WORKING PAPERS

N° 1400

December 2024

“Climate Patents and Financial Markets”

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Climate Patents and Financial Markets*

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December 2024

Abstract

We study the impact of climate patents on financial markets. Exploiting quasi-random variations in patent examiner leniency, we show that firms are rewarded with significant positive stock returns over a 12-month horizon when they receive fortuitous climate patent grants, compared with similarly innovative but unlucky firms. We observe concomitant trends of reduced costs of capital, shareholder rotations towards environment-focused institutional investors and better environmental ratings. We do not observe similar reactions for other patents, including other green patents. We corroborate the distinctive nature of the market reaction to climate innovation by showing that it is amplified during periods of high attention to climate change, for firms with high climate exposure, and for first-time grants of climate patents. Random grants of climate patents do not produce improvements in the innovator's operating performance or carbon emissions, but the underlying climate technologies do, suggesting that financial markets react rationally to the signal value of climate patent grants.

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

JEL classification: G11, G23, G24, O34.

*We thank Florian Berg, Milo Bianchi, Patrick Coen, Haoyu Gao, Alexander Guembel, Jarrad Harford, Hans Hvide, Julian Koelbel, Kai Li, Sophie Moinas, Lubos Pastor, David Robinson, Caterina Santi, Yucheng Xu, David Zerbib, Kangying Zhou, Dexing Zhou, and seminar participants at the HEC Paris-HKUST Sustainable Finance Workshop, the 5th FirmOrgDyn conference, the 2022 AFFI meeting, the 2024 CICF conference, the NHH Center for Corporate Finance Conference, the WHU Conference on CSR, Economy and Financial Markets, for valuable comments and suggestions. Financial support from Peking University Research Funding, ADEME (ClimPat grant), ANR (under Grant No. ANR-17-EURE-0010, "Investissements d'Avenir"), and the TSE research initiative on Sustainable Finance and Responsible Investments (FDIR) is gratefully acknowledged.

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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.

We aim to advance the understanding of climate innovation by asking whether financial markets react to the disclosure of climate patents tagged under the Y02 scheme in ways that provide incentives for innovating firms. Furthermore, we ask whether the recent salience of climate change concerns leads a specific attention to climate patents that sets them apart from other patents, including other green patents, and whether such a unique market response to climate innovation can be linked to the growing attention to climate change. Therefore, we investigate specific climate-related mechanisms that may explain a distinctive market reaction to: time-varying 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 in recognition of climate innovators' contribution to social performance.

Since the existence of climate-specific mechanisms and transmission channels raises concerns about endogeneity,[4] we deploy from the outset an identification strategy based on quasi-random

[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] E.g., Acemoglu, Aghion, Bursztyn, and Hemous (2012); 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. We also exclude the Y02A category that focuses on climate change adaptation patents, because there are few of them, so that our analysis focuses on climate change mitigation patents.

[4] For example, firms that are committed to climate-friendly policies and expect to benefit from better 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

shocks in the probability of patent approvals. At the U.S. Patent and Trademark Office (USPTO), patent examiners differ in their leniency or strictness and are generally assigned quasi-randomly to patent applications.[5] We instrument the number of new climate patents with the average leniency of examiners who assess a firm's patent applications and compare in our panel analysis 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] Building on the exogenous variations in examiner leniency allows us to make causal inferences, a problem that has long vexed the broader study of the link between firms' climate mitigation effort (and generally firms' ESG policies) and financial performance (Berg, Koelbel, Pavlova, and Rigobon, 2021). We argue that the details of the patent review process provide a unique opportunity to address this challenge that looms large in the rapidly growing literature linking ESG and financial performance.

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

We then conduct a series of investigations to understand why the various forms of financial market responses that we find are limited to climate innovation, and do not carry over to other forms of innovation. We look at three different dimensions of possible climate-specific linkages.

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).

[5]See Cockburn, Kortum, and Stern (2002); Sampat and Williams (2019). The quasi-random assignment of examiners is prevalent at most USPTO art units. There are about 900 art units, and patent applications are assigned to art units of patent examiners by technological specialization.

[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 the examiner leniency instrument.

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

First, we consider the effect of changes over time 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 find that in periods of high public attention to climate change, markets react immediately with a significant short-term abnormal return (2-day window), while the response is muted in periods of lower climate change concerns.

Second, we investigate whether we can identify a firm-specific dimension in the link between climate concerns and market reactions to climate innovation. To do so, we consider firms' exposure to climate change, employing the measure of Sautner, van Lent, Vilkov, and Zhang (2020). We divide the sample into two groups according to this measure: 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 change exposure 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.

Third, we investigate whether financial markets specifically recognize the achievements of firms that are making their debut as climate innovators. We show that the financial market response is strongest for a firm's initial ten climate patents. Specifically, we find that firms experience a significant abnormal stock return of up to 20% in reaction to its first ten climate patents (the lowest tercile of firm-years by climate patent stock). We show that this return then diminishes and is no longer statistically significant for firms with a larger stock of climate patents. This finding corroborates the interpretation that climate patent grants have a signaling effect about a firm's decision to commit to mitigating climate change. While the three dimensions of climate-specific reactions we explore are far from a complete explanation for the distinct market reaction to climate patents, they should at least lend plausibility to our main conclusion: financial markets express a conviction about the impact of climate change mitigation technologies that differs from the impact of other green (or brown) technologies, a conclusion that echoes the findings of Pástor, Stambaugh, and Taylor (2022) when dissecting the drivers of returns.

Up to this point, our analysis is limited to realized returns. Next, 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 a 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 (formerly Refinitiv) ESG, MSCI, and S&P Global ESG. We find that these ratings react to lucky climate patent grants by raising their environmental scores, thereby contributing to boost stock prices (Pástor et al., 2022).

We conduct the same 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 central 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 transition risk, 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 risk (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 showing 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). This suggests that it is the certification embedded in the USPTO patent granting, and not the monopoly privilege associated to patent protection, that is triggering the reaction of financial markets.

Finally we look at the effects of non-instrumented raw climate patent counts as a measure of increased climate innovation. This enables us to explore the real impact of the underlying climate-related technologies, independently of the climate certification and of the 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 climate certification nor patent protection.

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

Our paper contributes to four strands of the literature. First, a small set of papers looks at the association between green patents and financial performance. They do not provide 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. 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 as a narrow set of patent classes) are associated with a decrease in firm value (Tobin's Q) whereas other patents are 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 to this line of investigation. 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 the reaction is specific to climate patents and absent for other patents, we link it to climate-specific determinants (attention to climate change and climate exposure) and transmission channels (environmental ratings and climate-conscious investors), and we document effects on short-run realized returns and on the cost of capital.

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 emissions, 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 there is a causal impact of climate innovation on financial markets and that it 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.

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

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, decision date, the examiner who assesses the focal patent application, and the examiner's technology art unit for each US utility patent application.[10] As is customary, we consider that patent applications are eventually either granted or abandoned (Graham et al., 2018). For the decision date of granted patents, we use the date at which a patent is finally granted. For abandoned applications, we use the date of final rejection (CTFR) or non-final rejection (CTNF) as the decision date.[11] In general, rejection decisions are not publicly available, and abandoned patent applications (applications that end with either a final or a non-final rejection as the final observed decision) serve as our control group, assuming the market should not react to the private information in rejection letters.

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

[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 a non-final rejection date. This means that applicants abandon the application by failing 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

only covers granted patents, we expand the matched sample by applying the same matching procedure to abandoned 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 patent application in 2013 that was eventually abandoned, we match it 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 of 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 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 include two new categories that were recently added (in 2019) to the "Y02" tagging scheme: 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

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 match manually.

[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 grids) 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.

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 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

[19] Our sample differs somewhat from Cohen et al. (2021) since (i) we focus on application data, containing both granted and abandoned 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.

[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.

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 abandoned) 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 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 holdings[25] and sort for every quarter institutions by their portfolio Environmental Score to get a measure of their revealed preference 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 Ken French's Data Library.[26]

3 Identification Strategy

3.1 Institutional Background of Patent Examinations

We briefly introduce the institutional background of patent examinations.[27] The examination process involves two steps: (i) the USPTO first attaches a set of technology classes (USPC or CPC

[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 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).

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 assessment.

Our exogenous variation lies in the second step of the examination process. 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 propensity to approve 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 (climate, other green or non-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 the patent examination process: 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 granting decision, if any. When the patent is granted, 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 granting 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. The decision date for abandoned applications is the date of the first action letter. 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]

[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

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 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:

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

where $Num\_ClimPats\_Granted_{i,t}$, the number of climate patents granted by USPTO 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 at the 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 relative within an art unit.

We calculate an examiner's leniency considering her past and future evaluated applications. We

from the patent examiner lottery. This would not only require that the examiner name is immediately available, but in addition that comprehensive and detailed data and sophisticated analysis are available: 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).

[31]When calculating an examiner's granting ratio, we use all patent applications, including both green and non-green patent applications. We only consider examiners who assessed at least ten applications.

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 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 time period. Among pairs of firms with identical patent application numbers in a given time period, 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

[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.

[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.

and reach qualitatively similar results.

One potential concern is that the instrumental variable might weaken when a firm has numerous climate patent applications receiving decisions in month t. Online Appendix Table A2, however, demonstrates that this concern is not warranted: even in the top tercile of the firm-month sample (with an average of 13 applications), our instrumental variable remains strong and effective.

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 that 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 address this concern in two ways. 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 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 and 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 that our analysis suffers from the endogeneity issue raised by Righi and Simcoe (2019).

Third, Barber and Diestre (2022) show that, since patent citations influence examiner assignments, some firms use citations strategically to influence the assignment decision, a practice known as "examiner shopping". First, we attempt to partially alleviate the issue of examiner shopping with our choice to use not only past but also future application decisions when constructing our instrument as future outcomes of applications are not observable. Second, this concern might be less relevant in our context as firms with the strongest incentive to engage in 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 (Tables A1 through A4).

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]

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

In equation (3), t denotes month, and i 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 i in month t, is instrumented by the firm's average examiner leniency score following equations (1) and (2). Following Berg et al. (2021)'s return regression, $\mathbf{X}_{i,t}$ includes log of market capitalization (LnMV), Tobin's q, Cash, ROA, R&D expenditures, momentum, volatility, and environmental

[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.

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.[37] 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, (non-climate) general and (non-climate) green patents.[38] 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 first at Figure 2, Panel A, we find a positive and significant effect of climate patents 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.[39] Turning to Panel B, we find no effect of non-climate general patents on CARs. Similarly, Panel C shows no effects for green but 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. We note that

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

[37]When adding this fixed effect, We only include observations when multiple firms have the same number of patent applications in a given month. Singletons (only a single firm with that number of patent applications) are omitted in our regressions, but singletons account only for 8% of our sample and hence they do not affect the resulte (as we verify in robustness checks that include singletons, using various normalizations and granular intervals of patent numbers).

[38]In Figure 2, Panels A, B and C, the independent variable is the number of climate patents, general non-climate patents and other green non-climate patents, respectively, granted to firm s in month t, and the number of applications fixed effects τ_{app} are constructed using only the patents of each of these categories.

[39]Our regression allows 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 gives an estimate of the marginal effect for one patent: $\frac{\partial CAR}{\partial Num\_Clim\_Patents} = \frac{\partial CAR}{\partial ln(1+Num\_Patents)} = \frac{\partial CAR}{\partial Num\_Patents} \times \frac{\partial Num\_Patents}{\partial ln(1+Num\_Patents)} = \frac{\partial CAR}{\partial Num\_Patents} \times (1 + Num\_Patents)$. To find the marginal impact of one additional climate patent, we then divide this 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, this back-of-the-envelope estimate is admittedly very crude and cannot precisely estimate the true marginal effect, as discussed by Cohn, Liu, and Wardlaw (2022).

our findings for general patents are in line with the literature.[40] The sharp difference between climate and other green patents is in line with a unique signaling effect of climate innovation and it echoes survey evidence indicating that investors are more concerned about climate change than about other environmental issues (Krueger, Sautner, and Starks, 2020).

