Climate Patents and Financial Markets

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Keywords: climate patents, examiner leniency, climate change, implied cost of capital, ESG ratings, responsible investors, CO2 emissions

JEL Classifications: G11, G23, G24, O34

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Climate Patents and Financial Markets*

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1 Introduction

The crucial role of climate innovation in achieving net-zero carbon emissions has been emphasized by international policy institutions[1] and extensively examined in the academic literature.[2] Since 2010, the European and US patent offices have jointly adopted the Y02 tagging scheme for patents contributing to climate mitigation to enhance their visibility, in response to a call of the United Nations Framework Convention on Climate Change (UNFCCC).[3] This tagging system has revealed a substantial level of climate innovation activity, with climate patents accounting for approximately 9% of all U.S. patent grants in 2020. However, in spite of this notable activity in climate patenting and its possible key role in addressing climate change, little is known about its drivers and effects on firms, motivating the need for more research.

This paper aims to contribute to the understanding of climate innovation by examining the reaction of financial markets to the disclosure of climate patents. We ask whether financial markets pay attention to climate patents tagged under the Y02 scheme and whether this attention translates into significant financial gains that provide incentives for the effort of innovating firms.

In particular, we aim to make headway on two closely related issues. First, given the growing attention to climate change, we ask whether the financial market response is specific to climate patents and distinct from that of other patent announcements, including other green patents. We investigate specific climate-related mechanisms and transmission channels that may explain such a distinctive reaction: attention to climate change, firms' climate exposure, environmental ratings, and investors' climate consciousness. We also explore whether investors are willing to accept lower financial returns from climate innovators in recognition of their contribution to social performance.

Second, the existence of climate-specific mechanisms and transmission channels raises concerns about the endogeneity of the financial market reaction to climate patent announcements. For example, firms that are committed to climate-friendly policies and expect to benefit from better

[1] The International Energy Agency (IEA) predicts that half of the greenhouse gas reductions to reach net-zero emissions by 2050 will stem from new technologies that are currently not widely utilized (IEA, 2021). The Intergovernmental Panel on Climate Change (IPCC) acknowledges the pivotal role of climate innovation in its 6th assessment report (IPCC, 2022).

[2] See, e.g., Acemoglu, Aghion, Bursztyn, and Hemous (2012) and Acemoglu, Aghion, Barrage, and Hémous (2023).

[3] See Calel and Dechezleprêtre (2016). The scheme is also known as the Y02/Y04S scheme because it includes the Y04S category of patents dedicated to smart electricity grids. Very few Y04S patents have been granted and they are omitted from our study. Hence we refer to the Y02 scheme for simplicity.

environmental ratings and a positive reaction of climate-conscious investors may engage in more climate innovation activity as part of their overall climate and environmental strategy. Similarly, firms that expect a higher future valuation (and a lower cost of capital) may be more willing to invest in green innovation than financially distressed firms (Xu and Kim, 2022; Hartzmark and Shue, 2023), and firms with better governance may be more successful in managing their climate innovation process and, consequently, enjoy higher returns (Gompers, Ishii, and Metrick, 2003).[4]

Our identification strategy exploits quasi-random shocks in the probability of patent approvals. At the U.S. Patent and Trademark Office (USPTO), patent examiners differ in their person-specific leniency or strictness in granting patents and they are generally assigned to patent applications in a quasi-random fashion (Cockburn, Kortum, and Stern, 2002; Sampat and Williams, 2019).[5] Building on this exogenous variations in examiner leniency, we can abstract from the potential impact of the underlying technologies and focus on the signaling (or information) effect of climate patent approvals due to a lucky draw of lenient examiners. In our panel analysis, we instrument our main variable of interest, the number of new climate patents in period t, with the average leniency of examiners who assess a firm's patent applications, and we compare two similar firms with identical climate patent application frequencies in the same art unit and year but different leniency attitudes of their patent examiners, using fixed effects.[6]

Our main results are as follows. We find that companies that obtain climate patents through fortuitous patent examiner assignments 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.[7] Crucially, we show that the 12-month positive abnormal returns are specific to climate patents. Our results do not carry over to (instrumented) patent announcements in general, and to (instrumented) other green patents that are unrelated to climate change (such

[4]Similar concerns have long vexed the broader study of the link between firms' climate change mitigation effort and financial market reactions, and more generally, the rapidly growing literature on the link between ESG and financial performance (Berg, Koelbel, Pavlova, and Rigobon, 2021). We argue that the institutional details of the patent review process provide a unique opportunity to address this challenge that looms large in the literature linking ESG performance and financial performance.

[5]The quasi-random assignment of examiners is prevalent at most USPTO art units. Patent applications are assigned to art units of patent examiners by technological specialization. There are about 900 art units, a rather granular partition of the technology space.

[6]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 leniency instrument.

[7]The per-patent calculation is a rough estimate, as we will discuss later.

as water saving and pollution abatement). The contrast is striking. It demonstrates the particular role of climate action in companies' interaction with financial markets. Our findings are specific to climate innovation and are not due to a general tendency of markets to react positively to random variations in patent grants.

To better understand the specific financial market response to climate innovation, we conduct a series of additional investigations. We consider the effect of changes in public attention to climate change by using the MCCC index, a daily index of climate coverage and negativity in leading U.S. newspapers (Ardia, Bluteau, Boudt, and Inghelbrecht, 2020). We find that abnormal returns after (random shocks in) patent approvals are significantly higher (approximately 20%) in periods of high attention to climate change (top tercile), but are statistically insignificant during periods of lower climate attention. We also investigate whether there are firm-specific variations in this reaction. To do so, we consider firms' exposure to climate change. We divide the sample into two groups, employing the measure of Sautner, van Lent, Vilkov, and Zhang (2020): firms with above-median and with below-median exposure to climate change. We find that the medium-term abnormal returns are only significantly positive for firms with high climate change exposure. By contrast, firms with low climate risk also display an increase in their returns, but it is not statistically significant. These findings corroborate the interpretation that the positive abnormal returns after fortuitous climate patent grants are specifically related to climate change issues.

In addition, we show that the financial market response is strongest for a firm's initial set of climate patents. This finding corroborates the interpretation that climate patent grants have a signaling effect about the firm's commitment to mitigate climate change. Specifically, we find that during their first ten climate patents (the lowest tercile of firm years by climate patent stock), firms experience a significant abnormal stock return of up to 20%. However, this effect diminishes and is no longer statistically significant for firms with a larger stock of climate patents.

After analyzing realized returns, we turn to their counterpart, expected returns. We use the implied cost of capital (ICC) to measure expected returns and find that a one standard deviation increase in the number of new climate patents issued is associated with a decline in the ICC of approximately 0.9% over the subsequent 12 months. Thus, the positive abnormal returns are accompanied by a concomitant decrease in the ICC over roughly the same time horizon. Importantly, further analysis confirms that the decrease is most pronounced (and only consistently significant) when patents are granted during peak periods of public attention to climate change. This finding is consistent with the idea that the temporary change in ICC is mainly the effect of financial market reaction, rather than an anticipation of a reduction in future risks that could lower the cost of capital, such as risks related to environmental litigation or controversies (Chava, 2014).

To investigate the drivers of the stock market reaction to climate patenting, we examine two non-exclusive transmission channels: the demand-driven price pressure of institutional investors (Gibson Brandon, Krueger, and Mitali, 2020) and the response of ESG rating agencies.

With regard to the institutional investors channel, we find that institutional investors react positively to climate patent news. A one standard deviation increase in the number of patent grants leads to an approximately 6% increase in total institutional ownership within one year. This increase steadily rises over the first four quarters following patent grants. Importantly, the effect is significant only during periods when there is heightened attention to climate change. Next, we rank investors based on their revealed preferences for environmental issues, using the value-weighted LSEG Environmental Score of their portfolio holdings, as proposed by Gibson Brandon et al. (2020). Our findings indicate that only institutions with an above-average environmental focus adjust their portfolio holdings following climate patent grants. Again, this adjustment is observed only during periods of heightened attention to climate change. In conclusion, we argue that institutional investors demand likely contributes to the positive reaction in stock prices.

Regarding the ESG ratings channel, we assess the response of environmental ratings from prominent ESG rating agencies, including LSEG ESG (formerly Refinitiv ESG), MSCI, and S&P Global ESG. We find that these rating agencies react favorably to lucky climate patent grants by raising their environmental scores, thereby giving a boost to stock prices (Pástor, Stambaugh, and Taylor, 2022).

We conduct similar tests for general (non-climate) patents and other green patents. We do not find any evidence of higher realized returns, lower expected returns, increased institutional investor holdings, or higher ESG ratings for either general patent or other green patent grants. All our results suggest that the observed financial market reactions are unique to climate patents.

We then turn to real effects of climate patent announcements, in order to investigate other possible drivers of our main result of positive realized stock returns. Specifically, we explore the cash flow channel, the idea that climate innovation leads to improvements in firms' operating performance. Using a variety of measures, we find that there are no statistically significant changes, suggesting that significant realized returns after lucky climate patent grants are unlikely to be driven by changes in expected cash flows. Another possible explanation is the risk channel, explaining a lower discount rate for future cash flows. As a measure of the effect of climate patents on firms' exposure to climate risks, we look at the impact on future CO2 emissions and energy use. Again, we find that random shocks to patent grants have no significant effect, suggesting that fortuitous climate patent grants are unlikely to reduce firms' future carbon risks (Bolton and Kacperczyk, 2021). Our earlier findings of a reduced implied cost of capital may thus reflect non-pecuniary benefits for ESG-minded investors rather than a lower risk premium.[8] This interpretation is in line with experimental evidence of that investors are willing to pay and invest more in assets that are associated with a positive impact on ESG issues (Brodback, Guenster, Pouget, and Wang, 2020; Humphrey, Kogan, Sagi, and Starks, 2021; Bonnefon, Landier, Sastry, and Thesmar, 2022).

Finally we look at the effects of non-instrumented raw climate patent counts as measure of increased climate innovation. This enables us to explore the real impact of the underlying climate-related technologies, independently of the granting of patent protection for these technologies. We find significant improvements in operating performance, in line with similar effects documented in the literature for non-climate patents (Kogan, Papanikolaou, Seru, and Stoffman, 2017), and also significant reductions in direct (Scope 1) emission intensity starting in year 3 after the climate patent application. Thus, in line with our interpretation of the signal value of climate patents, we find that improvements in climate innovators' operating performance and carbon efficiency are linked to the underlying technology and not to the innovator being granted patent protection.

Our paper contributes to four strands of the literature. First, our work is closely related to a small set of papers looking at the association between green patents and financial performance. These papers do not provide any clear evidence in favor of a positive reaction to climate patents. In event studies for the U.S. and green patents generally, Andriosopoulos, Czarnowski, and Marshall (2022) find no evidence that investors value green innovation when comparing green patents with other patents. Kuang and Liang (2022) show that firms with high carbon risk and low climate patent activity significantly underperform relative to benchmark firms, whereas firms with similar carbon risk but high climate patent activity show no abnormal performance. Dechezleprêtre, Muckley, and Neelakantan (2019) find that some climate patents (dirty patents, defined to be in a narrow set of patent classes) are associated with a decrease in firm value (Tobin's Q) whereas other patents are

[8]This interpretation, however, must be viewed with utmost caution since we only look at one dimension of firm risk, the exposure to future climate risk, and measure it imperfectly (carbon emissions).

associated with an increase. Reza and Wu (2023) specifically focus on the role of environmental regulation and firms' exposure to regulatory risk and find that both positively affect the value of green patents in general (not directly related to climate change). We make several contributions. In contrast to earlier work, our instrumental variable approach allows us to uncover a significant medium-term abnormal return to climate patent announcements and also to establish a causal effect. We show that this reaction is specific to climate patents and not present for other green patents or patents in general, and we also find an effect on short-run realized returns and on the cost of capital. We are able to link these reactions to climate-specific determinants (attention to climate change and climate exposure) and transmission channels (environmental ratings and climate-conscious investors).

Second, several papers investigate the link between green patents and environmental performance. Cohen, Gurun, and Nguyen (2021) document that listed firms in the energy sector produce many green patents but receive lower ESG ratings and are frequently excluded from the investment scope of ESG funds. Extending the analysis to non-listed firms, Dalla Fontana and Nanda (2023) show that climate patents granted to venture capital-backed firms represent a small share of climate patents but that these patents are more likely to cite fundamental science and to be subsequently cited. 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 (2023) focus on the determinants and the emission impact of corporate green innovation and show that in general, green innovators do not lower their subsequent carbon innovations, whereas Hege, Li, and Zhang (2023) show that climate product innovations produce a significant reduction in carbon emissions at customer firms. We contribute to this literature by showing that the causal impact of climate innovation on financial rewards is more pronounced for firms with higher climate risk exposure and during periods of heightened attention to climate change.

Third, our paper is also related to the literature on corporate innovation and stock returns. Kogan et al. (2017) investigate the market response to patent approval news and measure patent valuations. 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) find that exploitative innovation strategies allow firms to enjoy higher abnormal returns. We contribute to this literature the finding of positive short-term and long-term abnormal returns of fortuitous climate patent grants.

Finally, our paper speaks to the broader literature on the relationship between climate and 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. In, Park, and Monk (2019) find that firms with low relative (revenue-adjusted) emissions experience positive abnormal return over the period 2010-2015.[9] 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, Li, and Tsou (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. Our contribution to this literature is that we establish a causal link between one dimension of corporate climate action and various financial market responses, using the patent examiner instrument.

The rest of the paper proceeds as follows. Section 2 describes the data and summary statistics, and Section 3 develops our key identification strategy. Section 4 provides our main results on financial market reactions, and Section 5 offers evidence on the underlying mechanisms. Section 6 presents further results on the real effects of climate patents, and Section 7 concludes.

2 Data and Sample Construction

2.1 Data on Climate Patents

We construct our dataset of climate 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. We also construct two comparison samples, one for the universe of patent applications (general patents) and another sample for other green (non-climate) 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, de-

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

cision date, the examiner who assesses the focal patent application, and the examiner's technology art unit for each US utility patent application.[10] We define the decision date of a patent application as the grant date when 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.[11]

PatEx does not provide any information on the owner of each patent application (the assignee) or on Cooperative Patent Classification (CPC) codes. For these missing items, we obtain assignee information from the USPTO Patent Assignment database by matching PatEx with the application numbers and using only employee-to-employer assignments with a single assignee. We obtain each application's CPC codes from PatentsView.

We then match each assignee of a patent application to CRSP/Compustat listed firms, applying the matching concordance provided by Arora, Belenzon, and Sheer (2021).[12] Since the concordance only covers granted patents, we expand the matched 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.[13] 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%. Appendix B provides details.

The final step is to identify climate patents in this set of 1,316,275 patent applications. In 2010, the USPTO and the European Patent Office 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

[10] 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.

[11] 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.

[12] We use the concordance provided by Arora et al. (2021) instead of the one by Kogan et al. (2017) because (i) Arora et al. (2021) also include patents filed by private subsidiaries of listed corporations, and (ii) they consider various name changes of public firms in their (patent assignee)–(firm name) fuzzy matching which according to Arora et al. (2021) significantly improves the matching. See Appendix B for details.

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

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 patents as patents tagged with one of the following "Y02" categories: Y02B (Building), Y02D (ICT), Y02E (Energy), Y02P (Production Process), and Y02T (Transportation).[17]

To identify other (non-climate) green patents, we employ the methodology developed by the OECD (Haščič and Migotto, 2015). We classify a patent application as "other green patent" if at least one of its CPC codes falls into the set of green patents defined by Haščič and Migotto (2015) and if it is not tagged with a "Y02" label.[18]

Table 1, Panel A, provides summary statistics for our sample of green patent applications. In total, there are 66,796 climate patent and 19,567 other green (non-climate) patent applications (together about 5% of the patents in our dataset) with a 73% granting rate. Panel A provides statistics for climate and other green patent applications separately. Climate patents have a lower granting rate on average and a longer time window from application to decision dates. Panel B tabulates the top five FF-48 (Fama-French) industries with the largest number of climate and other green patent applications, separately. The energy sector contributes a lot to green patents as highlighted in Cohen et al. (2021).[19] Panel C shows that firms obtain on average 22.72 (5.26) patent decisions in a year (month) with climate patent decisions.

