, 2015).[35] The main explanatory variable of interest, the number of climate patents issued to firm $i$ in month $t$, is instrumented by the firm's average examiner's relative leniency score following Equations (1) and (2). Following Berg et al. (2021)'s return regression, $\mathbf{X}_{t,s}$ includes log of market capitalization (LnMV), Tobin's Q, Cash, ROA, R&D expenditures, momentum, volatility, and environmental score. All accounting controls are measured in year $t-1$. In all the regressions in this paper, we winsorize our dependent variables symmetrically at the 1% level.[36]

We add three sets of high-dimensional fixed effects: Industry $\times$ Month F.E. ($\nu_{j,t}$) help control for any industry shocks affecting performance; Art Unit $\times$ Year F.E. ($\iota_{a,t}$) ensure the validity of our instrument and control for heterogeneity across technology classes; F.E. for the number of green applications that receive USPTO decisions in month $t$ ($\tau_{app}$) allow us to compare firms with the same underlying level of innovative capacity as perceived in month $t$. Finally, we cluster standard

[33]Taking Refinitiv ESG ratings (that we use) as an example, the data point $En\_En\_ER\_DP001$ is a dummy for the following question: Does the company set specific objectives to be achieved on emission reduction? This question leaves room regarding the definition of what "specific objectives" are.

[34]Recall that the regression sample only retains observations of firm-month in which a firm receives at least one decision from USPTO (positive or negative) about its climate-related patent applications.

[35]The time-varying factor loadings are estimated using the firm's past 60-month return data, and we require at least 36 months with non-missing returns.

[36]Our results hold if we do not winsorize our dependent variables.

errors along the firm and industry-year dimensions to address potential correlation in error terms.

The baseline results are shown in Figure 2, separately for climate-related patents and other (non-climate) green patents.[37] In each panel, we plot the point estimate of $\alpha$ in Equation (3) and its 90% confidence interval for $k$ equals 1 to 18 months. Looking at Figure 2, Panel A, we first find a positive and significant effect on CARs: A one standard deviation increase in the (log) number of climate-related patents leads to an approximately 10% increase in CARs over the next 18 months. This effect translates into a 12- to 18-month CAR of around 2% for a single additional patent due to luck in the patent examiner lottery.[38] Turning to Panel B, we find no effect of other (non-climate) green patents on CARs. That is, investors react positively to the issuance of climate-related patents but not to other green patents, consistent with other findings that society is more concerned about climate change than other environmental issues (Krueger et al., 2020). The differential impact of climate and other green patents may also be attributed to the absence of specific tag for other green patents. It might thus be more difficult for financial market participants to identify a patent as green when it is not a climate-related patent, recognized as such by a Y02 tag.

Figure 2, Panel A also allows us to investigate dynamics of the patent granting effect. We discover that the effect on CARs is tiny in the first several months, increasing monotonically until the 12th month after the climate patent granting. The long-term CARs are consistent with recent arguments in the innovation literature that information about innovation, particularly sophisticated and non-salient innovation information, takes time for the market to incorporate (Cohen et al., 2013; Hirshleifer et al., 2013; Fitzgerald et al., 2021). Between months 12 and 18, the CARs remain stable. In Figure A3 in the Online Appendix, we extend the horizon to month 36 and find a significant drop of CARs, consistent with the prediction in Pástor et al. (2022) that outperformance caused by unanticipated shocks is followed by a lower expected returns of green stocks going forward.[39]

[37] In Figure 2, Panel A, the independent variable is the number of climate-related patents granted to firm $i$ in month $t$, and the number of applications fixed effect ($\tau_{app}$) is constructed only using climate-related green patents. In Figure 2, Panel B, the independent variable is the number of other green patents granted to firm $i$ in month $t$, and the number of applications fixed effect ($\tau_{app}$) is constructed only using other green patents.

[38] Our regression enables us to estimate $\frac{\partial CAR}{\partial Num\_Clim\_Patents} = 10\%$, after twelve months. Since the variable $Num\_Climate\_Patents$, is defined using a $ln(1+x)$ transformation, the following calculation is needed to obtain the marginal effect for one patent: $\frac{\partial CAR}{\partial Num\_Clim\_Patents} = \frac{\partial CAR}{\partial ln(1+Num\_Patents)} = \frac{\partial CAR}{\partial Num\_Patents} \times \frac{\partial Num\_Patents}{\partial ln(1+Num\_Patents)} = \frac{\partial CAR}{\partial Num\_Patents} \times (1 + Num\_Patents)$. To find the marginal impact of an additional climate patent, we thus need to divide our regression estimate by 1 plus the mean number of climate patents granted in a month, which is 3.9 as per Table I, Panel C. We thus obtain $\frac{10\%}{1+3.9}$, which is around 2%.

[39] Berg et al. (2021)'s model develops a similar argument: unexpected arrivals of ESG-minded investors will raise the price, followed by a decline in future returns.

The Online Appendix documents various robustness checks for our baseline results of monthly CAR. Figure A1 uses the Fama-French 3-factor model to calculate monthly abnormal returns. Figure A2 replaces our dependent variable, the CARs, with stock price changes in natural log. In all cases, we find a strong and significant information effect of climate-related patents on returns or prices as well as similar dynamics.

## B. *Attention to Climate Change and Announcement Returns*

What accounts for the significant impact of issuing a climate-related patent on stock returns? Our central perspective is that it occurs through an information channel. Issuance of climate-related patents sends a signal to the market that the firm is engaging in green initiatives that help mitigate climate change. Investors react positively to this information. If it is true, we hypothesize that this signaling effect is more substantial during periods when society shows heightened attention to climate change concerns.

To test this conjecture, we use the Media Coverage of Climate Change (MCCC) index compiled by Ardia et al. (2020). The MCCC index is constructed from the eight leading U.S. newspapers and captures the number of climate news stories each day as well as their negativity and risk, using textual analysis. We follow Pástor et al. (2022) and first aggregate the daily index into monthly averages and then apply an investor memory model as the sum of the previous 36 monthly MCCC indices with a memory loss discount factor equal to 0.94.[40]

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \tag{4}$$

We further sort $\overline{MCCC}_t$ into terciles and interact three tercile dummies with our main independent variable, the number of climate patents granted in month $t$, in our new regression:

$$CAR[t:t+k]_{t,s} = \alpha_1 Num\_Clim\widehat{atePats}\_Granted_{t,s} \times \overline{MCCC}\_High_t + \alpha_2 Num\_Clim\widehat{atePats}\_Granted_{t,s} \times \overline{MCCC}\_Mid_t + \alpha_3 Num\_Clim\widehat{atePats}\_Granted_{t,s} \times \overline{MCCC}\_Low_t + \delta_1 \overline{MCCC}\_High_t + \delta_2 \overline{MCCC}\_Mid_t + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{5}$$

The variable $Num\_ClimatePats\_Granted$ is again instrumented by examiner's leniency. The result is plotted in Figure 3, where we show the coefficients $\alpha_1$, $\alpha_2$, and $\alpha_3$ individually in Panels

[40] We use the same coefficient of 0.94 as Pástor et al. (2022). This specific implementation of the investor memory model implies that memories have a half-life of slightly less than 12 months, i.e., past climate change concerns will gradually fade from investor memories but still influence their decisions.

A, B, and C, respectively, for months 1 to 18. Figure 3 reveals that the effect on CARs is the largest and the most significant in Panel A (the top tercile of the MCCC index), consistent with the fact that CAR are indeed related to the climate action of firms. We measure $\overline{MCCC}_t$ in month $t$, the period when public information about climate patent grants is available to investors. In the Online Appendix, we find similar results when we measure $\overline{MCCC}_t$ in month $t+k$, at the end of the compounding period for CARs.

In addition, in Panel A, the signal effect begins extremely quickly (in month 1), implying that investors respond faster during high MCCC periods. We test whether $\alpha_1$ and $\alpha_2$ are significantly different across panels for fixed $k$, and find this to be the case in most comparisons.

## C. *Short-term Abnormal Returns*

We also investigate short-term abnormal returns following patent grants. We examine short-term (daily) abnormal returns around granting and rejection dates of climate-related patents, where rejected climate patents serve as a control group (in the placebo sense). We conduct a similar regression as in Equation (5) and replace the monthly CARs with daily CARs in a [-3 day, $+k$ day] event window ($k = -3, -2, -1, 0, +1, +2, +3$). We do not run an event study directly on climate patents granted, without using our lucky patent instrument, because such study would capture not only the signaling effect but also the impact of the underlying technological improvement (Kogan et al., 2017). In contrast, our 2SLS regressions should single out the signaling effect.

We distinguish by level of public attention to climate change, again using terciles of the MCCC index. The results of our 2SLS regressions are plotted in Figure 4 and documented in Table III.[41] The results show that daily CARs are significant when the patent is granted in a period of heightened (top-tercile) climate change attention (Table III, Panel A). By contrast, we do not detect abnormal short-run announcement returns during periods with lower attention to climate change (Table III, Panels B and C). In Table III, Panel A (high MCCC tercile), the signaling effect is positive and statistically significant, with a one standard-deviation increase in the (log) number of climate patents (issued in a given day) leading to an average positive CAR of 0.5 to 0.8%. Daily abnormal returns are significant already on the announcement day and tend to increase when accumulated over the next three days.

[41] The regression sample is at the firm-day level. We measure the $\overline{MCCC}$ in the month of the patent decision date (granting or rejection).

## D. Recent versus Seasoned Climate Innovators: the Climate Patent Stock

Farre-Mensa et al. (2020) document that the first patent granted to an entrepreneurial company is critical for its future success, but not its subsequent second and third patent grants. Similarly, we expect the first batch of climate-related patents to send a much stronger signal to the market about a firm's commitment to corporate climate action than follow-on patents. When a company already holds a large number of climate-related patents, the marginal effect of additional patents should be small.

Figure 5 looks at this hypothesis by investigating a new variable called Climate Patent Stock. It is defined as the number of climate-related patents that have already been granted to a firm prior to month $t$. Next, we sort this variable into terciles and then interact tercile dummies with our main variable of interest, the number of climate patents (newly) granted in month $t$. We again plot the three coefficients, one for each tercile, separately. The findings are aligned with our hypothesis, with firms in the low tercile of climate patent stock having the strongest CAR effects (Figure 5, Panel A). The lowest tercile of the Climate Patent stock corresponds to firms with less than 10 climate-related patents. By contrast, we find no significant effect for the medium and high terciles of Climate Patent Stock (Figure 5, Panels B and C).

## E. Analysis of Possible Time-Varying Excess Returns

We conduct a pseudo-portfolio analysis following Bolton and Kacperczyk (2021) to explore whether investment strategies based on climate-related patent signals are able to command consistent abnormal returns over time.[42] This analysis allows us to assess whether our results on cumulative abnormal returns are robust across time. We run the following new regression:

$$CAR[t+1:t+12]_{t,s} = \sum_{Year=2006}^{2020} \alpha_{Year} Num\_\widehat{ClimatePats}\_Granted_{t,s} \times I(Year)_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s}. \quad (6)$$

[42] Two considerations prevent us from conducting a formal long-short portfolio analysis based on the leniency of climate patent examiners. First, the fixed effects in Equation 3 are hard to incorporate into a portfolio analysis. Without the number of patent applications F.E., $\tau_{app}$, comparing two firms' examiner leniency has little meaning. Second, the examiner's leniency measure is not observable to investors at the time of portfolio construction.

Thus, the purpose of this regression is to analyze time-varying excess returns that are captured by the annual regression coefficient $\alpha_{Year}$. The dependent variable is the cumulative abnormal returns in the [t+1, t+12] month window.[43] The main independent variable, the number of new climate patents issued to firm $i$ in month $t$, is interacted with a set of calendar year dummies, $I(Year)$ to measure time-varying reactions of the CAR. We then cumulatively sum the coefficients $\alpha_{Year}$ from 2006 to 2020 and plot the sum in Figure 6. It is worth noting that the $\alpha_{Year}$ coefficients are positive in almost all calendar years (except 2009, 2012, and 2020), as shown by the positive slope of the plotted sum. This result indicates that the financial impact of lucky climate-related patents is robust across years. Also, we note that the $\alpha_i$ are bigger in the early years 2006 and 2007. In these years, energy-saving patents were rare, they were tagged as "Y02" only years later, and energy prices were rapidly rising. These elements could explain the stronger stock market responses in these years.[44]

## F. *Climate-Related Patents and Implied Cost of Capital*

After documenting a large and significant effect on realized returns, we turn to their counterparts: expected returns.[45] We follow the approach in Pástor et al. (2022) and measure a firm's expected return using the method of implied cost of capital (ICC).[46] We implement Gebhardt, Lee, and Swaminathan (2001)'s residual income valuation model to calculate $r$, the implied cost of capital, as follows:

$$P_t \times Num\_Shares_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}}, \tag{7}$$

where $ROE_{t+\tau}$ is the forecasted Return on Book Equity, which is equal to earning forecast in dollars scaled by the value of book equity in the previous year ($B_{t+\tau-1}$). We use Hou, Van Dijk, and Zhang (2012)'s regression-based method to predict earning forecasts in dollars.[47] Finally, we

[43]Because there are not enough observations in 2005, the $\alpha_{2005}$ cannot be properly estimated. We set it to zero in Figure 6.

[44]In this particular plot, years are equally weighted. On the other hand, our regressions weight years according to the annual number of firms with climate-related patents, so that the early years carry little weight.

[45]Both Chava (2014) and Pástor et al. (2022) find that firms with better environmental performance enjoy a lower cost of capital. We complement their investigations by establishing a causal relationship and focusing specifically on climate change issues.

[46]Detailed procedures about our ICC measure are in the Online Appendix of Pástor et al. (2022).

[47]Following Lee, So, and Wang (2021), we estimate earning forecast in dollars three years ahead using regression predictions as in Hou et al. (2012). For the earning forecasts in years four to 12, we use extrap-

numerically solve out the $r$ in the above equation for each firm in each month and bring the ICC into our 2SLS regression analysis.

Figure 7 shows our regression results. Figure 7, Panel A shows the evolution in the regression coefficient from month $t$ to $t+k$ when regressing the number of new (lucky) climate-related patents granted in month $t$ on the estimated ICC (other green patents are plotted in Figure 7, Panel B). In Figure 7, Panel A, we show that a one standard deviation increase in the number of climate-related patents results in about a 1% drop in ICC in month 18 after the patent grant. Similar to our CAR results, we find a monotonically decreasing pattern of coefficients from month $k = 1$ to 12. This finding, accompanied by our results on CARs, is consistent with recent asset pricing research documenting an inverse relationship between realized returns and expected returns (Pástor and Stambaugh, 2001, 2009). In contrast, we do not find any significant results in Figure 7, Panel B that repeats the same analysis for other (non-climate) green patents.

Figure 8 plots the same regression results for climate-related patents with an interacts with the level of attention to climate change (MCCC tercile dummies). It shows that the ICC drop is strongest and statistically most significant for patents issued in months in the top tercile of public attention to climate change.

In the Online Appendix, we show that our results are robust if we use realized earnings (Compustat item $IB$) instead of the regression-based earning forecasts in our calculation of ICCs.

# V. Driving Forces Behind Financial Markets' Reaction

This section explores the potential determinants behind the impact of lucky climate-patent draws on financial markets. We consider two non-exclusive channels: ESG rating agencies' response to climate patenting and institutional investors' demand-driven price pressure.

olation by assuming that they will gradually revert to the industry median ROE. This approach appears appropriate given our finding that operating performance is not affected by lucky patent draws (see, Table A2 in the Online Appendix).

## A. *The Reaction of ESG Ratings Agencies*

We study how ESG rating agencies react to information about newly approved climate-related patents. We expect rating agencies should react because (i) climate patents are clear and countable indicators that ESG rating agencies can consider to build their scores, and (ii) climate patent grants may make it to the news, a phenomenon that ESG rating agencies, including Refinitiv, incorporate into their scoring methodologies (Berg et al., 2021). Therefore, we hypothesize that random variations in climate patent approvals affect a firm's ESG score.

To test this hypothesis, we use the Refinitiv Environmental Score that measures a firm's comprehensive environmental performance, and also the three environmental "pillar" subscores: Emissions Score, Resource Usage Score, and Innovation Score. We conduct 2SLS regressions on our firm-year sample using the following empirical specification:

$$Envrn\_Score_{i,t+k} - Envrn\_Score_{i,t} = \alpha \widehat{Num\_Climate\_Pats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \mu_{j,t} + \nu_{a,t} + \tau_{app} + \varepsilon_{i,t}. \tag{8}$$

The dependent variable captures future improvements (or declines) of the Environmental Score of Firm $i$ over the next two years following its climate-related patent grants ($k = 1$ or 2 years).

Table IV provides the results of the 2SLS regression given by Equation (8). We conduct again separate regressions for climate-related patents and for other green patents.[48] The coefficients of *Num_Clim_Pats_Granted* are positive and significant at the 5% level, as illustrated in Table IV, Panel A, Columns (1) and (2), implying that climate-related patents have a positive and causal impact on companies' future ESG ratings. The economic magnitude is also significant. The estimated coefficients imply that a single (chance-driven) climate-related patent approval leads to an increase in the environmental score of around 1%. In contrast, the coefficients of *Num_Other_GreenPatents_Granted* in Table IV, Panel B, Columns (1) and (2) are insignificant and sometimes even negative, implying that ESG rating agencies take climate-related patents into account, but not other green patents (even though their environmental score in principle should cover both).

Columns (3) – (8) of Panel A in Table IV look at sub-scores of the Refinitiv Environmental Score. Lucky climate patents boost the emissions and innovation scores, but not the resource

[48] Table IV, Panel A only uses climate-related patents in the construction of the instrument and fixed effects while Panel B uses other green patents.

usage score. This finding indicates that the relationship between climate patents and ESG score is relatively granular, affecting sub-components of ESG ratings that are quite directly linked to climate innovation, such as the innovation score, but also sub-components only indirectly related, such as emissions. One implication is that ESG ratings agencies appear discerning in their use of climate patent information. Finally, in the Online Appendix, we show that our results are robust if we use S&P Global ESG scores.[49] We find that climate-related patents improve a firm's climate strategy score, but not other green patents.[50]

To summarize, ESG rating agencies respond positively to climate-related patents but not to other green patents, just as the stock market does (in our CAR and ICC regressions). Moreover, our results suggest that the positive correlation between ESG ratings and realized (long-term) stock returns found in the literature, e.g., in Pástor et al. (2022), is partly due to an omitted variable, namely, firms' climate innovation.

## *B. Climate-Related Patents and Institutional Ownership*

In the last decade, the role of institutional investors in various global initiatives for climate change mitigation and in initiating or supporting climate action at the corporate level has strongly increased. Globally, more than 50% of financial assets under management are now managed by institutions and asset managers that have signed the UN Principles for Responsible Investments (PRI) and thus indicate that they want to be viewed as ESG-minded institutions (Gibson et al., 2020). We investigate whether institutional investors, and especially ESG-minded institutions, respond to approvals of climate-related patents, measured by our instrument of exogenous shocks in patent grants.

A priori, the answer is not obvious. On one hand, if institutions live up to their responsible investment commitment, we expect them to react positively to news about climate-related patents

[49] Berg et al. (2020) recently argue that Refinitiv backwards updates its historical ESG scores, and that the updates of the environmental score in particular lead to a closer statistical relationship between environmental scores and stock returns. The test conducted in this section is the only test in our research design that is potentially affected by this critique since all other results do not depend on ESG scores and their quality. Therefore, the robustness of our findings when using S&P Global ESG scores is important since similar concerns have not been raised about their data.

[50] A caveat of this analysis is the small sample size. S&P Global ESG starts reporting its scores in 2013 only. When we merge it with our climate-related patent firm-year sample, there are only 800 observations left. After conducting the difference for our dependent variable and adding three fixed effects, our sample shrinks to 150 firm-year observations only.

and to increase their holdings.[51] On the other hand, the use of non-financial ESG information is more limited in the US compared to other places in the world, notably Europe (Amel-Zadeh and Serafeim, 2018), so that a tendency to pay lip service to environmental commitments and a rather passive attitude to climate-related corporate news could be pervasive. For example, Gibson et al. (2020) provide evidence in this direction, showing that US institutions that are PRI signatories do not have a better ESG footprint than other investors.

Table V explores this question by running 2SLS regressions where the dependent variable is the change of total institutional ownership (IO) from quarter $t-1$ to $t+k$ ($k = 0, 1, 2, 3$) and where $t$ is again the quarter in which the number of climate-related patent grants of firm $i$ is measured, instrumented by the examiner leniency shock (the firm-quarter sample is used in this regression).[52] In Table V, Panel A, our main independent variable is the number of climate-related patents newly issued in quarter $t$, instrumented by examiner's leniency. Similar to Figure 2, we add Industry $\times$ Quarter F.E., Art Unit $\times$ Year F.E., and the number of climate patent application F.E., and cluster standard errors at the firm level.

Column (1) of Table V, Panel A, shows that there is no significant IO change prior to the issuance of climate patents. On the other hand, IO increases monotonically following lucky grants of climate patents, as can be seen in Table V, Columns (2) to (5). In the third quarter after the grant, a one standard deviation rise in $Num\_ClimPatents\_Granted$ leads to a 7% increase in IO. Further, institutional responses begin in the same quarter as the climate patent award, as seen in Column (2). In Columns (6) and (7), we see that the IO reaction is in fact statistically positive during the top MCCC tercile, i.e., when society places a high priority on climate change mitigation efforts. This finding completes a pervasive and consistent pattern when using the MCCC index: in addition to long-term CARs, short-term CARs, ICC, IO also responds significantly more in the top MCCC tercile periods. In contrast, as Panel B of Table V shows, IO does not respond to other green patents, echoing earlier non-results for other green patent grants in terms of CARs and ICC.