Figure 2, Panel A also displays the dynamics of the patent granting effect. We find that the CARs are small in the first few months and then increase monotonically until month 12 after the patent grant. This pattern is consistent with the innovation literature indicating that financial markets take time to incorporate information about patents, 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 A9 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 increase, reflecting the noise in long-term stock returns.

We repeat the analysis of Figure 2 using Poisson regressions without the $ln(1+x)$ transformation of the dependent variable in the first stage regression, to account for the concerns of Cohn et al. (2022) regarding the $ln(1 + x)$ transformation of count variables. We use the predicted value of the dependent variable, the number of climate patents, as the main variable of interest in the second stage, running the 2SLS manually. As Figure A2 in the Online Appendix shows, these main results remain similarly strong and robust when we use the Poisson regression design.

An important concern is that financial markets might learn about promising climate patent applications before the USPTO makes successful patent grant decisions public. In particular, since 2001, the USPTO is required to publish the vast majority of patent application documents 18 months after they are filed. One might hypothesize that the market incorporates the information contained in patent application documents into stock prices at the time of this release. To evaluate this hypothesis, we conduct regressions for a different event date, namely the date when the USPTO is obligated to make the patent application documents public, 18 months after their filing (if this date is earlier than the granting date).

Following Equation 3, we again include fixed effects for the number of climate patent applications published in month t, thus comparing firms with the same number of climate patent appli-

[40] Kogan et al. (2017), the most systematic and widely cited study on the financial market reaction to patent announcements, find that mean announcement returns are close to zero and that more than half of patent grants are associated with negative announcement returns.

cations published in month t, but differing in the number of climate patents ultimately granted because of their different exposure to the examiner leniency instrument.

We repeat our original 2SLS regressions of Equation 3 with the examiner leniency instrument for this separate event date. As Figure A4 in the Online Appendix shows, we do not observe any significant effect of the instrument conditional on the month of the patent application release (as opposed to the granting month, as reported in Figure 2). This makes sense since the released application documents do not contain any information about patent examiners. Thus, our main findings displayed in Figure 2 can indeed be interpreted as the reaction to the unexpected component in the patent grant, due to the examiner leniency shock.[41]

As a further robustness check, we also run OLS regressions, using the raw number of patents grants as variable of interest instead of the number predicted by the leniency instrument. Figure A5 in the Online Appendix shows that our results are robust to this change with comparable levels of significance. Our parameter estimates in the OLS regressions are smaller than those in the instrumented regressions, a typical phenomenon in instrumental variables regressions in finance, as Jiang (2017) documents.[42]

Finally, we recognize the importance of properly estimating abnormal returns in long-term return studies (Kothari and Warner, 2007). Therefore, we document in the Online Appendix results

[41]When we use OLS regressions in which the variable of interest is the raw number of patents grants, we find a positive reaction in stock market prices, see Panel A of Figure A3 in the Online Appendix. This lends support to the notion that markets incorporate the information contained in patents applications into stock prices, at least partially, at the time at which the applications are released but no decision has been made yet. This suggests that our headline results in Figure 2 only capture a fraction of the valuation impact of climate patents since the full value impact should compound the reaction to the public release of the application and the reaction to the eventual patent grant that on average arrives 18 months later.

[42]The ratio of β_{2SLS} (depicted in Figure 2, Panel A) and β_{OLS} (in Figure A5, Panel A) falls within the typical range for finance papers, reported by Jiang (2017) to be between 3 and 9, depending on the nature of bias in the OLS regression. Among the possible explanations suggested by Jiang (2017), it seems unlikely that in our case the higher β_{2SLS} is due to weak instruments given the strong F-statistics of 545.8 and explanatory power of 0.878 (Adj R2) in the first stage reported in Table 2. In the institutional context of patent examiner assignments, it seems unlikely that violations of the monotonicity requirement (suggesting that patents granted by tough examiners also be granted by lenient examiners, and vice versa for rejected patents, see Aronow and Miller (2019)) could be the origin of higher β_{2SLS} estimates. It is possible that our tests fall into the category of "corrective endogeneity" where the OLS estimates exhibit a downward bias. For example, emission-intensive firms (such as firms in the energy sector) typically produce more climate patents but tend to have lower market-to-book ratios (Pástor et al., 2022) and to be divested by ESG funds (Cohen et al., 2021). Finally, we cannot rule out that our regressions reflect a local average treatment effect (LATE) for compliers that exceeds the population average treatment effect. However, the natural hypothesis that the examiner assignment matters most for the granting decision of patents in the intermediate value range - when we inspect our data, we find patterns suggesting that this might be the case - does not imply in any obvious way a heightened LATE for compliers relative to the population average.

for a comprehensive set of alternative specifications for our results of monthly CARs. Figure A6 includes the 4-month pre-event window into regressions. Figure A7 displays analyses that use the Fama-French 3-factor model to calculate monthly abnormal returns, while Figure A8 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.

4.2 Attention to Climate Change and Announcement Returns

Why do markets react in a distinct fashion to climate patents that we do not observe for other green patents, or for patents in general? In other words, what explains the prominence of climate issues in the market perception of innovation? We propose three different tests for the tenet that climate issues stand out among issues that the market perceives as important in firms' innovation agenda. All revolve around the idea that the issuance of climate patents serves as a signal that a firm is actively involved in initiatives to mitigate climate change. Investors react positively to this information, leading to positive stock returns.

Our first test explores the idea that, if this general hypothesis is true, we should expect the signaling effect to be more pronounced during periods when climate change concerns are particularly salient. When climate change is at the forefront of public discourse and environmental issues are receiving increased attention, investors should respond more 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 (see Figure A1) 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 the negativity and risk they reflect, 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:[43]

[43] 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 half-life of slightly less than 12 months.

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

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:

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

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

Our second test of the idea that climate patents are perceived as a signal for firms' commitment to corporate climate action looks into firm-specific determinants of the signal value. If the general idea is true, then the signaling value should be larger for firms that are more affected by climate issues. Hence, we investigate cross-sectional variations in the financial market reaction to climate patent announcements by looking into the role of firm-specific exposure to climate change. We use the measure developed by Sautner et al. (2020) that captures the frequency and prominence of climate-related topics discussed in firms' quarterly earnings conference calls.[44]

[44] 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,

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 Climate Patent Stocks: New versus Seasoned Innovators

Our third test investigates the signaling value when firms are making their debut as climate innovators. When a firm obtains its first batch of climate patents, we expect them to send a strong signal to financial markets about the firm's commitment to climate action. On the other hand, 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. 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 5 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

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.

again plot the three coefficients, one for each tercile, separately. The findings are aligned with our hypothesis, with firms in the low tercile of climate patent stock having the strongest CAR effects (Figure 5, Panel A). The lowest tercile of the Climate Patent stock corresponds to firms with less than 10 climate patents. By contrast, we find no significant effect for the medium and high terciles of Climate Patent Stock (Figure 5, Panels B and C).

4.5 Short-Term Abnormal Returns

We next investigate the short-term market stock price reaction to climate patent announcements. We examine daily abnormal returns around granting and rejection dates of climate patents, where abandoned climate patents serve as a control group (in the placebo sense). We conduct similar regressions as in equation (5) and replace the monthly CARs with daily CARs for three event windows: [-3 , +3], [-2 , +2] and [-1 , +1] days. Our 2SLS regressions isolate the signaling effect of the patent grant.[45]

We distinguish by level of public attention to climate change, using again terciles of the MCCC index.[46] The results, plotted in Figure 6 and reported in Table 3, show that daily CARs are significant when the patent is granted in a period of heightened (top-tercile) climate change attention (Figure 6, Panel A). Daily abnormal returns are significant for the three windows we consider, and 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% (Table 3, Panel A).

By contrast, we do not detect abnormal short-run announcement returns during periods with lower attention to climate change (Figure 6, Panels B and C) and the results are weak when not differentiating by MCCC index. This highlights again the role played by the salience of climate change concerns. Also, there is no short-term stock market reaction to non-climate green patents or other non-climate patents (Table 3, Panels B and C), consistent with our earlier findings that there are no medium- and long-term reactions to non-climate lucky patents.

[45] A direct event study of climate patents granted, without the lucky patent instrument, would also capture the value of the underlying technology (Kogan et al., 2017).

[46] We use the monthly average $\overline{MCCC}$ in the month of the patent decision.

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.[47] We follow the approach in Pástor et al. (2022) and measure a firm's expected return using the method of implied cost of capital (ICC). We implement Gebhardt, Lee, and Swaminathan (2001)'s residual income valuation model to calculate r, the implied cost of capital, as follows:

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

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.[48] 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

[47] Chava (2014) and Pástor et al. (2022) find that firms with better environmental performance enjoy a lower cost of capital. Focusing on climate patents, we are able to show that this relationship is causal.

[48] Following Lee, So, and Wang (2021), we estimate earning forecasts three years ahead using regression predictions as in Hou et al. (2012), and we use extrapolation by assuming that they will gradually revert to the industry median ROE for years four to 12. This approach appears warranted given our finding that operating performance is not affected by lucky patent draws (see Table A2, Online Appendix).

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.

5 Transmission Channels

We now offer an investigation into the mechanisms behind the specific market reaction to fortuitous climate patents. We study what sets them apart from other green patents and general patents with a focus on 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.

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:

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

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).[49]

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.[50] We find that climate patents improve a firm's climate strategy score, but not other general patents.[51]

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.[52] Our study aims to examine whether institutional investors, particularly those prioritizing ESG

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

[50] 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.

[51] 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.

[52] 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).

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 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 UN PRI 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.[53] 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 the analyses displayed in 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) of Panel A. 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) 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 Panels B and C of Table 5 shows, IO does not respond to general and other green non-climate patents, echoing earlier (non-)results for these patent grants.

[53] 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.

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 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 periods 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) coincide 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 (top tercile of the MCCC index), suggesting that price pressure emanating from increased institutional investor demand could plausibly contribute to abnormal stock returns.

6 Real Effects and Alternative Explanations

Our leading explanation for the documented market reaction to lucky climate patent grants is a signal effect that appear to work through ESG ratings and climate-conscious investors. But we also need to account for alternative explanations, in particular the possibility that the observed return patterns reflect changes in firm fundamentals, or real effects, 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).[54] We analyze these two possible channels in turn, using operating performance as a proxy for future cash flows, and carbon emissions as a proxy for the exposure to climate transition risks.

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 cash-flow channel as an alternative explanation for our results, 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 A8 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.[55]

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

[55] We divide the number of granted climate patents of 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 a patent truncation bias in the most recent years. We include all observations of 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.

The results are documented in Table A7 in the Appendix. We now generally find a positive 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 in Figure 2 cannot be attributed to the cash flow channel. 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. We undertake a limited analysis of this risk channel by focusing exclusively on climate transition risk. While there are other possible effects on firm risk, they arguably represent the one dimension of risk most directly related to the underlying climate innovation. As a proxy for a firm's exposure to climate transition risk, we look at the innovator's future carbon emissions. In other words, we analyze whether investors expect climate innovation to reduce carbon emissions and hence transition risk which could then translate into a lower discount factor and thus trigger 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: 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.[56] Thus, our dependent variable, the change of log emission intensity, approximates a rate of change.[57]

We first look at fortuitous patent grants, using our instrumental variable of shocks in examiner leniency. The results are documented in Table A10 in the Appendix. We find no significant effects of patent grant shocks on CO2 emissions nor on renewable and clean energy used.

In a second step, we ask whether real impacts are detectable when we look at our measure of

[56] 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.

[57] 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.

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).[58]

To conclude, the striking contrast between the findings for the lucky patent instrument and 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 decision to grant patent protection, similar to what we found when looking at operating performance.[59]

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. Using an instrumental variable approach that exploits exogenous variations in patent approvals, based on differences in the leniency of randomly assigned patent examiners, we establish a causal link between climate patents and financial market reactions.

[58] 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 reflect the effect 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.

[59] By isolating the random component in patent grants in our 2SLS analysis, we are able to distinguish between the impact of the underlying technology and the certification signal offered by patents. In the absence of easily available heuristics on examiner leniency, market participants should have much less ability to do so. Thus, it is rational for such market participants to view patent approvals as informative signals even though they are noisy, with examiner leniency being one (significant) source of such noise.

