Climate Change and Green Technology: Evidence from Patent Examiners*

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Abstract

This paper investigates the influence of climate change on green innovation by studying U.S. patent examiners. We leverage local climatic disasters as exogenous shocks to examiners' climate change beliefs and find that exposed examiners grant more green patents of higher quality. The higher quality stems from increased efforts by examiners. This "greening" of gatekeepers has real economic effects, as these patents are associated with greater corporate carbon emissions reductions and improved firm performance. Our findings highlight that climate change can significantly influence the advancement of green technologies by shifting the attitudes and efforts of individuals toward green innovation.

Keywords: climate change, professional decision-making, patent examiner, green technology

JEL Classifications: G30, G41, O30, Q54, Q55

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1 Introduction

Climate change presents a paramount societal challenge that is reshaping financial markets and corporate behavior (Gillan, Koch, and Starks, 2021). Addressing this challenge demands a rapid and systemic shift toward sustainable technologies (Acemoglu et al., 2012). The success of such technologies, particularly the advancement of green innovation, depends not only on their creation but also on how they are evaluated by key gatekeepers. In this paper, we provide novel micro-level evidence on how climate change impacts individuals' professional judgment and, in turn, green innovation outcomes. Specifically, we examine how the exogenous shocks from local climatic disasters affect the decision-making of a key group of professionals: U.S. patent examiners who evaluate green technologies. This analysis not only deepens our understanding of the drivers of green innovation, but also sheds light on an underexplored mechanism through which climate shocks may translate into broader economic outcomes.

Recent literature demonstrates that heterogeneity among U.S. patent examiners significantly influences patent outcomes (e.g., Farre-Mensa, Hegde, and Ljungqvist, 2020; Shu, Tian, and Zhan, 2022). As a result, examiners' personal beliefs about climate change may influence their evaluation of green patents and the review outcomes. However, measuring a patent examiner's beliefs poses an empirical challenge, as these beliefs are often correlated with or confounded by other examiner characteristics. To address this identification challenge, we exploit variation in examiners' geographical locations and the timing of local climatic disasters. Climatic disasters provide plausibly exogenous shocks to examiners' awareness of and concern about climate change.[1] Since these events are unlikely to be related to examiners' individual traits but likely to influence perceptions of environmental

[1] According to the National Academy of Sciences (2016), the incidence of extreme disasters is regarded as an increased salience of climate change. Climatic natural disasters, such as drought, hurricanes, and wildfires, are extreme consequences of climate change. Since 1980, the U.S. has experienced 377 billion-dollar climatic natural disasters by 2023, with their frequency and severity directly linked to the accelerating impacts of climate change, resulting in a total cost of more than $2.67 trillion.

urgency, they offer a unique opportunity to isolate the effect of climate beliefs on examiners' decision-making. We investigate whether examiners exposed to climatic disasters exhibit a greater propensity to approve green patents, as such experiences may reinforce their beliefs in the importance of climate-related innovation. The answer is unclear ex ante, as examiners might separate professional decisions from personal beliefs. Moreover, the United States Patent and Trademark Office (USPTO)'s monitoring system could mitigate the influence of examiners' personal beliefs by ensuring consistency in patent evaluations.

We construct a comprehensive dataset that combines climate-disaster exposure, patent outcomes, and examiner characteristics. Data on county-year major climatic natural disasters are sourced from the Spatial Hazard and Loss Database for the United States (SHELDUS), while information on U.S. patent examiners and patents is obtained from the official USPTO websites. We focus on the period since 2012, when the USPTO implements its work-from-anywhere (WFA) program, which introduces geographical variations in examiner locations. Our sample contains 58,161 examiner-year observations covering 8,248 unique examiners from 2012 to 2020.

We begin by investigating whether exposure to climatic disasters affects patent examiners' propensity to grant green patents. For each examiner-year, we construct *Green Patent Ratio* as the share of green patents among all patents granted by the examiner in the year. Using a difference-in-differences (DiD) analysis, we find that in the year following climatic disasters, exposed examiners exhibit a significant 10% increase in *Green Patent Ratio* relative to their peers. It is unlikely that a general rise in interest in green technologies drives this result, as our comparison is within-year across exposed and unexposed examiners. Moreover, since the USPTO randomly assigns patent applications to examiners, our findings are unlikely to be confounded by shifts in firms' innovation strategies (e.g., increased investment in green technology and green patent applications).[2]

[2]Green patents can be categorized into those targeting climate change mitigation and adaptation. We expect our baseline findings to apply to both technology types, as disaster experience underscores the need for both adaptation and mitigation. Consistent with our prediction, we find that climate-disaster exposure increases examiners' propensity to grant green patents across both categories.