In Figure 1, Panel A, we plot the annual number of climate patents granted for the five Y02 subcategories that we consider. This number grew quickly over the sample period. Consistent with Table 1, Panel A, the transportation sector encompasses the most climate patents, followed

[14] Dalla Fontana and Nanda (2023) confirm that Y02 patents are indeed climate patents by applying text-based analysis to their titles.

[15] Climate patents may reduce CO2 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 (CO2 capture and storage), Y02W (wastewater treatment) and Y04S (smart girds) since the number of patents in these groups is very small. Our results go through if we include these patents.

[18] The OECD defines three categories of other green patents: patents for environmental management technologies, water-related adaptation technologies, and bio-diversity protection technologies.

[19] Our sample differs somewhat from Cohen et al. (2021) since (i) we focus on application data, containing both issued and rejected patents; (ii) we include the recent expansion of the Y02 scheme and include the new subcategories Y02D and Y02P; and (iii) we cover a different time period.

by energy and IT. Figure 1, Panel B, displays the annual number of patent applications with a decision, by application year.[20]

2.2 Data on ESG Ratings, Institutional Ownership, and Stock Returns

We collect ESG data from LSEG ESG (formerly Refinitiv ESG)[21] and MSCI ESG, and for robustness also from S&P Global ESG. For LSEG ESG, we use the Environmental Score (*envrnscore*), an industry-adjusted and percentile ranking score, as our primary metric for firm-level environmental performance. The coverage of LSEG ESG is S&P 500 plus NASDAQ 100 during 2003 – 2009, and later it expands to Russell 1000 in 2010, and Russell 3000 in 2017.[22] LSEG splits the Environmental Score into three sub-scores (pillars): emissions, resource consumption, and innovation. The scores for all three pillars are percentile-ranked. We obtain data on the direct (Scope 1) CO2 equivalent emissions from LSEG. As a robustness check, we also employ MSCI Environmental ratings which ranges from 0 to 10 as well as S&P Global ESG rankings.[23]

We merge our climate patents data with the LSEG 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 1, Panel C provides summary statistics. In our final matched sample, there are 419 unique firms receiving 56,150 decisions about their climate 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.[24] Since both the number of patent applications and

[20]The sharp decrease in patent applications with a decision by the end of the sample period reflects the classical truncation bias well-known in the patent literature (Lerner and Seru, 2021): most applications filed between 2018 and 2020 have not yet received decisions at the time of our analysis. Our paper is largely immune to this truncation bias since our main variables are based on the patent *decision year*, not the *application year*.

[21]Data provider LSEG was known as Refinitiv until August 2023, and as Thomson Reuters prior to 2018.

[22]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. A possible interpretation is that markets pay more attention to climate patent signals of larger firms that play a more prominent role in corporate actions to mitigate climate change.

[23]The robustness of our results indicates that they do not seem to depend on issues related to the backwards updating of LSEG ESG data, see Berg, Fabisik, and Sautner (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 LSEG ESG scores, namely the tests in Section 5.1. See the discussion there.

[24]The average number of years in which a firm has at least one climate patent is 5.93. The average number

granted patents are highly skewed, we take the natural logarithm of these two variables ($ln(1+x)$) in all subsequent regression analyses. Alternatively, we also run Poisson regressions without the log transformation. All variable definitions are in Appendix A.

We get institutional investors' stock holdings data from the LSEG 13F Database. Following Gibson Brandon et al. (2020), we calculate each institution's quarterly portfolio Environmental Score as the value-weighted average (LSEG) Environmental Score of its holding portfolio in that quarter.[25] 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 shares outstanding 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.[26]

3 Identification Strategy

3.1 Institutional Background of Patent Examinations

We brief introduce the institutional background of patent examinations.[27] Examinations 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) and Sampat and Williams (2019) 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. Crucially, 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

of months in a given year in which a firm has climate patents is 3.97.

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

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

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

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. This strategy allows us to isolate a potential signaling or information effect of green patents from the impact of the underlying invention.

Since we want to identify the effect of exogenous shocks in climate patent grants on financial markets, it is important to choose the right date in the patent application process when the patent signal becomes publicly known. There are three possible dates to be considered that are associated with the three key steps of a patent examination: the application date when the patent application is filed with the USPTO, the date of the first action letter,[28] and the date of the final decision. When the patent is granted in the final decision, the USPTO makes the decision public and the patent signal about the value of the underlying technology becomes publicly known. Since our empirical design focuses on signaling effects, we choose the date when the signal about a patent approval is reliably made public and study the financial market reaction to the patent signal at this date. In line with the literature using the patent examiner instrument (Sampat and Williams, 2019), our identifying assumption is that the market reaction to the patent signal does not fully correct for the examiner's leniency.[29]

3.2 Identification: Average Leniency of Patent Examiners

In this section, we formally introduce our main identification strategy. We implement the random leniency assignment developed by Sampat and Williams (2019) in a firm-time period sample, where the time period can be a year, a quarter, or a month[30]. We illustrate it 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 LSEG ESG dataset. We conduct a two-stage least-squares (2SLS) regression analysis with the following first stage:

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

[28] About 87% of first action letters contain a non-final decision that asks that the patent applicant revise the patent claims and descriptions.

[29] This assumption would only be invalid if investors were able to infer the shock to the patent signal arising from the patent examiner lottery. This would not only require that the examiner name is immediately available, but in addition comprehensive and detailed data and sophisticated analysis: investors would need to track an individual examiner's leniency and be able to benchmark it against the expected mean leniency of the same art unit and time period. Finally, a sufficient mass of investors would have to do so to have a neutralizing effect on the market response.

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

where $Num\_ClimPats\_Granted_{i,t}$, the number of climate patents granted by USPTO and issued to Firm i in Year t, is instrumented using $Avr\_Leniency_{i,t}$, the average relative leniency of examiners who assess Firm i's climate patent applications. In other words, the leniency instrument is constructed using the set of climate patent applications for which the firm receives decisions from USPTO in year t. We use a leave-one-out methodology when 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 climate patent applications filed by Firm i that receive 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 method.[31] The same method is applied to the calculation of 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 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 $\times$ Year F.E. ($\nu_{j,t}$) and Art Unit $\times$ Year F.E. ($\iota_{a,t}$).[32] Importantly, we add a set of fixed effects for each annual number of climate patent applications filed by individual firms and receiving results in Year t (τ_{app}). By including the

[31] When calculating 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.

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

fixed effects (τ_{app}) that control for the climate 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. 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 2, 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 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 patent applications being approved by USPTO for a firm in a single year of 1.79 ($= 1.127 \times (1 + 16.7) \times 0.09$).[33] This number approximately corresponds to 10% of the mean number of patents per year and 50% of the median. In Table A1 (Online Appendix), we conduct Poisson regressions without the $ln(1 + x)$ transformation for our dependent variable and reach qualitatively similar results.

3.3 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 and argue that examiner 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 be correlated with the unobserved technological heterogeneity of climate patents. We do two things to mitigate this concern. First, we employ a measure that compares an individual examiner's leniency with other examiners' leniency in the same art unit. Second, we control for technology classes in a rather fine

[33] Since the dependent variable, $Num\_ClimPats\_Granted$, 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 1 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 1 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.

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) indicate that a patent applicant's identity (the assignee name) may have an impact on the examiner assignment. In other words, the same assignee may frequently be assigned to the same examiner. To mitigate this endogeneity concern, we conduct a series of placebo tests in Table 2, 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 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 leniency; thus, we control for firm size in our second-stage regression). Column (7) of Table 2, Panel B shows that past average leniency does not predict current one, making it unlikely tht our analysis suffers from the endogeneity issue raised by Righi and Simcoe (2019).

Third, Barber and Diestre (2022) 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 application decisions when constructing our instrument for a specific examiner partially alleviates the issue of examiner shopping as future outcomes of applications are not observable. Second, firms with the strongest incentive to engage into examiner shopping should be the ones with the worst environmental performance since they will arguably get the biggest boost from signaling climate virtue to the market by ways of climate patents. However, we find no evidence in support of this idea, as we show in Column (1) of Table 2, Panel B. We provide additional validity tests for our instrument in the Online Appendix.

4 Results on Financial Market Reactions

We analyze how fortuitous climate patent grants affect firms' financial returns by considering three different return measures: medium-term cumulative abnormal returns, short-term announcement returns, and expected returns (implied cost of capital). Our hypothesis is that climate patent grants send a positive and credible signal to market participants regarding a firm's commitment to climate action. We employ 2SLS regressions to exploit differences in examiner leniency.

4.1 Climate-Related Patents and Stock Returns

To study abnormal returns following exogenous examiner leniency shocks in patent grant announcements, we run the following 2SLS regression on our panel of firm-month observations:[34]

$$CAR[t:t+k]_{t,s} = \alpha Num\_\widehat{ClimPats}\_Granted_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{3}$$

In equation (3), t denotes month, and s denotes a firm's stock. The dependent variable is the cumulative abnormal return (CAR) starting from the month t in which climate patent application results are announced and covering a period from t to $t+k$, where k ranges from 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 s 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 control for three sets of high-dimensional fixed effects: (1) Industry $\times$ Month F.E. ($\nu_{j,t}$) help control for any industry shocks affecting performance; (2) Art Unit $\times$ Year F.E. ($\iota_{a,t}$) ensure the validity of our instrument and control for heterogeneity across technology classes; (3) F.E. for the number of climate patent applications that receive USPTO decisions in month t (τ_{app}) allow us to compare firms with the same number of climate patent applications as perceived in month t. Finally, we cluster standard errors along the art unit and industry-year dimensions to address potential correlation in error terms.

The baseline results are shown in Figure 2, separately for climate patents, general and other green (non-climate) patents.[37] In each panel, we plot the point estimate of α in equation (3) and its 90% confidence interval, for k equals 1 to 18 months. Looking at Figure 2, Panel A, we first find

[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 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.

[37]In Figure 2, Panel A, the independent variable is the number of climate patents granted to firm s in month t, and the number of applications fixed effect (τ_{app}) is constructed only using climate patents. In Figure 2, Panel B, the independent variable is the number of other general patents granted to firm s in month t, and the number of applications fixed effect (τ_{app}) is constructed only using other general patents.

a positive and significant effect on CARs: A one standard deviation increase in the (log) number of climate 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) general patents on CARs. Similarly, Panel C shows no effects for other green (non-climate) patents. These findings confirm that our main result is not due to a general tendency of markets to react positively to lucky draws in the patent lottery, but are specific to climate innovation. That is, investors only react positively to the issuance of climate patents but not to non-climate patents, whether they are general patents or other green patents. The sharp difference between climate and other green patents is consistent with earlier findings that investors are more concerned about climate change than about other environmental issues (Krueger, Sautner, and Starks, 2020).

Figure 2, Panel A also allows us to investigate dynamics of the patent granting effect. We find that the effect on CARs is small in the first several months and then increases monotonically until the 12th month after the climate patent granting. These mid-term CARs are consistent with the innovation literature indicating that financial markets take time to incorporate information about innovations, particularly sophisticated and non-salient ones (Cohen et al., 2013; Hirshleifer et al., 2013; Fitzgerald et al., 2021). Between months 12 and 18, the CARs remain stable. In Figure A6 in the Online Appendix, we extend the horizon to month 36. At the end of the 36-month period, the CARs are still at around 10% but the confidence intervals are larger reflecting the noise inherent to long-term stock returns.

In response to the criticism of Cohn et al. (2022) regarding the $ln(1+x)$ transformation of count variable, Figure A2 (in the Online Appendix) repeats the analysis of Figure 2 by conducting Poisson regressions without the $ln(1+x)$ transformation of the dependent variable in the first stage regression. In our second stage, we use the predicted value of the first stage dependent variable as the main variable of interest, the number of climate patents, and run the 2SLS manually. Figure

[38]Our regression enables us to estimate $\frac{\partial CAR}{\partial Num\_Clim\_Patents} = 10\%$, after twelve months. Since the variable $Num\_Clim\_Patents$, is defined using a $ln(1+x)$ transformation, the following calculation is needed to obtain the marginal effect for one patent: $\frac{\partial CAR}{\partial Num\_Clim\_Patents} = \frac{\partial CAR}{\partial ln(1+Num\_Patents)} = \frac{\partial CAR}{\partial Num\_Patents} \times \frac{\partial Num\_Patents}{\partial ln(1+Num\_Patents)} = \frac{\partial CAR}{\partial Num\_Patents} \times (1 + Num\_Patents)$. Hence, to find the marginal impact of an additional climate patent, we need to divide our regression estimate by 1 plus the mean number of climate patents granted in a month, which is 3.9 as shown in Table 1, Panel C. We thus obtain $\frac{10\%}{1+3.9}$, which is around 2%. However, we admit that this back-of-the-envelope estimate is very rough and cannot precisely help us deduce the true marginal effect of each climate patent, as documented in the issues discussed by Cohn, Liu, and Wardlaw (2022) regarding the ln(1+x) transformation. Therefore, we conduct the Poisson regression in Figure A2.

A2 shows similarly strong results. All our main results are very robust when we use the Poisson regression design, indicating that the Cohn et al. (2022) critique is not a major concern.

We acknowledge the importance of properly estimating abnormal returns in long-term return studies (Kothari and Warner, 2007). Therefore, we document in the Online Appendix results for a comprehensive set of alternative specifications for our results of monthly CARs. Figure A3 includes the 4-month pre-event window into regressions. Figure A4 displays analyses that use the Fama-French 3-factor model to calculate monthly abnormal returns, while Figure A5 replaces the dependent variable (CARs) with stock price changes in natural log. In all cases, we consistently find a strong and significant information effect of climate patents on returns or prices, with similar dynamics. In summary, our robustness checks demonstrate that our baseline results are not sensitive to the use of a specific asset pricing model or abnormal return measure. Finally, Figure A6 shows that OLS regressions produce similar findings with comparable levels of significance, albeit with smaller economic magnitudes.

4.2 Attention to Climate Change and Announcement Returns

What accounts for the significant impact of new climate patents on stock returns? Our leading explanation is that the issuance of climate patents serves as a signal to the market, indicating that the firm is actively involved in initiatives to mitigate climate change. Investors react positively to this information, leading to an increase in stock returns. If our hypothesis holds true, we would expect the signaling effect to be more pronounced during periods when society demonstrates heightened attention to climate change concerns. When climate change is at the forefront of public discourse and environmental issues are receiving increased attention, investors should be more likely to respond positively to news that firms are actively engaged in climate-related innovation.

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:[39]

[39] We use the same coefficient of 0.94 as Pástor et al. (2022). This specific implementation of the investor memory model implies that past climate change concerns will gradually fade from investor memories with a

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

We further sort $\overline{MCCC}_t$ into terciles and interact three tercile dummies $\overline{MCCC}_{jt}$, where $j \in \{H, M, L\}$ denotes the high, medium and low tercile, with our main independent variable, the number of climate patents granted in month t, in our new regression:

$$CAR[t:t+k]_{t,s} = \alpha_1 Num\_\widehat{ClimPats}\_Gr_{t,s} \times \overline{MCCC}_{Ht} + \alpha_2 Num\_\widehat{ClimPats}\_Gr_{t,s} \times \overline{MCCC}_{Mt} + \alpha_3 Num\_\widehat{ClimPats}\_Gr_{t,s} \times \overline{MCCC}_{Lt} + \delta_1 \overline{MCCC}_{Ht} + \delta_2 \overline{MCCC}_{Mt} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{5}$$

The variable $Num\_ClimPats\_Granted$ (shortened in eq. (5)) is again instrumented by examiner leniency. The result is plotted in Figure 3, showing the coefficients α_1, α_2, and α_3 for the high, medium and low tercile in Panels A, B, and C, for months 1 to 18. Figure 3 reveals that the effect on CARs is large and only consistently significant for the high tercile of the MCCC index (in Panel A), consistent with the ideas that CARs are related to the salience of climate news. 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 α_1 and α_2 are significantly different across panels for fixed k, and find this to be the case in most comparisons. 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.