We find that companies that obtain lucky climate patent grants exhibit significant medium-term (12 to 18 months) cumulative abnormal returns and a concomitant reduction in the implied cost of capital. These effects are specific to climate patents, as we do not find abnormal returns or reduced costs of capital for non-climate green patents or for other non-climate patents. We undertake several tests to understand why markets pay particular attention to climate patents. First, we look at the salience of climate change concerns and find that the abnormal return is strongly significant only in periods of heightened climate change attention, and that in these periods firms also exhibit significant short-term (one to three days) returns. Second, we explore cross-sectional variations in the exposure to climate change and find that the market reaction is only significant for firm's with high exposure. Third, we look at firms' debut as climate innovators and find that the effect is strong only for the first ten climate patents.

We find evidence 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 effects of climate patents, we find no measurable impact on operating performance or carbon emissions when we look at randomly obtained climate patents. By contrast, when we study the underlying climate technology, we find a strong association with subsequent gains in operating performance and emission 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 is due to a signal effect: from the point of view of market participants, patent approvals are noisy but informative signals about firms' commitment to corporate climate action.

Our strong and robust findings on the reaction of financial markets, buoyed by the salience of climate change, firms' climate risk exposure and fund flows of climate-focused investors, offers evidence that financial markets reward the development of climate technology. They provide encouraging news for decision-makers concerned about adequate incentives for climate innovators.

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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:

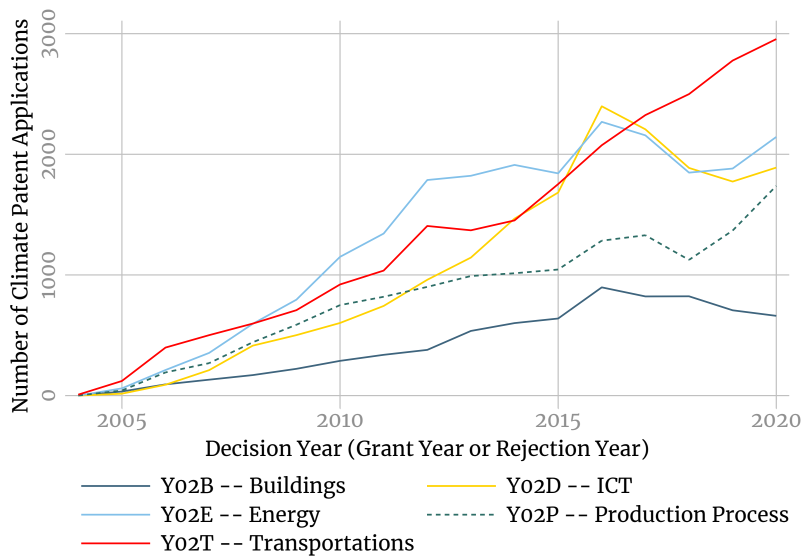
Assignee Name	Assignee Address	PERMNO	Matching Start Year	Matching End Year
ABBOTT LAB	60064	20482	2001	2015

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 abandoned), 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 with a decision by Application Year

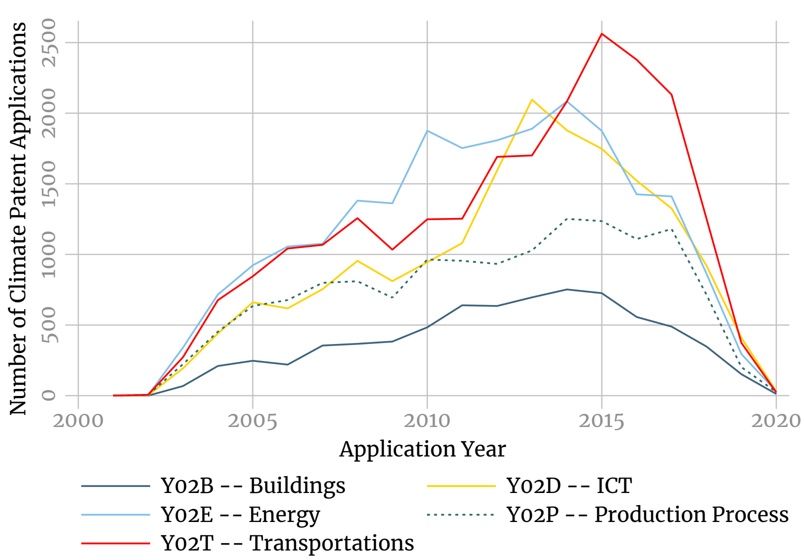


Figure 2. Climate Patents and Monthly Abnormal Stock Returns

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, respectively . 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 patent applications in the considered patent category (climate, general, other green) in that month. The dependent variable is the cumulative abnormal return (CAR) 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. In Panel A, only climate patents are considered, and the main independent variable is $Num\_ClimPats\_Granted$, counting the number of climate patents issued to the firm during month t. We similarly consider general (non-climate) patents in Panel B and other green (non-climate) patents in Panel C, and define the dependent variables accordingly. We instrument these variables 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. $\mathbf{X}_{i,t}$ 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 Number of Patent Applications F.E. with decisions in that month. Standard errors are double-clustered at the art-unit and industry-year level. The Patent Applications F.E. only counts the corresponding type of patents (climate patents in Panel A, general patents in Panel B, and other green patents in Panel C). Confidence intervals are plotted at the 90% confidence level.

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

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

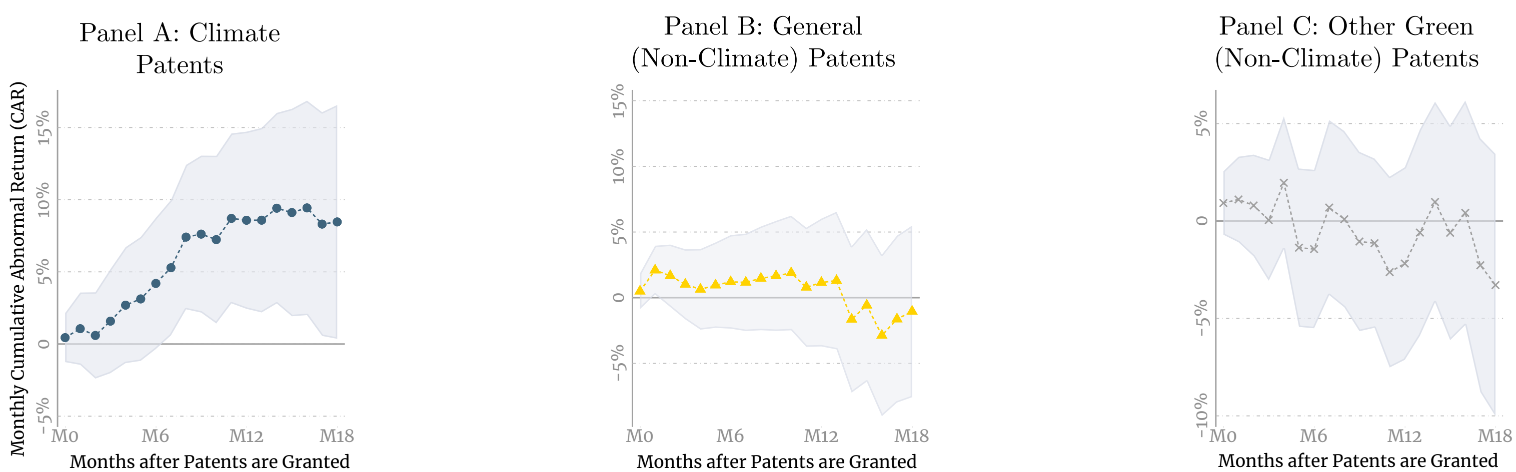


Figure 3. Climate Patents, Media Coverage of Climate Change, and Abnormal Stock Returns

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:

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

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. $\mathbf{X}_{i,t}$ 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.

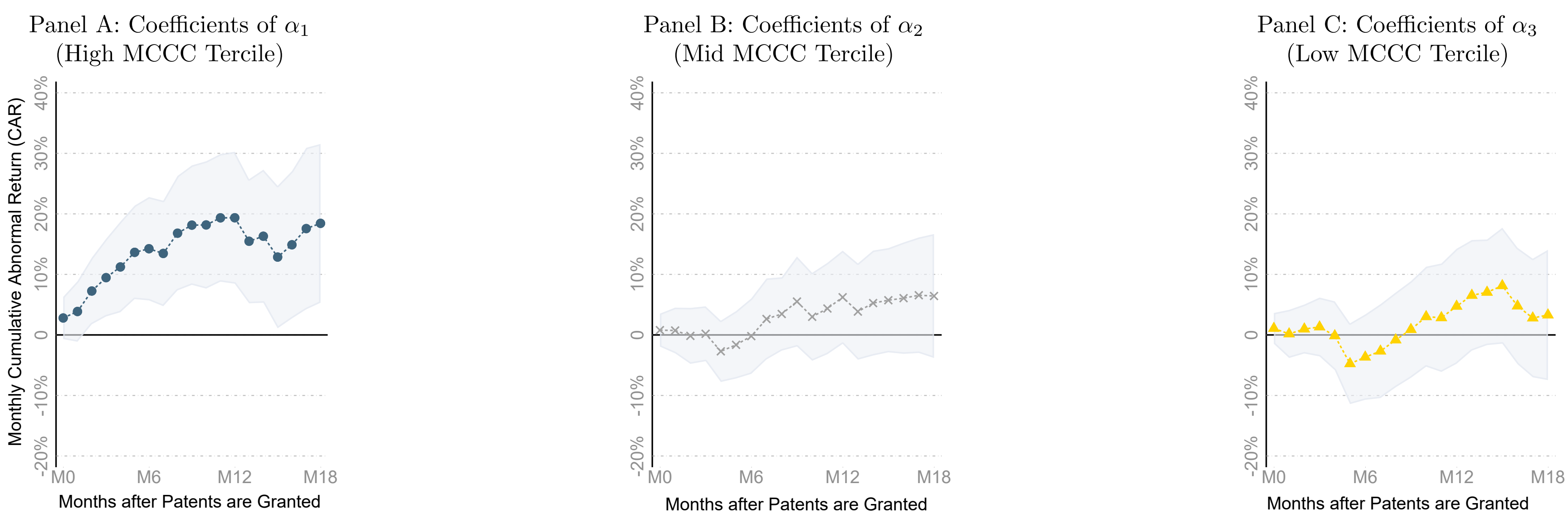


Figure 4. Climate Patents, Firm-level Climate Exposure, and Abnormal Stock Returns

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. $\mathbf{X}_{i,t}$ 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.