We acknowledge that a higher *Green Patent Ratio* among disaster-exposed examiners could reflect either a greater propensity to grant green patents or a higher share of green patent applications among all patent applications reviewed by the exposed examiners. This latter explanation is, however, unlikely because patent applications are randomly assigned to examiners, making any increase in green patent applications unlikely to be concentrated among those exposed to climatic disasters. We nevertheless directly test this possibility and find no evidence that climatic disasters increase the proportion of green patent applications assigned to exposed examiners.

Our findings hold in several robust tests. First, we use extreme heat as an alternative proxy for climatic shocks to examine how climate beliefs influence examiners' patent review behavior. Second, to account for potential heterogeneity in technological fields, we match disaster-exposed examiners with non-exposed examiners within the same art unit in the year preceding climatic disasters. Third, we exclude patent applicant firms located in the same state as the examiners to rule out the possibility that geographic proximity facilitates information spillover between examiners and applicant firms. For all these robustness tests, we find coherent results that climatic disasters lead examiners to approve more climate-related green patents in their granted patent portfolios. Moreover, when we replace climatic disasters with other types of natural disasters, we find no evidence that examiners alter their green patent granting behavior following non-climatic disasters.

Next, we examine plausible underlying mechanisms through which exposure to climatic disasters affects examiners' green patent granting decisions. Given that examiners face significant time constraints and cognitive limitations, two competing explanations emerge. First, increased leniency toward granting green patents could lead to a potential compromise in the quality of these patents (the "leniency" explanation). Alternatively, exposure to climatic disasters could motivate examiners to allocate greater attention and effort to evaluating green innovations. More thorough reviews therefore could enhance both the approval rate and the quality of granted green patents (the "effort" explanation).

To distinguish between the leniency and effort explanations, we assess green patent quality using truncation-adjusted patent citations (Hall, Jaffe, and Trajtenberg, 2001). Our analysis reveals that examiners' exposure to climatic disasters significantly increases the quality of granted green patents by 7.4% relative to the mean. In contrast, we find no significant effect of climate-disaster experience on the quality of granted non-green patents. These results support the effort explanation, suggesting that disaster exposure prompts examiners to conduct more thorough evaluations of green patent applications.

To further investigate the effort explanation, we directly assess examiners' review effort using three proxies. First, we analyze the number of claims reviewed per patent application. Given that each claim requires careful examination to establish legal boundaries, more claims necessitate greater examiner effort (Harhoff and Wagner, 2009). Second, we examine the total number of backward citations (prior art references) added by examiners, as compiling relevant prior art demands significant search and evaluation effort. Third, we examine whether examiners cite at least one prior art reference when rejecting applications for art-based reasons (i.e., lack of novelty or obviousness). Across all three measures, we find that disaster-exposed examiners exert greater effort specifically in reviewing green patent applications post-disaster, while maintaining their usual effort levels for non-green patent examinations.

An important assumption of our study is that climate-disaster exposure strengthens examiners' climate change beliefs, subsequently affecting their evaluation of green patents. To validate this assumption and gauge belief changes, we analyze examiners' political donations to the Democratic Party, which has consistently emphasized climate change initiatives (Di Giuli and Kostovetsky, 2014; Bernstein et al., 2022). Consistent with our argument, examiners increase their donations to the Democratic Party by 8.9% relative to the mean following exposure to climatic disasters.

To further substantiate the role of climate change beliefs, we examine heterogeneity in our main results. We expect disaster exposure to have a stronger effect among examiners who are more concerned about climate change. To test this conjecture, we conduct cross-

sectional analyses using three proxies for climate concern: whether the examiner is located in a region governed by the Democratic Party, whether the examiner's state has joined the U.S. Climate Alliance, and local climate-change-related Google search volume. Consistent with our conjecture, climatic disasters have a more pronounced effect on examiners in regions governed by Democrats, in states that joined the Climate Alliance, and in states with higher climate-related Google search volume. We also expect more salient disasters to have a stronger influence on examiners' beliefs. Consistent with this prediction, we find that the impact of disaster exposure strengthens with disaster severity, as measured by greater monetary losses, more fatalities, and longer durations.

Finally, we examine the real effects of improved green patent quality driven by examiners' disaster exposure on innovating firms. We find that firms with a greater proportion of green patents granted by disaster-affected examiners experience significantly greater reductions in GHG emission intensity and carbon risk exposure. This evidence aligns with the high quality of green patents granted by disaster-exposed examiners. Moreover, we find that the innovating firms have higher sales growth rates when more green patents are granted by disaster-exposed examiners. Taken together, we find suggestive evidence that patent examiners' climate change beliefs affect firm outcomes by reducing environmental externalities and enhancing firm performance.