4.3 Firm-Specific Exposure to Climate Change

We also investigate whether there are firm-specific variations in the financial market reaction to climate patent announcements. To assess this, we utilize a measure of firm-specific exposure to climate change developed by Sautner et al. (2020). This measure captures the frequency and prominence of climate-related topics discussed in firms' quarterly earnings conference calls.[40]

half-life of slightly less than 12 months.

[40]More precisely, Sautner et al. (2020) use transcripts of earnings calls to construct a time-varying measure of firms' exposure to different facets of climate change, capturing the attention of financial analysts and management to climate change topics at a given point in time. Unlike measures such as carbon emissions, their measure also aims to reflect "soft" information contained in informal communication between managers and analysts. Following other work on textual analysis of earnings calls, they define "exposure" to climate change as the share of the conversation in a transcript devoted to four related sets of climate change bigrams: general aspects of climate change, opportunities, physical shocks, and regulatory shocks.

We split our sample into two groups: firms with high (above-median) climate change exposure and firms with below-median climate change exposure. The results of our analysis are presented in Figure 4. Cumulative abnormal returns are significantly positive only for the sample of firms with high climate change exposure: this subgroup experiences a substantial and lasting increase in relative stock valuation following climate patent announcements. By contrast, firms with below-median climate change exposure only exhibit abnormal returns that are initially positive, though not significantly different from zero, but then revert back to zero over an 18-month horizon. These findings suggest that the financial market reaction to climate patent announcements varies with a firm's exposure to climate change.

4.4 Short-Term Abnormal Returns

We also investigate the short-term market reaction. We examine daily abnormal returns around granting and rejection dates of climate 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 value (Kogan et al., 2017). In contrast, our 2SLS regressions isolate 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 5 and documented in Table 3.[41] The results show that daily CARs are significant when the patent is granted in a period of heightened (top-tercile) climate change attention (Figure 5, Panel A). By contrast, we do not detect abnormal short-run announcement returns during periods with lower attention to climate change (Figure 5, Panels B and C).

In Table 3, Panel A, 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 for the three windows we consider. There is no short-term stock market reaction to other lucky non-climate

[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).

general and green patents, as shown in Table 3, Panels B and C, consistent with our earlier findings that there are no medium- and long-term reactions to non-climate patents.

4.5 Climate Patent Stocks: Recent versus Seasoned Innovators

When a company already holds a large number of climate patents, the marginal effect of additional patents should decrease because the firm has already shown its climate commitment. Thus, we expect the first batch of climate patents to send a stronger signal to financial markets about a firm's commitment to climate action compared with subsequent patents. This idea is related to the finding for private entrepreneurial companies in Farre-Mensa, Hegde, and Ljungqvist (2020) that the first patent granted to a start-up is critical for its future success, but not its second and third patent grants. However, our perspective and use of the patent examiner leniency instrument highlighted by Sampat and Williams (2019) is very different from that of Farre-Mensa et al. (2020): Our sample consists of publicly traded companies, not private start-ups, with climate innovators in our sample typically among the largest companies by market capitalization. We look at entire patent portfolios, not just the first patent, and we focus on stock returns, both realized and expected.

Figure 6 looks at this hypothesis by constructing a variable called Climate Patent Stock that is defined as the number of climate patents that have already been granted to a firm prior to month t. Next, we sort firms into terciles according to this variable 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 6, Panel A). The lowest tercile of the Climate Patent stock corresponds to firms with less than 10 climate patents. By contrast, we find no significant effect for the medium and high terciles of Climate Patent Stock (Figure 6, Panels B and C).

4.6 Climate Patents and Implied Cost of Capital

After documenting large effects of fortuitous climate patents on realized returns, we turn to their counterparts: expected returns.[42] We follow the approach in Pástor et al. (2022) and measure a

[42] Chava (2014) and Pástor et al. (2022) find that firms with better environmental performance enjoy a lower cost of capital. We complement this result by establishing a causal relationship and focusing on climate issues.

firm's expected return using the method of implied cost of capital (ICC). We implement Gebhardt, Lee, and Swaminathan (2001)'s residual income valuation model to calculate r, the implied cost of capital, as follows:

$$P_t \times Num\_Shares_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}}, \qquad (6)$$

where $ROE_{t+\tau}$ is the predicted 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.[43] Finally, we numerically solve for 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. Panel A shows the evolution in the regression coefficient from month t to $t+k$ when regressing the number of new (lucky) climate patents granted in month t on the estimated ICC. In Panel A, we show that a one standard deviation increase in the number of climate 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, along with 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 and C, that repeat the same analysis for other general and other green (non-climate) patents. Figure A13 shows that our results remain the same using the Poisson regression.

Figure 8 plots the same regression results for climate patents with an interaction term for 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.

[43]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 extrapolation 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).

5 Transmission Channels

Our results so far call for an investigation into the mechanisms behind the specific market reaction to fortuitous climate patents, and specifically the question of what sets them apart from other green patents and general patents, including the salient role played by climate change attention and climate change exposure. We explore two non-exclusive potential transmission channels: ESG rating agencies' response and institutional investors' portfolio movements and demand-driven price pressure.

5.1 The Reaction of ESG Ratings Agencies

We study how ESG rating agencies react to information about newly approved climate patents. We expect rating agencies should react because (i) climate patents are clear and countable indicators that they can incorporate to build their scores, and (ii) climate-patent grants may make it to the news, a phenomenon that ESG rating agencies, including LSEG and RepRisk, 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 employ the LSEG Environmental Score, which evaluates a firm's overall environmental performance, and the MSCI ESG Environmental Scores. Both scores are percentile rank measures specific to every industry. The LSEG score ranges from 0 to 1, while the MSCI score ranges from 0 to 10. We conduct 2SLS regressions on our firm-year sample using the following empirical specification:

$$Envrn\_Score_{s,t+k} - Envrn\_Score_{s,t} = \alpha Num\_Clim\widehat{Pats}\_Granted_{s,t} + \beta \mathbf{X}_{s,t} + \mu_{j,t} + \nu_{a,t} + \tau_{app} + \varepsilon_{s,t}. \tag{7}$$

The dependent variable captures future improvements (or declines) of the environmental score of firm s over the next three years following its climate patent grants ($k = 1$, 2 or 3 years).

Table 4 provides the results of the 2SLS regression given by Equation (7). The coefficients of $Num\_ClimPats\_Granted$ are positive and significant at the 5% level, as illustrated in Table 4, Panel A, implying that climate patents have a positive and causal impact on companies' future ESG ratings for both LSEG and MSCI. The economic magnitude is also significant. The estimated coefficients imply that a single (chance-driven) climate patent approval leads to an increase in the environmental score of around 1%. Table 4, Panel B, shows that lucky climate patents increase the environmental innovation score (a direct effect) but also the emission score (an indirect effect).[44]

We conduct again separate regressions for climate patents and for non-climate patents, documented in Table 4, Panels C and D. The contrast is again striking: fortuitous non-climate patents, whether general or green, do not affect ESG ratings. This suggests that agencies issuing such ratings react differently to climate patents than to non-climate patents. In the Online Appendix, we show that our results are robust if we use S&P Global ESG scores.[45] We find that climate patents improve a firm's climate strategy score, but not other general patents.[46]

To summarize, ESG rating agencies respond positively to climate patents but not to non-climate patents, in line with our findings on the stock market reaction. 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), may be (partly) due to omitted variables such as firms' climate innovation.

5.2 Climate Patents and Institutional Ownership

Over the last decade, institutional investors have increasingly adopted policies of responsible investment and supported actions taken by corporations in favor of climate change mitigation.[47] Our study aims to examine whether institutional investors, particularly those prioritizing ESG considerations, respond to climate patents.

A priori, the answer is not obvious. On one hand, we might expect institutional investors who are committed to responsible investment practices to respond positively to climate patents and

[44] Table 4, Panel A only uses climate patents in the construction of the instrument and fixed effects while Panel B uses general patents.

[45] Berg et al. (2020) recently argue that LSEG 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 and MSCI ESG scores is important since similar concerns have not been raised about their data.

[46] 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 patent and 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.

[47] For example, in recent years more than 50% of financial assets under management are overseen by institutions and asset managers that have endorsed the UN Principles for Responsible Investments (PRI) and publicly declared their commitment to ESG-focused investing (Gibson, Glossner, Krueger, Matos, and Steffen, 2020).

increase their holdings, consistent with their stated goals (CFA Institute, 2015). However, the utilization of ESG information in the US is more limited compared to other regions such as Europe (Amel-Zadeh and Serafeim, 2018), which might lead to a tendency among investors to pay lip service to environmental commitments rather than actively pursuing them. For instance, Gibson et al. (2020) document that US signatories of the UH PRI (Principles of Responsible Investment) do not necessarily have a better ESG footprint than non-signatories, suggesting a passive attitude towards climate-related corporate news.

Table 5 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 patent grants of firm i is measured, instrumented by the examiner leniency shock.[48] In Table 5, Panel A, our main independent variable is the number of climate patents newly issued in quarter t, instrumented by examiner leniency. Similar to Figure 2, we add Industry × Quarter F.E., Art Unit × Year F.E., and the number of climate patent application F.E., and cluster standard errors at the firm level.

IO increases steadily following lucky grants of climate patents, as can be seen in Table 5, Columns (2) to (5). In the third quarter after the grant, a one standard deviation rise in the number of granted climate patents leads to a 7% increase in IO. Further, IO responses begin in the same quarter as the climate patent award, as seen in Column (2). As a placebo check, Column (1) of Table 5, Panel A, shows that there is no significant IO change prior to the issuance of climate patents.

In Columns (6) and (7), we see that the IO reaction is in fact statistically positive during the top MCCC tercile, when society pays attention to climate change. This finding completes a pervasive and consistent pattern when using the MCCC index: in addition to long-term CARs, short-term CARs and ICC, IO also responds significantly more in the top MCCC tercile periods. In contrast, as Panel B of Table 5 shows, IO does not respond to general (non-climate) patents, echoing earlier (non-)results for general patent grants.

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 6, we

[48] We use the firm-quarter sample in this regression, given the frequency of available ownership data. 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.

distinguish between environment-focused and other institutions by looking at institution-level difference in their environmental footprints. Following Starks, Venkat, and Zhu (2017) and Gibson Brandon, Krueger, and Schmidt (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 6, Panel A, shows regressions for environment-focused institutional ownership, Panel B for other institutions. The results suggest that environment-focused institutions react strongly and account for the majority of the growth in IO following climate patent grants. By contrast, all coefficients are positive but insignificant in Table 6, Panel B, indicating that institutions that care little about the environmental footprint of their portfolio show a limited response.

We argue that the strong reaction of ESG-minded institutional investors is a plausible 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 first to the 12th month after climate patent issuance) and of institutional ownership (from the first to the 4th quarter and including the quarter of the climate patent issuance) coincides reasonably well, according to Figure 2 and Table 6. Moreover, the effect on abnormal returns and on IO are both concentrated in periods with heightened attention to climate change (high tercile of the MCCC index). This coincidence suggests that the increase in stock prices could be driven by price pressure emanating from increased institutional investor demand.

6 Real Effects and Alternative Explanations

Our leading explanation for the documented market reaction to lucky climate patent grants is a signal effect that notably works through ESG ratings and climate-conscious investors. But we also need to account for the possibility that the observed return patterns reflect changes in firm fundamentals, or real effects, that are generated by lucky patent grants. We follow the standard dichotomy that changes in present values reflect changes either in future cash flows (cash flow channel) or in discount factors (risk channel).[49] We analyze these two possible channels or alternative explanations in turn, using operating performance as a proxy for future cash flows, and carbon

[49] See for instance Hsu et al. (2022) for a discussion.

emissions as a proxy for the exposure to climate transition risks.[50]

6.1 Operating Performance

Climate innovation has the potential to alter future cash flows of the innovating firm. For instance, when a firm incorporates new climate technology into its products, it can strengthen its competitive edge and boost sales and profits, and patent protection granted can act as a deterrent for competitors that may also translate into higher cash flows (Kogan et al., 2017).

To explore this alternative explanation, the cash flow channel, we conduct 2SLS regressions for a variety of measures of future operating performance, including changes in return on assets (ROA), sales, profits, number of employees, and capital stock over the next five years following lucky patent grants. Our findings, presented in Table A6 in the Online Appendix, indicate that fortuitous climate patent grants do not have a significant impact on the subsequent operating performance for most of the measures. This suggests that expected changes in future cash flow do not explain the documented market reaction. The only marginally significant effect, an increase in the capital stock after two years, might be due to firms enjoying lucky climate patent grants taking advantage of the previously documented decrease in their cost of funds to raise new capital.

Our next step is to explore whether there are real effects to climate patents that do not appear when we limit attention to our instrumental variable of fortuitous patent grants. Specifically, we are interested in finding out whether the underlying climate technology, rather than random shocks to patent grants, leads to measurable effects on operating performance. To undertake this analysis, we perform OLS regressions where the independent variable is simply the number of new climate patents obtained by a firm (without the examiner leniency instrument). 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.[51]

The results are documented in Table A7 in the Appendix. We now generally find a positive

[50]Our exploration of the risk channel is limited to this single dimension of risk, and hence constitutes only an incomplete exploration of possible effects on risk.

[51]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. We include all observations od climate patent applications regardless of their status in the sample. This is in contrast to our 2SLS regressions where we use the sub-sample of firm-year (or firm-quarter and firm-month) observations with decisions on climate patent applications. In our OLS regressions, we also include firm-year observations with no climate patent decisions, including those of firms that never file any climate patent application.

impact on operating performance, in line with the findings of Kogan et al. (2017) for patents in general. This finding suggests that what truly determines future operating performance is the underlying climate technology, not whether that technology obtains patent protection.

In summary, our analysis suggests that our key findings depicted in Figure 2 cannot be attributed to the cash flow channel, an expected increase in cash flows stemming from lucky climate patent grants. As our findings based on raw patent grants (OLS regressions) show, any effect on operating performance can only be attributed to new climate technologies, not their patent protection.

6.2 Carbon Emissions

The second alternative explanation for the observed change in innovators' stock market value concerns possible adjustments in discount factors, linked to a reduction in risk (risk channel). We undertake a limited analysis of this possibility by focusing exclusively on climate transition risks. This is an incomplete representation of possible effects on firm risk but arguably the one dimension most directly related to the underlying climate innovation. As a proxy for a firm's exposure to climate transition risks, we look at the innovator's future carbon emissions. In other words, we analyze whether investors are right when they expect climate innovation to reduce carbon emissions and hence transition risk. Such a reduction in risk could then translate into a lower discount factor and hence an abnormal positive realized stock return. Specifically, we analyze whether climate patent grants are associated with lower subsequent carbon intensity, measured as the ratio of direct carbon emissions to revenues:[52] 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 rate of change.[53]

We first look at fortuitous patent grants, using our instrumental variable of shocks in examiner leniency. The results are documented in Table A9 in the Appendix. We find no significant effects of patent grant shocks on CO2 emissions nor on renewable and clean energy used.

[52]We focus on carbon intensity because it measures whether the use of greener technologies enables a firm to emit less carbon for a given level of economic activity and improve its carbon efficiency. Absolute emissions could be biased by changes in sales triggered by the innovation.