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

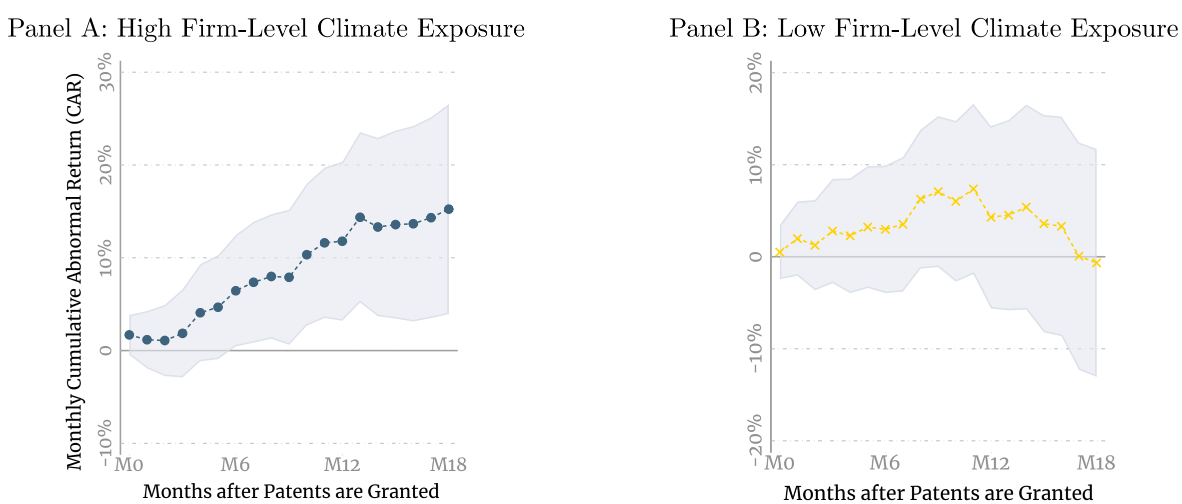


Figure 5. Climate Patents, Climate Patents Stock, and Abnormal Stock Returns

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

$$CAR[t:t+k]_{i,t} = \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times Clim\_PatStock\_High_{i,t} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times Clim\_PatStock\_Mid_{i,t} + \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times Clim\_PatStock\_Low_{i,t} + \delta_1 Clim\_PatStock\_High_{i,t} + \delta_2 Clim\_PatStock\_Mid_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \quad (13)$$

$Clim\_PatStock$ 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. $\mathbf{X}_{i,t}$ includes log of market cap, Tobin's Q, Cash, ROA, R&D expenditures, past 12-month stock performance, return volatility, and environmental score, all measured in Year $t-1$. Fixed effects include Industry $\times$ Month F.E., Art Unit $\times$ Year F.E., and the Num of Climate Patent Applications (receiving results in that month). F.E. Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

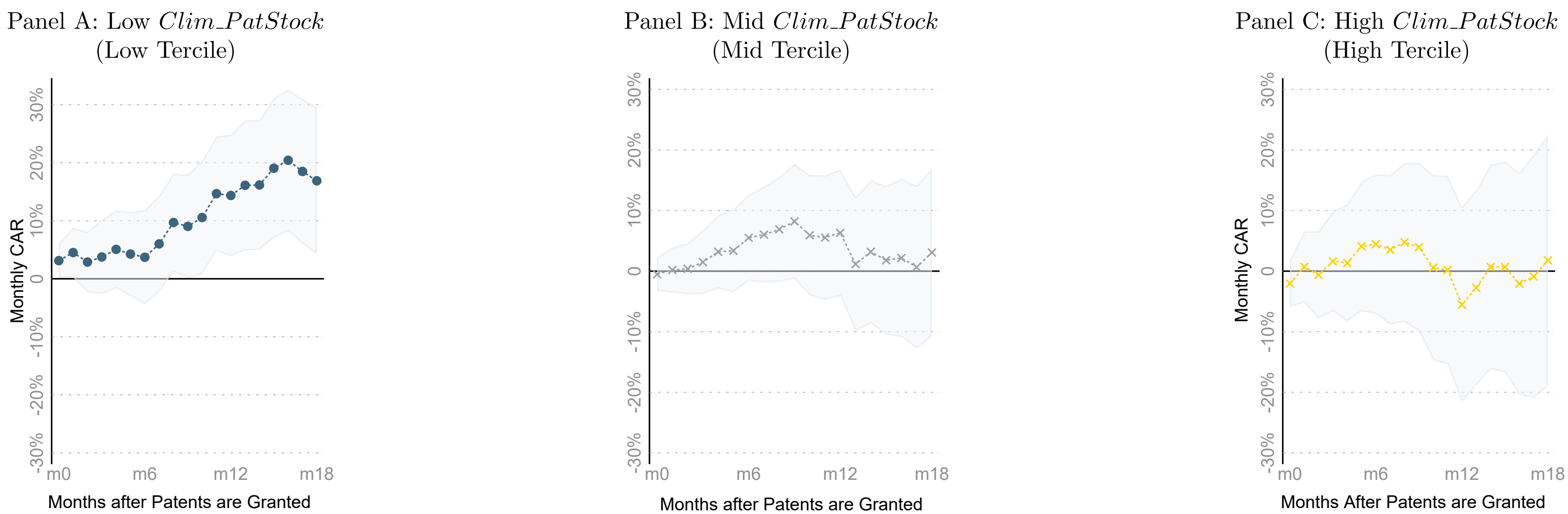


Figure 6. Climate Patents, MCCC Index, and Daily Abnormal Stock Returns

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

$$
\begin{aligned}
Daily\_CAR[t-3:t+k]_{i,t} = {} & \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{Ht} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{Mt} + \\
& \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{Lt} + \delta_1 \overline{MCCC}_{Ht} + \delta_2 \overline{MCCC}_{Mt} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \quad (14)
\end{aligned}
$$

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):

$$
\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad (15)
$$

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. $\mathbf{X}_{i,t}$ 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. The Patent Applications F.E. only counts the corresponding type of patents (climate patents in Panel A, general patents in Panel B, and other green patents in Panel C). Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

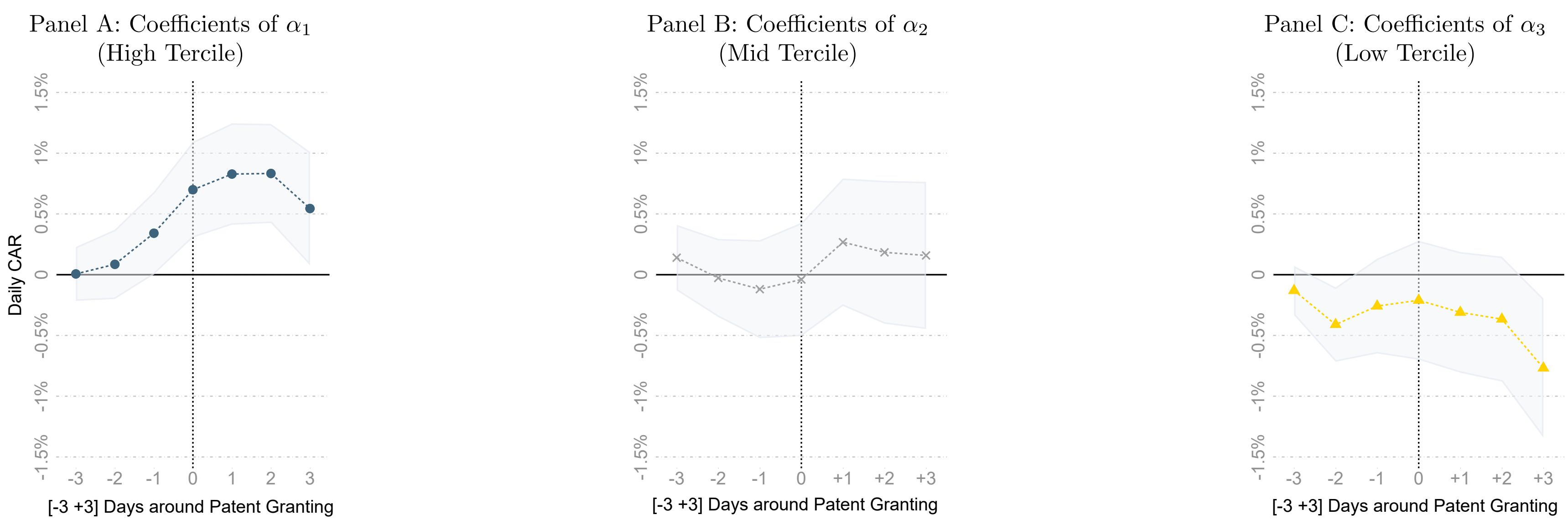


Figure 7. Climate Patents and Implied Cost of Capital

This figure shows how the exogenous issuance of patents influences 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, respectively. 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 $t+k$. In Panel A, the main independent variable is $Num\_ClimPats\_Granted$, counting the number of climate patents issued to the firm during the month t. We construct analogous count variables for general (non-climate) patents in Panel B and for other green (non-climate) patents in Panel C. We instrument these variables 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 × Month F.E., Art Unit × Year F.E., and Number of Patent Applications F.E. (with decisions in that month). The Patent Applications F.E. only counts the corresponding type of patents (climate patents in Panel A, general patents in Panel B, and other green patents in Panel C). Standard errors are double-clustered at the firm and industry-year level. Confidence intervals are plotted at the 90% confidence level.

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

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

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:

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

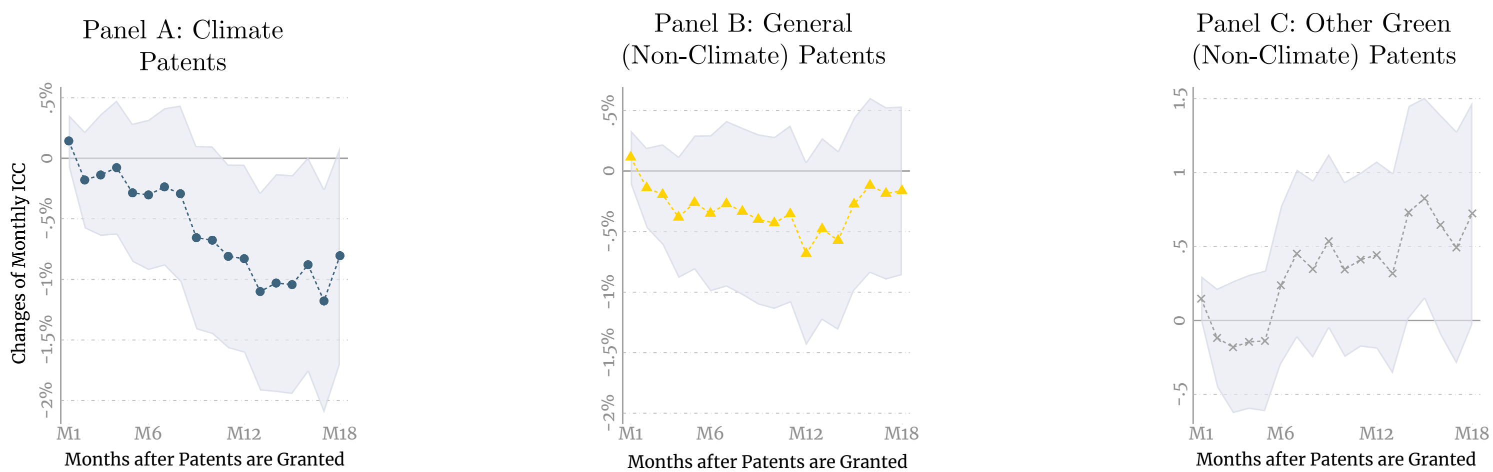


Figure 8. Climate Patents, Media Coverage of Climate Change, and ICC

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:

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

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:

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

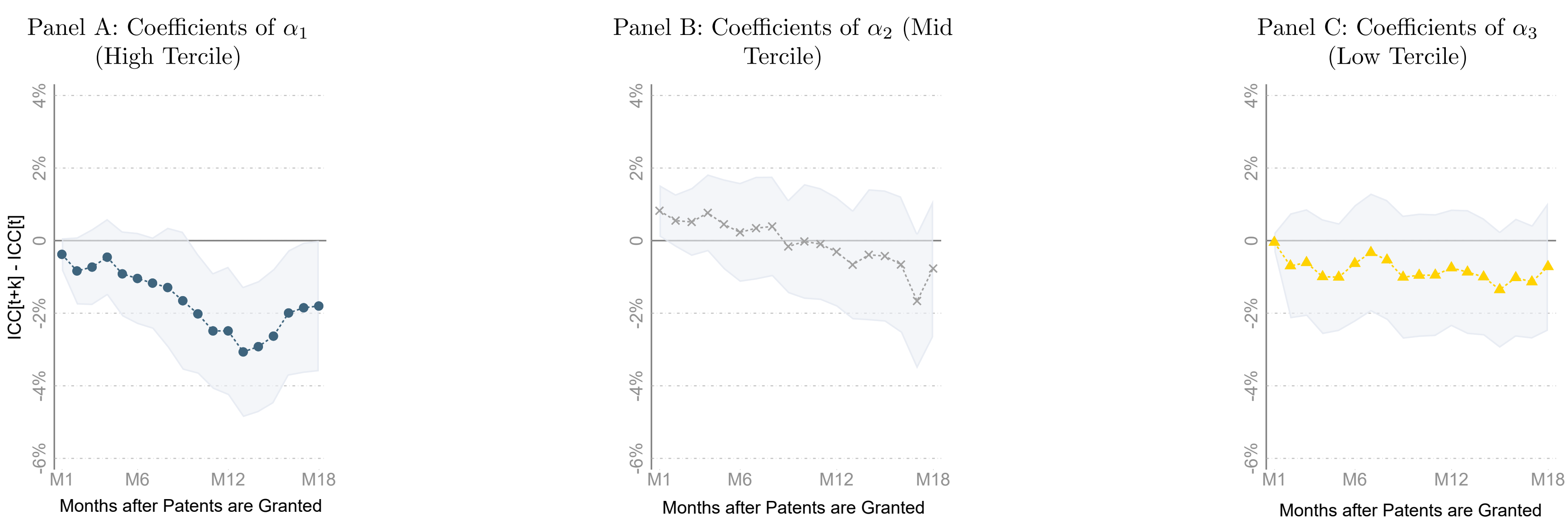


Table 1: Summary Statistics

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
All (General) Patents	
Number of All Patent Applications	1,730,582
Number of Granted Applications	1,235,261 (71%)
Average Years between Application and Granting	3.10
Average Years between Application and Rejection	2.95
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
Adj R2	0.921	0.912	0.878