Do Environment-focused institutions react to climate patent approvals differently than other institutions that show less attention to climate action in their portfolio choice? In Table VI, we distinguish between Environment-focused and other institutions by looking at institution-level

[51] Such a commitment is emphasized by many professional bodies of asset managers, e.g., the CFA Institute, the most important qualification body for asset managers (CFA Institute, 2015).

[52] The firm-level institutional ownership is defined as the total shares of the firm held by 13F institutions in a given quarter divided by the total shares outstanding at the end of that quarter. In some rare cases, we replace institutional ownership with one if the measure yields a value larger than one.

difference in their environmental footprints. Following Starks et al. (2017) and Gibson Brandon et al. (2021), we define an institution's environmental footprint as the value-weighted average environmental score of its quarterly stock portfolio. We sort all 13F institutions by their environmental footprints every quarter, and classify institutions that score above (below) the median as Environment-focused (Other).

Table VI, Panel A, shows regressions for Environment-focused institutional ownership, Panel B for Other institutions. The results show that Environment-focused institutions react strongly and account for the majority of the growth in IO following climate-related patent grants. By contrast, all coefficients are insignificant in Panel B, showing that institutions that care little about the environmental footprint of their portfolio show only a very small response.

Finally, in Table VII, we investigate individual institutions' stock holding changes following climate patent grants. Following Gibson Brandon et al. (2021), we expand the sample to observations at the level of Institution $\times$ Quarter $\times$ Stock. We use a more granular distinction of environmental footprints, comparing the top and bottom quintile of value-weighted Environmental Scores.[53] Consistently with our previous results, Table VII shows that institutions with top quintile environmental footprints increase their stock holdings on average by 5 percentage points when firms experience a one standard deviation (chance-driven) shock in climate patent grants, while institutions with bottom quintile ones appear not to react.

We argue that the strong reaction of ESG-minded institutional investors can at least partly account for the transmission channel from shocks in climate patent approvals to positive and significant 18-month abnormal stock returns. The period of growth of long-term stock returns (from the 1st to the 12th month after climate patent issuance) and of institutional ownership (from the 1st to the 4th quarter and including the quarter of the climate patent issuance) fits reasonably well, according to Figure 2 and Table VI. Moreover, the effect on abnormal returns and on IO are both concentrated in periods with heightenened atention to climate change (top tercile of the MCCC index). This overlap makes it plausible that the increases in stock prices is driven by price pressure emanating from increased institutional investor demand.

[53] We do not use a median split because of technical reasons: the sample would be too large to run our 2SLS regression.

# VI. Climate-Related Patents and Climate Change Mitigation

Our key insight so far is that climate patent issuance is interpreted by ESG-minded institutional investors as an ESG signal indicating that firms are making efforts towards climate change mitigation and is translated into a series of consistent results about the financial markets' response. But is the market making a correct inference about the meaning of climate-related patents? In other words, do patent holders really contribute to climate mitigation and reduce emissions? We next turn to this question. More specifically, we explore the following issue: do firms with climate-related patents use these technologies to reduce their own CO2 emissions or improve energy efficiency?[54]

The answer to this question is not obvious. For example, there are professional patent troll companies earning money from patent litigation using patents of little social value (Cohen, Gurun, and Kominers, 2019). Moreover, some firms may accumulate patents with the effect of blocking entry of new companies rather than actually putting them to use (Boldrin and Levine, 2013). Such practices may also be in use for climate-related patents and could thereby reduce the impact of such patents on a firm's environmental performance.

We study whether climate-related patent grants are subsequently associated with lower carbon intensity, measured as the ratio of direct carbon emissions to revenues. We focus on relative carbon emissions because it measures a firm's carbon efficiency: this enables to test whether the use of greener technologies enables a firm to emit less carbon for a given level of economic activity. A climate performance measure based on absolute emissions would be affected by factors that are not controlled by firms such as consumers' and competitors' behavior.

We make two changes to our empirical set-up. First, we conduct regressions using the full firm-year sample.[55] Second, we no longer confine the analysis to exogenous shocks in patent granting

[54] Ultimately, the socially relevant question concerning green patents and climate change is a bigger one: do climate-related patent grants create a net positive impact on climate change mitigation? There are long-standing controversies in the innovation literature about the welfare impact of patent grants. For example, Boldrin and Levine (2013) argue that, although, in partial equilibrium, patenting provides a monopoly power to a company and increases the ex-ante incentive to innovate, in general equilibrium, patenting destroys welfare by blocking follow-on innovation and reducing competition. In the specific case of climate patents, an important issue is whether issuing climate patents might enhance or reduce other firms' opportunities to conduct follow-on climate innovation. This question is beyond the scope of this paper. We focus here on the more limited question of the impact on the climate behavior of the holder of new climate-related patents.

[55] This is in contrast to all previous regressions where we use the sub-sample of firm-year (or firm-quarter and firm-month) observations with decisions on climate patent applications. Here, we also include firm-year observations with no climate patent decisions, including those of firms that never file any climate-related

driven by random variations in examiner leniency. The reason is that we want to investigate the real impact of climate-related technologies behind those patents. The use of these technologies by the inventor may arguably not depend on the granting of patent protection for the innovation.

We thus conduct OLS regressions that no longer instrument by variation in examiner leniency. Our independent variable is then simply the number of new climate-related patents obtained by a firm. We sort climate patents by application year since this date better captures the time at which a firm is able to use its own new technology compared with the granting/rejection year. We divide the annual number of granted climate patent applications by a firm in a specific year by the number of all climate patent applications submitted by all firms in that year. This adjustment is crucial to avoid the patent truncation bias in the most recent years. The dependent variable is the change of direct firm-level CO2 equivalent emissions (Scope 1) from year $t$ to year $t+k$, where $k = 1, 2, 3, 4, 5$. We scale the emission level by the firm's total output (million US dollars) and take the natural logarithm of the ratio (emissions/output) to get a meaningful measure of emission intensity. Thus, our dependent variable, the change of log emission intensity, approximates a change rate.[56]

Table VIII, Panel A reports our OLS estimates for climate-related patents: they are associated with significant reductions in Scope 1 carbon emission intensity starting in year 3 after the patent grants.[57] In Table VIII, Panels B, C, and D, we document that firms with climate-related patents in transportation (Y02T), production of goods (Y02P), energy (Y02E), the three largest of the four categories that are aggregated in Panel A, all significantly reduce their direct (Scope 1) CO2 emission intensity. Climate patents involving transportation and goods have the largest impact measured, in terms of both economic magnitude and statistical significance, whereas energy shows the weakest reaction. Table VIII, Panels E and F show no impact for climate-related patents in information technologies (Y02D) and buildings (tag Y02B), respectively. This is in line with the USPTO documentation which indicates that patents in these two categories are more likely to be

patent application.

[56]Following Kogan et al. (2017), the total output is the total net sales plus the change in inventories. We adjust for inflation in the output using the 2000's consumer price index as a benchmark.

[57]We do not find any significant results when we study Scope 2 and 3 emission intensities. The absence of Scope 3 results (that in principle could be expected to reflect the impact of product innovations) could be due to very limited data availability (only since 2017, and for a small subset of firms) and to reporting issues. Our results hold for goods (Y02P) and energy (Y02E) categories when we study absolute Scope 1 emissions instead of Scope 1 emissions intensity, see Table A8 in the Online Appendix. As indicated at the beginning of the subsection, absolute emissions depend on other factors than a given firm behavior (including market share changes following innovation) so it is not clear what one should expect regarding the impact of climate-related patents on this variable.

related to customers' emissions (Scope 3), e.g., users of digital tools or buyers of building materials, and thus should not affect direct emissions (Scope 1).

Our result of a significant relationship between climate-related patents and subsequent reduction in carbon intensity is in contrast to Bolton et al. (2022) who do not find a measurable impact of green patents on carbon emissions. However, they limit the analysis to a short horizon of 2 years for which the relationship is also absent (or very weak) in our data. We find a strong relationship only for long horizons of 4 to 5 years that are not analyzed by Bolton et al. (2022). Moreover, there are many other differences in samples and variables: Bolton et al. (2022) study a worldwide sample dominated by private firms and use a broad scope of "green patents",[58] whereas we focus on climate-related patents of US listed firms.

Our findings that climate-related patents are associated with reductions in carbon intensity in OLS regressions are also in contrast to the results we obtain when we focus on random variations in patent granting. Using our instrument variable of shocks in examiner leniency, we find no significant effects of patent grant shocks on CO2 emissions, neither for all categories aggregated nor for individual categories, and also not for total energy used. A representative sample of these (negative) results is reported in Table A1 in the Online Appendix.

The contrast between the results for the underlying innovation (OLS regressions) and the incremental effect of patent grant (isolated in the 2SLS regressions by the variation in examiner leniency) leads us to conclude that climate-related patents have an impact on a patent holders' emission intensity, but that this impact appears entirely linked to the underlying technology. Innovators use the technology independently of the patent decision, as indicated in Table VIII, and their climate mitigation effect seems to be unaffected by the USPTO's decision to grant patent protection, as indicated in Table A1.

# VII. Conclusion

This paper studies whether corporate climate action, a major type of ESG policies, has an impact on financial markets. We focus on climate-related patents, i.e., patents on technologies that aim at mitigating climate change and that are identified as such in the Cooperative Patent Classification (CPC) by the Y02 tag. We address concerns about endogeneity with an instrumental

[58]Green patents are based on definitions supplied by the data provider (Bureau van Dijk).

variable approach that exploits quasi-random variations in the probability of patent approvals, based on patent examiners' chance-driven assignment and differences in their leniency to grant patents. We establish a causal link between climate-related patents and its effects on financial markets.

We find that companies that experience a positive shock of climate-related patent grants exhibit significant cumulative abnormal returns over the next 12 to 18 months, and a concomitant reduction in their implied cost of capital. We uncover two main channels for these effects on corporate valuation. First, we show that environment-focused institutional investors reallocate their portfolios and reinforce their holdings in these companies. Abnormal returns and investor reallocations are substantially higher in periods of heightened public attention to climate change concerns. Companies that are granted climate-related patents also benefit from an increase in the environmental score attributed by ESG rating agencies. The documented effects are limited to climate innovation and are absent for green patents in other areas that are not assigned a specific tag in the CPC.

Exploring the real climate change impact of innovation, when we look at randomly obtained additional climate-related patent approvals, we find no measurable impact on carbon emissions of the innovating companies. By contrast, when we study the underlying climate technology (in regressions that dispense with the instrumental variable approach), we find a strong association of climate innovation with subsequent gains in climate change mitigation of innovators (Scope 1). We conclude that climate innovation allows innovators to mitigate their climate impact, but these gains are linked to the underlying technology itself, not the granting of patent protection. At the same time, market participants react to patent approvals that from their point of view are noisy but informative signals, an interpretation that is supported by our finding of a positive climate impact of the underlying green technology.

Thus, on one hand we show strong evidence for financial market reactions, buoyed by investor attention and fund flows of ESG-minded institutional investors. On the other hand, we document that random components in patent approvals do not lead to climate mitigation effects. This suggests that the impact of climate patents is largely limited to signal effects. Overall, our results show that financial market participants and rating agencies take the information content of climate-related patent approvals into account, even though the real effects on emissions are linked to the underlying green technology. In future research, it could be interesting to study what type of green innovation is most conducive to mitigating corporate impacts on climate change.

# REFERENCES


Acemoglu, Daron, Philippe Aghion, Lint Barrage, and David Hémous, 2020, Climate change, directed innovation and energy transition: Long-run consequences of the shale gas revolution, Federal Reserve Bank of Richmond.

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, 2012, The environment and directed technical change, *American Economic Review* 102, 131–66.

Amel-Zadeh, Amir, and George Serafeim, 2018, Why and How Investors Use ESG Information: Evidence from a Global Survey, *Financial Analysts Journal* 74, 87–103.

Andriosopoulos, Dimitris, Pawel Czarnowski, and Andrew P Marshall, 2022, Does green innovation increase shareholder wealth?, Available at SSRN, https://ssrn.com/abstract=4012633.

Angrist, Joshua, and Alan Krueger, 2001, Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments, *Journal of Economic Perspectives* 15, 69–85.

Ardia, David, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht, 2020, Climate Change Concerns and the Performance of Green versus Brown Stocks, National Bank of Belgium, Working Paper Research 395.

Arora, Ashish, Sharon Belenzon, and Lia Sheer, 2021, Knowledge Spillovers and Corporate Investment in Scientific Research, *American Economic Review* 111, 871–98.

Aswani, Jitendra, Aneesh Raghunandan, and Shivaram Rajgopal, 2022, Are carbon emissions associated with stock returns?, Columbia Business School Research Paper, *forthcoming*.

Barber, Benjamin, and Luis Diestre, 2022, Can Firms Avoid Tough Patent Examiners Through Examiner-Shopping? Strategic Timing of Citations in USPTO Patent Applications, *Strategic Management Journal, forthcoming*.

Berg, Florian, Kornelia Fabisik, and Zacharias Sautner, 2020, Is history repeating itself? the (un) predictable past of esg ratings, ECGI–Finance Working Paper No. 708. Available at SSRN, https://ssrn.com/abstract=3049943.

Berg, Florian, Julian Koelbel, and Roberto Rigobon, 2022, Aggregate Confusion: The Divergence of ESG Ratings, *Review of Finance, forthcoming*.

Berg, Florian, Julian F Koelbel, Anna Pavlova, and Roberto Rigobon, 2021, ESG Confusion and Stock Returns: Tackling the Problem of Noise, NBER Working Paper No. 30562, http://www.nber.org/papers/w30562.

Boldrin, Michele, and David K. Levine, 2013, The Case Against Patents, *Journal of Economic Perspectives* 27, 3–22.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do Investors Care about Carbon Risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, Marcin T. Kacperczyk, and Moritz Wiedemann, 2022, The co2 question: Technical progress and the climate crisis, Available at SSRN, https://ssrn.com/abstract=4212567.

CDP, 2017, CDP Carbon Majors Report 2017, Available at https://cdn.cdp.net/cdp-production/cms/reports/documents/000/002/327/original/Carbon-Majors-Report-2017.pdf?1501833772.

CFA Institute, 2015, Environmental, Social, and Governance Issues in Investing: A Guide for Investment Professionals, Center for Financial Analysis London, England.

Chava, Sudheer, 2014, Environmental Externalities and Cost of Capital, *Management Science* 60, 2223–2247.

Cockburn, Iain M., Samuel S. Kortum, and Scott Stern, 2002, Are All Patent Examiners Equal? The Impact of Examiner Characteristics, National Bureau of Economic Research.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing Innovation, *The Review of Financial Studies* 26, 635–666.

Cohen, Lauren, Umit G Gurun, and Scott Duke Kominers, 2019, Patent trolls: Evidence from targeted firms, *Management Science* 65, 5461–5486.

Cohen, Lauren, Umit G. Gurun, and Quoc H. Nguyen, 2021, The ESG-Innovation Disconnect: Evidence From Green Patenting, Technical report, National Bureau of Economic Research.

Dalla Fontana, Silvia, and Ramana Nanda, 2022, *Innovating to Net Zero: Can Venture Capital and Startups Play a Meaningful Role?* (National Bureau of Economic Research, USA).

Dechezleprêtre, Antoine, Cal Muckley, and Parvati Neelakantan, 2019, Is firm-level clean or dirty innovation valued more?, Grantham Research Institute on Climate Change and the Environment Working Paper No. 326.

Dimson, Elroy, Paul Marsh, and Mike Staunton, 2020, Divergent ESG Ratings, *Journal of Portfolio Management* 47, 75–87.

Fama, Eugene F., and Kenneth R. French, 2015, A Five-factor Asset Pricing Model, *Journal of Financial Economics* 116, 1–22.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist, 2020, What is a Patent Worth? Evidence From the US Patent “Lottery”, *The Journal of Finance* 75, 639–682.

Fitzgerald, Tristan, Benjamin Balsmeier, Lee Fleming, and Gustavo Manso, 2021, Innovation Search Strategy and Predictable Returns, *Management Science* 67, 1109–1137.

Flammer, Caroline, 2015, Does Corporate Social Responsibility Lead to Superior Financial Performance? A Regression Discontinuity Approach, *Management Science* 61, 2549–2568.

Gao, Ming, and Xuelin Li, 2021, The environmental impact of green innovation, Available at SSRN, https://ssrn.com/abstract=3955402.

Gaule, Patrick, 2018, Patents and the Success of Venture-Capital Backed Startups: Using Examiner Assignment to Estimate Causal Effects, *The Journal of Industrial Economics* 66, 350–376.

Gebhardt, William R., Charles M.C. Lee, and Bhaskaran Swaminathan, 2001, Toward an Implied Cost of Capital, *Journal of Accounting Research* 39, 135–176.

Gibson, Rajna, Simon Glossner, Philipp Krueger, Pedro Matos, and Tom Steffen, 2020, Responsible Institutional Investing around the World, Swiss Finance Institute Research Paper No. 20-13.

Gibson Brandon, Rajna, Philipp Krueger, and Shema F. Mitali, 2020, The Sustainability Footprint of Institutional Investors: ESG Driven Price Pressure and Performance, Swiss Finance Institute Research Paper No. 17-05.

Gibson Brandon, Rajna, Philipp Krueger, and Peter Steffen Schmidt, 2021, ESG Rating Disagreement and Stock Returns, *Financial Analysts Journal* 77, 104–127.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate Governance and Equity Prices, *The Quarterly Journal of Economics* 118, 107–156.

Graham, Stuart J.H., Alan C. Marco, and Richard Miller, 2018, The USPTO Patent Examination Research Dataset: A Window on Patent Processing, *Journal of Economics & Management Strategy* 27, 554–578.

Haščič, Ivan, and Mauro Migotto, 2015, Measuring Environmental Innovation Using Patent Data, OECD Environment Working Papers, https://doi.org/10.1787/5js009kf48xw-en.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative Efficiency and Stock Returns, *Journal of Financial Economics* 107, 632–654.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2018, Innovative originality, profitability, and stock returns, *The Review of Financial Studies* 31, 2553–2605.

Hou, Kewei, Mathijs A. Van Dijk, and Yinglei Zhang, 2012, The Implied Cost of Capital: A New Approach, *Journal of Accounting and Economics* 53, 504–526.

Hsu, Po-Hsuan, Kai Li, and Chi-Yang Tsou, 2022, The pollution premium, *Journal of Finance, forthcoming*.

In, Soh Young, Ki Young Park, and Ashby Monk, 2019, Is "Being Green" Rewarded in the Market? An Empirical Investigation of Decarbonization Risk and Stock Returns, Stanford Global Project Center WP, available at https://ssrn.com/abstract=3020304.

IPCC, 2022, IPCC Sixth Assessment Report: Impacts, Adaptation and Vulnerability .

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological Innovation, Resource Allocation, and Growth, *The Quarterly Journal of Economics* 132, 665–712.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, 2020, The importance of climate risks for institutional investors, *The Review of Financial Studies* 33, 1067–1111.

Lee, Charles M.C., Eric C. So, and Charles C.Y. Wang, 2021, Evaluating Firm-level Expected-return Proxies: Implications for Estimating Treatment Effects, *The Review of Financial Studies* 34, 1907–1951.

Lemley, Mark A., and Bhaven Sampat, 2012, Examiner Characteristics and Patent Office Outcomes, *Review of Economics and Statistics* 94, 817–827.

Lerner, Josh, and Amit Seru, 2021, The Use and Misuse of Patent Data: Issues for Finance and Beyond, *The Review of Financial Studies* 35, 2667–2704.

Li, Wenquan, Suman Neupane-Joshi, and Kelvin Jui Keng Tan, 2022, Toxic emissions and corporate green innovation, Available at SSRN, https://ssrn.com/abstract=4113290.

Marquis, Christopher, Michael W Toffel, and Yanhua Zhou, 2016, Scrutiny, Norms, and Selective Disclosure: A Global Study of Greenwashing, *Organization Science* 27, 483–504.

Melero, Eduardo, Neus Palomeras, and David Wehrheim, 2020, The Effect of Patent Protection on Inventor Mobility, *Management Science* 66, 5485–5504.

Pástor, Ľuboš, and Robert F. Stambaugh, 2001, The Equity Premium and Structural Breaks, *The Journal of Finance* 56, 1207–1239.

Pástor, Ľuboš, and Robert F. Stambaugh, 2009, Predictive Systems: Living with Imperfect Predictors, *The Journal of Finance* 64, 1583–1628.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting Green Returns, *Journal of Financial Economics* 146, 403–424.

Righi, Cesare, and Timothy Simcoe, 2019, Patent Examiner Specialization, *Research Policy* 48, 137–148.

Sampat, Bhaven, and Heidi L. Williams, 2019, How do Patents Affect Follow-on Innovation? Evidence from the Human Genome, *American Economic Review* 109, 203–36.

Sauzet, Maxime, and Olivier David Zerbib, 2022, When Green Investors are Green Consumers, Working Paper. Available at SSRN, https://ssrn.com/abstract=4098124.

Starks, Laura T., Parth Venkat, and Qifei Zhu, 2017, Corporate ESG Profiles and Investor Horizons, Available at SSRN, https://ssrn.com/abstract=3049943.