[53]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.

In a second step, we ask whether real impacts are detectable when we look at our measure of raw climate patent grants, that is, at the underlying climate-related technologies (rather than at lucky patent grants). As in the case of operating performance, we conduct OLS regressions using the same raw measure of climate patents, and we include the full firm-year sample. The dependent variable is the change of direct firm-level CO2 equivalent emissions (Scope 1) from year t to year $t + k$, where $k = 1, 2, 3, 4, 5$.

Table 8 shows our results. Panel A reports that climate patents are associated with significant reductions in Scope 1 carbon emission intensity starting in year 3 after the patent grants. In Panels B, C, and D, we document that firms with climate 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. Panels E and F show no impact for climate 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 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).[54]

To conclude, the striking contrast between the findings for the lucky patent instrument and those for the raw patent measure suggests that any effect of climate innovation on carbon emissions of innovators can be linked to the underlying technology itself, not to the patent office's decision to grant patent protection, similar to what we found when looking at operating performance. By isolating the random component in patent grants in our 2SLS analysis, we are able to distinguish between grant event and its information content. But market participants are arguably much less able to do so, in the absence of easily available heuristics on examiner leniency; thus, it is rational for investors to view patent approvals as informative signals even though they are noisy, with examiner leniency being one (significant) source of such noise.

7 Conclusion

This paper studies the reaction of financial markets to patents with the potential to mitigate climate change, identified under the Y02 tagging scheme of the world's leading patent offices. We

[54] 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.

address concerns about endogeneity with an instrumental variable approach that exploits quasi-random variations in the probability of patent approvals, based on patent chance-driven assignment of examiners and differences in their leniency. We establish a causal link between climate patents and financial market reactions.

We find that companies with a positive shock in obtaining climate patent grants exhibit significant short-term (one to three days) and medium-term cumulative (12 to 18 months) abnormal returns. We also document a concomitant reduction in the implied cost of capital of firms that were granted lucky climate patents. The effect is strongly significant only in times of heightened climate change attention and for firm's with high exposure to climate change.

We find evidene for two main channels for these effects. First, environment-focused institutional investors reallocate their portfolios and reinforce their holdings in these companies. Investor reallocations are substantially higher in periods of heightened public attention to climate change concerns. Second, companies with lucky climate patents 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 other green patents and for other general patents.

Exploring the real effect of climate innovation, when we look at randomly obtained climate patents, we find no measurable impact on operating performance or carbon emissions. By contrast, when we study the underlying climate technology, we find a strong association of climate innovation with subsequent gains in operating performance and emissions reductions. We conclude that climate innovation allows innovators to mitigate their climate impact, but these gains are linked to the underlying technology, not the granting of patent protection. Our findings are consistent with the idea that the financial markets reaction to climate patent grants is due to a signal effect: market participants react to patent approvals that from their point of view are noisy but informative signals about the engagement of firms in corporate climate action.

Our results provide encouraging news for any decision-maker concerned about adequate incentives for climate innovators. Our pervasive and robust findings on the reaction of financial markets, buoyed by investor attention and fund flows of climate-focused investors, present the strongest evidence to date that financial markets pay attention to and offer rewards for the development of climate technology.

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A Variable Definitions

Variable Name	Definition of Variable	Data Source
Firm-Month Sample		
CAR[t, t+k]	Cumulative abnormal returns 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_ClimPats_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_ClimPats_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

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:

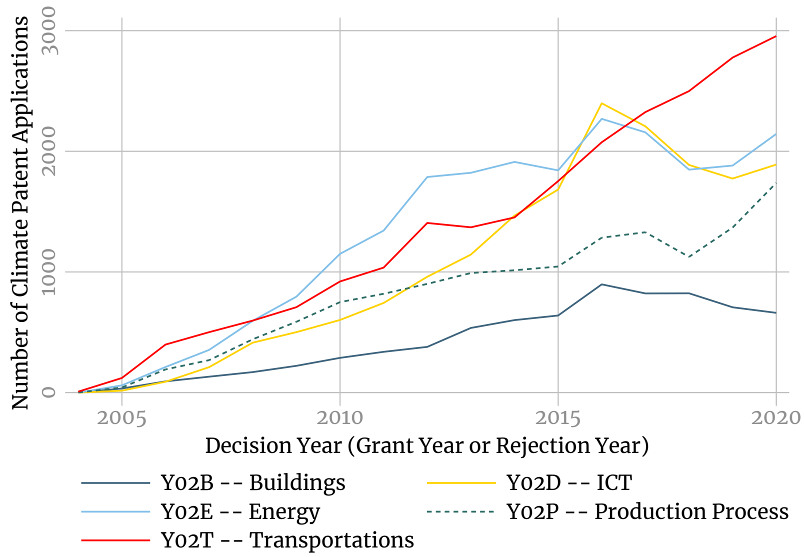
Assignee Name	Assignee Address	PERMNO	Matching Start Year	Matching End Year
ABBOTT LAB	60064	20482	2001	2015

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 Patent Applications

This figure plots the annual number of climate patent applications filed by US-headquartered and publicly-listed corporations from 2001 to 2020. We keep only patent applications that already received USPTO decisions at the time of sample construction (2023). Panel A sorts patent applications by patent decision year (either granted or rejected), and Panel B sorts by patent application year. 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 with a decision by USPTO Decision Year



Panel B: Number of Patent Applications by Application Year

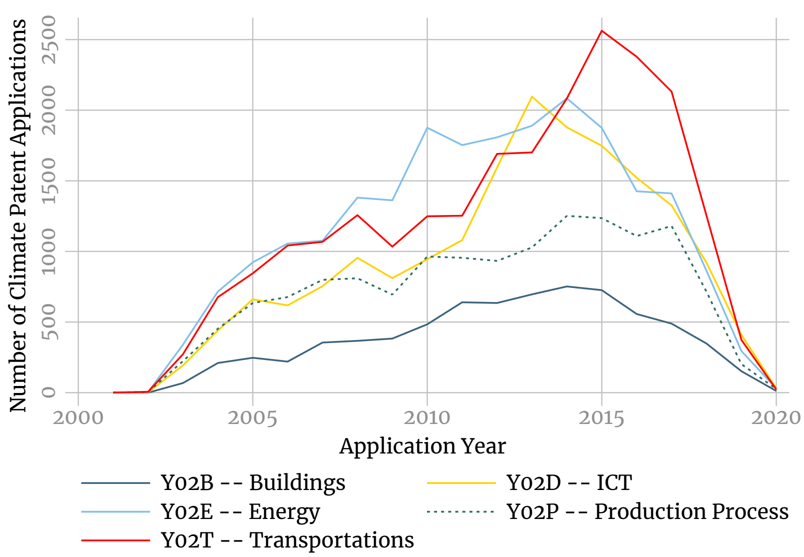


Figure 2. Climate Patents and Monthly Abnormal Stock Returns

This figure shows how exogenous shocks to climate patent grants influence firms' monthly abnormal stock returns. Panels A, B and C plot the results for climate patents, general (non-climate) patents, and other green (non-climate) patents separately. For each panel, we run the 2SLS regressions laid out below and plot the coefficients α for each month 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 climate 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 $Num\_ClimPats\_Granted$, counting the number of climate 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 Climate Patent Applications (receiving results in that month). F.E. Standard errors are double-clustered at the art-unit and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha Num\_Clim\widehat{Pats}\_Granted_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{8}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{9}$$

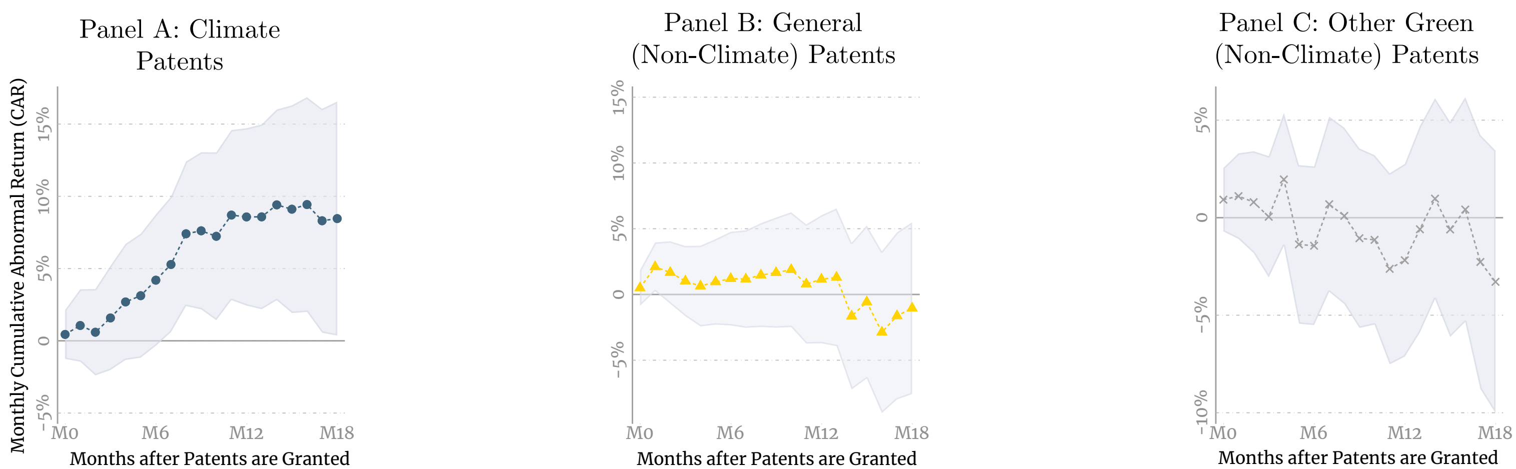


Figure 3. Climate Patents, Media Coverage of Climate Change, and Abnormal Stock Returns

This figure presents an extension to the analysis of Figure 2 with Panels A, B and C for climate patents, general (non-climate) patents, and other (non-climate) patents, respectively. The second stage regression follows the equation:

$$CAR[t:t+k]_{t,s} = \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Ht} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Mt} + \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Lt} + \delta_1 \overline{MCCC}_{Ht} + \delta_2 \overline{MCCC}_{Mt} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad (10)$$

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):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad (11)$$

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 $Num\_ClimPats\_Granted$, counting the number of climate 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. $Num\_ClimPats\_Granted$ 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 art-unit and industry-year level. Confidence intervals are plotted at the 90% confidence level.

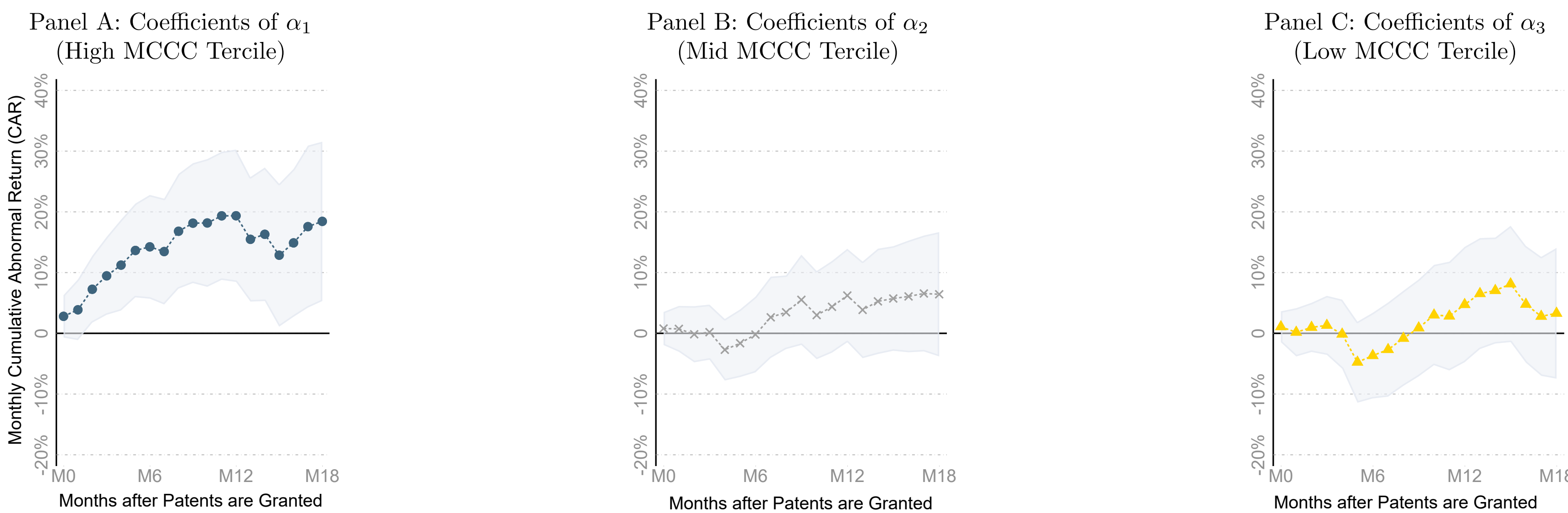


Figure 4. Climate Patents, Firm-level Climate Exposure, and Abnormal Stock Returns

This figure studies climate patents, firm-level climate exposure, and monthly stock returns. We run the 2SLS regressions laid out below in each panel and plot the coefficients α_1 and α_2 for each k equal to 0 to 18. The firm-level climate exposure measure is from Sautner et al. (2020). Data is at the firm-month level. The sample requires that a firm receives at least one decision on its climate 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 $Num\_ClimPats\_Granted$, counting the number of climate 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 × 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 double-clustered at the art-unit and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$\begin{aligned} 2nd\ Stage: \quad CAR[t:t+k]_{t,s} = {} & \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times I(HighClimateExpo)_{t,s} + \\ & \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times I(LowClimateExpo)_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \end{aligned} \tag{12}$$

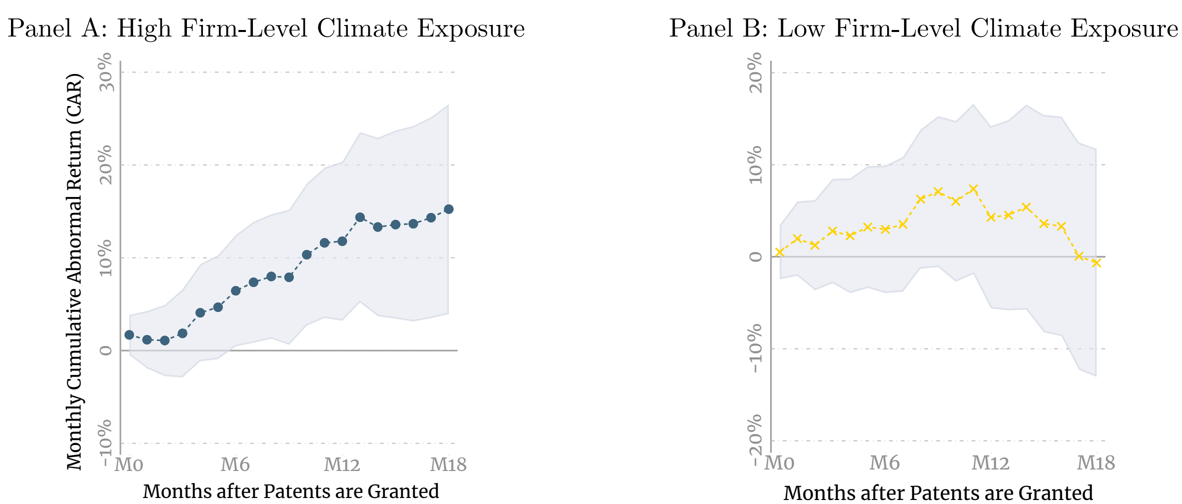


Figure 5. Climate Patents, MCCC Index, and Daily Abnormal Stock Returns

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

$$\begin{aligned} Daily\_CAR[t-3:t+k]_{t,s} = {} & \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Ht} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Mt} + \\ & \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Lt} + \delta_1 \overline{MCCC}_{Ht} + \delta_2 \overline{MCCC}_{Mt} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \end{aligned} \tag{13}$$

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):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \tag{14}$$

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 $Num\_ClimPats\_Granted$, counting the number of climate 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. $Num\_ClimPats\_Granted$ 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 × Month F.E., Art Unit × 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.