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. In Panel A, the second stage regression follows the equation:

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

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%. In Panel A, the main independent variable is $Num\_ClimPats\_Granted$, counting the number of climate patents (non-climate general patents) issued to the firm during the day t. In Panels B and C, we construct the variables $Num\_GenPats\_Granted$ and $Num\_OtherGreen\_Granted$ accordingly, using (non-climate) general patents and (non-climate) other green patents, respectively. We instrument these variables using the average relative leniency of examiners who assess these patent applications of the firm. The main independent variable takes the $ln(1+x)$ transformation and it 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 Environmental Scores (a ESG sub-score). All regressions are 2SLS regressions. 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. In Panel A and B, 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. In Panel C, we define the main independent variable $Num\_GenPats\_Granted$ accordingly for the number of (non-climate) general patents. The main independent variable 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.

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

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

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, B and C investigate climate patents, general (non-climate) patents and other green (non-climate) patents, respectively. 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. In Panel A, 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. In Panels B and C, the main independent variable is constructed accordingly for general (non-climate) patents and other green (non-climate) patents, respectively. The main independent variable 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.

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

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:

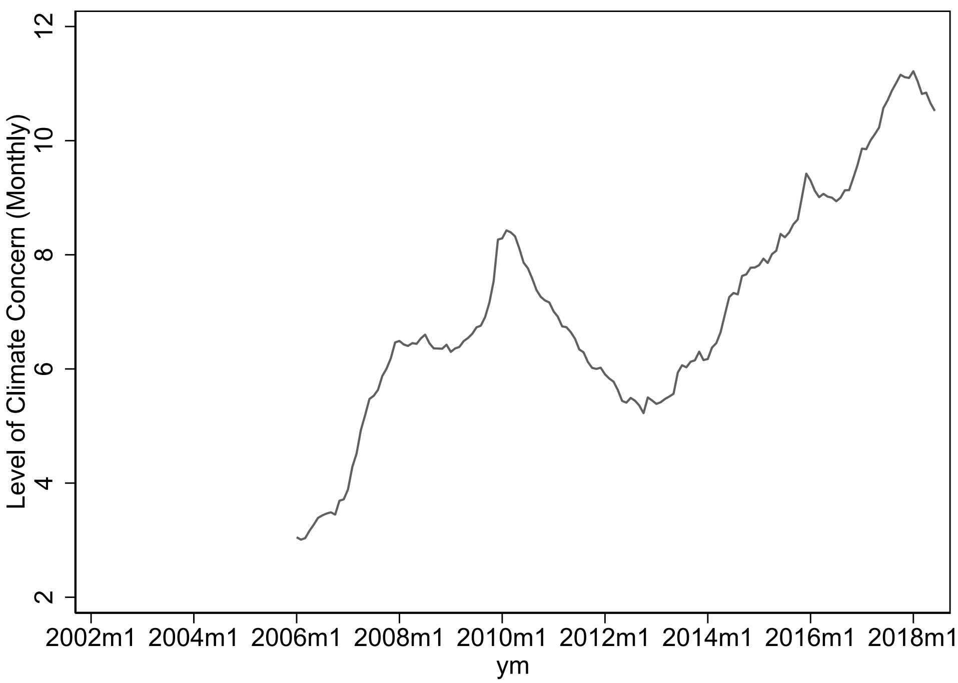
Climate Patents and Financial Markets

List of Figures

List of Tables

Note: For brevity, the captions for Figures A2 to A11 and for Figure A14 and for Tables A5, A6, and A7 state the construction of the main independent variable only for the case of climate patents (*Num_ClimPat_Granted*), shown in Panel A. We construct the main independent variable in the other panels for the number of general (non-climate) patents and for other green (non-climate) patents accordingly, exactly as explained in the figures and tables of the main paper.

Figure A1. MCCC Index (Monthly)



The original Media Climate Change Coverage (MCCC) index is a monthly measure of media attention to climate change, developed by Ardia, Bluteau, Boudt, and Inghelbrecht (2020). We construct $\overline{MCCC}_t$ following the monthly memory model proposed by Pástor, Stambaugh, and Taylor (2022), which captures investors' memory of media coverage over the past 36 months:

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

In the figure above, 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 depict the outcomes for climate patents, general (non-climate) patents, and other green (non-climate) patents, respectively. In each panel, 2SLS regressions are conducted following the outlined procedure, 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 condition 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 et al., 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 $\mathbf{X}_{i,t}$ includes 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.

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

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

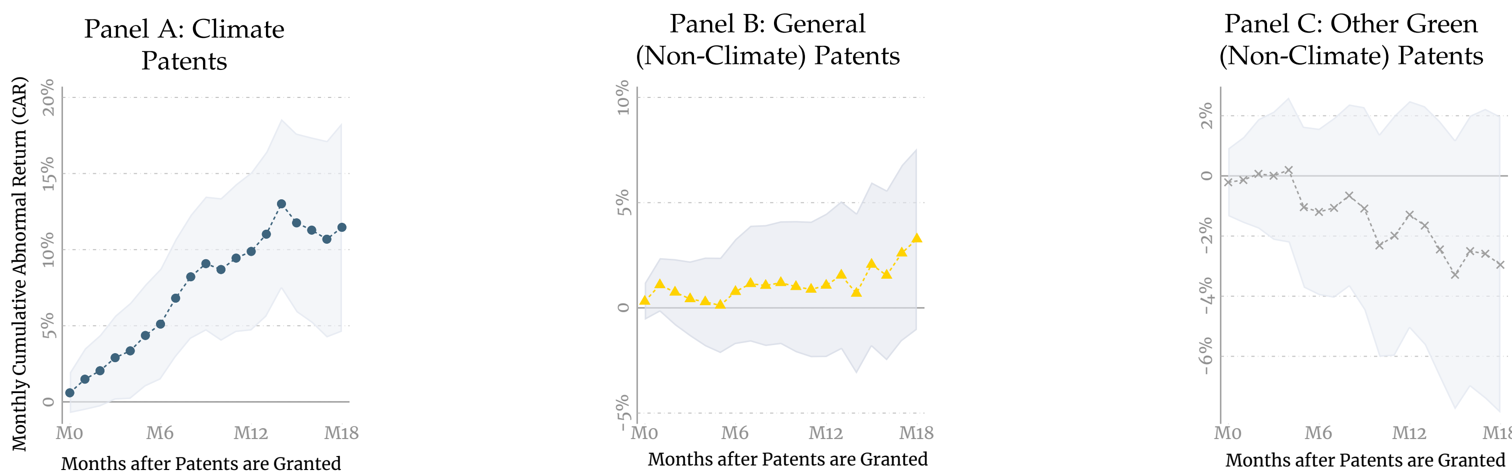


Figure A3. Climate Patents and Monthly Stock Returns (OLS with Patent Publication Date)

This figure presents OLS regression results for our main analysis. Panels A, B, and C separately examine climate patents, general (non-climate) patents, and other green (non-climate) patents. We utilize the **patent application publication date** as the alternative signal date, assuming that the market comprehends all publication documents of patent applications and can discern which ones will ultimately be granted. In each panel, we conduct OLS regressions and plot the coefficients (α) for each k ranging from 0 to 18. The data is at the firm-month level, and the sample requires that a firm has at least one climate patent application published by the USPTO in that month. The dependent variable is the cumulative abnormal returns (CARs) from time t to time $t+k$, where t is the patent publication month. Abnormal Returns (ARs) represent alphas in the Fama-French 5-Factor model (Fama et al., 2015), with factor loadings estimated using the previous 60-month returns data. The main independent variable is $Num\_ClimPats\_Granted$, which counts the number of climate patents issued by the USPTO whose application information was published during month t. We apply a log transformation, $ln(1+x)$, to our main independent variable. The vector $\mathbf{X}_{i,t}$ includes 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 comprise industry $\times$ month fixed effects, art unit $\times$ year fixed effects, and the number of climate patent publications fixed effects (τ_{pub}). Standard errors are double-clustered at the art-unit and industry-year levels. Confidence intervals are plotted at the 90% confidence level.

$$OLS\ Regression: \quad CAR[t:t+k]_{i,t} = \alpha Num\_ClimPats\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{pub} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A4}$$

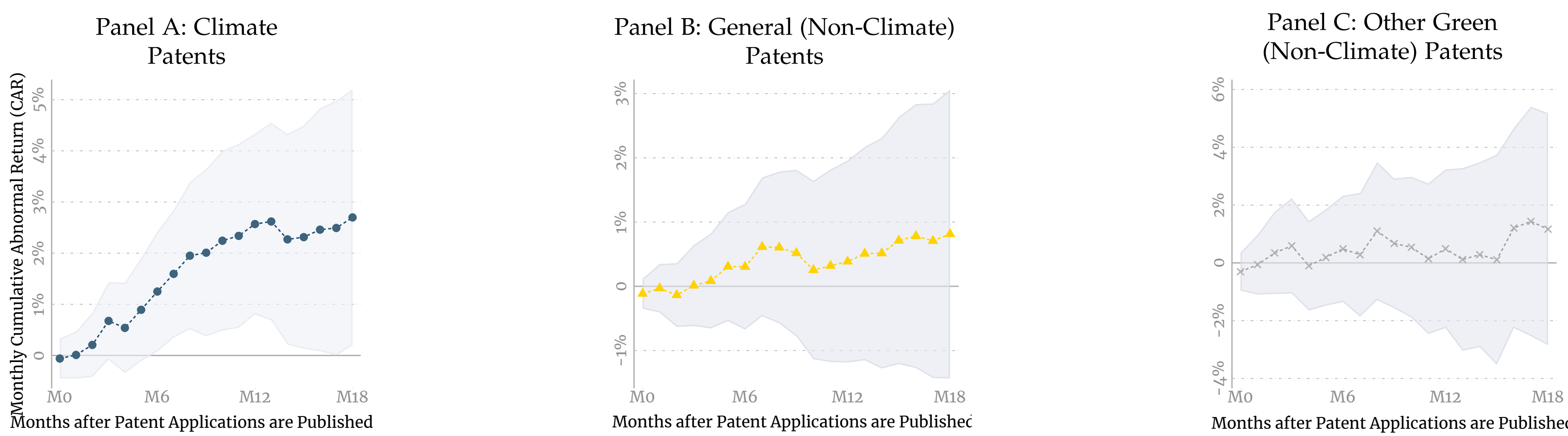


Figure A4. Climate Patents and Monthly Abnormal Stock Returns (2SLS with Patent Publication Date)

This figure shows the placebo tests of 2SLS return regressions. Panels A, B and C plot the results for climate patents, general (non-climate) patents, and other green (non-climate) patents separately. We utilize the **patent application publication date** as the alternative date of signals. 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 has at least one publication on its climate patent applications in that month. The dependent variable is the cumulative abnormal returns (CARs) from time t to time $t+k$, where t is the month of patent publication. 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 ultimately issued to the firm and published by USPTO 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. $\mathbf{X}_{i,t}$ 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 (published in that month). F.E. (τ_{pub}). Standard errors are double-clustered at the art-unit and industry-year level. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{i,t} = \alpha \widehat{Num\_ClimPats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{pub} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A5}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{pub} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A6}$$