# Appendix A. Variable Definition

| Variable Name | Definition of Variable | Data Source |
|---|---|---|
| Firm-Month Sample | | |
| CAR[t, t+k] | Cumulative abnormal returns cumulated from month $t$ to $t+k$. Abnormal returns (monthly) are calculated using the Fama-French 5-factor model. | CRSP |
| ΔPRC[t, t+k] | Changes of log of stock price from month $t$ to $t+k$ | CRSP |
| ΔICC[t, t+k] | Changes of implied cost of capital (ICC) from month $t$ to $t+k$. ICC is calculated following the online appendix of Pástor et al. (2022). | CRSP |
| $\overline{MCCC}$ | MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). $\overline{MCCC}_t$ is constructed following the investor monthly memory fomular in Pástor et al. (2022): $\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau}$ | Ardia et al. (2020) |
| Num_Clim_Pats_Granted | Number of climate-related patents granted by USPTO and newly issued to the firm in month $t$. Climate patents are defined by CPC codes ($Y02$) | PatEx and PatentsView |
| Clim_Pat_Stock | Climate patent stock (the total number of climate patents granted to the firm before month $t$) | PatEx and PatentsView |
| Num_OtherGreen_Grant | Number of non-climate-related (other green) patents granted by USPTO and newly issued to the firm in month $t$. Other green patents are defined as in Haščič and Migotto (2015) | PatEx and PatentsView |
| Avr_Leniency | Average of examiner's leniency who examined the firm's patent applications | PatEx |
| MarketCap | The log of market cap. Market cap is equal to the monthly stock price times monthly total shares outstanding | CRSP |
| Past Return | Defined as the average past 12-month returns | CRSP |
| Return Volatility | Defined as the standard deviation of past 12-month returns | CRSP |
| Firm-Year Sample | | |
| ΔEnvrn_Score[t, t+k] | Changes of the environmental score from year $t$ to year $t+k$ | Refinitiv ESG |
| ΔEmission_Score[t, t+k] | Changes of the emission score from year $t$ to year $t+k$ | Refinitiv ESG |
| ΔResource_Score[t, t+k] | Changes of the resource usage score from year $t$ to year $t+k$ | Refinitiv ESG |
| ΔInnov_Score[t, t+k] | Changes of the environmental innovation score from year $t$ to year $t+k$ | Refinitiv ESG |
| ΔScope1_CO2[t, t+k] | Changes of log of Scope 1 CO2 equivalents emissions from year $t$ to year $t+k$. CO2 emissions are scaled by the firm's total outputs in the same fiscal year. | Refinitiv ESG |
| Num_Clim_Pats_Granted | Number of climate-related patents granted by USPTO and newly issued to the firm in year $t$. Climate patents are defined by CPC codes $Y02$ | PatEx and PatentsView |
| Num_OtherGreen_Grant | Number of non-climate-related (other green) patents granted by USPTO and newly issued to the firm in year $t$. Other green patents are defined following Haščič and Migotto (2015) | PatEx and PatentsView |
| Firm Size (MarketCap) | Firm size, measured as natural logarithm of the firm's market capitalization (Compustat item $CSHO_t$ × item $PRCC\_F_t$) | Compustat |

Continued on next page

**Appendix A continued from previous page**

| Variable name | Definition of variable | Data Source |
|---|---|---|
| Tobin's Q | Market-to-book ratio in assets. Market value of assets equals the book value of assets (item $AT_t$) + the market value of common equity at fiscal year-end (item $CSHO_t$ × item $PRCC\_F_t$) − the book value of common equity (item $CEQ_t$) − balance sheet deferred taxes (item $TXDB_t$) | Compustat |
| R&D | R&D expenditure, measured as item $XRD_t$ scaled by lagged book assets (item $AT_{t-1}$). If this variable is missing, we replace it with the industry-year median R&D expenditure. | Compustat |
| Cash | Defined as cash and cash equivalents (item $CHE_t$) scaled by lagged book assets | Compustat |
| ROA | Return on assets, defined as EBITDA scaled by lagged book assets | Compustat |
| Book Leverage | Book leverage, defined as debt including long-term debt (item $DLTT_t$) plus debt in current liabilities (item $DLC_t$) divided by the sum of debt and book value of common equity (item $CEQ_t$) | Compustat |
| CAPX | Capital expenditure, measured as item $CAPX_t$ scaled by lagged book assets | Compustat |
| Firm-Quarter Sample | | |
| ΔIO[t, t+k] | Changes of institutional ownership from quarter $t$ to quarter $t+k$. Institutional ownership is defined as the sum of quarterly shares held by 13F institutions divided by shares outstanding in the end of that quarter. | Refinitiv 13F |

# Appendix B. Matching Patent Applications to CRSP-Compustat

This appendix describes in detail how to match assignees (retrieved from the USPTO Patent Assignment database) of USPTO patent applications (downloaded from the USPTO PatEx Research database) to CRSP-Compustat publicly-listed firms. Before matching, we only keep patent applications (filed after 2001) that are either finally granted by USPTO or have received final (CTFR) or non-final (CTNF) rejection letters from USPTO.

Matching granted patents to CRSP-Compustat is relatively easy. We apply the existing concordance between the USPTO patent number and $PERMNO$ (the unique stock identifier in CRSP) provided by Arora et al. (2021). Arora et al. (2021) provides matching between US-headquartered listed firms and any patents granted to these firms from 1980 to 2015, with extensive manual checking.

We use the concordance provided by Arora et al. (2021) instead of the one by Kogan et al. (2017) for two reasons. First, Arora et al. (2021) includes not only patents of listed corporations but also those filed by private subsidiaries of listed corporations. This helps us identify patents filed by subsidiaries and ultimately owned by a public corporate parent. Second, they consider various name changes of public firms in their (patent assignee)–(firm name) fuzzy matching. Kogan et al. (2017) follows an old matching concordance of the NBER Patent Project, and the NBER Patent Database does not conduct this dynamic name matching. As argued by Arora et al. (2021), their matching significantly improves the original matching offered by the NBER.

The matching from Arora et al. (2021) allows us to obtain all patents granted to US-listed firms from 1980 to 2015. However, we also need to get rejected patent applications filed by these listed firms and patents granted or rejected after 2015. Therefore, based on Arora et al. (2021)'s dataset, we construct a new concordance between two sets of variables. The first set contains two variables: the assignee name and the assignee's 5-digit ZIP code. The second set of variables is the $PERMNO$ (the unique stock identifier in CRSP). Our new concordance helps to link assignee's name and address to CRSP unique firm identifier even for rejected patent applications.

To do that, we first clean assignee names of all patent applications (both rejected and granted) following Arora et al. (2021)'s procedures. Then, we use the granted patent applications to link assignee information in patent applications and PERMNO. For each assignee name and assignee address pair, we allow only one unique matching to a PERMNO in a year. If there are multiple PERMNOs, we select the PERMNO with the most number of patents granted to the assignee with the specific address. Next, for each link between assignee name – address and PERMNO, we set up the matching start date and end date. This constructed concordance helps us to match rejected applications to CRSP firms.

Here is a simple example of our concordance:

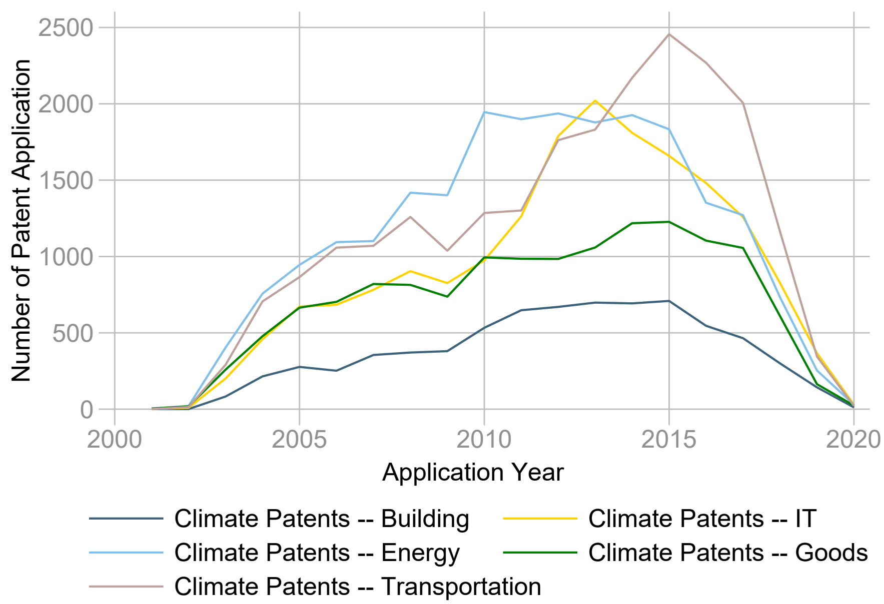
| Assignee Name | Assignee Address | PERMNO | Matching Start Year | Matching End Year |
|---|---|---|---|---|
| ABBOTT LAB | 60064 | 20482 | 2001 | 2015 |

It implies that any patent applications that are granted or rejected between 2001 to 2015 and with the cleaned assignee name "ABBOTT LAB " (ZIP code: 60064) should be matched to CRSP firm with PERMNO = 20482. Finally, we extend our matching to 2020 by replacing the Matching End Year value 2015 with 2020 for all matching in our concordance. In the last step, we conduct extensive manual checking for our new extended concordance.

**Figure 1.** Number of Climate-related Patent Applications

This figure plots the annual number of climate-related patent applications filed by US-headquartered and publicly-listed corporations from 2001 to 2020. Panel A sorts patent applications by patent application year, and Panel B sorts by patent decision year (either granted or rejected). In each panel, we plot annual patent applications by different categories of climate patents. The categories follow the USPTO CPC (Y02) codes (https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html). We exclude the Y02C (storage and capture of carbon gas) and Y02W (water) patents from our main analyses since the number of patents in these groups is tiny.

Panel A: Number of Patent Applications by Application Year




Panel B: Number of Patent Applications by USPTO Decision Year

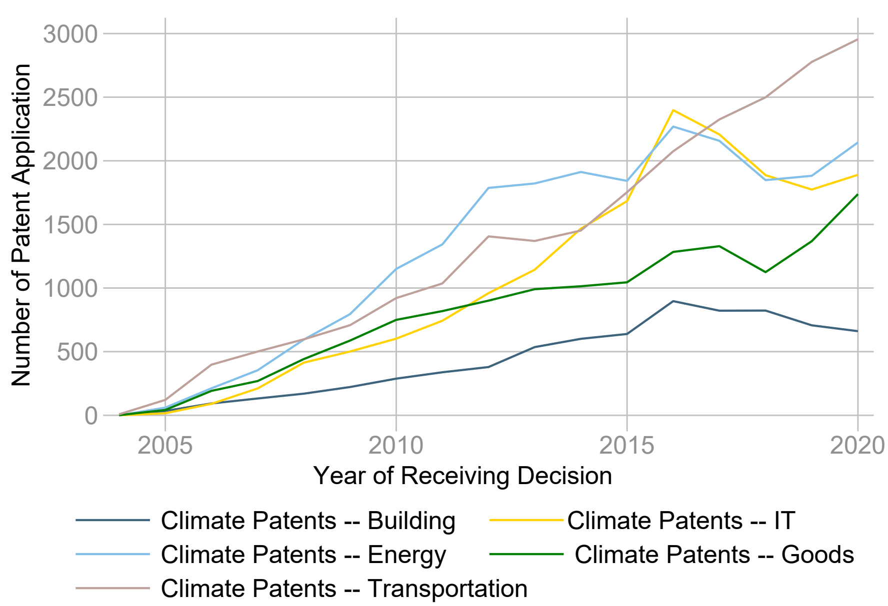


**Figure 2.** Green Patents and Monthly Stock Returns

This figure investigates how exogenous issuance of green patents influence firms' monthly stock returns. Panels A and B study the climate-related and other (non-climate) green patents separately. We run the 2SLS regressions laid out below in each panel and plot the coefficients $\alpha$ for each $k$ equal to 0 to 18. Data is at the firm-month level. The sample requires that a firm receives at least one decision on its green patent applications in that month. The dependent variable is the cumulative abnormal returns (CARs) from time $t$ to time $t+k$. Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). Factor loadings are estimated using the previous 60-month returns data. The main independent variable is $Num\_Climate\_Pats\_Granted$, counting the number of green patents issued to the firm during month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. We use a log transformation, $ln(1+x)$, for our main independent variable. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Green Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha Num\_Climate\_\widehat{Pats}\_Granted_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{B1}$$

$$1st\ Stage: \quad Num\_Climate\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{B2}$$

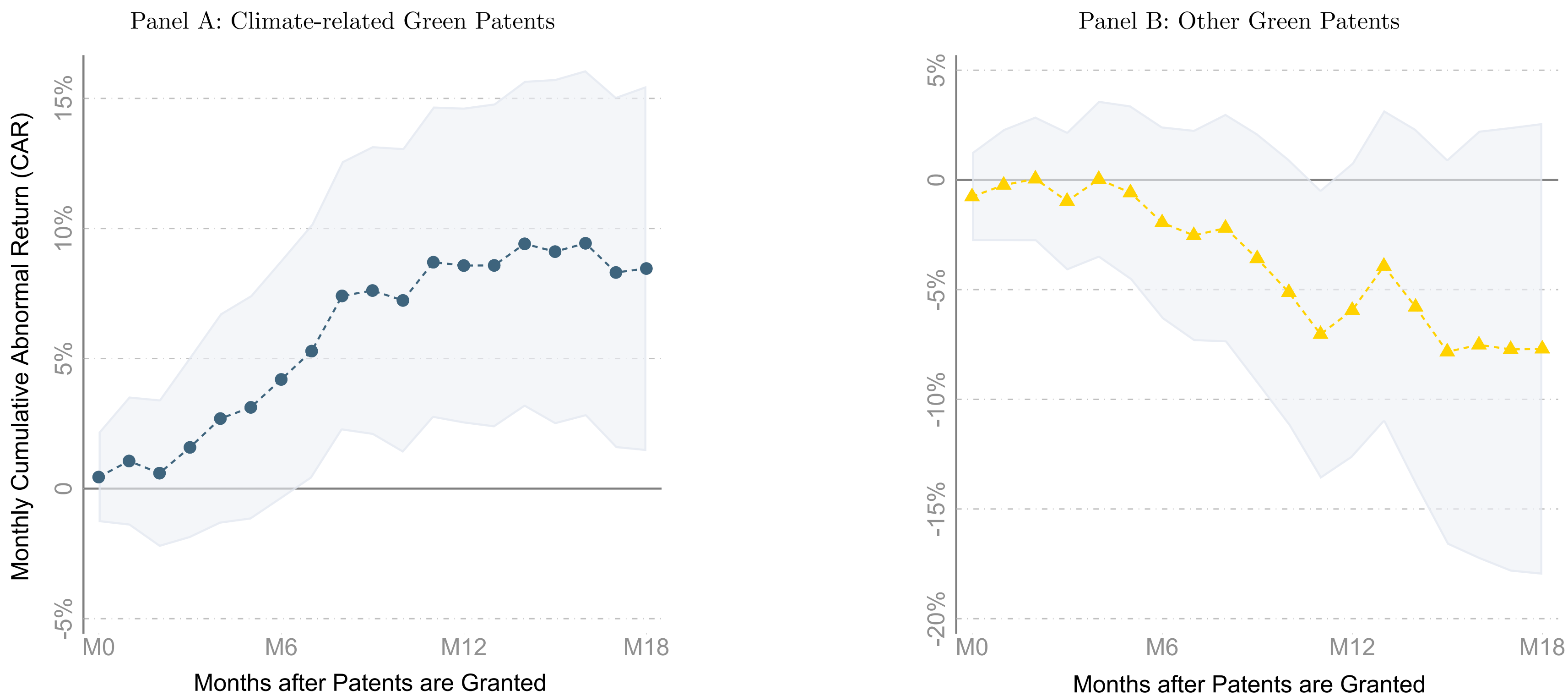


**Figure 3.** Climate-related Patents, Media Coverage of Climate Change, and Stock Returns

This figure presents an extensional analysis of Figure 2. The second stage regression follows the equation:

$$
\begin{aligned}
CAR[t:t+k]_{t,s} = {} & \alpha_1 Num\_\widehat{ClimatePats}\_Granted_{t,s} \times \overline{MCCC}\_High_t + \alpha_2 Num\_\widehat{ClimatePats}\_Granted_{t,s} \times \overline{MCCC}\_Mid_t + \\
& \alpha_3 Num\_\widehat{ClimatePats}\_Granted_{t,s} \times \overline{MCCC}\_Low_t + \delta_1 \overline{MCCC}\_High_t + \delta_2 \overline{MCCC}\_Mid_t + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s}
\end{aligned}
\quad \text{(B3)}
$$

MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). $\overline{MCCC}_t$ is constructed following the monthly memory model in Pástor et al. (2022):

$$
\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad \text{(B4)}
$$

We sort $\overline{MCCC}_t$ into terciles and define three tercile dummies. The dependent variable is the cumulative abnormal returns (CARs) from time $t$ to time $t+k$. Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). The main independent variable is $Num\_ClimatePats\_Granted$, counting the number of climate-related patents issued to the firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Climate-related Patents Granted, takes the $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Climate Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

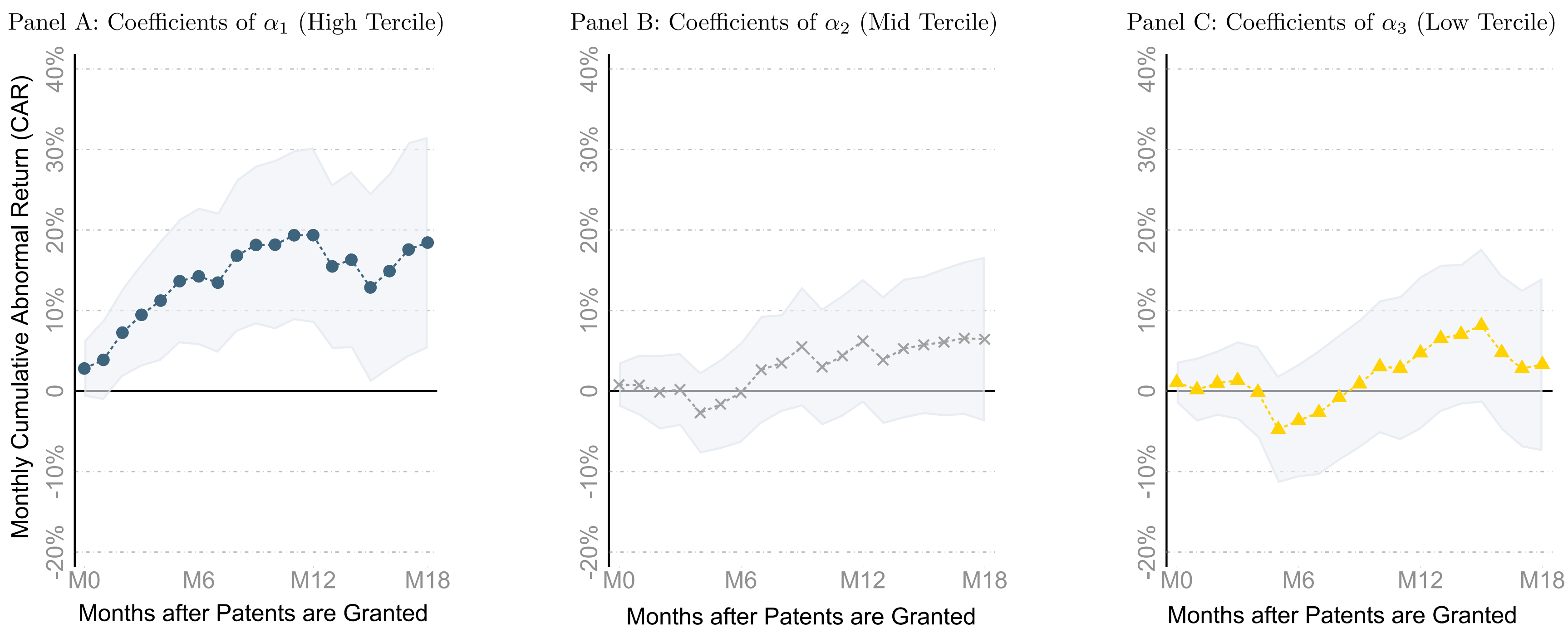


**Figure 4.** Climate-related Patents, MCCC Index, and Daily Stock Returns

This figure presents regressions of daily cumulative abnormal returns. The second stage regression follows the equation:

$$\begin{aligned} Daily\_CAR[t-3:t+k]_{t,s} = {} & \alpha_1 Num\_Climate\widehat{Pats\_Granted}_{t,s} \times \overline{MCCC}\_High_t + \alpha_2 Num\_Climate\widehat{Pats\_Granted}_{t,s} \times \overline{MCCC}\_Mid_t + \\ & \alpha_3 Num\_Climate\widehat{Pats\_Granted}_{t,s} \times \overline{MCCC}\_Low_t + \delta_1 \overline{MCCC}\_High_t + \delta_2 \overline{MCCC}\_Mid_t + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \end{aligned} \tag{B5}$$

MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). $\overline{MCCC_t}$ is constructed following the monthly memory model in Pástor et al. (2022):

$$\overline{MCCC_t} = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \tag{B6}$$

We sort $\overline{MCCC_t}$ into terciles and define three tercile dummies. The dependent variable is the daily cumulative abnormal returns (CARs) from -3 day to day $k$. $k$ is equal to -3 to +3. Abnormal Returns (ARs) are market adjusted daily returns winsorized in 1% and 99%. The main independent variable is $Num\_ClimatePats\_Granted$, counting the number of climate-related patents issued to the firm during the day $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Climate-related Patents Granted, takes the $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Climate Patent Applications (receiving results on that day) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