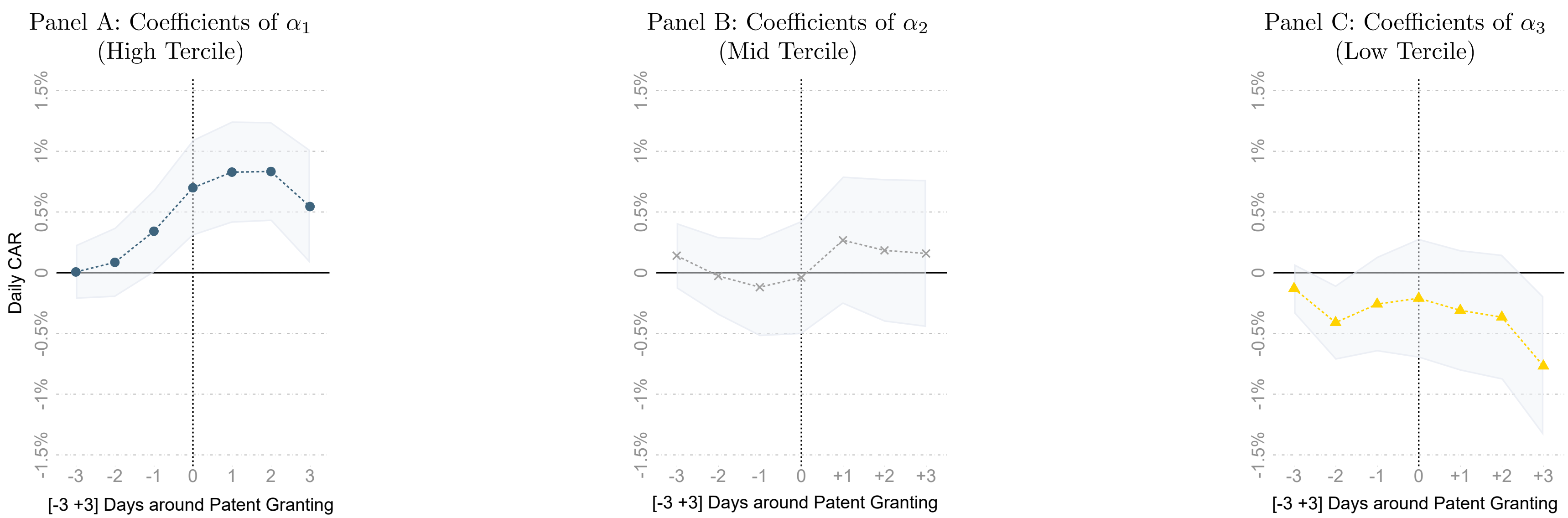


Figure 6. Climate Patents, Climate Patents Stock, and Abnormal Stock Returns

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

$$CAR[t:t+k]_{t,s} = \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times Clim\_PatStock\_High_{t,s} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times Clim\_PatStock\_Mid_{t,s} + \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times Clim\_PatStock\_Low_{t,s} + \delta_1 Clim\_PatStock\_High_{t,s} + \delta_2 Clim\_PatStock\_Mid_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad (15)$$

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_ClimPats_Granted*, counting the number of climate patents issued to the firm during the month t that takes the $ln(1+x)$ transformation. We instrument it using the average relative leniency of examiners who assess these patent applications of the firm. $\mathbf{X}_{t,s}$ 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 × 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 double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

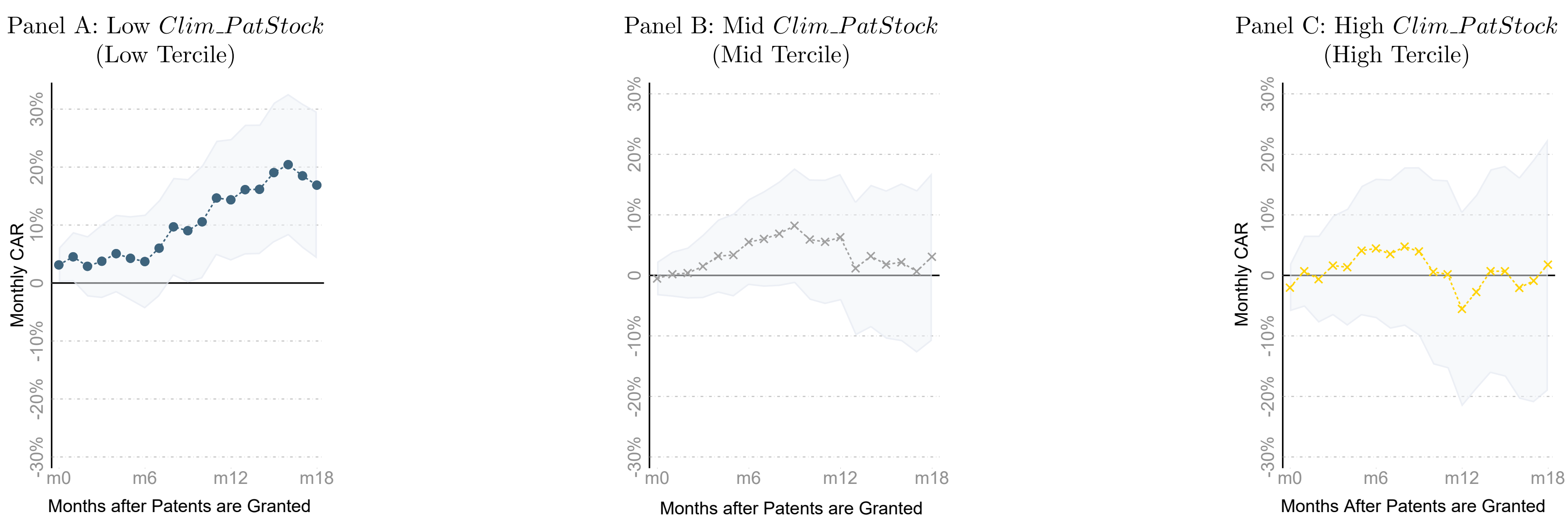


Figure 7. Climate Patents and Implied Cost of Capital

This figure shows how exogenous issuance of climate patents influence firms' implied cost of capital (ICC). Panels A, B and C plot the results for climate patents, general (non-climate) patents, and other (non-climate) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 $Num\_ClimPats\_Granted$, counting the number of climate 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 is standardized such that its standard deviation is equal to 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.

$$2nd\ Stage: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{16}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{17}$$

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:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{18}$$

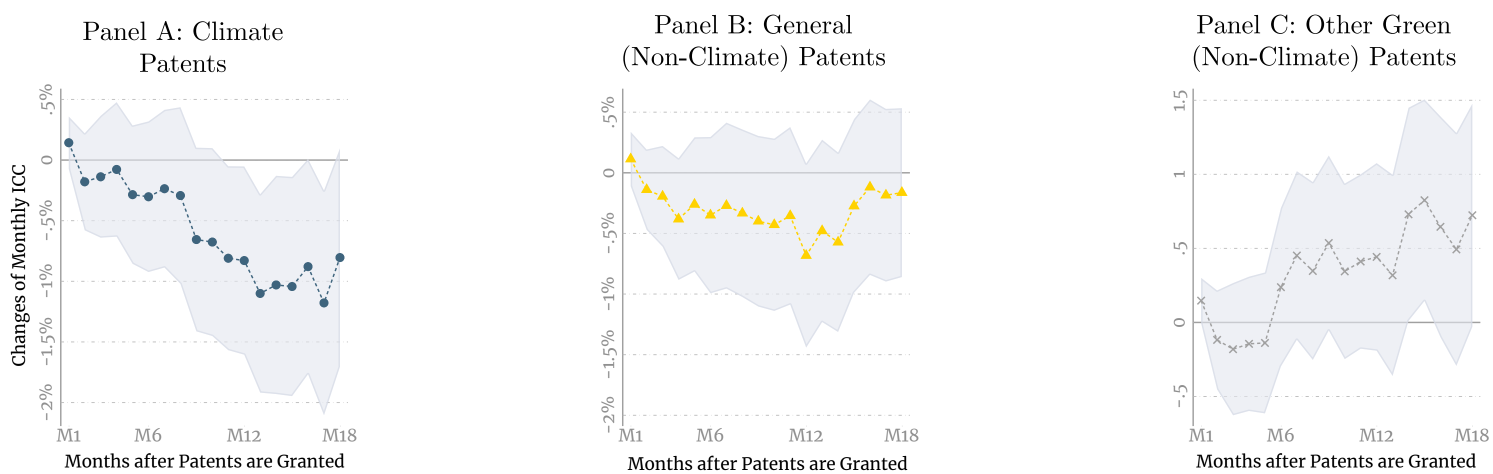


Figure 8. Climate Patents, Media Coverage of Climate Change, and ICC

This figure presents an extension to the analysis of Figure 7. Panels A, B and C plot the results for climate patents, general (non-climate) patents, and other (non-climate) patents separately. The second stage regression follows the equation:

$$ICC_{t+k,s} - ICC_{t,s} = \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times MCCC_{Ht} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times MCCC_{Mt} + \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times MCCC_{Lt} + \delta_1 MCCC_{Ht} + \delta_2 MCCC_{Mt} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad (19)$$

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 $Num\_ClimPats\_Granted$, counting the number of climate 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 $\times$ 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 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:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^\tau} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \quad (20)$$

Panel A: Coefficients of α_1 (High Tercile) | Panel B: Coefficients of α_2 (Mid Tercile) | Panel C: Coefficients of α_3 (Low Tercile)

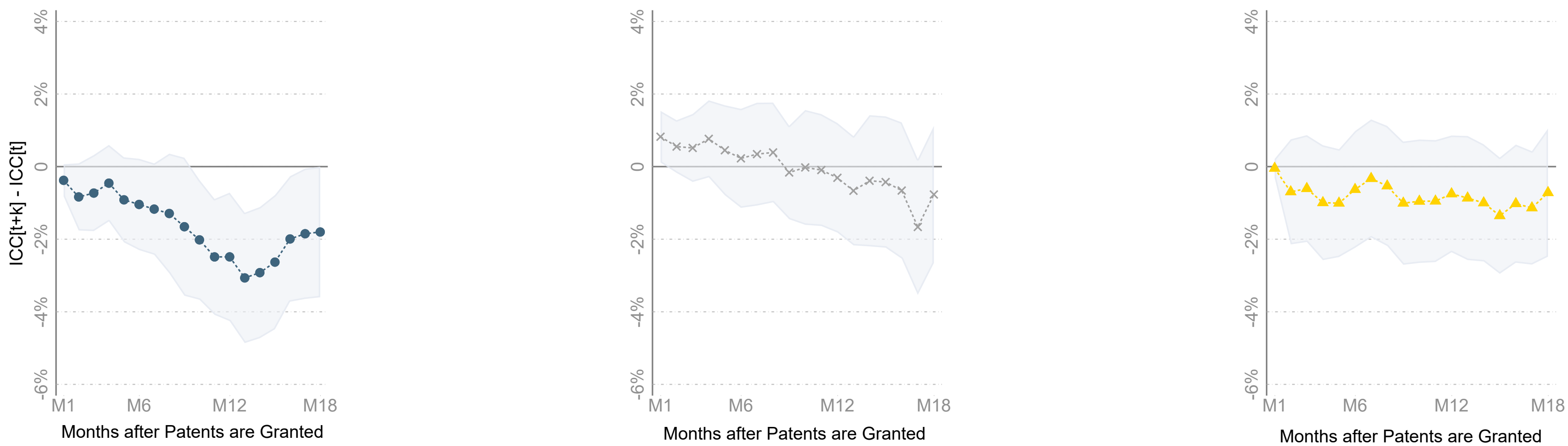


Table 1: Summary Statistics

This table presents summary statistics. Panel A presents the descriptive statistics of the sample of all climate and other 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 and other green (non-climate) patent applications. Climate 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`). Other green (non-climate) 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 LESG (formerly 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 LSEG. Panel D provides a short list of firms with the most climate patent applications in the LSEG sample.

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

Panel B: Industries with the Most Green Patent Applications			
Climate Patents		Other Green (Non-Climate) 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: LSEG ESG Sample (Merged with Climate Patents)

Number of Unique Firms:	419
Number of Climate 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 Patents 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 Patents 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 LSEG

Company	Num. Climate Patents
Climate Patents – Buildings (Y02B)	
General Electric Co	763
Intl Business Machines Corp	419
Texas Instruments Inc	276
Climate Patents – ICT (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 – Production Process (Y02P)	
General Electric Co	1415
Intl Business Machines Corp	1033
Honeywell International Corp	845
Climate Patents – Transportations (Y02T)	
Ford Motor Co	4864
General Electric Co	3520
Raytheon Technologies Corp	2725
Boeing Inc	1353

Table 2: Validity Test of the Instrumental Variable

This table presents validity tests for the instrumental variable, specifically the average relative leniency of examiners, focusing exclusively on climate-related patents. In Panel A, we showcase the first stage OLS regression, following the equation detailed in (1). The estimation is performed across three distinct samples: firm-year, firm-quarter, and firm-month. Each observation in the sample necessitates that a firm receives at least one decision regarding climate patent applications during the specified observation period. The dependent variable is the count of climate-related patents granted to the firm in period t, with the period defined as either a month, quarter, or a year. A log transformation, $ln(1+x)$, is applied to the dependent variable. The instrument's construction adheres to Equation (2) and is computed as the average relative leniency of examiners responsible for assessing the firm's patent applications. Firm-level control variables are measured in Year $t-1$. Standard errors are double-clustered at the firm and industry-year levels. In Panel B, regressions are conducted to assess the exclusivity condition of the instrument. Firm-level control variables are also measured in Year $t-1$. Standard errors are double-clustered at the firm and industry-year levels. Statistical significance levels are denoted by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage Regression (OLS Regressions)			
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.	1351	5005	10666

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 3: Climate Patents and Daily Abnormal Returns

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

$$Daily\_CAR[t-k:t+k]_{t,s} = \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Ht} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Mt} + \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{Lt} + \delta_1 \overline{MCCC}_{Ht} + \delta_2 \overline{MCCC}_{Mt} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad (21)$$

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 $Num\_ClimPats\_Granted$, counting the number of climate 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. $Num\_ClimPats\_Granted$ takes the $ln(1+x)$ transformation. The main independent variable is standardized such that its standard deviation is equal to 1. 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 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: General (Non-Climate) 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_GenPat_Granted × MCCC_High	0.000417	0.000243	0.000540	0.000704	-0.0000889	0.000162
(Instrumented by Leniency)	(0.000988)	(0.00101)	(0.00131)	(0.00132)	(0.00152)	(0.00153)
Num_GenPat_Granted × MCCC_Mid	0.00141	0.00148	-0.000992	-0.000892	-0.0000441	-0.000767
(Instrumented by Leniency)	(0.00105)	(0.00104)	(0.00129)	(0.00122)	(0.00158)	(0.00146)
Num_GenPat_Granted × MCCC_Low	0.0000948	0.000606	-0.000415	-0.000499	0.000384	0.000474
(Instrumented by Leniency)	(0.00102)	(0.00105)	(0.00137)	(0.00137)	(0.00152)	(0.00152)
Art Unit × Year F.E.	Y	Y	Y	Y	Y	Y
Num OtherGenPat App F.E.	Y	Y	Y	Y	Y	Y
Industry × Year-Month F.E.		Y		Y		Y
Num Obs	145225	144715	145229	144725	145231	144716