Our paper contributes to the growing body of work in finance that studies the interaction between climate change and individual decision-making. Prior research shows that heightened attention to climate risks affects the beliefs and actions of investors and firms and consequently financial markets.[3] Hong, Wang, and Yang (2023) theoretically show that major climatic disasters could alter households' beliefs and actions toward climate change, and Bernard, Tzamourani, and Weber (2025) provide supporting experimental evidence. Our paper complements this literature by providing unique empirical evidence from patent

[3]An incomplete list of these papers includes Alok, Kumar, and Wermers (2020), Krueger, Sautner, and Starks (2020), Bolton and Kacperczyk (2021), Ilhan, Sautner, and Vilkov (2021), Cao et al. (2023), Huynh and Xia (2023), Cao et al. (2025a), and Cao et al. (2025b).

examiners, the gatekeepers of the U.S. patenting system. The granular action data of patent review allows us to capture the real effects of climate change beliefs on professional behavior. Furthermore, we document a novel behavioral mechanism: belief change does not manifest as a bias, but as an increased effort, thereby elevating the quality of granted green patents.

Our study also contributes to the growing literature on green innovation. Prior research has examined drivers of green innovation, such as firms' exposure to environmental spills (Chu, Liu, and Tian, 2023), the nature of business (Cohen, Gurun, and Nguyen, 2025), competition under intense environmental regulatory pressure (Dai, Duan, and Ng, 2025), and political uncertainty (Wang, Wurgler, and Zhang, 2026). However, we still lack evidence on how the patenting infrastructure, particularly patent examiners, shapes green innovation. We fill this gap by showing that examiners' climate change beliefs affect both the volume and quality of green patents.[4] We also speak to the mixed evidence on whether green innovation reduces corporate carbon emissions (e.g., Bolton, Kacperczyk, and Wiedemann, 2025; Hege, Pouget, and Zhang, 2025; Cheng, Lin, and Yang, 2024). By employing a plausibly exogenous shock to green patent quality, i.e., examiners' exposure to climatic disasters, we show that higher-quality green patents are associated with significant reductions in corporate carbon emissions and improvements in firm performance.

Finally, our paper extends the growing literature on patent examiners. Prior research has highlighted examiners' significant role in shaping patent approval and quality (e.g., Lemley and Sampat, 2012; Frakes and Wasserman, 2017; Kovács, 2017; Farre-Mensa, Hegde, and Ljungqvist, 2020; Choudhury, Foroughi, and Larson, 2021; Shu, Tian, and Zhan, 2022; Baek, 2023), but largely in the context of general patent grants. We contribute to this literature by providing novel evidence on how examiner beliefs form and their disproportionate impact on a specific category of innovation, i.e., green patents.

[4] Guo, Hu, and Wang (2024) run regressions of the number of green patents on extreme weather exposures at the monthly level, using data only from Beijing, China. The key distinction between our study and theirs is that we conduct an in-depth analysis of patent examiners' beliefs and the patent examination process at the examiner-year level, considering factors such as patent quality and examiners' effort, whereas their analysis is limited to documenting an increase in green patents following extreme heat and rainfall in Beijing.

2 Data and Sample

This section describes the data sets, including the sources of data on climatic natural disasters, patents, and patent examiners, as well as the process of sample construction.

2.1 Climatic Natural Disasters

We collect county-level information on natural disaster events in the U.S. from 2011 to 2019 using the Spatial Hazard and Loss Database for the United States (SHELDUS), maintained by Arizona State University. SHELDUS defines disaster areas as counties directly impacted by 18 types of natural disasters. For each county-year observation, the database reports the total dollar damage, the total number of injuries or fatalities, and the total duration of each disaster type.[5] We follow Alok, Kumar, and Wermers (2020)'s methodology and incorporate a classification-assisted ChatGPT to categorize natural disasters into two groups: those with strong links to climate change (*climatic natural disasters*) and others. Internet Appendix IA provides detailed scientific evidence supporting the association between each climatic natural disaster and climate change.