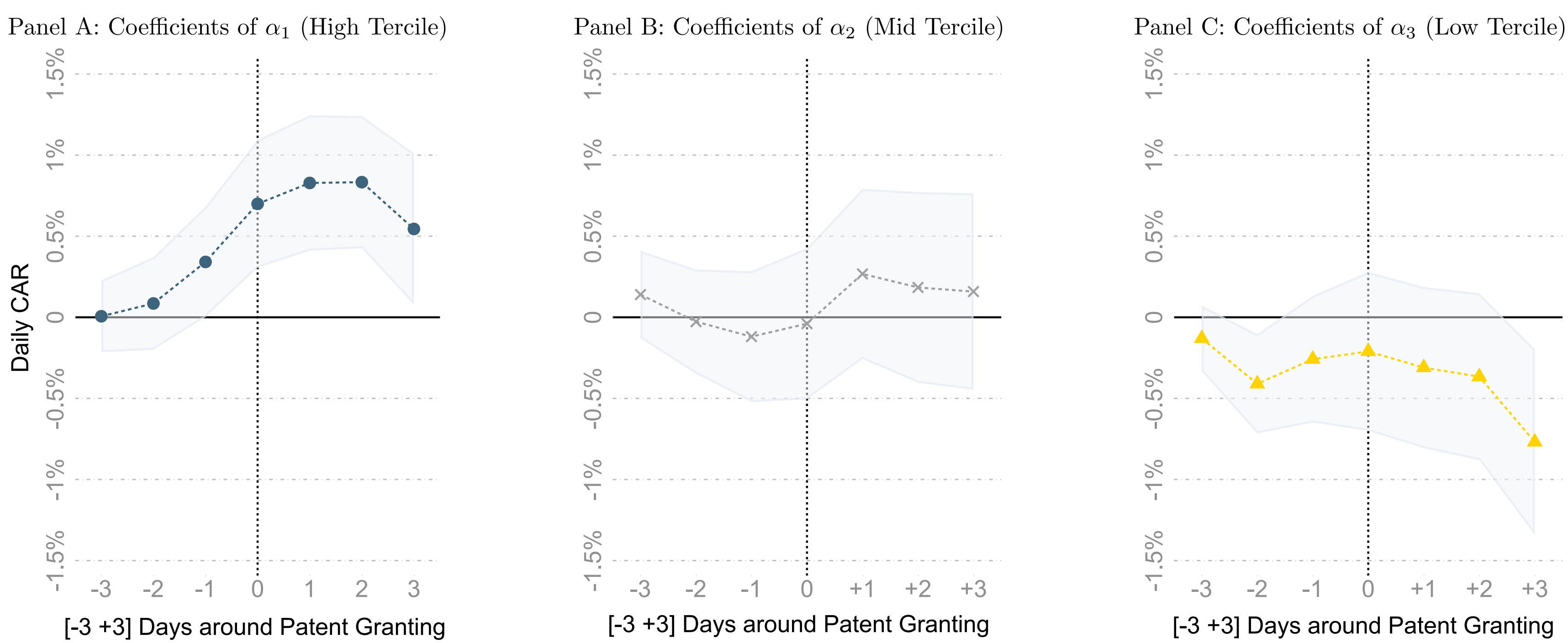


**Figure 5.** Climate-related Patents, Climate Patents Stock, and Stock Returns

This figure presents an extensional analysis of Figure 2. The second stage regression follows the equation:

$$CAR[t:t+k]_{t,s} = \alpha_1 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times Clim\_PatStock\_High_{t,s} + \alpha_2 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times Clim\_PatStock\_Mid_{t,s} + \alpha_3 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times Clim\_PatStock\_Low_{t,s} + \delta_1 Clim\_PatStock\_High_{t,s} + \delta_2 Clim\_PatStock\_Mid_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{B7}$$

$Clim\_PatStock$ is defined as the total number of climate patents granted and issued to the firm $i$ before month $t$. We sort $Clim\_PatStock$ into tercile and define three tercile dummies. The dependent variable is the cumulative abnormal returns (CARs) from time $t$ to time $t+k$. Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). The main independent variable is $Num\_ClimatePats\_Granted$, counting the number of climate-related patents issued to the firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Climate-related Patents Granted, takes the $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Climate Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

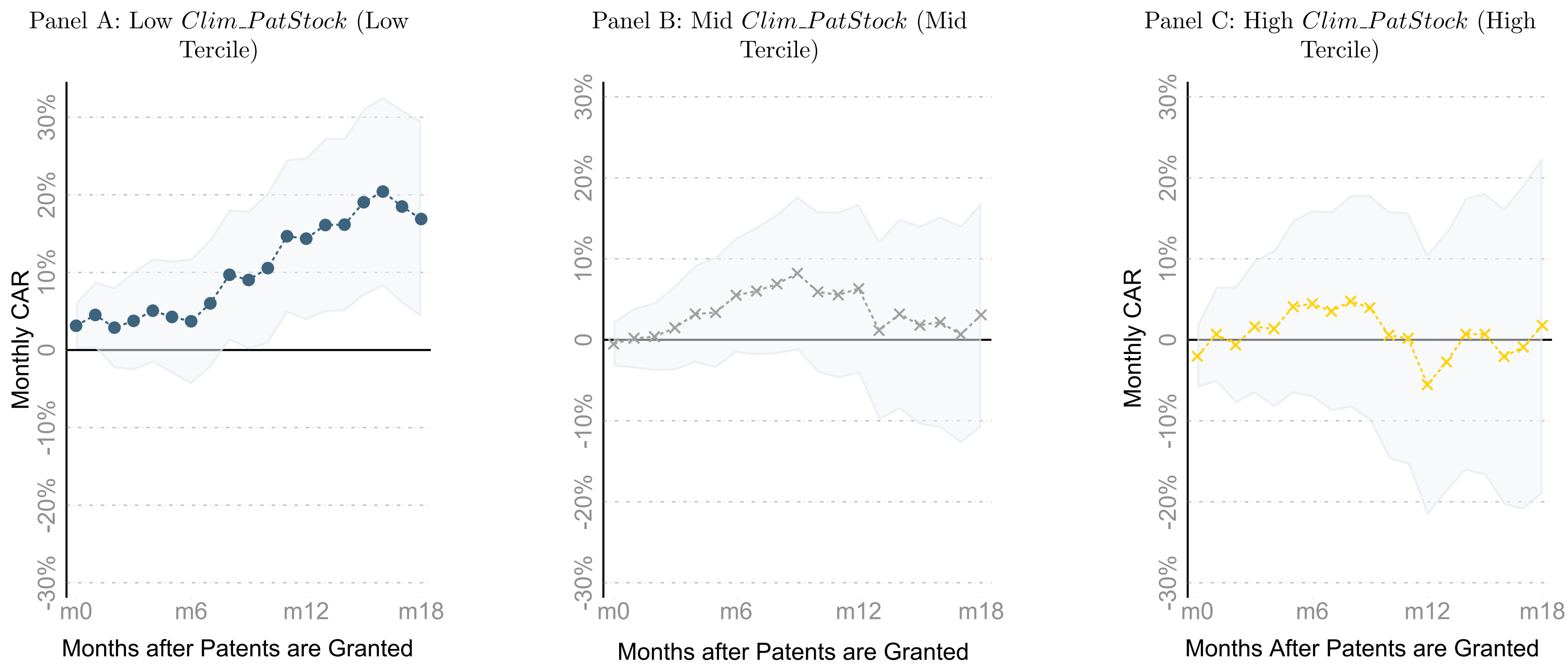
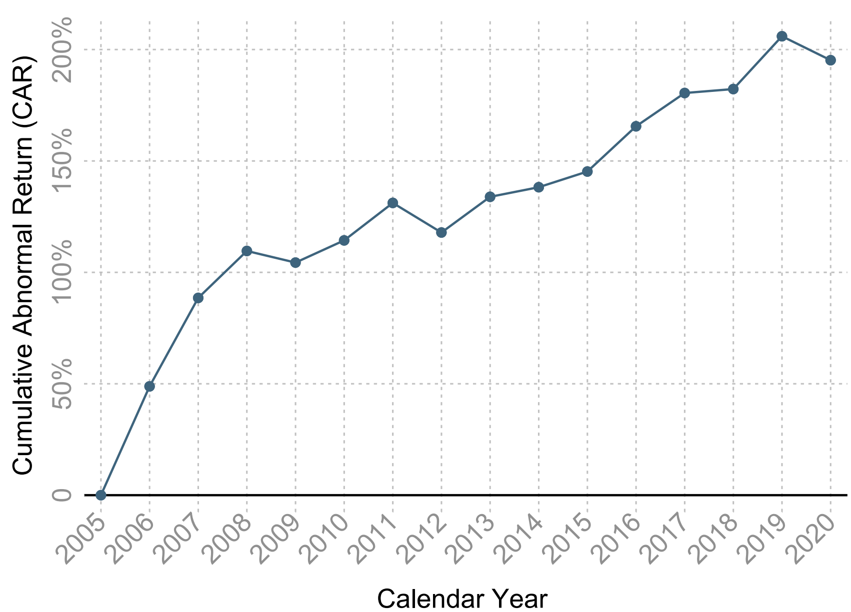


**Figure 6.** Time-varying Effect of Climate Patents on Monthly Returns

This figure presents the time-varying effect of climate patents on monthly returns. We conduct the following regression analysis (2SLS):

$$CAR[t+1:t+12]_{t,s} = \sum_{Year=2005}^{2020} \alpha_{Year} Num\_Climate\widehat{Pats}\_Granted_{t,s} \times I(Year)_t + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad \text{(B8)}$$

The dependent variable is the cumulative abnormal returns (CARs) from time $t+1$ to time $t+12$ (12-month CAR). Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). The main independent variable is $Num\_ClimatePats\_Granted$, counting the number of climate-related patents issued to the firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. $I(Year)$ is a dummy of each calendar year from 2005 to 2020. The main independent variable, Num Climate-related Patents Granted, takes the $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Climate Patent Applications (Receiving Results in that Month) F.E. In the following figure, we cumulatively sum the coefficients of $\alpha_{Year}$ and plot the sum in the following figure. $\alpha_{2005}$ is set to 0.



## **Figure 7.** Green Patents and Implied Cost of Capital

This figure investigates how exogenous issuance of green patents influence firms' implied cost of capital (ICC). Panels A and B study the climate-related and other (non-climate) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 1 to 18. Data is at the firm-month level. The dependent variable is the change of ICC from time $t$ to time $t + k$. The main independent variable is $Num\_Climate\_Pats\_Granted$, counting the number of green patents issued to the firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. Fixed effects include Industry × Month F.E., Art Unit × Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \widehat{Num\_Climate\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{B9}$$

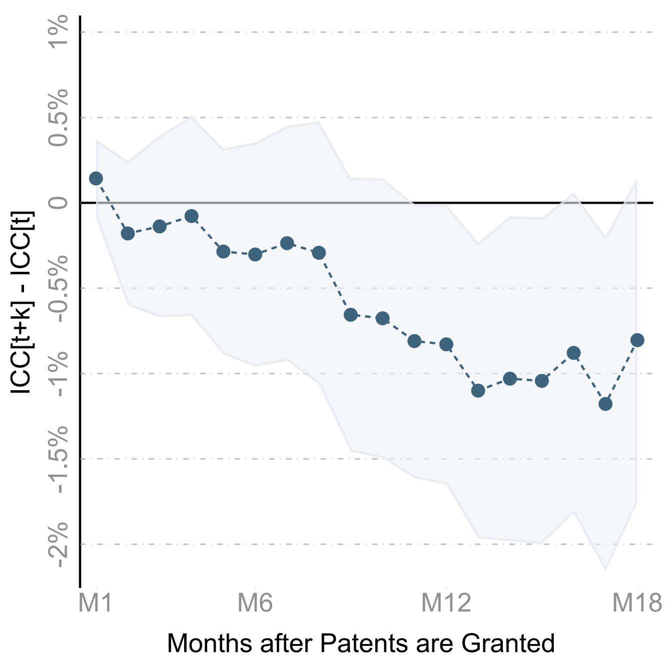
$$1st\ Stage: \quad Num\_Climate\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{B10}$$

ICC is calculated following the Online Appendix procedures of Pástor et al. (2022). We numerically solve and obtain $r$ for each month and year of firms using the following formula:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^\tau} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{B11}$$



Panel A: Climate-related Green Patents




Panel B: Other Green Patents

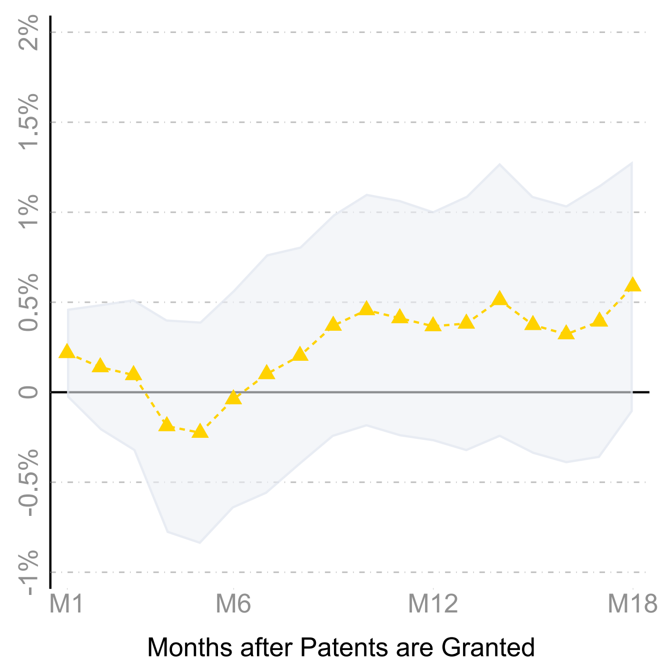


**Figure 8.** Climate-related Patents, Media Coverage of Climate Change, and ICC

This figure presents an extensional analysis of Figure 7. The second stage regression follows the equation:

$$ICC_{t+k,s} - ICC_{t,s} = \alpha_1 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times MCCC\_High_t + \alpha_2 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times MCCC\_Mid_t + \alpha_3 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times MCCC\_Low_t + \delta_1 MCCC\_High_t + \delta_2 MCCC\_Mid_t + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad \text{(B12)}$$

MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). The dependent variable is the change of ICC from time $t$ to time $t+k$. The main independent variable is $Num\_Climate\_Pats\_Granted$, counting the number of climate-related green patents issued to the firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. Fixed effects include Industry × Month F.E., Art Unit × Year F.E., and the Num of Climate Patent Applications (Receiving Results in that Month) F.E. Standard errors are clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level. ICC is calculated following the Online Appendix procedures of Pástor et al. (2022). We numerically solve and obtain $r$ for each month and year of firms using the following formula:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \quad \text{(B13)}$$

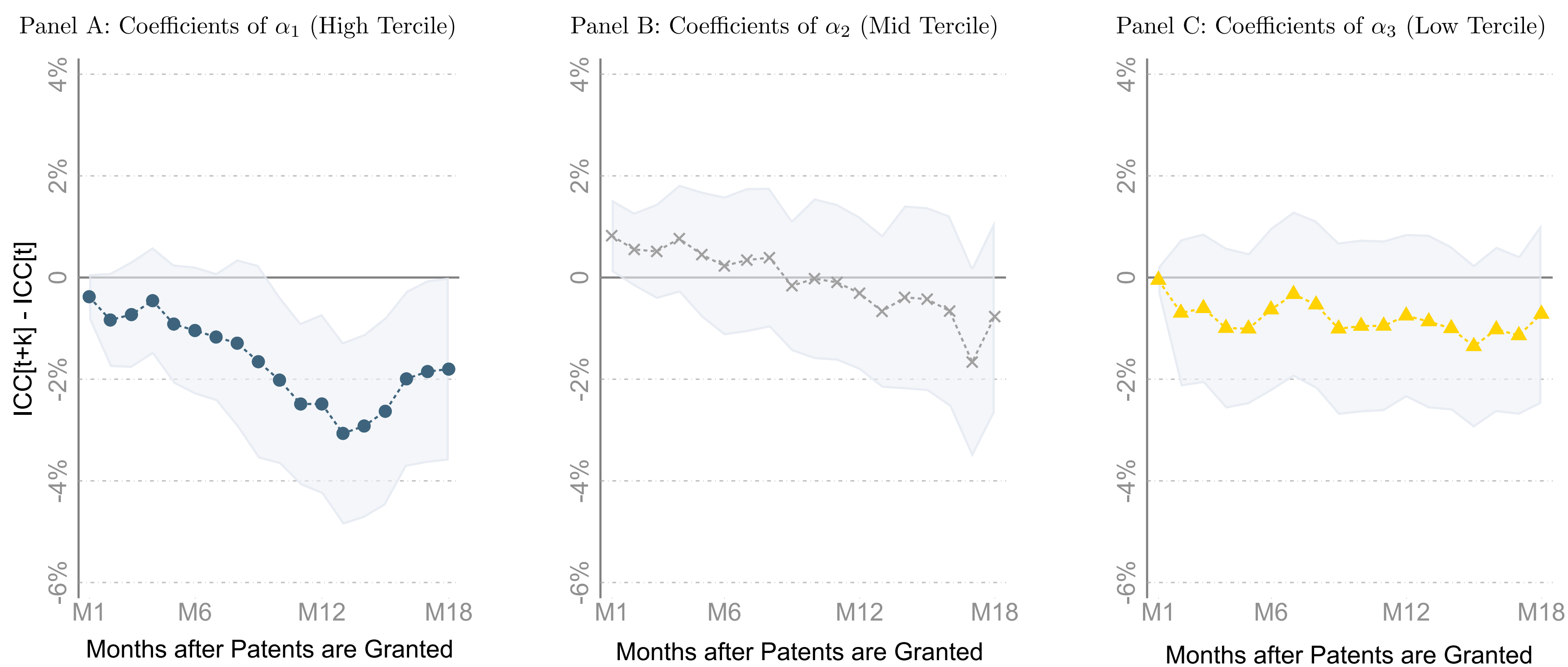


**Table I**: Summary Statistics

This table presents summary statistics. Panel A presents the descriptive statistics of the sample of all green patent applications filed by US-listed corporations in the CRSP-Compustat sample. Application data range from 2001 to 2020. We show the statistics separately for climate-related and other (non-climate-related) green patent applications. Climate-related patents are patents with the CPC codes equal to Y02. These patents include new technologies for climate change mitigation in energy, information technology, goods, transportation, and buildings industries. See details in USPTO CPC (Y02) codes (`https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html`). Non-climate-related green patents are patents for environmental management technologies, water-related adaptation technologies, and bio-diversity protection technologies. Details of non-climate green patents can be found in Table 3 of Haščič and Migotto (2015). Panel B lists the top five industries with the most green patent applications. Industries are Fama-French 48 industries. Panel C provides summary statistics for both firm-year and firm-month Refinitiv sample which is further merged with the climate patent sample. We use the patent decision year to aggregate the climate patent sample at the firm-year (or firm-month) level and merge it to Refinitiv. Panel D provides a short list of firms with the most climate patent applications in the Refinitiv sample.

| **Panel A: Sample of Green Patent Applications** | |
|---|---|
| Number of Green Patent Applications | 86,363 |
| Number of Granted Green Patents | 63,691 (73%) |
| Average Years between Application and Granting | 3.09 |
| Average Years between Application and Rejection | 2.93 |
| Climate Related Green Patents Only (CPC: Y02) | |
| Number of Green Patent Applications | 66,796 |
| Number of Granted Green Patents | 48,814 (73%) |
| Average Years between Application and Granting | 3.14 |
| Average Years between Application and Rejection | 2.98 |
| Other (Non-Climate Related) Green Patents Only | |
| Number of Green Patent Applications | 19,567 |
| Number of Granted Green Patents | 14,877 (75%) |
| Average Years between Application and Granting | 2.93 |
| Average Years between Application and Rejection | 2.73 |
| Climate Related Green Patents by Sectors | |
| Number of Climate Patents – Buildings (Y02B) | 7,342 |
| Number of Climate Patents – IT (Y02D) | 17,987 |
| Number of Climate Patents – Energy (Y02E) | 22,172 |
| Number of Climate Patents – Goods (Y02P) | 13,897 |
| Number of Climate Patents – Transportation (Y02T) | 22,902 |

**Panel B: Industries with the Most Green Patent Applications**

| Climate Related Green Patents | | Other (Non-Climate Related) Green Patents | |
|---|---|---|---|
| 1. Electronic Equipment | 16,360 | 1. Automobiles and Trucks | 4,288 |
| 2. Business Services | 9,151 | 2. Machinery | 3,399 |
| 3. Aircraft | 5,933 | 3. Aircraft | 1,465 |
| 4. Automobiles and Trucks | 4,676 | 4. Petroleum and Natural Gas | 975 |
| 5. Machinery | 2,462 | 5. Chemicals | 772 |
| . . . . . . | | | |
| 8. Petroleum and Natural Gas | 1,781 | | |

*Continued from the previous table*

**Panel C: Refinitiv ESG Sample (Merged with Climate-Related Patents)**

| | |
|---|---|
| Number of Unique Firms: | 419 |
| Number of Climate-related Green Patent Applications: | 56,150 |

| Variable | Mean | Median | SD | Min | Max | N |
|---|---|---|---|---|---|---|
| *Firm-Year Sample* | | | | | | |
| Num Climate Patent Applications | 22.72 | 4 | 70.02 | 1 | 1042 | 2471 |
| Num Climate Patent Granted | 16.67 | 3 | 52.49 | 0 | 670 | 2471 |
| Average Relative Leniency | 0.00 | 0.00 | 0.09 | -0.51 | 0.37 | 2471 |
| Environmental Score | 0.68 | 0.84 | 0.30 | 0.08 | 0.97 | 2471 |
| Governance Score | 0.80 | 0.84 | 0.15 | 0.02 | 0.98 | 2471 |
| Social Score | 0.66 | 0.75 | 0.27 | 0.04 | 0.99 | 2471 |
| Market Cap (Log) | 9.31 | 9.19 | 1.70 | 2.66 | 14.49 | 2471 |
| Tobin's Q | 2.27 | 1.83 | 1.49 | 0.66 | 16.48 | 2200 |
| Cash | 0.20 | 0.15 | 0.17 | 0.00 | 0.94 | 2470 |
| Book Leverage | 0.38 | 0.36 | 0.26 | 0.00 | 1.77 | 2453 |
| ROA | 0.14 | 0.14 | 0.11 | -0.87 | 0.54 | 2458 |
| CAPX | 0.04 | 0.03 | 0.04 | 0.00 | 0.42 | 2461 |
| R&D | 0.07 | 0.04 | 0.09 | 0.00 | 0.83 | 2398 |
| *Firm-Month Sample* | | | | | | |
| Num Climate Patent Applications | 5.26 | 2 | 10.26 | 1 | 184 | 11993 |
| Num Climate Patent Granted | 3.90 | 1 | 7.94 | 0 | 115 | 11993 |
| Average Relative Leniency | 0.00 | 0.00 | 0.11 | -0.72 | 0.40 | 11993 |
| CAR[t+1, t+12] (%) | 1.54 | 0.63 | 29.30 | -185.73 | 303.99 | 11842 |
| Market Cap (Log) | 9.93 | 9.96 | 1.70 | 3.20 | 14.62 | 11982 |
| Average Past 12-month Return | 0.01 | 0.01 | 0.03 | -0.17 | 0.40 | 11985 |
| Return Volatility | 0.09 | 0.08 | 0.05 | 0.02 | 0.91 | 11985 |