Continued from the Previous Table

Panel C: Other (Non-Climate) Green 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	0.000114	0.00367	0.000716	0.00644	0.0116	0.0131
(Instrumented by Leniency)	(0.00418)	(0.00456)	(0.00655)	(0.00752)	(0.00906)	(0.00883)
Num_OtherGreen_Granted × MCCC_Mid	-0.00301	-0.00863	0.00132	0.000959	-0.00206	0.00306
(Instrumented by Leniency)	(0.00492)	(0.00776)	(0.00632)	(0.00928)	(0.00618)	(0.00895)
Num_OtherGreen_Granted × MCCC_Low	-0.00666	0.000308	-0.00373	0.000620	-0.0160	-0.0188
(Instrumented by Leniency)	(0.00601)	(0.00621)	(0.00858)	(0.0108)	(0.00982)	(0.0125)
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	2933	2302	2933	2298	2931	2299

Table 4: Climate Patents and Environmental Score

This table studies how exogenous issuance of climate patents affect firms' subsequent ESG (Environmental) scores. All regressions are 2SLS regressions. Panels A and B study climate-related and other (non-climate-related) general patents separately. In each panel, the dependent variable is the change of LSEG and MSCI Environmental Score from year t to $t+k$, where k equals 1, 2, and 3. The main independent variable is $Num\_ClimPats\_Granted$, the number of climate patents granted and issued to the firm in year t, which is then instrumented by the average examiner leniency. $Num\_ClimPats\_Granted$ takes the $ln(1+x)$ transformation. In all regressions, we add Industry × Year, Art Units × Year, and Number of Climate Patent 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.

$$2nd\ Stage: \quad Envrn\_Score_{i,t+k} - Envrn\_Score_{i,t} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{22}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{23}$$

Panel A: Climate Patents	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Δ Environmental Score					
ESG Rating	LSEG			MSCI		
	t+1 - t	t+2 - t	t+3 - t	t+1 - t	t+2 - t	t+3 - t
Num. Climate Patents Granted	0.135**	0.140*	0.105	0.148	1.153**	1.452***
(Instrumented by Examiner Leniency)	(0.0585)	(0.0781)	(0.104)	(0.422)	(0.483)	(0.483)
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 Patent Applications F.E.	Y	Y	Y	Y	Y	Y
Num Obs.	1166	992	857	950	809	693

Panel B: LSEG Environmental Sub-Score	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Δ LSEG Environmental Sub-Score					
ESG Rating	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
Num. Climate Patents Granted	0.0554	0.253***	0.0789	0.115	0.108*	0.0821
(Instrumented by Examiner Leniency)	(0.0531)	(0.0830)	(0.0545)	(0.0780)	(0.0598)	(0.0898)
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 Patent Applications F.E.	Y	Y	Y	Y	Y	Y
Num Obs.	1132	965	1132	965	1132	965

Panel C: General (Non-Climate) Patents	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Δ Environmental Score					
ESG Rating	LSEG			MSCI		
	t+1 - t	t+2 - t	t+3 - t	t+1 - t	t+2 - t	t+3 - t
Num. General Patents Granted	0.00507	0.00406	0.0337	-0.0673	-0.105	0.225
(Instrumented by Examiner Leniency)	(0.0268)	(0.0402)	(0.0551)	(0.144)	(0.290)	(0.396)
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 Patent Applications F.E.	Y	Y	Y	Y	Y	Y
Num Obs.	5188	4383	3673	5270	4340	3538

Continued from the Previous Table

Panel D: Other Green (Non-Climate) Patents

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Δ Environmental Score					
ESG Rating	LSEG			MSCI		
	t+1 - t	t+2 - t	t+3 - t	t+1 - t	t+2 - t	t+3 - t
Num. Other Green Patents Granted	-0.0301	-0.0549	0.0114	-0.748	-0.274	-0.841
(Instrumented by Examiner Leniency)	(0.116)	(0.0990)	(0.0997)	(0.644)	(0.733)	(0.844)
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 Patent Applications F.E.	Y	Y	Y	Y	Y	Y
Num Obs.	554	480	400	584	503	428

Table 5: Climate 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) general 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 $Num\_ClimPats\_Granted$, the number of climate patents granted and issued to the firm in quarter t, which is then instrumented by the average examiner's leniency. $Num\_ClimPats\_Granted$ is standardized such that its standard deviation is equal to 1. In all regressions, we include Industry × Quarter, Art Units × Year, and Number of Climate Patent 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.

$$2nd\ Stage: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_Clim\widehat{Pats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{24}$$

Panel A: Climate 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: General (Non-Climate) 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 General Patents Granted	0.00579	-0.00382	-0.0213	0.000230	-0.0000589		
(Instrumented)	(0.00840)	(0.00900)	(0.0156)	(0.0190)	(0.0220)		
Num General Patents Granted × MCCC_High						0.00980	0.0211
(Instrumented)						(0.0132)	(0.0161)
Num General Patents Granted × MCCC_Mid						-0.00925	-0.00423
(Instrumented)						(0.0117)	(0.0146)
Num General Patents Granted × MCCC_Low						-0.0149	-0.0231
(Instrumented)						(0.0153)	(0.0182)
All F.E. in Panel A	Y	Y	Y	Y	Y	Y	Y
Num Obs.	18405	18403	17806	17208	16599	16073	15941

Continued from the Previous Table

Panel C: Other Green (Non-Climate) 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	-0.00568	0.0103	0.0000617	-0.00120	-0.00246		
(Instrumented)	(0.0139)	(0.0107)	(0.0157)	(0.0191)	(0.0197)		
Num Other Green Patents Granted × MCCC_High						-0.00884	-0.0374*
(Instrumented)						(0.0163)	(0.0208)
Num Other Green Patents Granted × MCCC_Mid						0.00160	0.00896
(Instrumented)						(0.0135)	(0.0170)
Num Other Green Patents Granted × MCCC_Low						0.00239	0.0228
(Instrumented)						(0.0155)	(0.0197)
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.	1901	1903	1834	1770	1699	1653	1647

Table 6: Climate Patents and Environment-Focused Institutional Ownership

This table offers an extensional analysis of Table 5 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 main independent variable is standardized such that its standard deviation is equal to 1. 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 7: Climate Patents and Emission-Focused Institutional Ownership

This table offers an extensional analysis of Table 5 Panel A. We only focus on climate patents. We decompose each firm's total institutional ownership into (i) emission-focused institutional ownership (IO) and (ii) other institutional ownership. Emission-focused 13F institutions are institutions with a quarterly Refinitiv emission score above the median score of all institutions in that quarter. The quarterly emission score is the value-weighted average emission 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: Emission-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	-0.0135	0.0233**	0.0295*	0.0383**	0.0414**		
(Instrumented)	(0.0105)	(0.0104)	(0.0158)	(0.0185)	(0.0198)		
Num Climate Patents Granted × MCCC_High						0.0460**	0.0403
(Instrumented)						(0.0232)	(0.0266)
Num Climate Patents Granted × MCCC_Mid						0.00618	0.0272
(Instrumented)						(0.0218)	(0.0251)
Num Climate Patents Granted × MCCC_Low						-0.00362	0.00885
(Instrumented)						(0.0138)	(0.0160)
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	4132	4113

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	0.0103	0.0127	0.0338*	0.0315	0.0361		
(Instrumented)	(0.0136)	(0.0121)	(0.0204)	(0.0225)	(0.0232)		
Num Climate Patents Granted × MCCC_High						-0.00224	0.000991
(Instrumented)						(0.0220)	(0.0262)
Num Climate Patents Granted × MCCC_Mid						-0.00261	0.0188
(Instrumented)						(0.0208)	(0.0246)
Num Climate Patents Granted × MCCC_Low						0.0106	-0.00105
(Instrumented)						(0.0131)	(0.0156)
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.	4723	4721	4576	4433	4297	4104	4086

Table 8: 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 – Transportations (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 – Production Process (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.		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	-0.00598	-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 × 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 – ICT (Y02D)					
	(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	-0.000576	-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 × 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 / 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 × 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

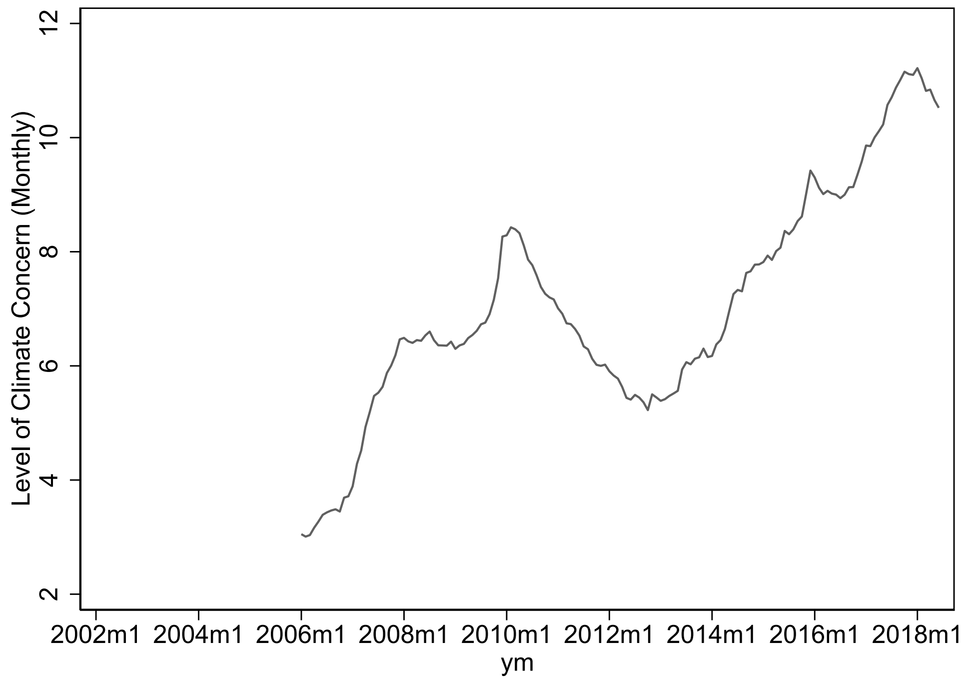
Internet Appendix for

Climate Patents and Financial Markets

List of Figures

List of Tables

Figure A1. MCCC Index (Monthly)



The original MCCC is a monthly index of media coverage of climate change constructed by 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. Climate Patents and Monthly Abnormal Stock Returns (Poisson Regressions)

This figure illustrates the impact of exogenous shocks to climate patent grants on firms' monthly abnormal stock returns. Panels A, B, and C present the outcomes for climate patents, general (non-climate) patents, and other green (non-climate) patents, respectively. In each panel, 2SLS regressions are performed as outlined below, and the coefficients (α) for each month (k) ranging from 0 to 18 are plotted. The data is organized at the firm-month level, with the stipulation that a firm must receive at least one decision on its climate patent applications in a given month to be included in the sample. The dependent variable is the cumulative abnormal returns (CARs) from time t to time $t+k$. Abnormal Returns (ARs) represent alphas in the Fama-French 5-factor model (Fama and French, 2015), with factor loadings estimated using the previous 60-month returns data. The key independent variable is $Num\_ClimPats\_Granted$, indicating the number of climate patents issued to the firm during month t. This variable is instrumented using the average relative leniency of examiners responsible for assessing the firm's climate patent applications. A log transformation, $ln(1+x)$, is applied only in the second stage. In the first stage, the dependent variable $Num\_ClimPats\_Granted$ is estimated without the log transformation using Poisson regressions. The vector $\mathbf{X}_{t,s}$ incorporates the logarithm 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 encompass Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Number of Climate Patent Applications (receiving results in that Month) F.E. Standard errors are double-clustered at the art-unit and industry-year levels, and confidence intervals are presented at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \ln(1 + \widehat{Num\_ClimPats\_Granted_{t,s}}) + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A2}$$

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

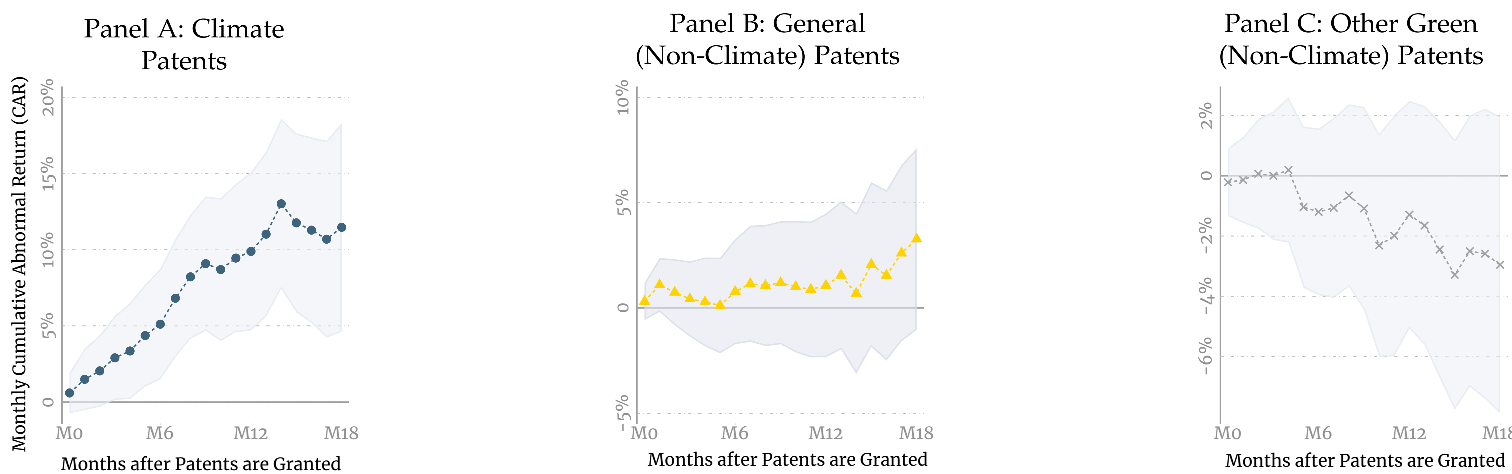


Figure A3. Climate Patents and Monthly Stock Returns (Including Pre-Trends)

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 month of patent grant annoucements. The main independent variable is *Num_ClimPats_Granted* (*Num_OtherGreen_Grant*), counting the number of climate patents (other 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. *Num_ClimPats_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.