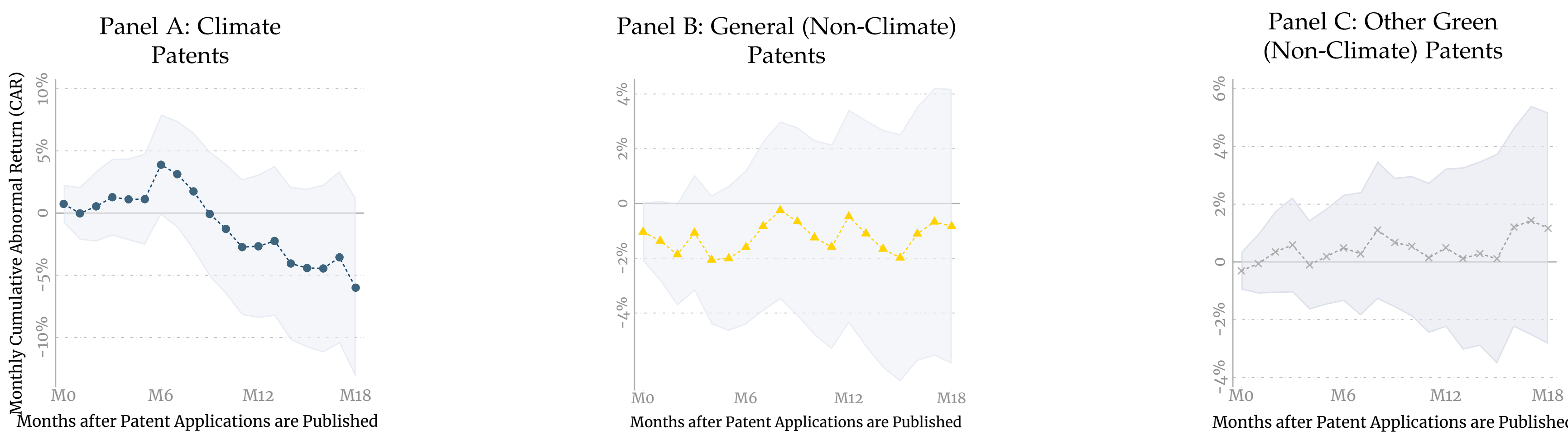


Figure A5. Climate Patents and Monthly Stock Returns (OLS Regression without the Instrument)

This figure presents OLS regression results for our main analysis. Panels A, B, and C examine climate patents, general (non-climate) patents, and other green (non-climate) patents separately. In each panel, we conduct the following OLS regressions and plot the coefficients (α) for each k ranging from 0 to 18. The data is at the firm-month level, and 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) represent alphas in the Fama-French 5-Factor model (Fama et al., 2015), with factor loadings estimated using the previous 60-month returns data. The main independent variable is $Num\_ClimPats\_Granted$, which counts the number of climate patents issued to the firm during month t. We apply a log transformation, $ln(1+x)$, to our main independent variable. The vector $\mathbf{X}_{i,t}$ includes 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 comprise industry $\times$ month fixed effects, art unit $\times$ year fixed effects, and the number of climate patent applications receiving decisions in that month fixed effects. Standard errors are double-clustered at the art-unit and industry-year levels. Confidence intervals are plotted at the 90% confidence level.

$$OLS\ Regression: \quad CAR[t:t+k]_{i,t} = \alpha Num\_ClimPats\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A7}$$

Panel A: Climate Patents

Panel B: General (Non-Climate) Patents

Panel C: Other Green (Non-Climate) Patents

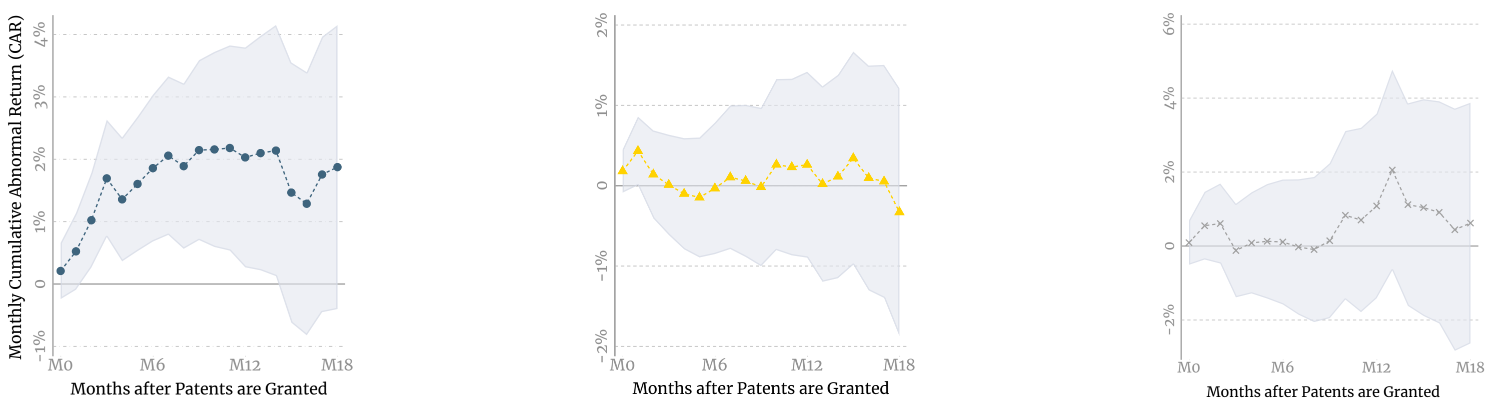


Figure A6. Climate Patents and Monthly Stock Returns (Including Pre-Trends)

This figure provides a robustness check of the exercise presented in Figure 2. The regression design mirrors that of Figure 2 with the exception that we include four months prior to month t, the month of patent grant announcements. 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 this variable using the average relative leniency of examiners who assess the firm's patent applications. $Num\_ClimPats\_Granted$ undergoes a $ln(1+x)$ transformation. The vector $\mathbf{X}_{i,t}$ includes 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 include industry $\times$ month fixed effects, art unit $\times$ year fixed effects, and the number of climate patent applications receiving decisions in that month fixed effects. Standard errors are double-clustered at the firm and industry-year levels. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t-4:t+k]_{i,t} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A8}$$

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

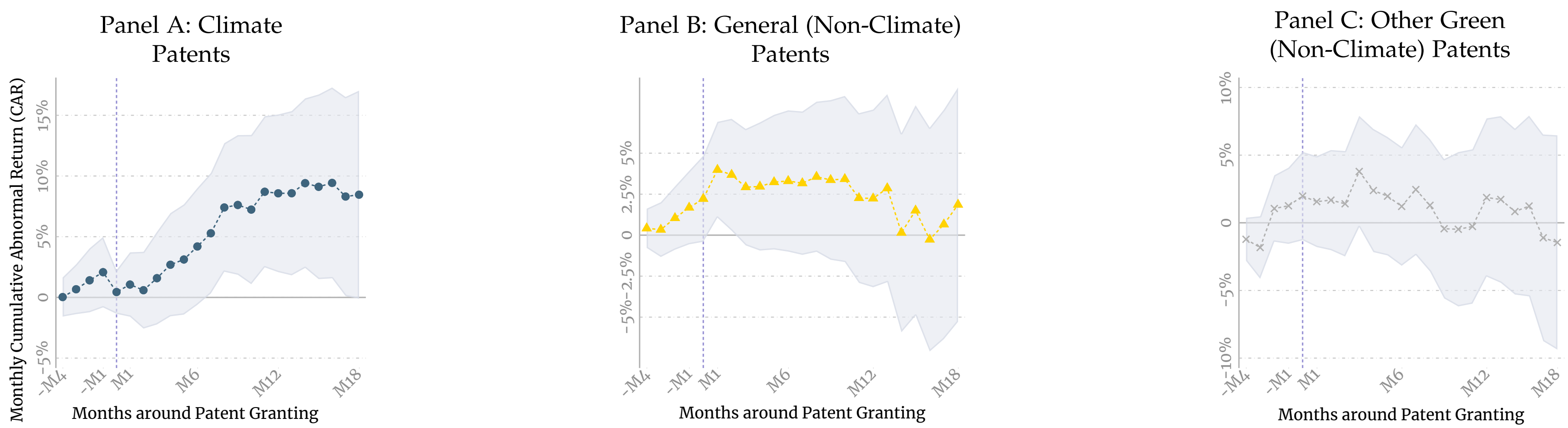


Figure A7. Climate Patents and Monthly Stock Returns (Fama-French 3-Factor Alpha)

This figure provides a robustness check of the exercise presented in Figure 2. The regression design mirrors that of Figure 2, with the exception that monthly abnormal returns are estimated using the Fama-French 3-factor model. The main independent variable is $Num\_ClimPats\_Granted$, which counts the number of climate patents newly issued to a firm during month t. We instrument this variable using the average relative leniency of examiners who assess the firm's patent applications. The main independent variable, $Num\_ClimPats\_Granted$, undergoes a $ln(1+x)$ transformation. The vector $\mathbf{X}_{i,t}$ includes 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 include industry $\times$ month fixed effects, art unit $\times$ year fixed effects, and the number of climate patent applications receiving decisions in that month fixed effects. Standard errors are double-clustered at the firm and industry-year levels. Confidence intervals are plotted at the 90% confidence level.

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

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

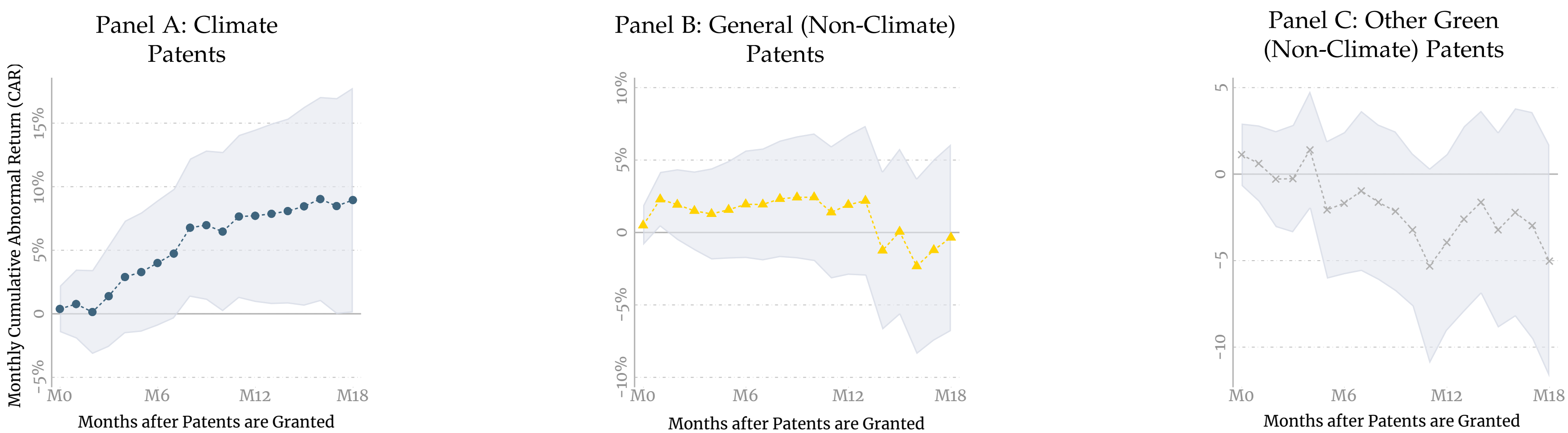


Figure A8. Climate Patents and Monthly Stock Price

This figure examines the impact of exogenous green patent issuance on firms' monthly stock prices. Panels A and B separately analyze climate patents and other green (non-climate) patents. In each panel, we conduct the following 2SLS regressions and plot the coefficients α for each k from 0 to 18. The data is at the firm-month level, with the sample requiring that a firm receives at least one decision on its patent applications in the given month. The dependent variable is the change in the logarithm of the stock price from month $t-1$ to month $t+k$. The main independent variable is $Num\_ClimPats\_Granted$, representing the number of climate patents newly issued to a firm during month t. This variable is instrumented using the average relative leniency of examiners who assess the firm's patent applications. The main independent variable undergoes a $ln(1+x)$ transformation. The control vector $\mathbf{X}_{i,t}$ includes 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 include industry $\times$ month fixed effects, art unit $\times$ year fixed effects, and the number of climate patent applications receiving results in that month fixed effects. Standard errors are double-clustered at the firm-year and industry-month levels. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad ln(Price_{i,t+k}) - ln(Price_{i,t-1}) = \alpha \widehat{Num\_ClimPats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A12}$$