**Panel D: Firms with Most Climate Patents in Refinitiv**

| Company | Num. Climate Patents |
|---|---|
| Climate Patents – Buildings (Y02B) | |
| General Electric Co | 763 |
| Intl Business Machines Corp | 419 |
| Texas Instruments Inc | 276 |
| Climate Patents – IT (Y02D) | |
| Intel Corp | 3039 |
| Qualcomm Inc | 2631 |
| Intl Business Machines Corp | 2605 |
| Climate Patents – Energy (Y02E) | |
| General Electric Co | 4154 |
| Intl Business Machines Corp | 1349 |
| Ford Motor Co | 833 |
| Climate Patents – Goods (Y02P) | |
| General Electric Co | 1415 |
| Intl Business Machines Corp | 1033 |
| Honeywell International Corp | 845 |
| Climate Patents – Transportation (Y02T) | |
| Ford Motor Co | 4864 |
| General Electric Co | 3520 |
| Raytheon Technologies Corp | 2725 |
| Boeing Inc | 1353 |

## **Table II**: Validity Test of the Instrumental Variable

This table presents validity tests of the instrumental variable: average relative leniency of examiners. In this table we include only climate-related patents. Panel A presents the first stage regression. The regression equation follows Equation (1). We estimate the equation in three different samples: Refinitiv firm-year, firm-quarter, and firm-month sample. Each observation of the sample requires that a firm receives at least one decision about climate patent applications in the specific period of the observation. The dependent variable is the number of climate-related patents granted to the firm in period $t$, where the period can be a month, quarter, or a year. We use a log transformation: $ln(1+x)$. The construction of the instrument follows Equation (2). It is equal to the average relative leniency of examiners who assess the patent applications of the firm. Panel B conducts regressions to check the exclusive condition of the instrument. All firm-level control variables are measured in Year $t-1$. In Panel B the sample is at the firm by year level. The standard errors are double-clustered at the firm and industry-year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

**Panel A: First Stage Regression**

| Dependent Var. | Num Climate Patents Granted | | |
|---|---|---|---|
| Sample | Firm-Year | Firm-Quarter | Firm-Month |
| Average Relative Leniency | 1.127*** | 0.856*** | 0.868*** |
| | (0.187) | (0.0734) | (0.0537) |
| F Test for Weak Instrument | 58.56 | 192.10 | 545.78 |
| Firm Controls | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y |
| Num Patent Application F.E. | Y | Y | Y |
| Num Obs. | 1,351 | 5,005 | 10,666 |
| Adj. $R^2$ | 0.914 | 0.912 | 0.882 |

**Panel B: Exogenous Tests**

| Dependent Var. | Average Relative Leniency[t] | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Environmental Score[t-1] | 0.0162 | | | | | | |
| | (0.0115) | | | | | | |
| Firm Size[t-1] | | 0.0051* | | | | | |
| | | (0.0026) | | | | | |
| CASH[t-1] | | | -0.0262 | | | | |
| | | | (0.0202) | | | | |
| ROA[t-1] | | | | 0.0268 | | | |
| | | | | (0.0245) | | | |
| CAPX[t-1] | | | | | -0.0408 | | |
| | | | | | (0.0641) | | |
| R&D[t-1] | | | | | | -0.0537 | |
| | | | | | | (0.0407) | |
| Average Relative Leniency[t-1] | | | | | | | 0.0269 |
| | | | | | | | (0.0526) |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Pat Application F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 1286 | 1286 | 1286 | 1267 | 1267 | 1224 | 943 |
| Adj. $R^2$ | 0.291 | 0.291 | 0.290 | 0.292 | 0.287 | 0.297 | 0.342 |

**Table III**: Climate Patents and Daily Abnormal Returns

This table presents regressions of daily cumulative abnormal returns. The second stage regression follows the equation:

$$Daily\_CAR[t-k:t+k]_{t,s} = \alpha_1 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}\_High_t + \alpha_2 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}\_Mid_t + \alpha_3 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}\_Low_t + \delta_1 \overline{MCCC}\_High_t + \delta_2 \overline{MCCC}\_Mid_t + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad \text{(B14)}$$

MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). We sort $\overline{MCCC}_t$ into tercile and define three tercile dummies. The dependent variable is the daily cumulative abnormal returns (CARs) from day -$k$ to day +$k$. $k$ is equal to 1 to 3. Abnormal Returns (ARs) are market-adjusted daily returns winsorized in 1% and 99%. The main independent variable is $Num\_ClimatePats\_Granted$, counting the number of climate-related patents issued to the firm during the day $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Climate-related Patents Granted, takes the $ln(1+x)$ transformation. The standard errors are double-clustered at the firm and industry-year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| **Panel A: Climate-related Patents** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Var. | Cumulative Abnormal Return around the Patent Decision Date | | | | | |
| Daily CAR Window | [-1, +1] | | [-2, +2] | | [-3, +3] | |
| Num_ClimPat_Granted × MCCC_High | 0.00627*** | 0.00536*** | 0.00818*** | 0.00722*** | 0.00831*** | 0.00545* |
| *(Instrumented by Leniency)* | (0.00186) | (0.00197) | (0.00236) | (0.00232) | (0.00294) | (0.00284) |
| Num_ClimPat_Granted × MCCC_Mid | 0.00119 | 0.000168 | 0.000741 | -0.00186 | -0.00306 | 0.00158 |
| *(Instrumented by Leniency)* | (0.00212) | (0.00222) | (0.00283) | (0.00314) | (0.00314) | (0.00348) |
| Num_ClimPat_Granted × MCCC_Low | -0.00128 | -0.000252 | -0.00157 | -0.000629 | -0.000701 | -0.00768** |
| *(Instrumented by Leniency)* | (0.00231) | (0.00280) | (0.00285) | (0.00326) | (0.00351) | (0.00368) |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y |
| Num ClimPat App F.E. | Y | Y | Y | Y | Y | Y |
| Industry × Year-Month F.E. | | Y | | Y | | Y |
| Num Obs | 20393 | 19745 | 20393 | 19743 | 20396 | 19735 |

| **Panel B: Other Green (Non-climate-related) Patents** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Var. | Cumulative Abnormal Return around the Patent Decision Date | | | | | |
| Daily CAR Window | [-1, +1] | | [-2, +2] | | [-3, +3] | |
| Num_OtherGreen_Granted × MCCC_High | 0.000451 | 0.00496 | -0.00121 | 0.00266 | 0.00959 | 0.00930 |
| *(Instrumented by Leniency)* | (0.00367) | (0.00408) | (0.00495) | (0.00490) | (0.00584) | (0.00573) |
| Num_OtherGreen_Granted × MCCC_Mid | -0.000295 | -0.00673 | 0.000637 | 0.00218 | -0.000538 | 0.00711 |
| *(Instrumented by Leniency)* | (0.00388) | (0.00499) | (0.00482) | (0.00592) | (0.00496) | (0.00605) |
| Num_OtherGreen_Granted × MCCC_Low | -0.00845 | -0.00622 | -0.00664 | -0.00613 | -0.0132* | -0.0195** |
| *(Instrumented by Leniency)* | (0.00572) | (0.00675) | (0.00578) | (0.00766) | (0.00795) | (0.00929) |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y |
| Num OtherGreenPat App F.E. | Y | Y | Y | Y | Y | Y |
| Industry × Year-Month F.E. | | Y | | Y | | Y |
| Num Obs | 3986 | 3300 | 3984 | 3308 | 3985 | 3299 |

## **Table IV**: Green Patents and Environmental Score

This table studies how exogenous issuances of green patents affect firms' subsequent ESG (Environmental) scores. All regressions are 2SLS regressions. Panels A and B study climate-related and other (non-climate-related) green patents separately. In each panel, the dependent variable is the change of Refinitiv Environmental Score from Year $t$ to $t+k$, where $k$ equals 1 or 2. In Columns (3) to (8), the Refinitiv Environmental Score is further decomposed into three-pillar scores: Emission Score, Resource Use Score, and Innovation Score. The main independent variable is the number of green patents granted and issued to the firm in Year $t$, which is then instrumented by the average examiner's leniency. The main independent variable takes the $ln(1+x)$ transformation. In all regressions, we add Industry × Year, Art Units × Year, and Number of Green Patents Applications (which receive decisions in Year $t$) fixed effects. Firm controls include firm size and R&D expenditure. The standard errors are double-clustered at the firm and industry-year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

$$2nd\ Stage: \quad Envrn\_Score_{i,t+k} - Envrn\_Score_{i,t} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{B15}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{B16}$$

**Panel A: Climate Related Green Patents**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Var. | Environmental Score | | Emission Score | | Resource Use Score | | Innovation Score | |
| | t+1 - t | t+2 - t | t+1 - t | t+2 - t | t+1 - t | t+2 - t | t+1 - t | t+2 - t |
| Num Climate-related Patents Granted | 0.139** | 0.166** | 0.0554 | 0.253*** | 0.0789 | 0.115 | 0.108* | 0.0821 |
| *(Instrumented by Leniency)* | (0.0625) | (0.0799) | (0.0531) | (0.0830) | (0.0545) | (0.0780) | (0.0598) | (0.0898) |
| F Statistic for Weak Instrument | 58.56 | 50.97 | 58.56 | 50.97 | 58.56 | 50.97 | 58.56 | 50.97 |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 1132 | 965 | 1132 | 965 | 1132 | 965 | 1132 | 965 |

**Panel B: Other Green Patents**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Var. | Environmental Score | | Emission Score | | Resource Use Score | | Innovation Score | |
| | t+1 - t | t+2 - t | t+1 - t | t+2 - t | t+1 - t | t+2 - t | t+1 - t | t+2 - t |
| Num Other Green Patents Granted | -0.0337 | -0.0493 | 0.00670 | 0.0132 | 0.0761 | 0.0751 | -0.0732 | -0.104 |
| *(Instrumented by Leniency)* | (0.107) | (0.0962) | (0.112) | (0.0924) | (0.114) | (0.104) | (0.135) | (0.202) |
| F Statistic for Weak Instrument | 22.86 | 30.12 | 22.86 | 30.12 | 22.86 | 30.12 | 22.86 | 30.12 |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 537 | 464 | 537 | 464 | 537 | 464 | 537 | 464 |

## **Table V**: Green Patents and Institutional Ownership

This table studies how exogenous issuances of green patents affect firms' institutional ownership. All regressions are 2SLS regressions. Panels A and B investigate climate-related and other (non-climate-related) green patents separately. The regression sample is at the firm-quarter level. Institutional ownership is defined as a firm's total institutional ownership at the end of quarter $t$ from 13F divided by total shares outstanding from CRSP at the end of that quarter. In each panel, the dependent variable is the change of institutional ownership from quarter $t-1$ to $t+k$, where $k$ equals 0 to 3. The main independent variable is the number of climate patents granted and issued to the firm in quarter $t$, which is then instrumented by the average examiner's leniency. In all regressions, we include Industry × Quarter, Art Units × Year, and Number of Green Patents Applications (which receive decisions in quarter $t$) fixed effects. Firm-level controls follow Figure 2. The standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. MCCC is measured in quarter $t$.

$$\textit{2nd Stage}: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_\widehat{Green\_Pats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{B17}$$

| **Panel A: Climate-related Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Climate Patents Granted | -0.0117 | 0.0416*** | 0.0629** | 0.0710** | 0.0708** | | |
| *(Instrumented)* | (0.0173) | (0.0160) | (0.0265) | (0.0302) | (0.0307) | | |
| Num Climate Patents Granted × MCCC_High | | | | | | 0.0390** | 0.0359* |
| *(Instrumented)* | | | | | | (0.0194) | (0.0212) |
| Num Climate Patents Granted × MCCC_Mid | | | | | | -0.00271 | 0.0169 |
| *(Instrumented)* | | | | | | (0.0182) | (0.0200) |
| Num Climate Patents Granted × MCCC_Low | | | | | | 0.00176 | 0.00725 |
| *(Instrumented)* | | | | | | (0.0115) | (0.0127) |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y |
| Industry × Year-Quarter F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 4745 | 4741 | 4598 | 4456 | 4327 | 4132 | 4114 |

| **Panel B: Other Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Other Green Patents Granted | -0.0262 | 0.00286 | 0.00225 | 0.00888 | 0.0228 | | |
| *(Instrumented)* | (0.0225) | (0.0157) | (0.0251) | (0.0311) | (0.0328) | | |
| Num Other Green Patents Granted × MCCC_High | | | | | | -0.00562 | 0.00140 |
| *(Instrumented)* | | | | | | (0.0132) | (0.0162) |
| Num Other Green Patents Granted × MCCC_Mid | | | | | | 0.00361 | 0.0191 |
| *(Instrumented)* | | | | | | (0.0108) | (0.0129) |
| Num Other Green Patents Granted × MCCC_Low | | | | | | 0.0141 | 0.00670 |
| *(Instrumented)* | | | | | | (0.0125) | (0.0152) |
| All F.E. in Panel A | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 1911 | 1910 | 1841 | 1776 | 1707 | 1665 | 1659 |

**Table VI**: Climate Patents and Environment-Focused Institutional Ownership

This table offers an extensional analysis of Table V Panel A. We only focus on climate patents. We decompose each firm's total institutional ownership into (i) environment-focused institutional ownership (IO) and (ii) other institutional ownership. Environment-focused 13F institutions are institutions with a quarterly environmental footprint above the median score of all institutions in that quarter. The quarterly environmental footprint is the value-weighted average environmental score of the institution's 13F quarterly portfolio. The standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| **Panel A: Environment-focused Institutional Ownership** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Environment-focused Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Climate Patents Granted | -0.0129 | 0.0230** | 0.0347** | 0.0425** | 0.0536*** | | |
| *(Instrumented)* | (0.00979) | (0.0105) | (0.0157) | (0.0173) | (0.0198) | | |
| Num Climate Patents Granted × MCCC_High | | | | | | 0.0953** | 0.0873* |
| *(Instrumented)* | | | | | | (0.0468) | (0.0446) |
| Num Climate Patents Granted × MCCC_Mid | | | | | | -0.00900 | -0.00975 |
| *(Instrumented)* | | | | | | (0.0337) | (0.0356) |
| Num Climate Patents Granted × MCCC_Low | | | | | | 0.0181 | 0.0317 |
| *(Instrumented)* | | | | | | (0.0242) | (0.0252) |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y |
| Industry × Quarter F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 4745 | 4741 | 4598 | 4455 | 4326 | 3857 | 3841 |

| **Panel B: Other Institutional Ownership** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Other Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Climate Patents Granted | 0.00657 | 0.0112 | 0.0219 | 0.0280 | 0.0274 | | |
| *(Instrumented)* | (0.0124) | (0.0113) | (0.0184) | (0.0207) | (0.0207) | | |
| Num Climate Patents Granted × MCCC_High | | | | | | -0.0209 | -0.0235 |
| *(Instrumented)* | | | | | | (0.0362) | (0.0447) |
| Num Climate Patents Granted × MCCC_Mid | | | | | | 0.0218 | 0.0657* |
| *(Instrumented)* | | | | | | (0.0286) | (0.0374) |
| Num Climate Patents Granted × MCCC_Low | | | | | | 0.0122 | -0.00229 |
| *(Instrumented)* | | | | | | (0.0199) | (0.0250) |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y |
| Industry × Year-Quarter F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 4726 | 4723 | 4577 | 4432 | 4295 | 3733 | 3715 |

**Table VII**: Climate Patents and Institutional Investor's Stock Holding Change

This table studies the relationship between climate patents and individual institution's stock holdings. The data is at the institution × stock × quarter level. The dependent variable is the change of stock holding of stock $s$ held by institution $i$ from quarter $t-1$ to $t+k$, where k = 0, 1, and 2. The main independent variable is the number of climate patents newly granted to firm (stock) $s$ in quarter $t$. Institution's quarterly environmental footprint is calculated as the value-weighted average environmental score of the institution's 13F quarterly portfolio. In each quarter, we sort the footprint scores into quintiles. In Panel A, the regression sample requires that an institution is included in the top quintile by carbon footprint in quarter $t-1$ and quarter $t+k$ and that it holds stock $s$ in these two quarters, and analogously for the bottom quintile in Panel B. Stock level controls follow Table V. The standard errors are clustered at the institution × stock level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

$$ln(Shares_{i,t+k,s}) - ln(Shares_{i,t-1,s}) = \alpha Num\_\widehat{ClimPats}\_Granted_{t,s} + \beta \mathbf{X}_{i,t,s} + \mu_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t,s} \tag{B18}$$

| **Panel A: Institutions with Top Quintile EnvrnScore Footprint** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable | Change of Stock Holding by Institution | | | | | |
| Period | t - t-1 | t - t-1 | t+1 - t-1 | t+1 - t-1 | t+2 - t-1 | t+2 - t-1 |
| Num Climate Patents Granted | 0.0375*** | 0.0506*** | 0.0451*** | 0.0538*** | 0.0534*** | 0.0569*** |
| *(Instrumented by Leniency)* | (0.00878) | (0.00992) | (0.0145) | (0.0159) | (0.0186) | (0.0203) |
| Firm Controls | Y | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y |
| Num Clim. Patent Applications F.E. | Y | Y | Y | Y | Y | Y |
| Investor × Quarter F.E. | Y | | Y | | Y | |
| Investor × Stock F.E. | | Y | | Y | | Y |
| Num Obs. | 682528 | 667878 | 581729 | 568384 | 500584 | 488291 |

| **Panel B: Institutions with Bottom Quintile EnvrnScore Footprint** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable | Change of Stock Holding by Institution | | | | | |
| Period | t - t-1 | t - t-1 | t+1 - t-1 | t+1 - t-1 | t+2 - t-1 | t+2 - t-1 |
| Num Climate Patents Granted | -0.0100 | -0.00571 | 0.00560 | -0.0129 | -0.0324 | -0.0633 |
| *(Instrumented by Leniency)* | (0.0257) | (0.0312) | (0.0353) | (0.0412) | (0.0439) | (0.0497) |
| Firm Controls | Y | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y |
| Num Clim. Patent Applications F.E. | Y | Y | Y | Y | Y | Y |
| Investor × Quarter F.E. | Y | | Y | | Y | |
| Investor × Stock F.E. | | Y | | Y | | Y |
| Num Obs. | 403962 | 381445 | 304237 | 287046 | 237191 | 222946 |

**Table VIII**: Climate Patents and CO2 Emission Intensity

This table studies climate patents and CO2 equivalent emissions of climate patent holders. We conduct regressions using the entire Refinitiv ESG firm-year sample, including firms that have never filed any climate patent applications. We conduct simple OLS regressions. The dependent variable is the change of log CO2 emission intensity (the natural logarithm of the ratio of CO2 equivalent emissions on output in million US dollars) from year $t$ to year $t+k$, where $k = 1, 2, 3, 4, 5$. CO2 equivalent emissions are reported by Refinitiv ESG. Emissions (in tons) are Scope 1 emissions. Following Kogan et al. (2017), the total output is the total net sales plus changes in inventories. We adjust the output using the CPI of year 2000 as a basis. We sort climate patents with the patent application year. Furthermore, the firm-level number of patents is adjusted by the total number of granted climate patents applied by all firms in the corresponding year for patent truncation bias. Firm controls include firm size, PPE, and R&D expenditures. Robust standard errors are clustered at the firm and industry-year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| **Panel A: All Climate Patents** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | Δ (Scope 1 CO2 Emissions / Output) | | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00301 | -0.00823 | -0.0186** | -0.0312** | -0.0358** |
| | (0.00298) | (0.00622) | (0.00906) | (0.0131) | (0.0157) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.022 | 0.016 | 0.004 | 0.018 |
| **Panel B: Climate Patents – Transports (Y02T)** | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | Δ (Scope 1 CO2 Emissions / Output) | | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00171 | -0.00419** | -0.00877*** | -0.0154*** | -0.0177** |
| | (0.00126) | (0.00197) | (0.00317) | (0.00587) | (0.00738) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.023 | 0.016 | 0.006 | 0.018 |
| **Panel C: Climate Patents – Goods (Y02P)** | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | Δ (Scope 1 CO2 Emissions / Output) | | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00512 | -0.0128** | -0.0264*** | -0.0402*** | -0.0489*** |
| | (0.00331) | (0.00632) | (0.0100) | (0.0149) | (0.0183) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.022 | 0.015 | 0.005 | 0.022 |

Continued from the Previous Table

**Panel D: Climate Patents – Energy (Y02E)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Var. | $\Delta$ (Scope 1 CO2 Emissions / Output) | | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00598 | -0.0153** | -0.0302*** | -0.0587*** | -0.0699*** |
| | (0.00469) | (0.00764) | (0.00874) | (0.0164) | (0.0239) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.023 | 0.015 | 0.001 | 0.013 |

**Panel E: Climate Patents – IT (Y02D)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Var. | $\Delta$ (Scope 1 CO2 Emissions / Output) | | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.000576 | -0.00258 | -0.00466 | -0.00886 | -0.00837 |
| | (0.00282) | (0.00622) | (0.00872) | (0.0113) | (0.0132) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.081 | 0.053 | 0.061 | 0.100 | 0.087 |

**Panel F: Climate Patents – Buildings (Y02B)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Var. | $\Delta$ (Scope 1 CO2 Emissions / Output) | | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.000265 | -0.00618 | -0.0216 | -0.0273 | -0.0373 |
| | (0.00616) | (0.0107) | (0.0149) | (0.0246) | (0.0311) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.081 | 0.053 | 0.061 | 0.100 | 0.087 |

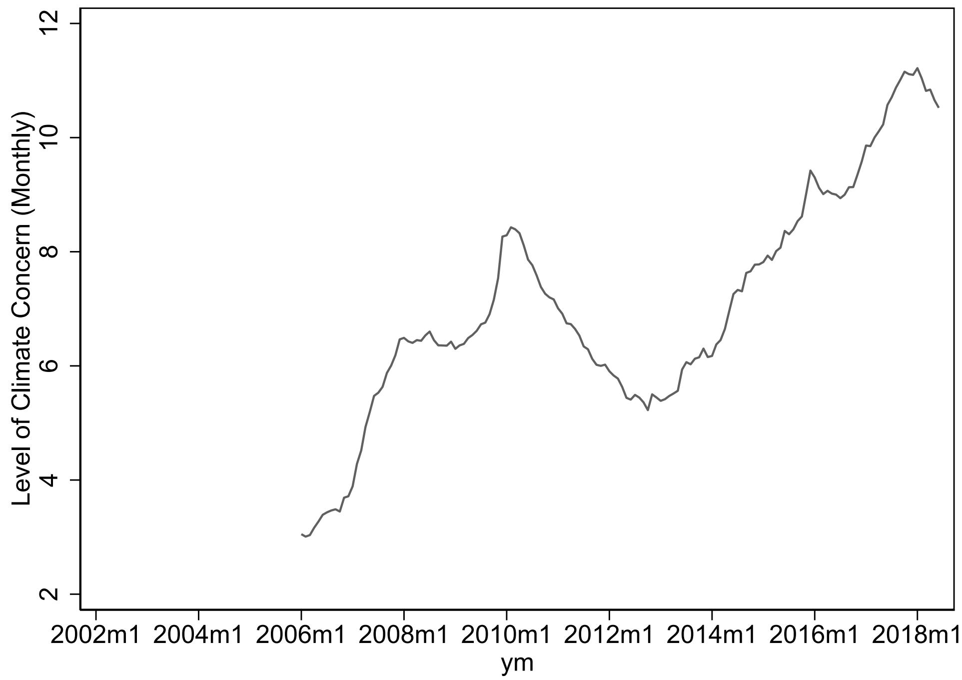
Internet Appendix

# The Impact of Corporate Climate Action on Financial Markets: Evidence from Climate-Related Patents

## List of Figures

# List of Tables

**Figure A1.** MCCC Index (Monthly)




The original MCCC is a monthly index of media coverage of climate changes constructed in Ardia, Bluteau, Boudt, and Inghelbrecht (2020). $\overline{MCCC}_t$ is constructed following the investor's monthly memory model in Pástor, Stambaugh, and Taylor (2022):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \tag{A1}$$

In the above figure, we plot $\overline{MCCC}_t$.