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

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

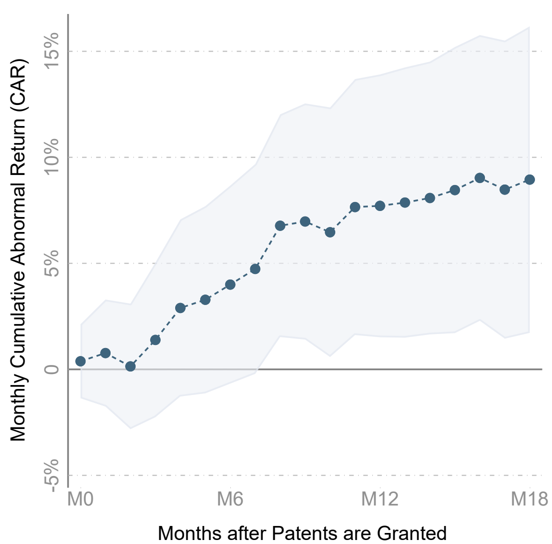
Figure A4. Climate Patents and Monthly Stock Returns (Fama-French 3-Factor Alpha)

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_ClimPats_Granted*, counting the number of climate 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_ClimPats_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.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A6}$$

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

Panel A: Climate Patents



Panel B: Other Green Patents

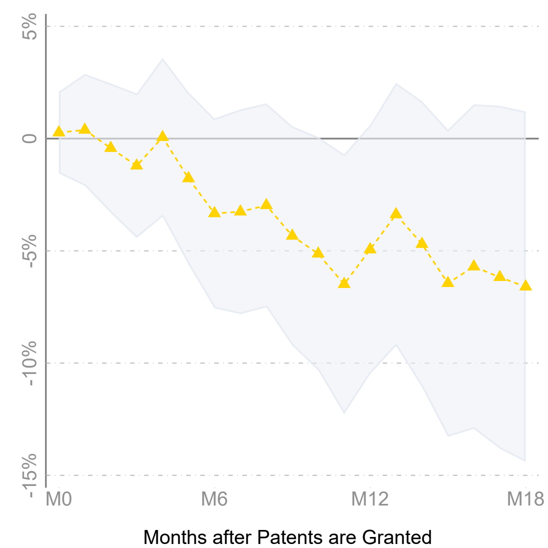


Figure A5. Climate Patents and Monthly Stock Price

This figure studies how exogenous issuance of green patents drive firm's monthly stock price. Panels A and B study climate patents and other green (non-climate) patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 $Num\_ClimPats\_Granted$, counting the number of climate 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. $Num\_ClimPats\_Granted$ 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-year and industry-month level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad ln(Price_{t+k,s}) - ln(Price_{t-1,s}) = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad \text{(A8)}$$

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

Panel A: Climate Patents

Panel B: Other Green Patents

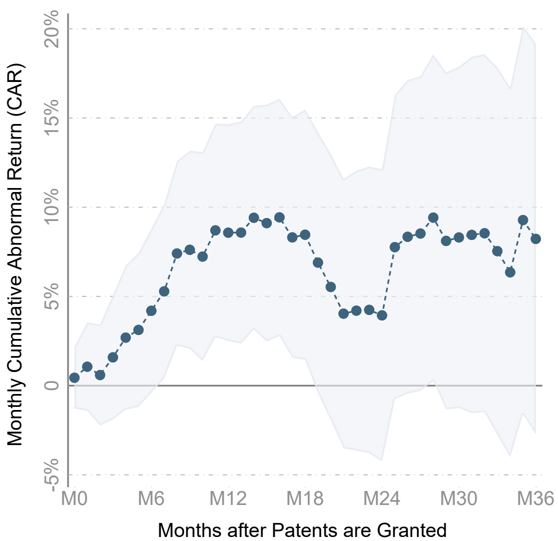
Figure A6. Climate Patents and Monthly Stock Returns (Extending the Window)

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 $\times$ 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-year and industry-month level. Confidence intervals are plotted at the 90% confidence level.

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

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

Panel A: Climate Patents



Panel B: Other Green Patents

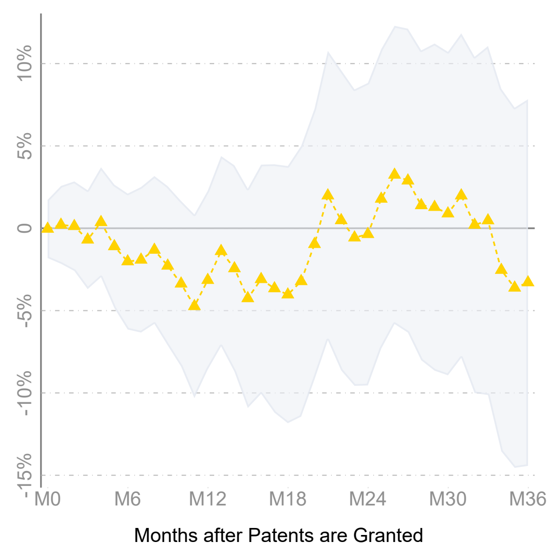


Figure A7. Climate Patents and Monthly Stock Returns (OLS Regression without the Instrument)

This figure provides OLS regression results for our main analysis. Panels A, B and C study climate patents, general (non-climate) patents and other green (non-climate) patents separately. We run the OLS regressions laid out below in each panel and plot the coefficients α 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 climate 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 $Num\_ClimPats\_Granted$, counting the number of climate patents issued to the firm during month t. 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 Climate Patent Applications (receiving results in that month). F.E. Standard errors are double-clustered at the art-unit and industry-year level. Confidence intervals are plotted at the 90% confidence level.

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

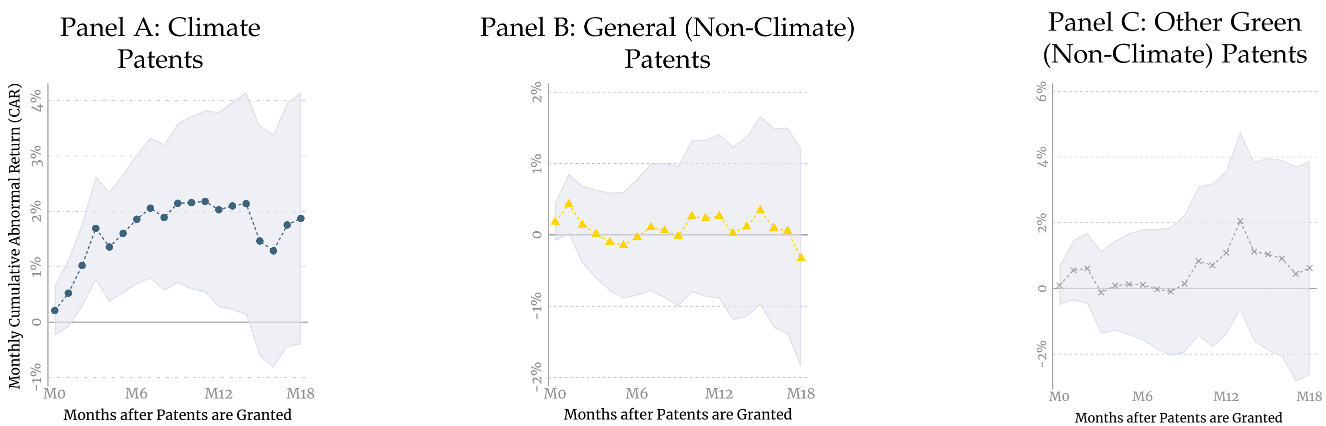


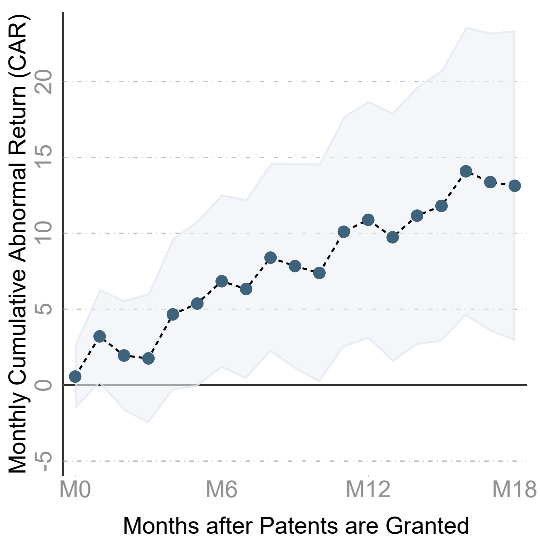
Figure A8. Climate Patents and Monthly Stock Returns (Using Alternative Methods to Construct Instrument)

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 and other green (non-climate) patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 climate 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 $Num\_ClimPats\_Granted$, the number of climate 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 $\times$ 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.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \qquad \text{(A13)}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \qquad \text{(A14)}$$

Panel A: Climate Patents



Panel B: Other Green Patents

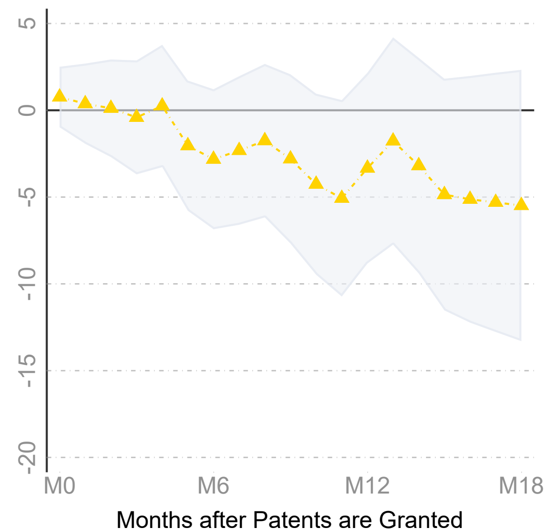


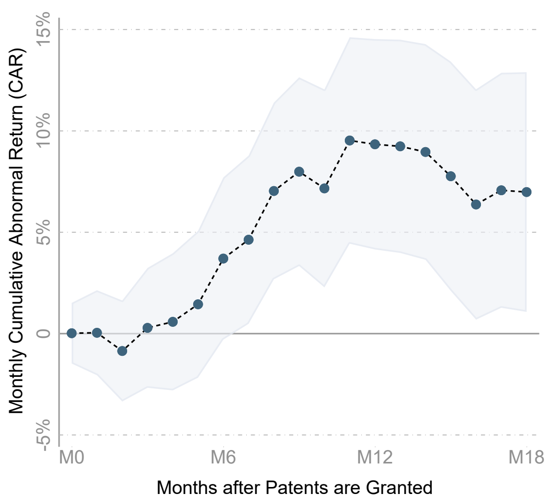
Figure A9. Climate Patents and Monthly Stock Returns (Russell 1000 Sample)

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 LSEG 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). We construct a balanced sample by tracking climate patent applications from 2004 to 2020 of these 1,301 firms. Panels A and B study the climate and other green (non-climate) patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 climate 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 $Num\_ClimPats\_Granted$, the number of climate 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 × 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 double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A15}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A16}$$

Panel A: Climate Patents



Panel B: Other Green Patents

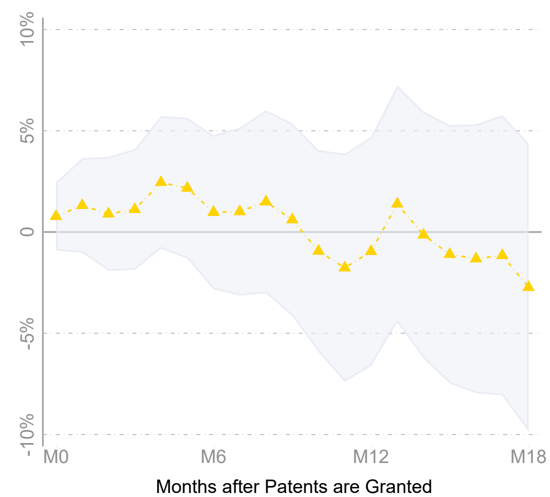


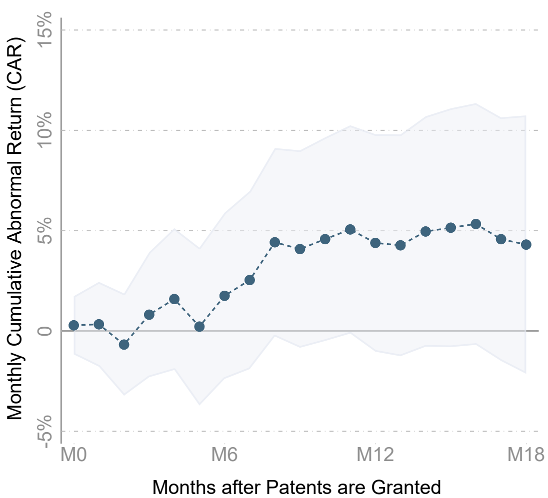
Figure A10. Climate Patents and Monthly Stock Returns (Russell 3000 Sample)

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 LSEG 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 climate and other green (non-climate) patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 climate 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 $Num\_ClimPats\_Granted$, the number of climate 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 $\times$ 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.

$$2nd\ Stage: \quad CAR[t:t+k]_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A17}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A18}$$

Panel A: Climate Patents



Panel B: Other Green Patents

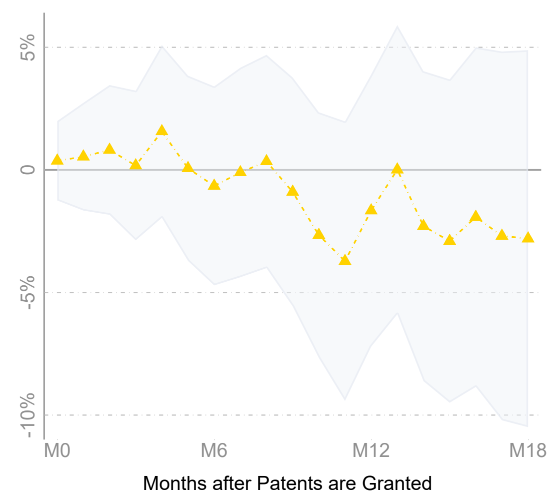


Figure A11. Climate Patents, Media Coverage of Climate Change, and Stock Returns (Robustness Check)

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:

$$CAR[t:t+k]_{t,s} = \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{H,t+k} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{M,t+k} + \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{L,t+k} + \delta_1 \overline{MCCC}_{H,t+k} + \delta_2 \overline{MCCC}_{M,t+k} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \quad (A19)$$

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):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad (A20)$$

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

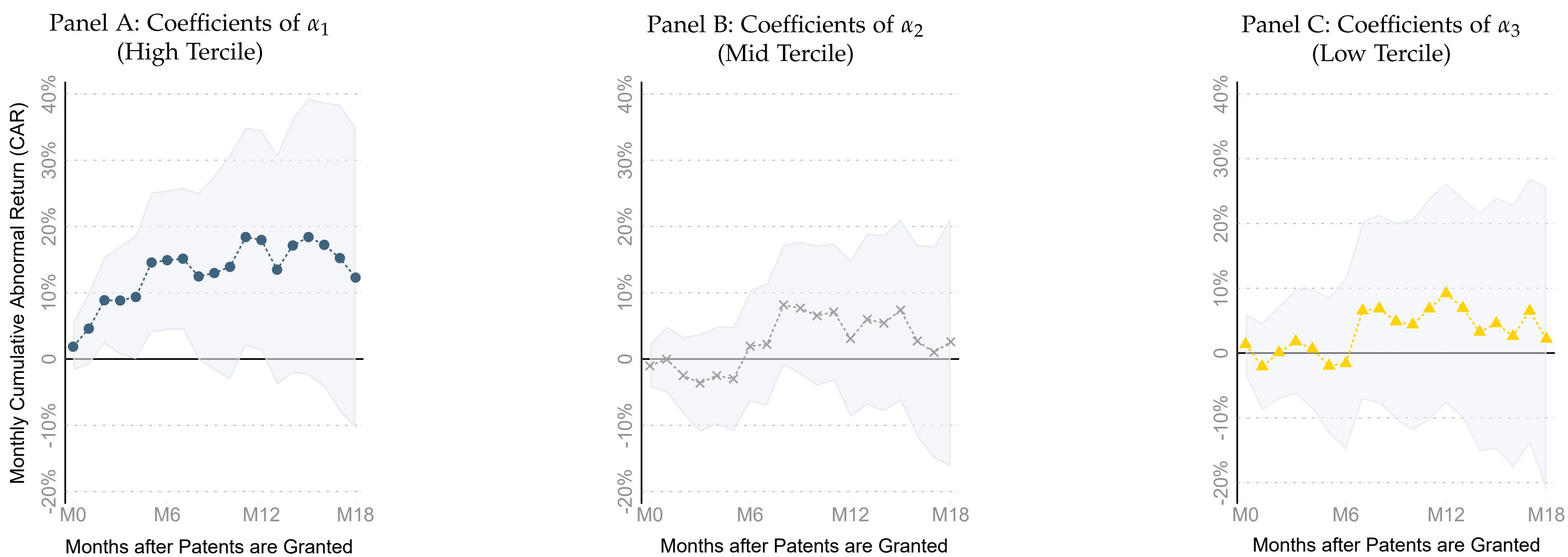


Figure A12. Climate Patents, Media Coverage of Climate Change, and Stock Returns (Russell 1000 Sample)