After identifying climatic natural disasters, we retain only disaster-county-year observations when the total estimated damage exceeds $10 million (in 2020 constant dollars) and the total duration is less than 30 days following Huynh and Xia (2023). We further require that each observation has at least one injury or fatality to ensure the disaster is salient enough to patent examiners in the affected county. Following these filters, our sample comprises six types of climatic disasters: flooding, hurricanes, tornadoes, wildfires, windstorms, and hailstorms. Panel A of Table 1 reports summary statistics for these climatic natural disasters, aggregated by disaster type. Tornados exhibit the lowest average annual monetary damage ($390 million), while hurricanes have the highest average monetary damage ($2.65 billion). Additionally, tornados cause the highest average injuries and fatalities (110), followed by

[5]The disasters mentioned later all refer to specific types of disaster events.

wildfires and flooding (10 and 7). Our final sample consists of 57 disaster-county-year events across these six types of climatic disasters, collectively responsible for $113.05 billion in damages and 1,383 casualties.

2.2 Examiners and Patents

We obtain data on all issued utility patents and patent examiners from the USPTO.[6] The patent records include patent IDs, examiner names, and issue dates. Using examiner names from the USPTO database, we match each examiner with their geographic location and salary information from FederalPay.org, a publicly available resource of U.S. government employee data.[7]

In the United States, the USPTO evaluates patent applications to determine their eligibility based on a set of standardized criteria. Specifically, inventions must be novel, non-obvious, useful, patent-eligible, and accompanied by comprehensive disclosures. Patent applications submitted to the USPTO contain detailed specifications, precise claims describing the invention's scope, and relevant prior art documentation. After an initial procedural screening, applications are classified based on technology classes and then assigned to specialized art units. Each art unit comprises patent examiners focused on specific technological domains. Within an art unit, patent applications are generally assigned to individual examiners by supervisory patent examiners in a largely random manner (e.g., Farre-Mensa, Hegde, and Ljungqvist, 2020; Shu, Tian, and Zhan, 2022). Prior research finds no systematic correlation between application assignment and application quality, supporting the view that the assignment process is mostly unbiased (e.g., Merges, 2001; Lemley and Sampat, 2012).

Our empirical strategy exploits geographical variation in examiner locations. Following the Telework Enhancement Act signed by President Obama in December 2010, which standardized remote work policies across federal agencies, the USPTO implements the Tele-

[6]The data websites are https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-examination-research-dataset-public-pairandhttps://patentsview.org.

[7]See https://www.federalpay.org/employees/patent-and-trademark-office.

work Enhancement Act Pilot Program (TEAPP) in early 2012. This program introduces a work-from-anywhere (WFA) policy, enabling examiners to reside and work anywhere in the contiguous United States. Crucially, the USPTO maintains uniform compensation for WFA participants regardless of their distance from headquarters. Therefore, we begin our sample in 2012 to capture meaningful geographical dispersion resulting from this policy change. As shown in Figure 1, while examiner locations remain concentrated near USPTO headquarters in Alexandria, Virginia, the WFA program generates substantial nationwide dispersion. This spatial variation allows us to identify the effects of exogenous climatic disasters on patent examiners across different locations.

We identify green patents using the Cooperative Patent Classification (CPC) codes, jointly defined by the USPTO and the European Patent Office (EPO). Following the CPC scheme, patents classified under Y02 codes are green patents, as this category specifically contains technologies intended for climate change mitigation or adaptation. This classification approach aligns with established practice in the literature (Calel, 2020) and is broadly consistent with the OECD definition of environmental technologies (Dussaux, Agnelli, and Es-Sadki, 2023).

2.3 Summary Statistics

Our sample period starts from 2012 to 2020. We identify 8,248 unique patent examiners with complete name and location information who grant at least one patent during this period, resulting in an examiner-year sample of 58,161 observations. Based on the Cooperative Patent Classification (CPC) scheme, we identify green and non-green patents. Specifically, our sample includes 220,555 green patents and 2,281,501 non-green patents.

We merge these examiner-year observations with climatic disaster data using year and county identifiers. To measure disaster exposure, we construct a binary measure, *Disaster*, that equals one if an examiner experiences any climatic disaster in their county of residence during year $t-1$, and zero otherwise. Approximately 1% of examiner-year observations have

Disaster = 1. At the examiner level, about 3.5% of patent examiners experience at least one climatic disaster during our sample period. This reflects the relatively rare incidence of climatic natural disasters in our sample period.

To capture an examiner's green patent review activity, we use an annual measure, *Green Patent Ratio*, as the proportion of green patents among all patents granted by the examiner in the year. This measure captures the examiners' propensity to grant green patents while controlling for their overall patent grants. As shown in Panel B of Table 1, green patents account for about 8% of all granted patents in our sample. *Green Patent Ratio* has a standard deviation of 0.16, indicating substantial variation across examiners in their attitudes towards green innovation. In addition to the main variable, we construct a set of measures to capture the examiners' review activities. We summarize these measures in Panel B of Table 1 and describe them in detail in Appendix A. These measures capture various dimensions of the patent examination process. We will describe these measures later in the paper when discussing their corresponding analyses.