**Figure A2.** Green Patents and Monthly Stock Returns (Include Periods before Granting)

This figure provides a robustness check of the exercise as in Figure 2. The regression design completely follows Figure 2 with the exception that we include 4 months before month $t$. The main independent variable is $Num\_Green\_Pats\_Granted$, counting the number of green patents newly issued to a firm during month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Green Patents Granted, takes the $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Year $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha Num\_Green\_\widehat{Pats}\_Granted_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A2}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A3}$$

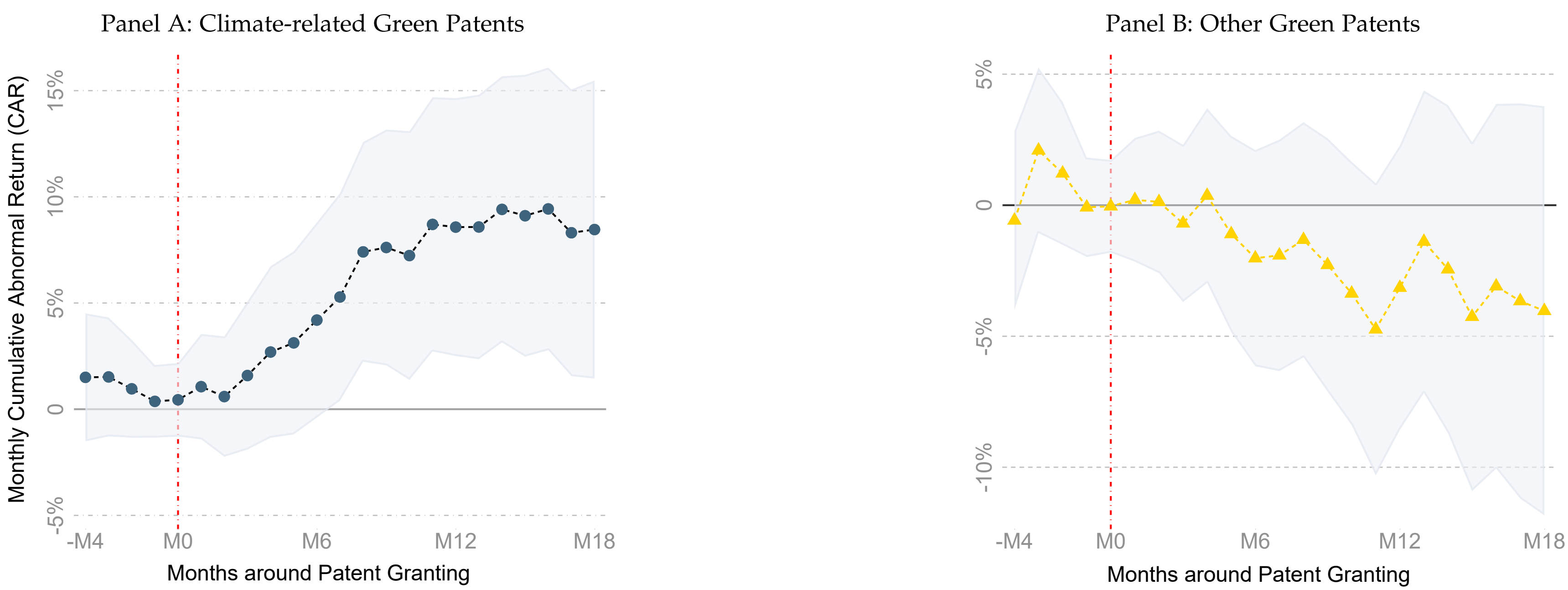


**Figure A3.** Green Patents and Monthly Stock Returns (Fama-French 3-Factor Alpha)

This figure provides a robustness check of the exercise as in Figure 2. The regression design completely follows Figure 2 with the exception that monthly abnormal returns are estimated with the Fama-French 3-factor model. The main independent variable is *Num_Green_Pats_Granted*, counting the number of green patents newly issued to a firm during month $t$. We instrument it using average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Green Patents Granted, takes $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Year $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A4}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A5}$$

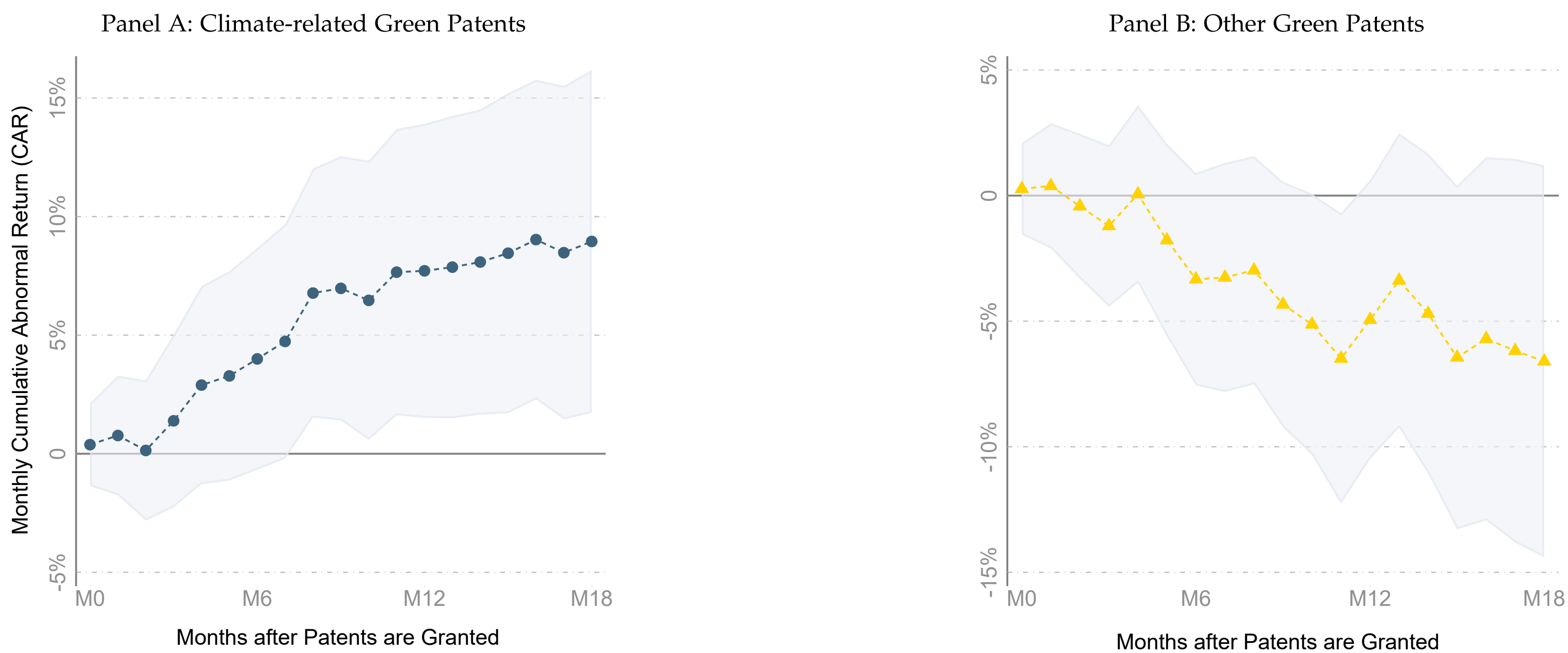


**Figure A4.** Green Patents and Monthly Stock Price

This figure studies how exogenous issuance of green patents drive firm's monthly stock price. Panels A and B study the climate-related and other (non-climate-related) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 0 to 18. Data is at the firm-month level. The sample requires each observation to satisfy that a firm receives at least one decision on its patent applications in that month. The dependent variable is the change of log of stock price from month $t-1$ to month $t+k$. The main independent variable is $Num\_Green\_Pats\_Granted$, counting the number of green patents newly issued to a firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable, Num Green Patents Granted, takes the $ln(1+x)$ transformation. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry × Year × Month F.E., Art Unit × Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm-year and industry-month level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad ln(Price_{t+k,s}) - ln(Price_{t-1,s}) = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad \text{(A6)}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad \text{(A7)}$$

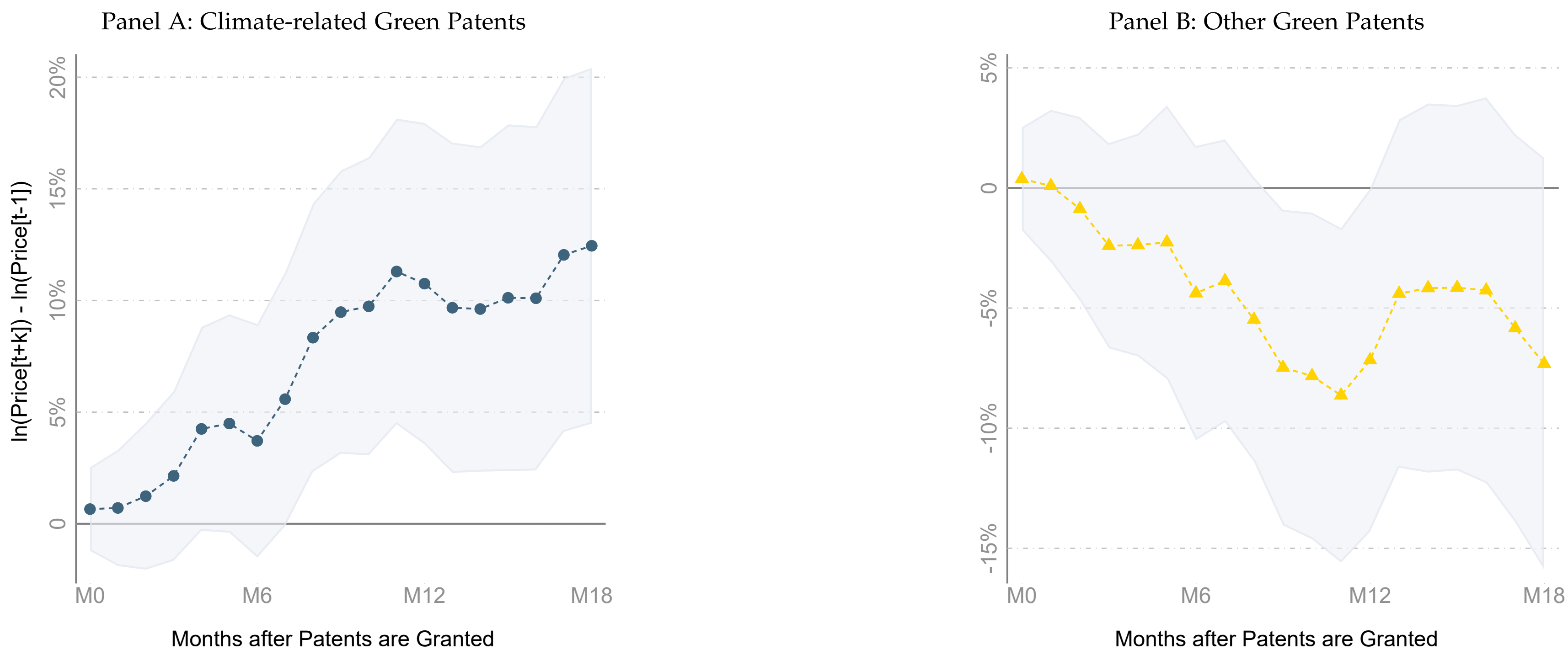


**Figure A5.** Green Patents and Monthly Stock Returns (Extending the Window)

This figure offers an extension of the exercise as in Figure 2. The regression design completely follows Figure 2 with the exception that $k$ is equal to 1 to 36. $\mathbf{X}_{t,s}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Year $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm-year and industry-month level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A8}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A9}$$

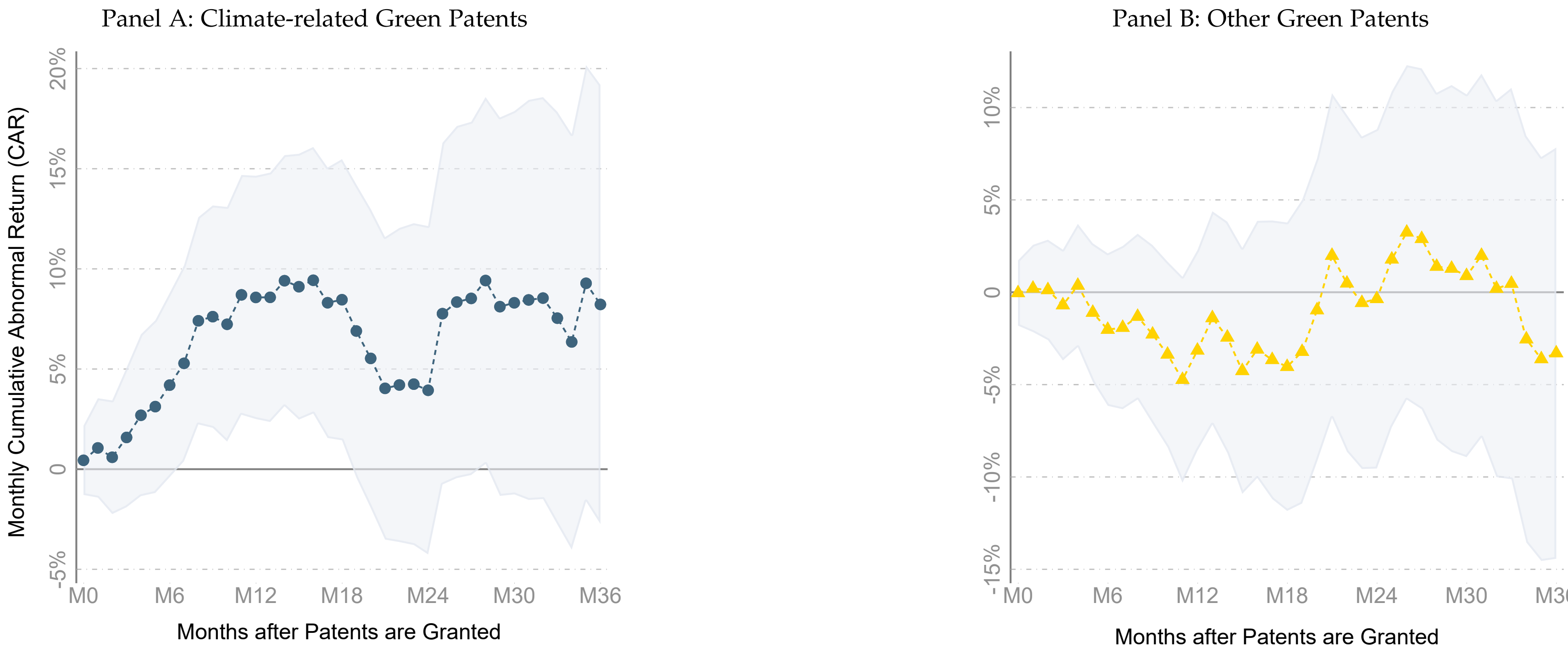


**Figure A6.** Green Patents and Monthly Stock Returns (Using Alternative Methods to Construct Instrument)

This figure presents a robust check of results in Figure 2 with an alternative method to construct our instrument, the examiner's leniency. In this exercise, we only use each examiner's past examination records to calculate the leniency measure. Panels A and B study the climate-related and other (non-climate-related) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 0 to 18. Data is at the firm-month level. The sample requires that a firm receives at least one decision on its green patent applications in that month. The dependent variable is the cumulative abnormal returns (CARs) from time $t$ to time $t+k$. Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). Factor loadings are estimated using the previous 60-month returns data. The main independent variable is $Num\_Green\_Pats\_Granted$, counting the number of green patents issued to the firm during month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. We use a log transformation, $ln(1+x)$, for our main independent variable. Fixed effects include Industry × Year × Month F.E., Art Unit × Year F.E., and the Num of Green Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A10}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A11}$$

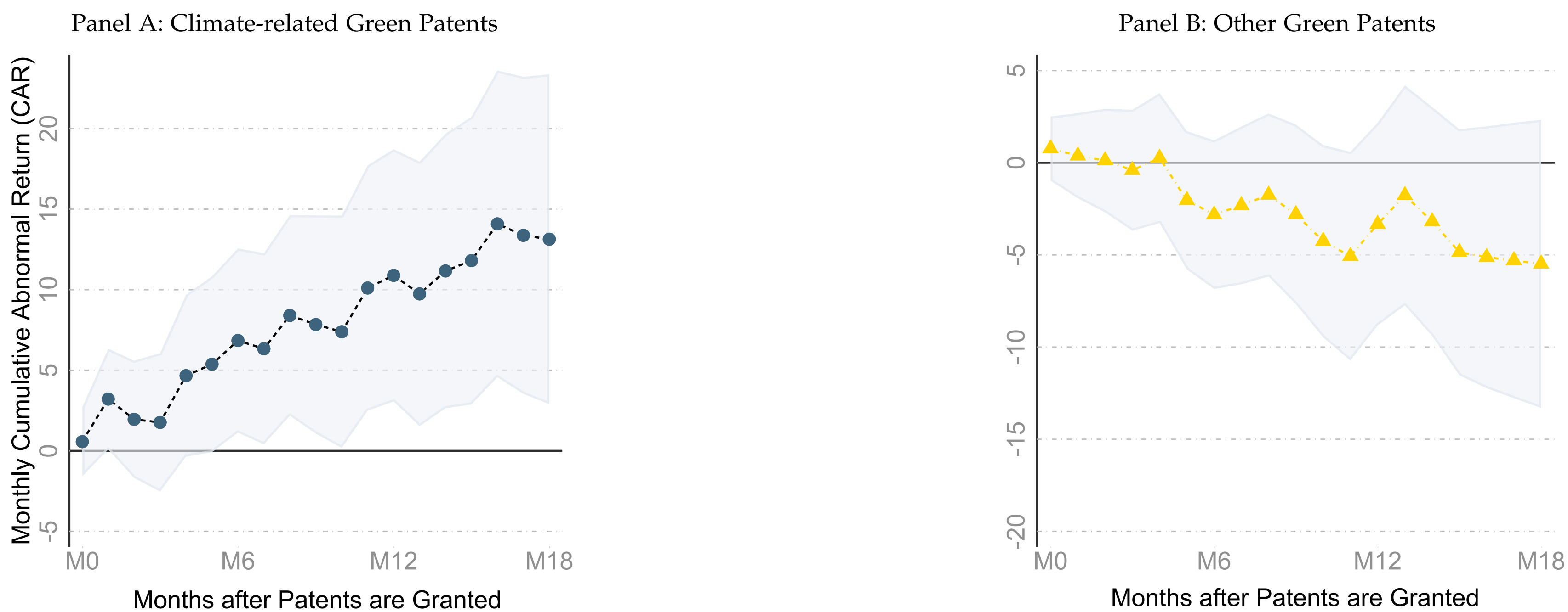


**Figure A7.** Green Patents and Monthly Stock Returns (Russell 1000 Sample)

This figure presents a robust check of results in Figure 2 with a new balanced sample of Russell 1000 index. Russell 1000 Index sample is defined as those firms appear at least once in the Refinitiv ESG from 2002 to 2011. There are 1,301 firms (these may include Russell 1000 firms in 2011 as well as some NASDAQ 100 firms). Then we construct a balanced sample by tracking those 1301 firm's climate patent applications from 2004 to 2020. Panels A and B study the climate-related and other (non-climate-related) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 0 to 18. Data is at the firm-month level. The sample requires that a firm receives at least one decision on its green patent applications in that month. The dependent variable is the cumulative abnormal returns (CARs) from time $t$ to time $t+k$. Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). The main independent variable is $Num\_Green\_Pats\_Granted$, counting the number of green patents issued to the firm during month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. We use a log transformation, $ln(1+x)$, for our main independent variable. Fixed effects include Industry $\times$ Year $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Green Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A12}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A13}$$