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:

$$\begin{aligned} CAR[t:t+k]_{t,s} = {} & \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{H,t+k} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{M,t+k} + \\ & \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{t,s} \times \overline{MCCC}_{L,t+k} + \delta_1 \overline{MCCC}_{H,t+k} + \delta_2 \overline{MCCC}_{M,t+k} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \end{aligned} \quad (A21)$$

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):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad (A22)$$

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

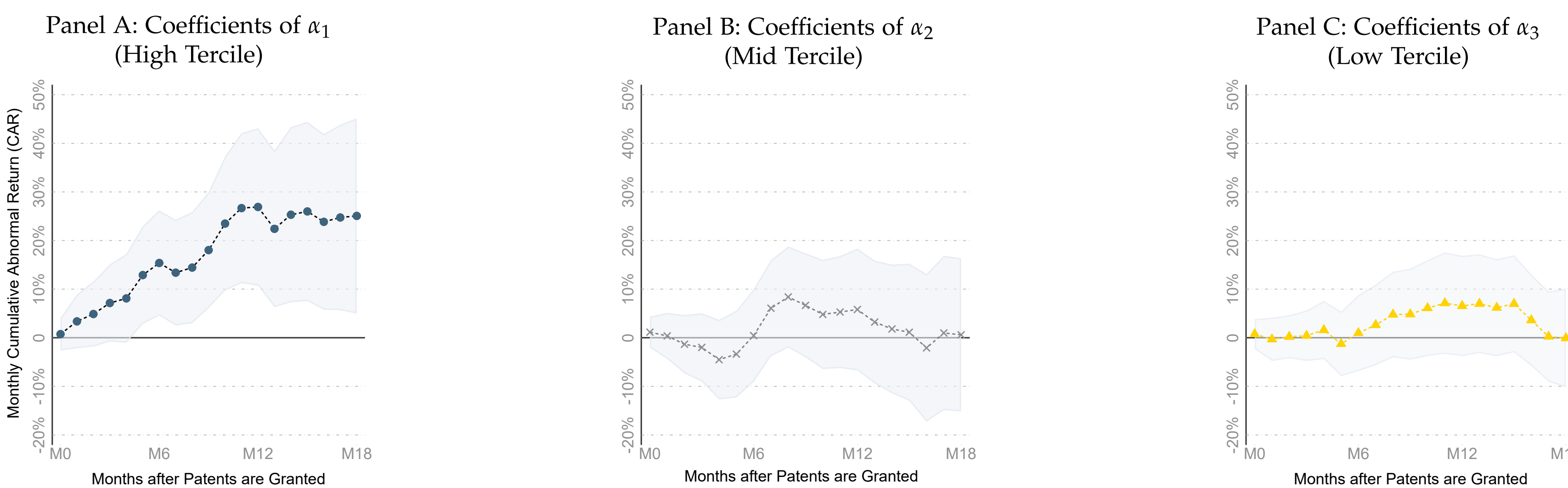


Figure A13. Climate Patents and Implied Cost of Capital (Poisson Regressions)

This figure shows how exogenous issuance of green patents influence firms' implied cost of capital (ICC). Panels A, B and C plot the results for climate patents, general (non-climate) patents, and other green (non-climate) patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 $Num\_ClimPats\_Granted$, the number of climate 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. We conduct Poisson regression in the first stage. 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.

$$2nd\ Stage: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \ln(1 + \widehat{Num\_ClimPats\_Granted}_{t,s}) + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A23}$$

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

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:

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

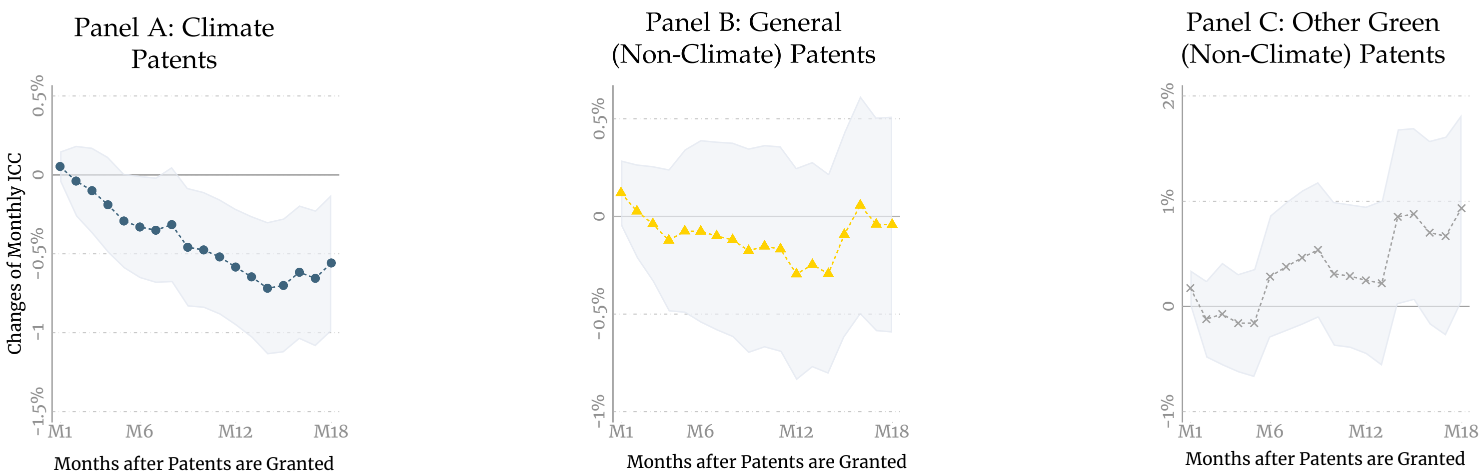


Figure A14. Climate Patents and Implied Cost of Capital (Robustness Check)

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 climate and other (non-climate) green patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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 $Num\_ClimPats\_Granted$, the number of climate 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 $\times$ 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.

$$2nd\ Stage: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A26}$$

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

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:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{A28}$$

Figure A15. Climate 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 and other green (non-climate) patents separately. We run the following 2SLS regressions in each panel and plot the coefficients α 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_ClimPats_Granted*, the number of climate 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 × 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 double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

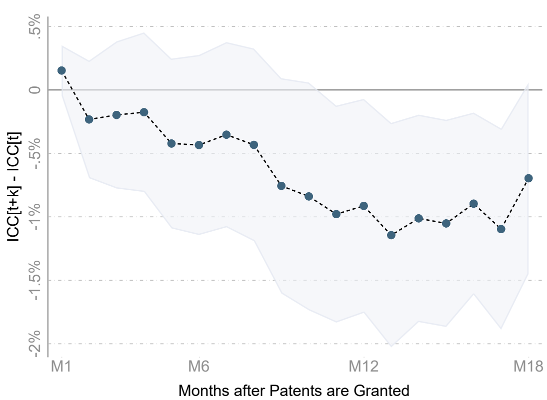
$$2nd\ Stage: \quad ICC_{t+k,s} - ICC_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A29}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A30}$$

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:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{A31}$$

Panel A: Climate Patents



Panel B: Other Green Patents

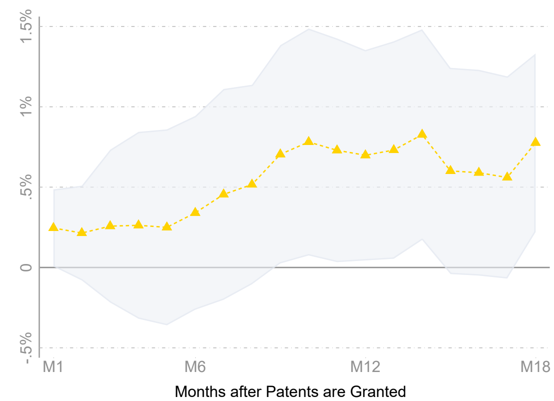


Figure A16. Climate Patents and Stock Price Volatility

This figure investigates how exogenous issuance of climate patents influence firms' stock price volatility. Panels A, B and C study climate patents, general (non-climate) patents, and other green (non-climate) patents separately. We run the 2SLS regressions laid out below in each panel and plot the coefficients α 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 climate patent applications in that month. The dependent variable is the standard deviation of daily stock price calculated in each month. The main independent variable is $Num\_ClimPats\_Granted$, the number of climate 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 Climate Patent Applications (receiving results in that month). F.E. Standard errors are double-clustered at the art-unit and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$\textit{2nd Stage}: \quad SD[t+k]_{t,s} = \alpha \widehat{Num\_ClimPats\_Granted}_{t,s} + \beta \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A32}$$

$$\textit{1st Stage}: \quad Num\_ClimPats\_Granted_{t,s} = \delta Avr\_Leniency_{t,s} + \pi \mathbf{X}_{t,s} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{t,s} \tag{A33}$$

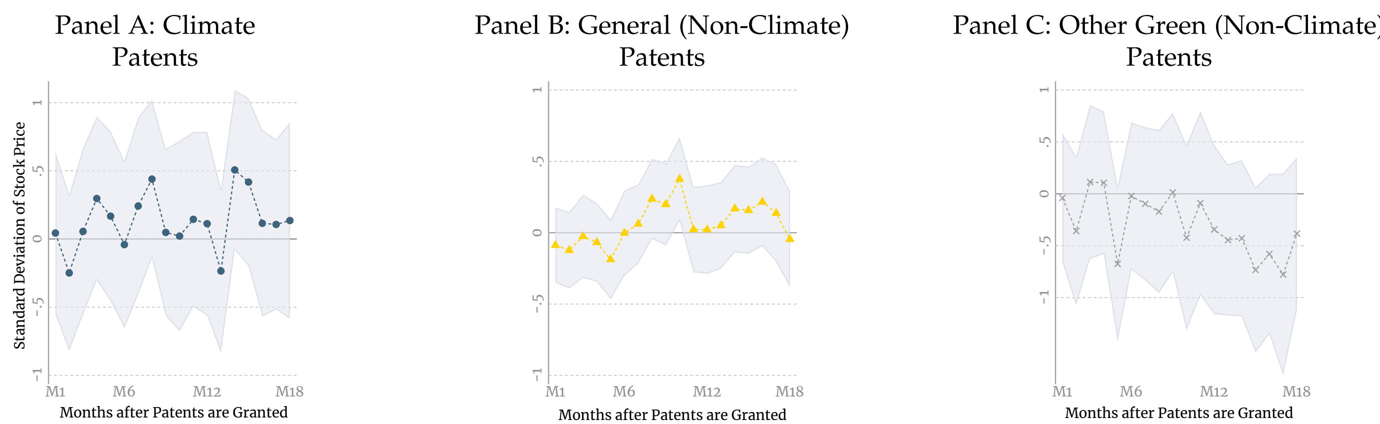


Table A1 Validity Test of the Instrumental Variable (Poisson Regression)

This table presents validity tests for the instrumental variable, specifically the average relative leniency of examiners, focusing exclusively on climate patents. In Panel A, we document the first stage Poisson regression, following Equation (1). The estimation is performed across three distinct samples: firm-year, firm-quarter, and firm-month. Each observation in the sample necessitates that a firm receives at least one decision regarding climate patent applications during the specified observation period. The dependent variable is the count of climate patents granted to the firm in period t, with the period defined as either a month, quarter, or a year. We run Poisson regressions. The instrument's construction follows Equation (2) and is computed as the average relative leniency of examiners responsible for assessing the firm's patent applications. Firm-level control variables are measured in Year $t-1$. Standard errors are double-clustered at the firm and industry-year levels. In Panel C, regressions are conducted to assess the exclusivity condition of the instrument. Firm-level control variables are also measured in Year $t-1$. Standard errors are double-clustered at the firm and industry-year levels. Statistical significance levels are denoted by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage Regression (Poisson Regressions)

Dependent Var.	Num Climate Patents Granted		
Sample	Firm-Year	Firm-Quarter	Firm-Month
Average Relative Leniency *(Standardized)*	1.963^{***} (0.256)	1.808^{***} (0.138)	1.774^{***} (0.110)
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.	1348	4962	10588

Panel C: 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 A2 Validity Test of the Instrumental Variable for Other 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: LSEG 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-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 A3 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. Industry × year F.E., art unit × 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-year level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Num Climate 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 A4 Green Patents and S&P Global Environmental Score

This table studies how exogenous shocks to climate patent grants 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 patents and other green (non-climate) 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 climate 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 Climate 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.

$$2nd\ Stage: \quad Envrn\_Score_{i,t+k} - Envrn\_Score_{i,t} = \alpha \widehat{Num\_ClimPats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{A34}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{A35}$$

Panel A: Climate 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 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 A5 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 patents and other green (non-climate) 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 Climate 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.

$$2nd\ Stage: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{A36}$$

Panel A: Climate 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
Panel B: Other Green (Non-Climate) 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 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 patents and other green (non-climate) 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 Climate 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.

$$2nd\ Stage:\quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{A37}$$

Panel A: Climate 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 A7 Climate Patents and Operating Performance (2SLS)

This table studies climate patents and firms' operating performance. All regressions are 2SLS. The standard errors are double-clustered at the industry-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 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 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 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 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 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 Operating Performance (OLS)

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

Panel A	ln(Sale[t+k])				
	k=1	k=2	k=3	k=4	k=5
Num Climate Patents Granted	0.0156**	0.0205**	0.0114	-0.00148	0.00464
	(0.00677)	(0.0101)	(0.0131)	(0.0159)	(0.0175)
Industry × Year F.E.	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y
N	72094	63613	56095	49170	43129
Panel B	ln(Profits[t+k])				
	k=1	k=2	k=3	k=4	k=5
Num Climate Patents Granted	0.0174**	0.0220**	0.00870	-0.000647	0.00305
	(0.00796)	(0.0105)	(0.0128)	(0.0156)	(0.0161)
Industry × Year F.E.	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y
N	67330	59385	52405	46048	40388
Panel C	ln(Employments[t+k])				
	k=1	k=2	k=3	k=4	k=5
Num Climate Patents Granted	0.0266***	0.0348***	0.0336***	0.0292***	0.0289**
	(0.00503)	(0.00745)	(0.00974)	(0.0113)	(0.0127)
Industry × Year F.E.	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y
N	74024	65311	57742	50807	44579
Panel D	ln(CapStock[t+k])				
	k=1	k=2	k=3	k=4	k=5
Num Climate Patents Granted	0.0134***	0.0208***	0.0200**	0.0106	0.0173
	(0.00397)	(0.00649)	(0.00830)	(0.00990)	(0.0115)
Industry × Year F.E.	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y
N	66558	58751	51897	45671	40042
Panel E	ROA[t+k]				
	k=1	k=2	k=3	k=4	k=5
Num Climate Patents Granted	0.0193**	0.0120	0.000853	0.00116	0.00899
	(0.00901)	(0.0105)	(0.0114)	(0.0115)	(0.0119)
Industry × Year F.E.	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y
N	57406	50578	44854	39723	35026

Table A9 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 8. In Panel A, the dependent variable is the change of estimated CO2 emissions divided by total outputs. We use the variable, $En\_En\_ER\_DP123$, in the LSEG 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 $En\_En\_ER\_DP046$ in LSEG. 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 $En\_En\_PI\_DP066$ in LSEG. The standard errors are double-clustered at the industry-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)
Δ (Estimated CO2 ÷ Output)	t+1 - t	t+2 - t	t+3 - t	t+4 - t	t+5 - t
Num Climate 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 × 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.	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 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 × 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.	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 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 × 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.	475	454	435	404	385

Table A10 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 LSEG 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 LSEG 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 by 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-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

	(1)	(2)	(3)	(4)	(5)
Panel D: Climate Patents – Energy (Y02E)					
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

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