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

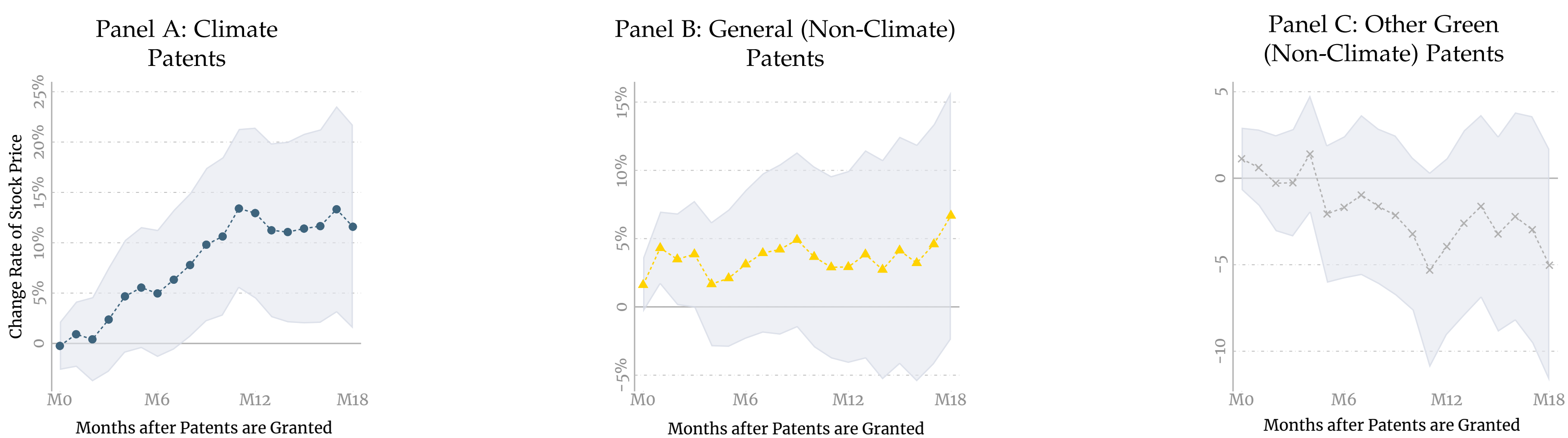


Figure A9. Climate Patents and Monthly Stock Returns (Extending the Window)

This figure extends the analysis from Figure 2. The regression design is identical to that of Figure 2, with the exception that k ranges from 1 to 36. The control vector $\mathbf{X}_{i,t}$ includes 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 fixed effects, art unit $\times$ year fixed effects, and the number of climate patent applications receiving results in that month fixed effects. Standard errors are double-clustered at the firm-year and industry-month levels. Confidence intervals are plotted at the 90% confidence level.

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

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

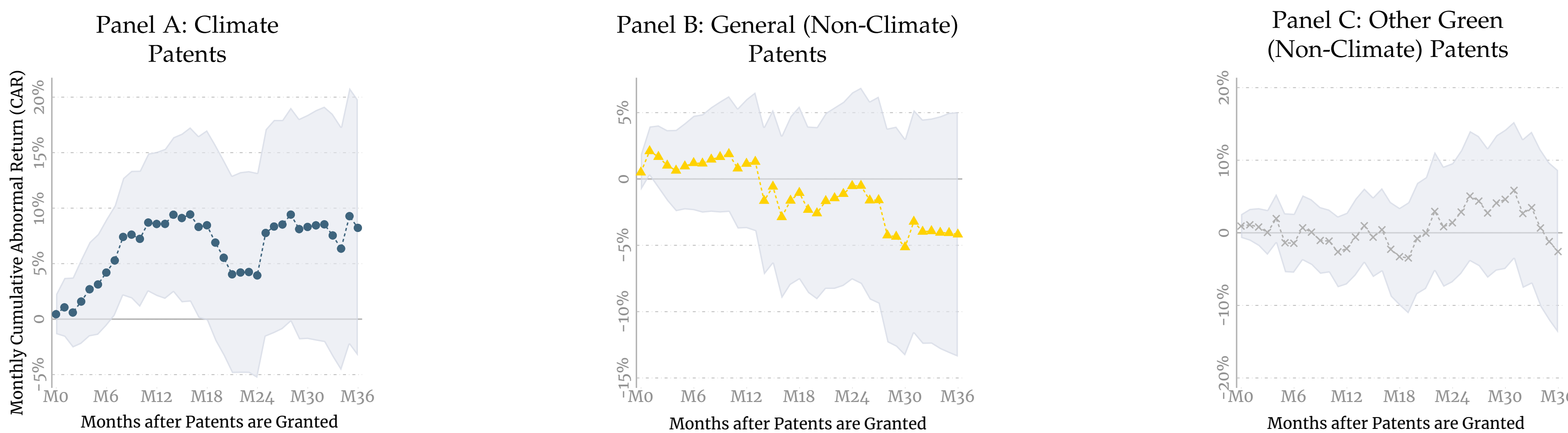


Figure A10. Climate Patents and Monthly Stock Returns (Using Alternative Methods to Construct Instrument)

This figure presents a robustness check of the results in Figure 2 using an alternative method to construct our instrument for examiner leniency. In this exercise, we only use each examiner's past examination records to calculate the leniency measure. Panels A and B examine 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 ranging from 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 fixed effects, art unit $\times$ year fixed effects, and the number of climate patent applications receiving results in that month fixed effects. Standard errors are double-clustered at the firm and industry-year levels. Confidence intervals are plotted at the 90% confidence level.

$$2nd\ Stage: \quad CAR[t:t+k]_{i,t} = \alpha \widehat{Num\_ClimPats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A16}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A17}$$

Figure A11. Climate Patents and Monthly Stock Returns (Russell 1000 Sample)

This figure presents a robustness check of the results from Figure 2 using a new balanced sample of Russell 1000 index firms. The Russell 1000 Index sample is defined as those firms appearing at least once in the LSEG ESG database from 2002 to 2011. This includes 1,301 firms, which may comprise Russell 1000 firms in 2011 and some NASDAQ 100 firms. We construct a balanced sample by tracking climate patent applications from 2004 to 2020 for these 1,301 firms. Panels A and B examine 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 from 0 to 18. The data is at the firm-month level, and the sample requires that a firm receives at least one decision on its climate patent applications in the given month. The dependent variable is the cumulative abnormal returns (CARs) from time t to time $t+k$. Abnormal returns (ARs) are alphas from the Fama-French 5-Factor model (Fama and French, 2015), with factor loadings estimated using the previous 60-month returns data. The main independent variable is $Num\_ClimPats\_Granted$, which counts the number of climate patents issued to the firm during month t. We instrument this variable using the average relative leniency of examiners who assess these patent applications of the firm. We apply a log transformation, $ln(1+x)$, to the main independent variable.

$$2nd\ Stage: \quad CAR[t:t+k]_{i,t} = \alpha \widehat{Num\_ClimPats\_Granted}_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A18}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A19}$$

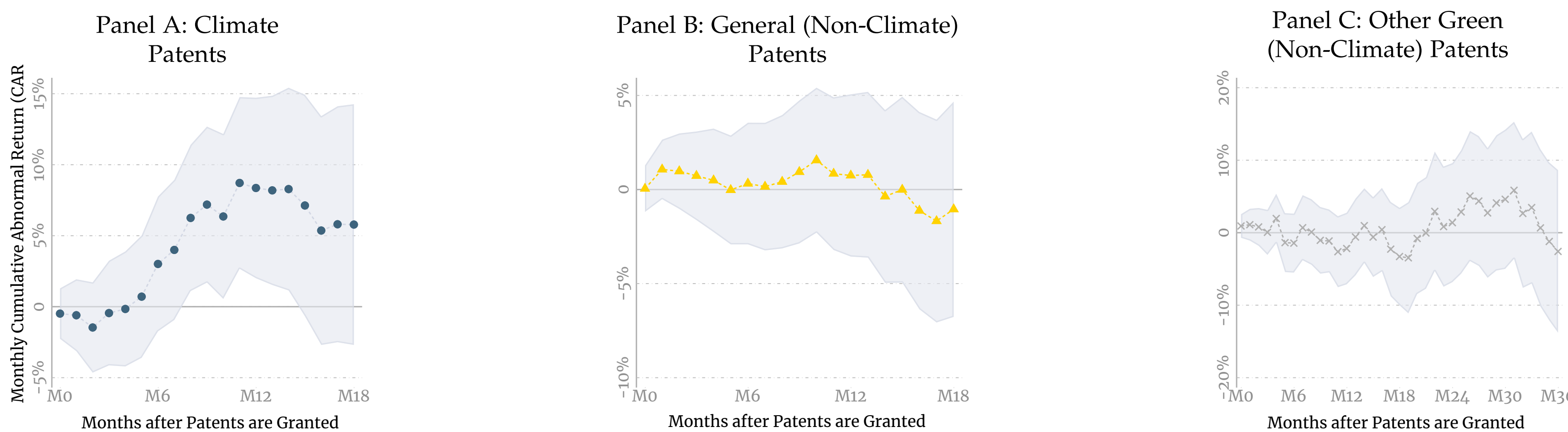


Figure A12. Climate Patents, Media Coverage of Climate Change, and Stock Returns (Robustness Check)

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:

$$
\begin{aligned}
CAR[t:t+k]_{i,t} = {} & \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{H,t+k} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{M,t+k} + \\
& \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{L,t+k} + \delta_1 \overline{MCCC}_{H,t+k} + \delta_2 \overline{MCCC}_{M,t+k} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \qquad \text{(A20)}
\end{aligned}
$$

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):

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \qquad \text{(A21)}$$

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

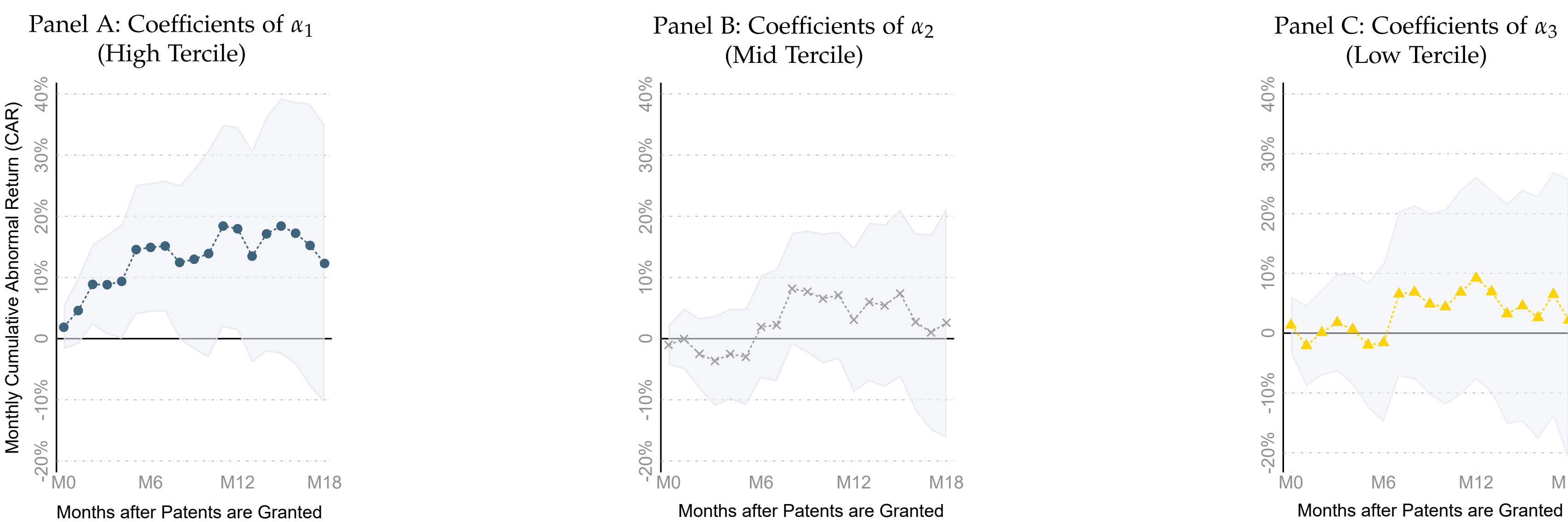


Figure A13. Climate Patents, Media Coverage of Climate Change, and Stock Returns (Russell 1000 Sample)