Panel A: Climate-related Green Patents

Panel B: Other Green Patents

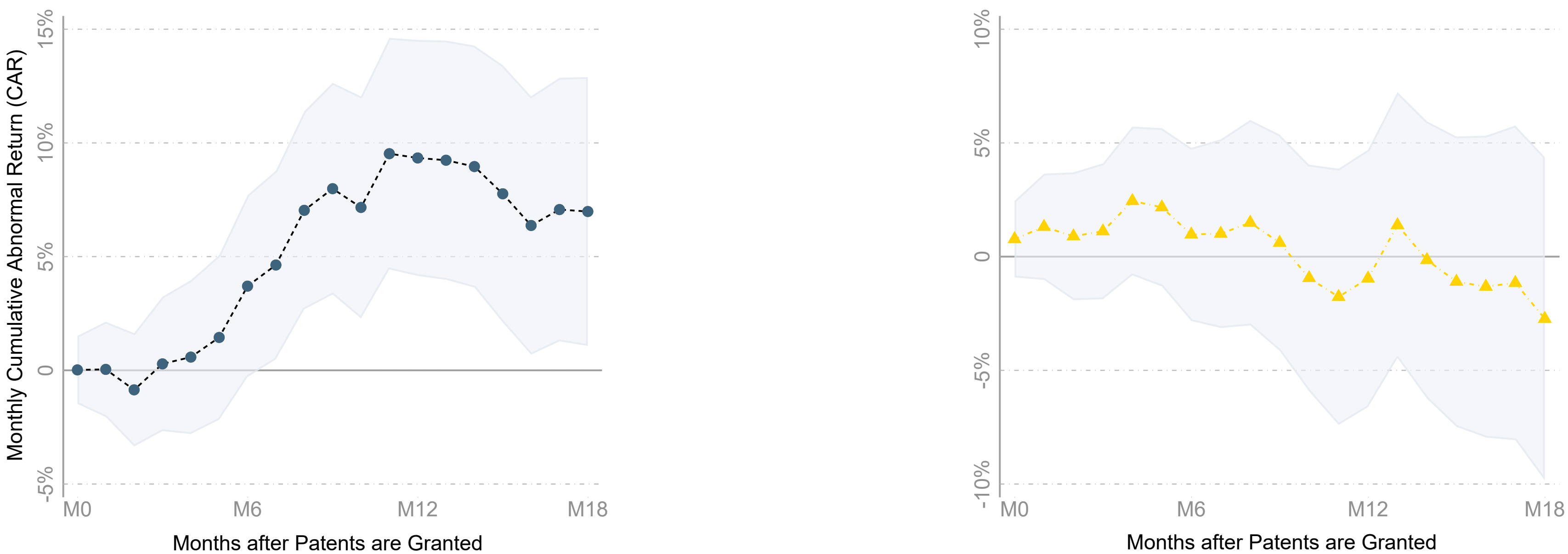


**Figure A8.** Green Patents and Monthly Stock Returns (Russell 3000 Sample)

This figure presents a robust check of results in Figure 2 with a new balanced sample of Russell 3000 index. Russell 3000 Index sample is defined as those firms appear at least once in the Refinitiv ESG from 2002 to 2017. There are 3623 firms (these may include Russell 3000 firms in 2017 as well as some (historical) NASDAQ 100 firms). Then we construct a balanced sample by tracking those 3623 firm's climate patent applications from 2004 to 2020. Panels A and B study the climate-related and other (non-climate-related) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 0 to 18. Data is at the firm-month level. The sample requires that a firm receives at least one decision on its green patent applications in that month. The dependent variable is the cumulative abnormal returns (CARs) from time $t$ to time $t+k$. Abnormal Returns (ARs) are alphas in the Fama-French 5-factor model (Fama and French, 2015). The main independent variable is $Num\_Green\_Pats\_Granted$, counting the number of green patents issued to the firm during month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. We use a log transformation, $ln(1+x)$, for our main independent variable. Fixed effects include Industry × Year × Month F.E., Art Unit × Year F.E., and the Num of Green Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A14}$$

$$1st\ Stage: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A15}$$

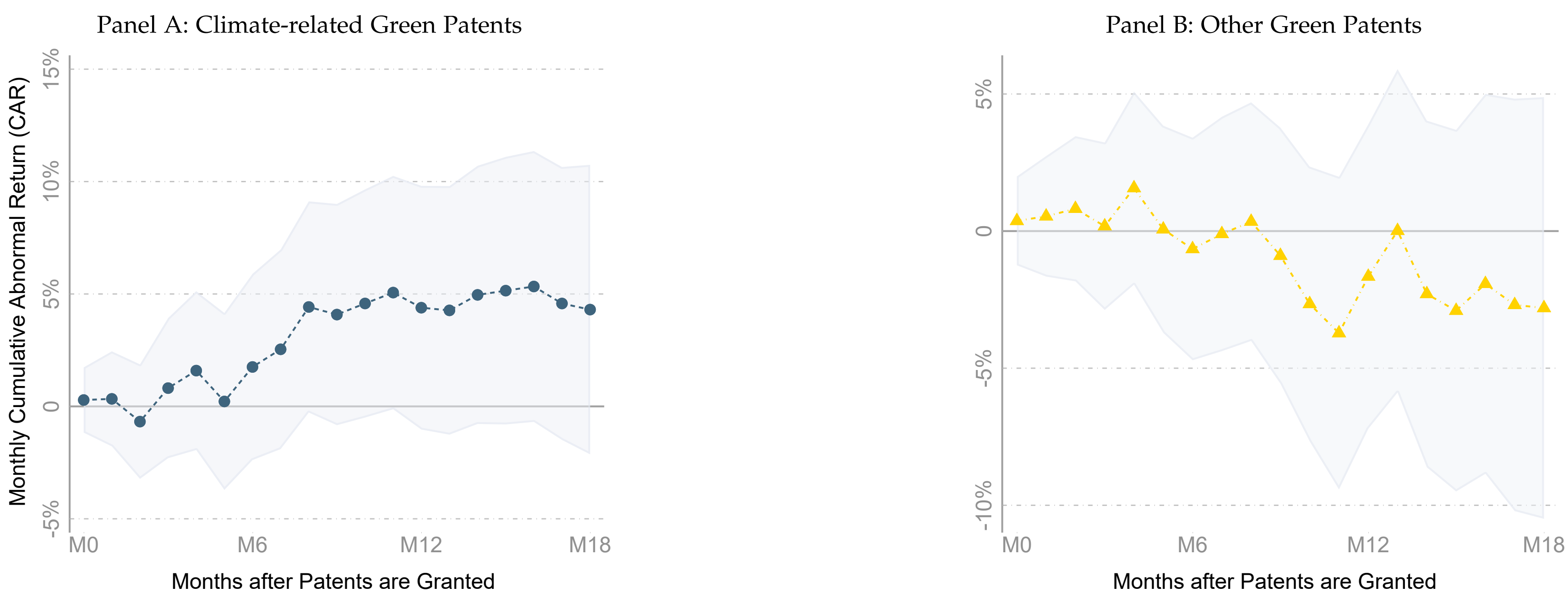


**Figure A9.** Climate-related Patents, Media Coverage of Climate Change, and Stock Returns (Robustness Check)

This figure presents a robustness check of Figure 3. Regression design completely follows Figure 3 with the exception that the $\overline{MCCC}$ is measured in month $t+k$ instead of $t$ as in Figure 3. The second stage regression follows the equation:

$$\begin{aligned} CAR[t:t+k]_{t,s} = {} & \alpha_1 Num\_\widehat{ClimatePats}\_Granted_{t,s} \times \overline{MCCC}\_High_{t+k} + \alpha_2 Num\_\widehat{ClimatePats}\_Granted_{t,s} \times \overline{MCCC}\_Mid_{t+k} + \\ & \alpha_3 Num\_\widehat{ClimatePats}\_Granted_{t,s} \times \overline{MCCC}\_Low_{t+k} + \delta_1 \overline{MCCC}\_High_{t+k} + \delta_2 \overline{MCCC}\_Mid_{t+k} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \end{aligned} \quad \text{(A16)}$$

MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). $\overline{MCCC}_t$ is constructed following the monthly memory model in Pástor et al. (2022):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad \text{(A17)}$$

Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

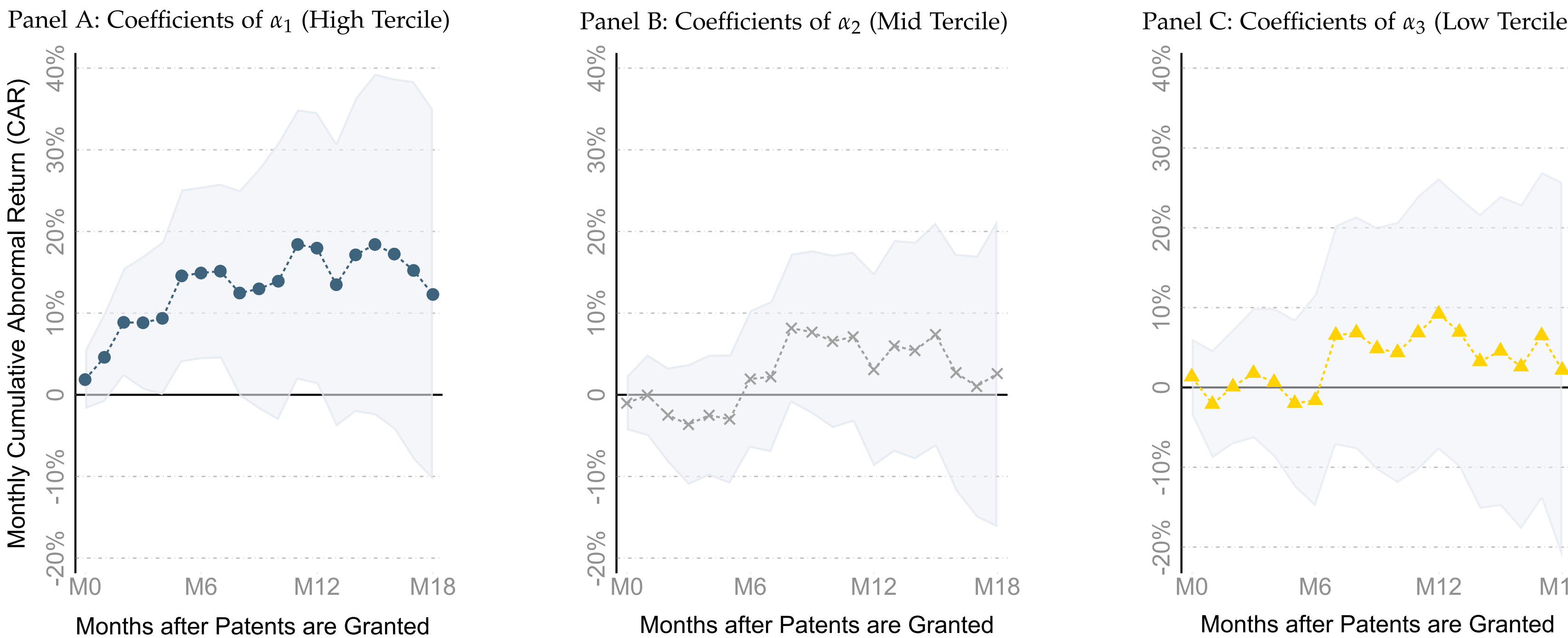


**Figure A10.** Climate-related Patents, Media Coverage of Climate Change, and Stock Returns (Russell 1000 Sample)

This figure presents a robustness check of Figure 3. Regression design completely follows Figure 3 with the exception that we use the Russell 1000 sample to run the same regression. The second stage regression follows the equation:

$$\begin{aligned} CAR[t:t+k]_{t,s} = {} & \alpha_1 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}\_High_{t+k} + \alpha_2 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}\_Mid_{t+k} + \\ & \alpha_3 Num\_Climate\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}\_Low_{t+k} + \delta_1 \overline{MCCC}\_High_{t+k} + \delta_2 \overline{MCCC}\_Mid_{t+k} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \end{aligned} \quad (A18)$$

MCCC is the index of media coverage of climate changes available from Ardia et al. (2020). $\overline{MCCC}_t$ is constructed following the monthly memory model in Pástor et al. (2022):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad (A19)$$

Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

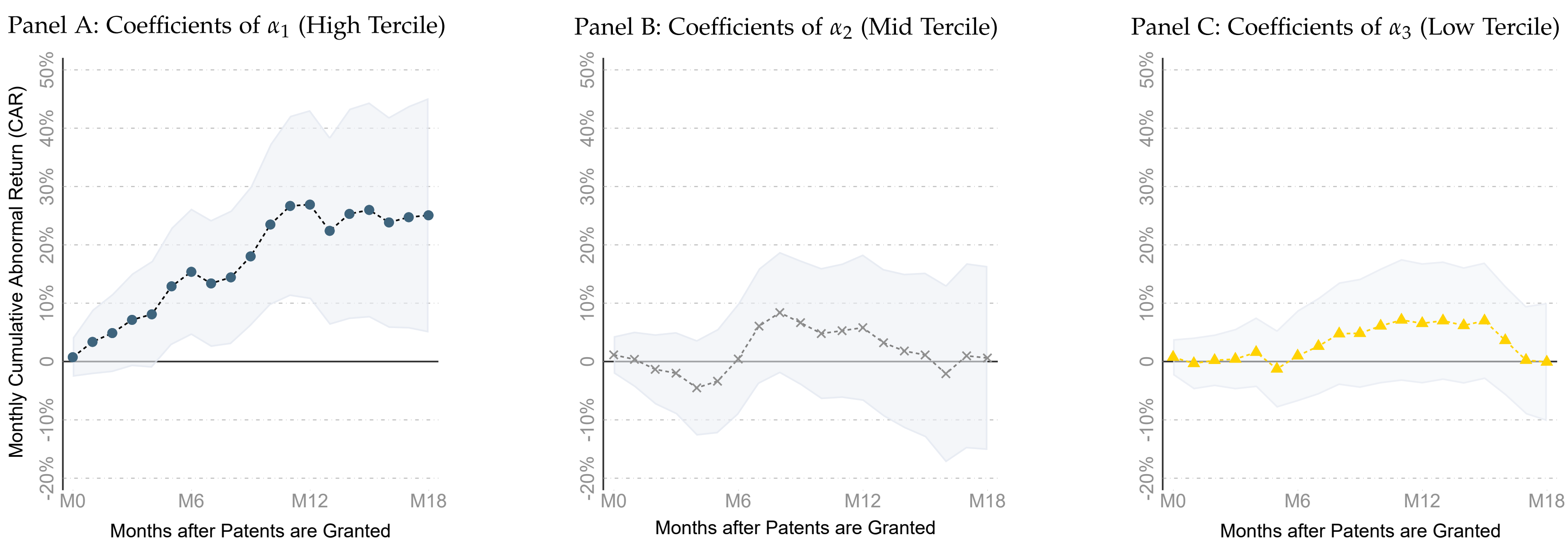


**Figure A11.** Green Patents and Implied Cost of Capital (Robustness Check)

This figure provides a robustness check of Figure 7. The only difference is that we use firm's realized earnings instead of regression-based earning forecasts in the calculation of ICC. Panels A and B study the climate-related and other (non-climate-related) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 1 to 18. Data is at the firm-month level. The dependent variable is changes of ICC from time $t$ to time $t+k$. The main independent variable is *Num_Green_Pats_Granted*, counting the number of green patents newly issued to a firm during month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. Fixed effects include Industry × Year × Month F.E., Art Unit × Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$\text{2nd Stage}: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A20}$$

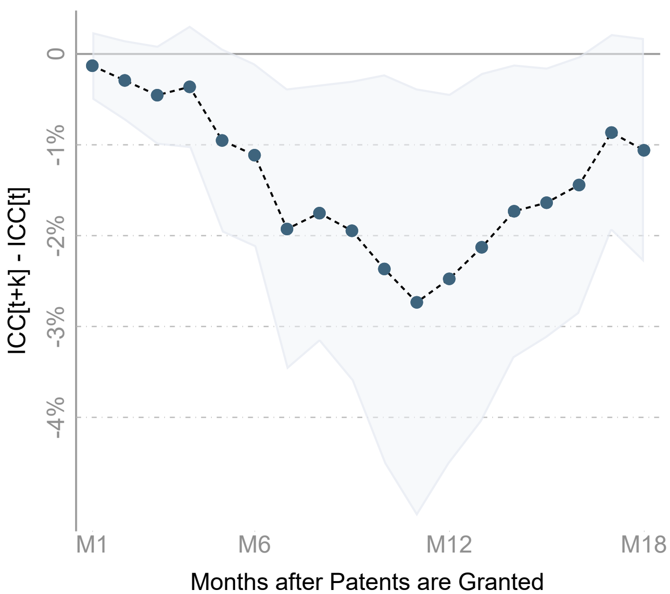
$$\text{1st Stage}: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A21}$$

ICC is calculated following the online appendix procedures of Pástor et al. (2022). We numerically solve and obtain $r$ for each month and year of firms using the following formula:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{A22}$$



Panel A: Climate-related Green Patents




Panel B: Other Green Patents

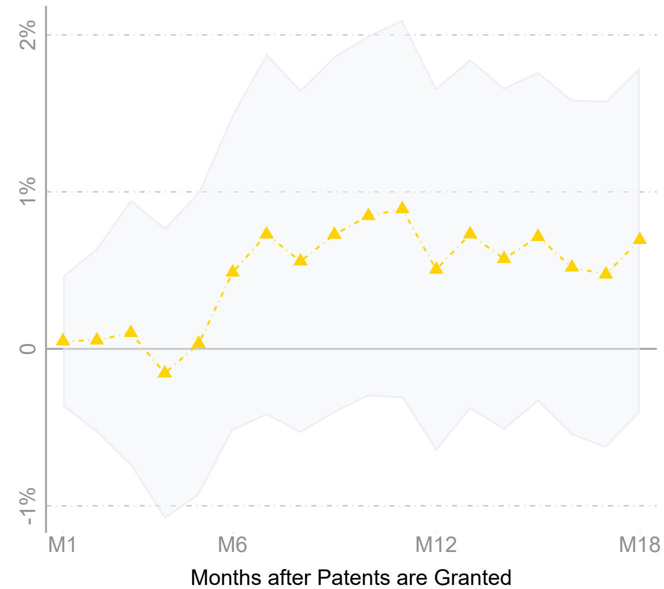


**Figure A12.** Green Patents and Implied Cost of Capital (Russell 1000 Sample)

This figure provides a robustness check of Figure 7. The only difference is that we use the Russell 1000 sample to run the same regression. Panels A and B study climate-related and other (non-climate-related) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients $\alpha$ for each $k$ equal to 1 to 18. Data is at the firm-month level. The dependent variable is changes of ICC from time $t$ to time $t+k$. The main independent variable is $Num\_Green\_Pats\_Granted$, counting the number of green patents newly issued to a firm during the month $t$. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. Fixed effects include Industry $\times$ Year $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Green Patent Applications (Receiving Results in that Month) F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$\textit{2nd Stage}: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A23}$$

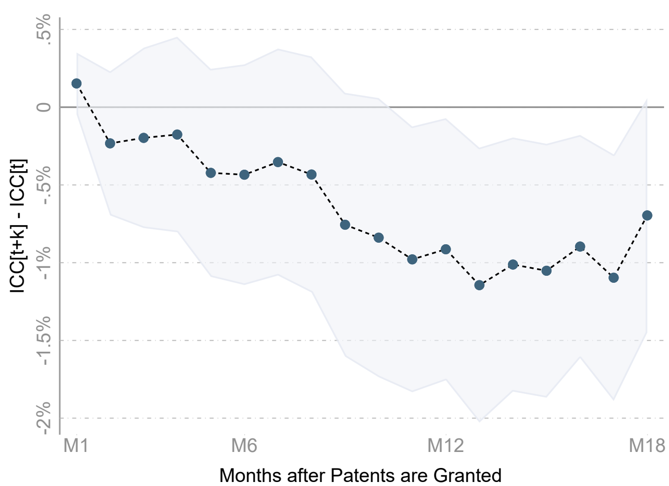
$$\textit{1st Stage}: \quad Num\_Green\_Pats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A24}$$

ICC is calculated following the online appendix procedures of Pástor et al. (2022). We numerically solve and obtain $r$ for each month and year of firms using the following formula:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{A25}$$