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:

$$\begin{aligned} CAR[t:t+k]_{i,t} = {} & \alpha_1 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{H,t+k} + \alpha_2 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{M,t+k} + \\ & \alpha_3 Num\_Clim\widehat{Pats}\_Granted_{i,t} \times \overline{MCCC}_{L,t+k} + \delta_1 \overline{MCCC}_{H,t+k} + \delta_2 \overline{MCCC}_{M,t+k} + \beta \mathbf{X}_{i,t} + \tau_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \end{aligned} \quad \text{(A22)}$$

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

$$\overline{MCCC}_t = \sum_{\tau=0}^{36} 0.94^{\tau} MCCC_{t-\tau} \quad \text{(A23)}$$

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

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

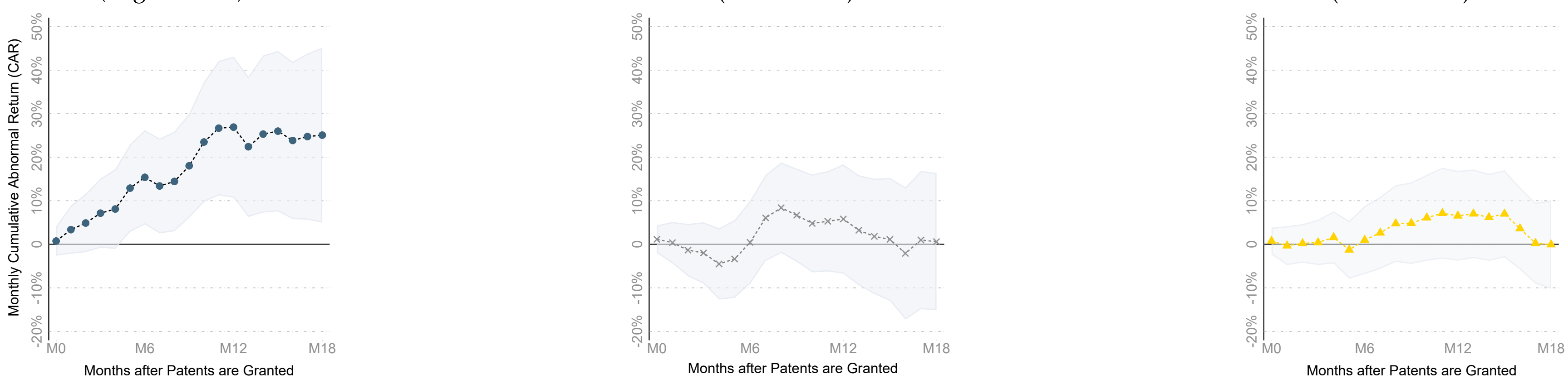


Figure A14. Climate Patents and Implied Cost of Capital (Poisson Regressions)

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.

$$2nd\ Stage: \quad ICC_{i,t+k} - ICC_{i,t} = \alpha \ln(1 + \widehat{Num\_ClimPats\_Granted_{i,t}}) + \beta \mathbf{X}_{i,t} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A24}$$

$$1st\ Stage\ (Poisson\ Regression): \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A25}$$

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:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{A26}$$

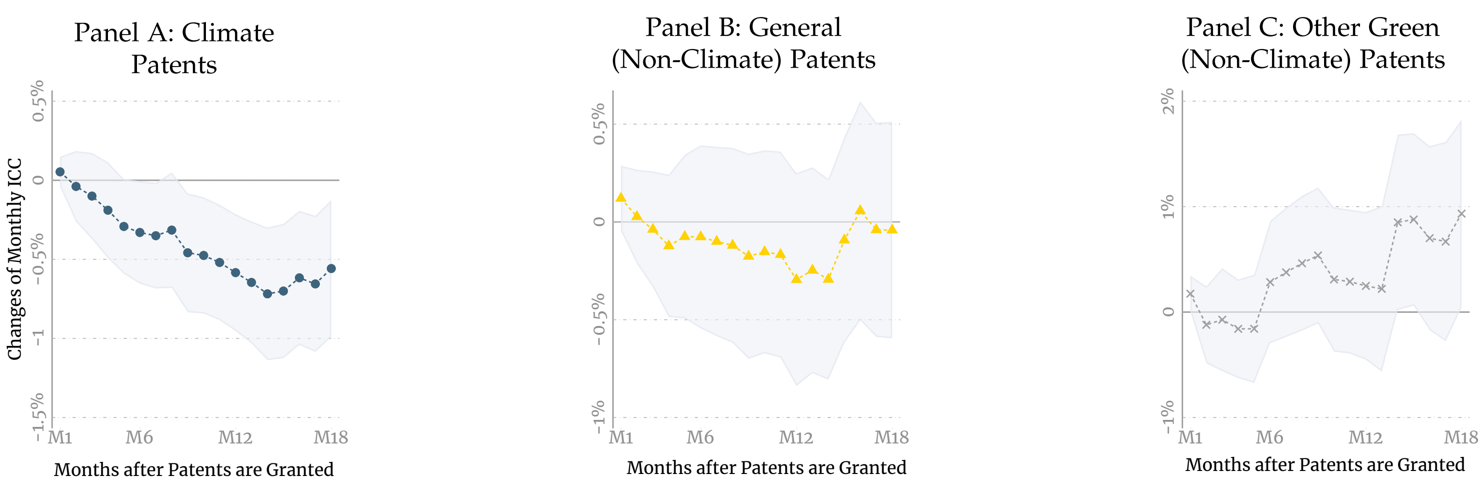


Figure A15. Climate Patents and Implied Cost of Capital (Robustness Check)

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.

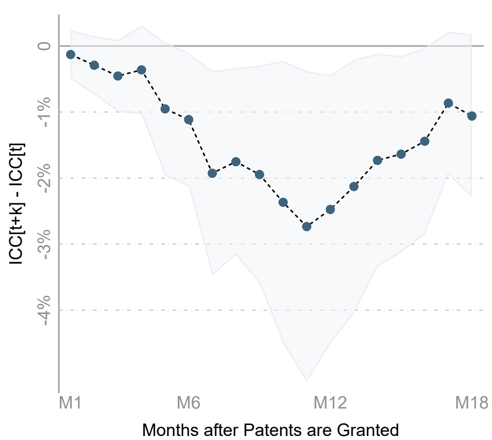
$$2nd\ Stage: \quad ICC_{i,t+k} - ICC_{i,t} = \alpha Num\_Clim\widehat{Pats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A27}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \mu_{app} + \nu_{j,t} + \iota_{a,t} + \varepsilon_{i,t} \tag{A28}$$

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:

$$P_t \times SHROUT_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[ROE_{t+\tau} - r]B_{t+\tau-1}}{(1+r)^{\tau}} + \frac{E_t[ROE_{t+12} - r]B_{t+11}}{r(1+r)^{11}} \tag{A29}$$

Panel A: Climate Patents



Panel B: Other Green Patents

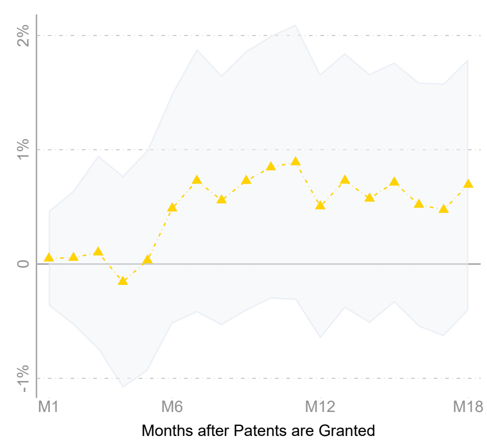


Table A1 Validity Test of the Instrumental Variable (Poisson Regression)

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	1.963***	1.808***	1.774***
(Standardized)	(0.256)	(0.138)	(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 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 A2 The First Stage of the Instrumental Variable (Split by Number of Applications)

This table presents the first stage OLS regression by splitting the sample based on the number of climate patent applications which receive results in month t. Estimations are conducted using a firm-month sample, where each observation requires that a firm receives at least one decision regarding climate patent applications during the specified period (month t). The dependent variable is the count of climate-related patents granted to the firm in period t, with the period. We apply a log transformation, $ln(1+x)$, to the dependent variable. 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. Statistical significance levels are denoted by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Dependent Variable = Number of Climate Patents Granted Firm-Month Sample		
	Tercile Split by Number of Climate Patent Applications		
	Bottom Tercile	Mid Tercile	Top Tercile
The Average Number of Applications	1	2.34	12.46
Average Relative Leniency	0.680***	0.898***	2.211***
	(0.0484)	(0.122)	(0.211)
F Test	72.93	21.69	40.06
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
N	4017	2069	3102
adj. R^2	0.242	0.323	0.885

Table A3 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 A4 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 A5 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.

$$2nd\ Stage: \quad Envrn\_Score_{i,t+k} - Envrn\_Score_{i,t} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{A30}$$

$$1st\ Stage: \quad Num\_ClimPats\_Granted_{i,t} = \delta Avr\_Leniency_{i,t} + \pi \mathbf{X}_{i,t} + \tau_{app} + \mu_{j,t} + \nu_{a,t} + \varepsilon_{i,t} \tag{A31}$$

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 A6 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.

$$2nd\ Stage: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{A32}$$

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 A7 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.

$$2nd\ Stage: \quad IO_{i,t+k} - IO_{i,t-1} = \alpha Num\_\widehat{ClimPats}\_Granted_{i,t} + \beta \mathbf{X}_{i,t} + \nu_{j,t} + \iota_{a,t} + \tau_{app} + \varepsilon_{i,t} \tag{A33}$$

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 *(Instrumented)*	-0.00882 (0.0172)	0.00866 (0.0143)	0.0413* (0.0242)	0.0620** (0.0277)	0.0658** (0.0288)		
Num Climate Patents Granted × MCCC_High *(Instrumented)*						0.0895 (0.0612)	0.0798 (0.0589)
Num Climate Patents Granted × MCCC_Mid *(Instrumented)*						-0.000806 (0.0252)	-0.00285 (0.0266)
Num Climate Patents Granted × MCCC_Low *(Instrumented)*						0.0122 (0.0214)	0.00712 (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 *(Instrumented)*	-0.0262 (0.0225)	0.00286 (0.0157)	0.00225 (0.0251)	0.00888 (0.0311)	0.0228 (0.0328)		
Num Other Green Patents Granted × MCCC_High *(Instrumented)*						-0.00562 (0.0132)	0.00140 (0.0162)
Num Other Green Patents Granted × MCCC_Mid *(Instrumented)*						0.00361 (0.0108)	0.0191 (0.0129)
Num Other Green Patents Granted × MCCC_Low *(Instrumented)*						0.0141 (0.0125)	0.00670 (0.0152)

Table A8 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 A9 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 A10 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_DP*123, 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_DP*046 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_DP*066 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 A11 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

Panel D: Climate Patents – Energy (Y02E)

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

Panel E: Climate Patents – IT (Y02D)

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

Panel F: Climate Patents – Buildings (Y02B)

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

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