Panel A: Climate-related Green Patents




Panel B: Other Green Patents

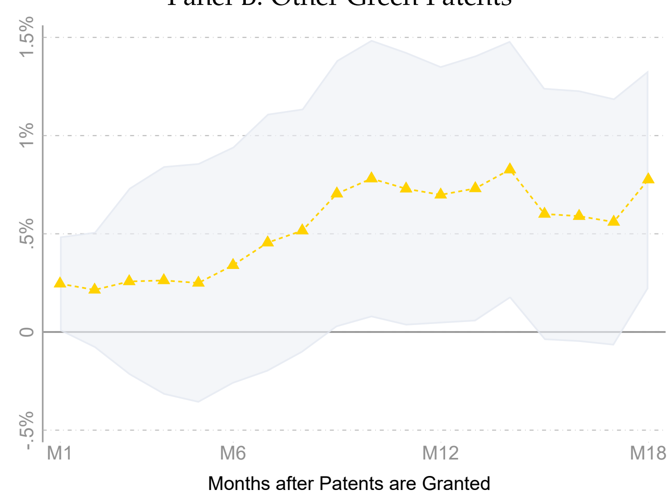


**Table A1** Validity Test of the Instrumental Variable for Other (Non-climate-related) Green Patents

This table presents validity tests of the instrumental variable: average relative leniency of examiners. Panel A presents the first stage regression. We estimate the equation in three different samples: Refinitiv firm-year, firm-quarter, and firm-month sample. Each observation of the sample requires that a firm receives at least one decision about other green patent applications in the specific period of the observation. The dependent variable is the number of other green patents granted to the firm in period $t$, where the period can be a month, quarter, or a year. We use a log transformation: $ln(1+x)$. The construction of the instrument follows Equation (2). It is equal to the average relative leniency of examiners who assess the patent applications of the firm. Panel B conducts regressions to check the exclusive condition of the instrument. All firm-level control variables are measured in Year $t-1$. In Panel B the sample is at the firm by year level. The standard errors are double-clustered at the firm and industry by year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| **Panel A: First Stage Regression** | | | |
|---|---|---|---|
| Dependent Var. | Num Other Green Patents Granted | | |
| Sample | Firm-Year | Firm-Quarter | Firm-Month |
| Average Relative Leniency | 0.913*** | 0.918*** | 0.921*** |
| | (0.232) | (0.102) | (0.0638) |
| F Test for Weak Instrument | 37.94 | 82.10 | 217.26 |
| Firm Controls | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y |
| Num Patent Application F.E. | Y | Y | Y |
| Num Obs. | 557 | 1834 | 3319 |
| Adj. $R^2$ | 0.867 | 0.866 | 0.882 |

| **Panel B: Exogenous Tests** | | | | | | | |
|---|---|---|---|---|---|---|---|
| Dependent Var. | Average Relative Leniency[t] | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Environmental Score[t-1] | -0.0306 | | | | | | |
| | (0.0316) | | | | | | |
| Firm Size[t-1] | | -0.00638 | | | | | |
| | | (0.00363) | | | | | |
| CASH[t-1] | | | 0.0975 | | | | |
| | | | (0.0725) | | | | |
| ROA[t-1] | | | | -0.153* | | | |
| | | | | (0.0844) | | | |
| CAPX[t-1] | | | | | 0.207 | | |
| | | | | | (0.174) | | |
| RND[t-1] | | | | | | 0.105 | |
| | | | | | | (0.0863) | |
| Average Relative Leniency[t-1] | | | | | | | 0.125 |
| | | | | | | | (0.0925) |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Pat Application F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 545 | 545 | 545 | 545 | 545 | 531 | 319 |
| adj. $R^2$ | 0.078 | 0.079 | 0.082 | 0.086 | 0.077 | 0.076 | 0.031 |

**Table A2** The first Stage Stable Tests about the Leniency Instrument

This table provides first stage stable tests about the leniency instrument following Farre-Mensa, Hegde, and Ljungqvist (2020)'s setup (Table 3). We conduct the first stage regressions using the firm by year sample. All control variables are measured in the previous year. The industry by year F.E., art unit by year F.E., and the number of green patent applications F.E. are added in all regressions. The standard errors are double-clustered at the firm and industry by year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Var. | Num Green Patents Granted | | | | | |
| Average Relative Leniency | 1.038*** | 1.014*** | 1.043*** | 1.042*** | 1.055*** | 1.019*** |
| | (0.193) | (0.191) | (0.195) | (0.192) | (0.195) | (0.211) |
| Envrn_Score[t-1] | 0.0536 | | | | | |
| | (0.0594) | | | | | |
| Firm Size[t-1] | | 0.0397*** | | | | |
| | | (0.0120) | | | | |
| CASH[t-1] | | | -0.0959 | | | |
| | | | (0.0882) | | | |
| ROA[t-1] | | | | 0.0847 | | |
| | | | | (0.131) | | |
| CAPX[t-1] | | | | | 0.195 | |
| | | | | | (0.406) | |
| RND[t-1] | | | | | | -0.238 |
| | | | | | | (0.254) |
| Industry × Year F.E. | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y |
| Num Pat Applications F.E. | Y | Y | Y | Y | Y | Y |
| $N$ | 1424 | 1424 | 1424 | 1408 | 1408 | 1363 |
| adj. $R^2$ | 0.918 | 0.919 | 0.918 | 0.917 | 0.918 | 0.916 |

## **Table A3** Green Patents and Trucost Environmental Score

This table studies how exogenous issuances of green patents affect firms' subsequent ESG (Environmental) scores. In this table, we employ the S&P Global ESG scores to conduct robustness checks. All regressions are 2SLS regressions. Panels A and B study climate-related and other (non-climate-related) green patents separately. In each panel, the dependent variable is the change of the Trucost Score from Year $t$ to $t+k$, where $k$ equals 1 or 3. The main independent variable is the number of green patents granted and issued to the firm in Year $t$, which is then instrumented by the average examiner's leniency. The main independent variable takes the $ln(1+x)$ transformation. In all regressions, we add Industry $\times$ Year, Art Units $\times$ Year, and Number of Green Patents Applications (which receive decisions in Year $t$) fixed effects. Firm controls include firm size and R&D expenditure. The standard errors are double-clustered at the firm and industry by year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

$$2nd\ Stage:\quad Envrn\_Score_{i,t+k} - Envrn\_Score_{i,t} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{A26}$$

$$1st\ Stage:\quad Num\_Green\_Pats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{A27}$$

| **Panel A: Climate Related Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Var. | Environmental Score | | Climate Strategy Score | | Environmental Policy Score | |
| | t+1 - t | t+2 - t | t+1 - t | t+2 - t | t+1 - t | t+2 - t |
| Num Climate-related Patents Granted | -5.479 | 0.538 | 11.63 | 4.594** | -16.23 | 0.573 |
| *(Instrumented by Leniency)* | (10.44) | (0.806) | (22.41) | (2.172) | (31.30) | (1.238) |
| Firm Controls | Y | Y | Y | Y | Y | Y |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y | Y |
| Art Unit $\times$ Year F.E. | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y |
| Num Obs. | 169 | 116 | 159 | 105 | 169 | 116 |

| **Panel B: Other Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Var. | Environmental Score | | Climate Strategy Score | | Environmental Policy Score | |
| | t+1 - t | t+2 - t | t+1 - t | t+2 - t | t+1 - t | t+2 - t |
| Num Other Green Patents Granted | -0.185 | -1.493 | -2.098 | -0.859 | -1.520 | -1.556 |
| *(Instrumented by Leniency)* | (1.785) | (0.953) | (3.102) | (3.715) | (1.543) | (1.594) |
| Firm Controls | Y | Y | Y | Y | Y | Y |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y | Y |
| Art Unit $\times$ Year F.E. | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y |
| Num Obs. | 160 | 123 | 123 | 80 | 160 | 123 |

**Table A4**: Green Patents and Institutional Ownership (Using Alternative Methods to Construct Instrument)

This table presents a robust check of results in Table V with an alternative method to construct our examiner's leniency instrument. In this exercise, we use only each examiner's past examination records to calculate the leniency measure. All regressions are 2SLS regressions. Panels A and B investigate climate-related and other (non-climate-related) green patents separately. The regression sample is at the firm-quarter level. Institutional ownership is defined as a firm's total institutional ownership at the end of quarter $t$ from 13F divided by total shares outstanding from CRSP at the end of that quarter. In each panel, the dependent variable is the change of institutional ownership from quarter $t-1$ to $t+k$, where $k$ equals 0 to 3. The main independent variable is the number of climate patents granted and issued to the firm in quarter $t$, which is then instrumented by the average examiner's leniency. In all regressions, we include Industry × Year-Quarter, Art Units × Year, and Number of Green Patents Applications (which receive decisions in quarter $t$) fixed effects. Firm-level controls follow Figure 2. The standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. MCCC is measured in quarter $t$.

$$2nd\ Stage: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_\widehat{Green\_Pats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{A28}$$

| **Panel A: Climate-related Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Climate Patents Granted | -0.0349 | 0.0443** | 0.0690** | 0.0668* | 0.0864* | | |
| *(Instrumented)* | (0.0217) | (0.0191) | (0.0335) | (0.0399) | (0.0493) | | |
| Num Climate Patents Granted × MCCC_High | | | | | | 0.0885 | 0.0778 |
| *(Instrumented)* | | | | | | (0.0612) | (0.0589) |
| Num Climate Patents Granted × MCCC_Mid | | | | | | -0.000806 | -0.00285 |
| *(Instrumented)* | | | | | | (0.0252) | (0.0266) |
| Num Climate Patents Granted × MCCC_Low | | | | | | 0.0122 | 0.00712 |
| *(Instrumented)* | | | | | | (0.0214) | (0.0231) |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y |
| Industry × Year-Quarter F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 4745 | 4741 | 4598 | 4456 | 4327 | 4132 | 4114 |

## **Table A5** Green Patents and Institutional Ownership (Russell 1000 Sample)

This table presents a robust check of results in Table V with the Russell 1000 sample. Panels A and B investigate climate-related and other (non-climate-related) green patents separately. The regression sample is at the firm-quarter level. Institutional ownership is defined as a firm's total institutional ownership at the end of quarter $t$ from 13F divided by total shares outstanding from CRSP at the end of that quarter. In each panel, the dependent variable is the change of institutional ownership from quarter $t-1$ to $t+k$, where $k$ equals 0 to 3. The main independent variable is the number of climate patents granted and issued to the firm in quarter $t$, which is then instrumented by the average examiner's leniency. In all regressions, we include Industry × Year-Quarter, Art Units × Year, and Number of Green Patents Applications (which receive decisions in quarter $t$) fixed effects. Firm-level controls follow Figure 2. The standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. MCCC is measured in quarter $t$.

$$2nd\ Stage: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha \widehat{Num\_Green\_Pats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{A29}$$

| **Panel A: Climate-related Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Climate Patents Granted | -0.00882 | 0.00866 | 0.0413* | 0.0620** | 0.0658** | | |
| *(Instrumented)* | (0.0172) | (0.0143) | (0.0242) | (0.0277) | (0.0288) | | |
| Num Climate Patents Granted × MCCC_High | | | | | | 0.0895 | 0.0798 |
| *(Instrumented)* | | | | | | (0.0612) | (0.0589) |
| Num Climate Patents Granted × MCCC_Mid | | | | | | -0.000806 | -0.00285 |
| *(Instrumented)* | | | | | | (0.0252) | (0.0266) |
| Num Climate Patents Granted × MCCC_Low | | | | | | 0.0122 | 0.00712 |
| *(Instrumented)* | | | | | | (0.0214) | (0.0231) |
| Firm Controls | Y | Y | Y | Y | Y | Y | Y |
| Industry × Year-Quarter F.E. | Y | Y | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y | Y | Y |
| Num Obs. | 4179 | 4178 | 4072 | 3979 | 3880 | 3902 | 3884 |

| **Panel B: Other Green Patents** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable | Change of Institutional Ownership | | | | | | |
| Period | t-1 - t-2 | t - t-1 | t+1 - t-1 | t+2 - t-1 | t+3 - t-1 | t+1 - t-1 | t+2- t-1 |
| Num Other Green Patents Granted | -0.0262 | 0.00286 | 0.00225 | 0.00888 | 0.0228 | | |
| *(Instrumented)* | (0.0225) | (0.0157) | (0.0251) | (0.0311) | (0.0328) | | |
| Num Other Green Patents Granted × MCCC_High | | | | | | -0.00562 | 0.00140 |
| *(Instrumented)* | | | | | | (0.0132) | (0.0162) |
| Num Other Green Patents Granted × MCCC_Mid | | | | | | 0.00361 | 0.0191 |
| *(Instrumented)* | | | | | | (0.0108) | (0.0129) |
| Num Other Green Patents Granted × MCCC_Low | | | | | | 0.0141 | 0.00670 |
| *(Instrumented)* | | | | | | (0.0125) | (0.0152) |

## **Table A6**: Climate Patents and CO2 Emissions (2SLS)

This table presents evidences of the real impact of patenting climate-related technologies. Only climate-related green patents are included in the analysis. All panels present results of 2SLS regressions, and the regression setup follows that in Table **??**. In Panel A, the dependent variable is the change of estimated CO2 emissions divided by total outputs. We use the variable, *En_En_ER_DP*123, in the Refinitive ESG database to capture firms' estimated CO2 emissions. Output equals net sales plus the inventories change, both adjusted by CPI. In Panel B, the dependent variable is a dummy equal to 1 if the firm makes use of renewable energy in its production process. The variable is constructed using the variable *En_En_ER_DP*046 in Refinitive. In Panel C, the dependent variable is equal to 1 if the firm develops and uses clean technology (wind, solar, hydro, geothermal, and biomass power). It is based on *En_En_PI_DP*066 in Refinitive. The standard errors are double-clustered at the industry by year and firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| **Panel A: Estimated CO2 Emissions** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\Delta$ (Estimated CO2 $\div$ Output) | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Related Patents Granted | -0.130 | -0.455 | -0.854 | -0.477 | -0.810 |
| *Instrumented by Leniency* | (0.314) | (0.849) | (1.724) | (0.748) | (0.729) |
| Firm Size | -0.000431 | -0.0187 | 0.0417 | -0.0108 | 0.00273 |
| | (0.0250) | (0.0276) | (0.0756) | (0.0514) | (0.0512) |
| R&D | -0.553 | -1.415** | -2.551 | -1.485 | -2.051 |
| | (0.634) | (0.643) | (1.653) | (1.045) | (1.677) |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Art Unit $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 417 | 395 | 374 | 338 | 299 |
| **Panel B: Use Renewable Energy** | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| I(Renewable Energy) | t+1 | t+2 | t+3 | t+4 | t+5 |
| Num Climate Related Patents Granted | 0.0716 | 0.276 | -0.313 | 0.153 | -0.0131 |
| *Instrumented by Leniency* | (0.270) | (0.241) | (0.403) | (0.358) | (0.416) |
| Firm Size | 0.191*** | 0.186*** | 0.186*** | 0.141*** | 0.101** |
| | (0.0314) | (0.0311) | (0.0361) | (0.0415) | (0.0388) |
| R&D | 0.827 | 1.037* | 0.381 | 1.202 | 0.805 |
| | (0.591) | (0.559) | (0.818) | (0.907) | (0.877) |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Art Unit $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 475 | 454 | 435 | 404 | 385 |
| **Panel C: Develop and Use Clean Energy** | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| I(Use Clean Energy) | t+1 | t+2 | t+3 | t+4 | t+5 |
| Num Climate Related Patents Granted | 0.129 | 0.300 | 0.371 | 0.411 | 0.477 |
| *Instrumented by Leniency* | (0.325) | (0.277) | (0.390) | (0.403) | (0.445) |
| Firm Size | 0.0159 | 0.000969 | -0.00377 | 0.0248 | 0.0118 |
| | (0.0335) | (0.0376) | (0.0350) | (0.0381) | (0.0366) |
| R&D | 0.00750 | -0.237 | -0.242 | -0.332 | -0.137 |
| | (0.426) | (0.479) | (0.524) | (0.472) | (0.535) |
| Industry $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Art Unit $\times$ Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 475 | 454 | 435 | 404 | 385 |

**Table A7**: Climate Patents and Operating Performance (2SLS)

This table studies climate patents and firm's operating performance. All regressions are 2SLS. The standard errors are double-clustered at the industry by year and firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| Panel A | ln(Sale[t+k]) − ln(Sale[t]) | | | | |
|---|---|---|---|---|---|
| | k=1 | k=2 | k=3 | k=4 | k=5 |
| Num Climate Related Patents Granted | -0.0728 | 0.150 | 0.221 | 0.320 | 0.259 |
| *Instrumented by Leniency* | (0.147) | (0.263) | (0.307) | (0.299) | (0.405) |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 904 | 843 | 785 | 746 | 633 |
| **Panel B** | **ln(Profits[t+k]) − ln(Profits[t])** | | | | |
| | k=1 | k=2 | k=3 | k=4 | k=5 |
| Num Climate Related Patents Granted | 0.114 | -0.0551 | -0.0615 | -0.0336 | 0.393 |
| *Instrumented by Leniency* | (0.164) | (0.271) | (0.304) | (0.357) | (0.543) |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 904 | 843 | 785 | 746 | 633 |
| **Panel C** | **ln(Employments[t+k]) − ln(Employments[t])** | | | | |
| | k=1 | k=2 | k=3 | k=4 | k=5 |
| Num Climate Related Patents Granted | 0.0413 | -0.0524 | -0.0273 | 0.00132 | 0.0207 |
| *Instrumented by Leniency* | (0.100) | (0.152) | (0.197) | (0.215) | (0.240) |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 1039 | 982 | 934 | 885 | 741 |
| **Panel D** | **ln(CapStock[t+k]) − ln(CapStock[t])** | | | | |
| | k=1 | k=2 | k=3 | k=4 | k=5 |
| Num Climate Related Patents Granted | 0.104 | 0.249* | 0.213 | 0.252 | 0.311 |
| *Instrumented by Leniency* | (0.0838) | (0.149) | (0.187) | (0.209) | (0.278) |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 1039 | 982 | 934 | 885 | 741 |
| **Panel E** | **ROA[t+k] − ROA[t]** | | | | |
| | k=1 | k=2 | k=3 | k=4 | k=5 |
| Num Climate Related Patents Granted | -0.0266 | 0.0101 | 0.0190 | -0.0282 | 0.0258 |
| *Instrumented by Leniency* | (0.0237) | (0.0375) | (0.0492) | (0.0440) | (0.0937) |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Art Unit × Year F.E. | Y | Y | Y | Y | Y |
| Num Patent Applications F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 1039 | 982 | 934 | 885 | 741 |

## **Table A8** Climate Patents and CO2 Emissions (Robustness)

This table provides the analog of Table VIII but with absolute direct carbon emissions instead of carbon intensity as a measure of corporate climate performance. As we explain in the main text, intensity is a better measure of the real outcome of climate innovation. However, for completeness, we use in this table the absolute level of CO2 emissions. We conduct regressions using the entire Refinitiv ESG firm-year sample, including firms that have never filed any climate patent applications. We conduct simple OLS regressions. The dependent variable is the change of the firm-level CO2 equivalent emissions (reported in Refinitiv ESG) from year t to year t + k, where k = 1, 2, 3, 4, 5. Emissions (in tons) are Scope 1 emissions. We sort climate patents with the patent application year. Furthermore, the firm-level number of patents is adjusted by the total number of granted climate patents applied by all firms in the corresponding year for patent truncation bias. Firm controls include the firm size, PPE, and R&D expenditures. Robust standard errors are clustered at the firm and industry by year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

| **Panel A: All Climate Patents** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | | | Δ (Scope 1 CO2 Emissions) | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00125 | -0.00303 | -0.00827 | -0.0154 | -0.0203 |
| | (0.00411) | (0.00804) | (0.0116) | (0.0174) | (0.0221) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.022 | 0.016 | 0.004 | 0.018 |

| **Panel B: Climate Patents – Transports (Y02T)** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | | | Δ (Scope 1 CO2 Emissions) | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00111 | -0.00100 | -0.00155 | -0.00415 | -0.00649 |
| | (0.00108) | (0.00187) | (0.00288) | (0.00476) | (0.00735) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.023 | 0.016 | 0.006 | 0.018 |

| **Panel C: Climate Patents – Goods (Y02P)** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | | | Δ (Scope 1 CO2 Emissions) | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00427 | -0.0103 | -0.0203* | -0.0329* | -0.0445* |
| | (0.00424) | (0.00806) | (0.0111) | (0.0176) | (0.0230) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.022 | 0.015 | 0.005 | 0.022 |

Continued from the Previous Table

| **Panel D: Climate Patents – Energy (Y02E)** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | | Δ (Scope 1 CO2 Emissions) | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.00223 | -0.00933 | -0.0216* | -0.0413* | -0.0591** |
| | (0.00593) | (0.0101) | (0.0111) | (0.0233) | (0.0294) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.030 | 0.023 | 0.015 | 0.001 | 0.013 |

| **Panel E: Climate Patents – IT (Y02D)** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | | Δ (Scope 1 CO2 Emissions) | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | 0.000785 | 0.000814 | 0.000801 | -0.00271 | -0.000895 |
| | (0.00412) | (0.00814) | (0.0118) | (0.0156) | (0.0186) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.081 | 0.053 | 0.061 | 0.100 | 0.087 |

| **Panel F: Climate Patents – Buildings (Y02B)** | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Dependent Var. | | Δ (Scope 1 CO2 Emissions) | | | |
| Period | t+1 - t | t+2 - t | t+3 - t | t+4 - t | t+5 - t |
| Num Climate Patents | -0.000920 | -0.00468 | -0.0164 | -0.0232 | -0.0327 |
| | (0.00637) | (0.0113) | (0.0154) | (0.0274) | (0.0326) |
| Firm Controls | Y | Y | Y | Y | Y |
| Industry × Year F.E. | Y | Y | Y | Y | Y |
| Num Obs. | 2386 | 1931 | 1599 | 1322 | 1094 |
| Adj. $R^2$ | 0.081 | 0.053 | 0.061 | 0.100 | 0.087 |

# REFERENCES

Ardia, David, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht, 2020, Climate Change Concerns and the Performance of Green versus Brown Stocks, National Bank of Belgium, Working Paper Research 395.

Fama, Eugene F., and Kenneth R. French, 2015, A Five-factor Asset Pricing Model, *Journal of Financial Economics* 116, 1–22.

Farre-Mensa, Joan, Deepak Hegde, and Alexander Ljungqvist, 2020, What is a Patent Worth? Evidence From the US Patent "Lottery", *The Journal of Finance* 75, 639–682.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting Green Returns, *Journal of Financial Economics* 146, 403–424.