3 Climate-Disaster Experience and Green Patent Review

We examine whether exposure to climatic disasters increases examiners' propensity to grant green patents. We first conduct a regression analysis of the green patent ratio. Next, we perform robustness tests and evaluate alternative explanations.

3.1 Climate-Disaster Experience and Grant Share of Green Patents

3.1.1 Baseline Results

To investigate whether examiners' exposure to climatic disasters affects their granting behavior for green patents, we estimate the following OLS regression:

$$Green\ Patent\ Ratio_{i,t} = \beta_0 + \beta_1\, Disaster_{i,t-1} + FEs + \varepsilon_{i,t}, \tag{1}$$

where the dependent variable, $Green\ Patent\ Ratio_{i,t}$, is the proportion of green patents among all patents granted by examiner i during year t, capturing the examiner's inclination toward green patents.[8] The main independent variable, $Disaster_{i,t-1}$, is a dummy variable that equals one if examiner i experiences a climatic disaster in year $t-1$, and zero otherwise. We include examiner and year fixed effects to control for unobserved heterogeneity across examiners and time. Standard errors are double-clustered at the county and year levels to account for spatial and temporal correlations. If exposure to climatic disasters significantly increases an examiner's propensity to grant green patents, we expect β_1 to be significantly positive.

Panel A of Table 2 reports the regression results, showing a significantly positive coefficient estimate on *Disaster* across both specifications. For example, the coefficient estimate in Column (1) suggests that examiners exposed to climatic disasters increase their green patent ratio by 0.79 percentage points, or equivalent to a 9.9% increase relative to the mean (0.0079/0.08). This finding suggests that exposure to climatic disasters strengthens examiners' belief in the urgency of climate issues, resulting in a greater propensity to grant green patents.

Figure 2 plots the dynamic effects of climatic disasters on the grant share of green patents. The results reveal a sharp increase in green patent ratio among exposed examiners in the year following the disaster, relative to their unaffected counterparts. However, this effect is transitory, dissipating after one year – consistent with a short-term behavioral response rather than a permanent shift in preferences. Crucially, Figure 2 shows no pre-trends in

[8]We use the annual share of granted patents that are green, rather than an approval rate, because the data do not support a year-specific approval metric. Outcomes are observed only at the time of a final decision (grant or final rejection). Although application dates are available, decisions occur with long and variable lags, and we do not observe the stock of pending applications by year, so the denominator for a year-t approval rate is unavailable, and any convention for assigning applications to years would be ad hoc. Our outcome is therefore the fraction of granted patents in year-t that are classified as green. In this construction, non-green patents form the benchmark within each year (and, in some specifications, within examiner or technology-class by year), implicitly controlling for contemporaneous shocks to examination intensity, technology mix, or filing volume. This approach avoids right-censoring and discretionary timing assumptions that would bias approval-rate measures.

green patent ratios prior to the disasters, supporting the exogenous occurrence of climatic disasters and lending credibility to a causal interpretation of the estimated effects.

A potential concern with our OLS specification is the censored nature of our dependent variable. As shown in Panel B of Table 1, *Green Patent Ratio* exhibits clustering at zero, with the 25th percentile equal to zero. To address this concern, we employ a Tobit model, which explicitly accounts for observations with values at boundary limits (Amemiya, 1984; Jiménez, Lopez, and Saurina, 2009; De Angelis, Grullon, and Michenaud, 2017). The Tobit regression results, presented in Panel A of Table IC1 (Internet Appendix IC), show that our findings remain qualitatively and quantitatively similar.

3.1.2 Examiner Behavior or Evolving Patent Applications?

While our finding of an increase in *Green Patent Ratio* is consistent with examiners developing a stronger propensity to grant green patents after climatic disasters, it could alternatively reflect a rise in the share of green patent applications (e.g., if climatic disasters motivate firms or inventors to conduct more green innovation). However, this alternative explanation is unlikely for two reasons. First, even if the share of green patent applications increases overall, it is unlikely that this increase is concentrated among treated examiners due to the random assignment of patent applications to examiners. Second, and more importantly, it takes an average of one year for patent applications to be assigned to examiners. Since *Green Patent Ratio* is based on patents granted in the year following climatic disasters, it mainly corresponds to patent applications submitted before or during the disaster years – meaning the increase is unlikely to be caused by a surge in green innovation in response to disasters.

Nevertheless, we still directly examine whether climatic disasters increase the proportion of green patent applications assigned to examiners during disaster years, which would subsequently raise green patents granted in the following year. We define *Green Patent Ratio* for an event examiner as the percentage of green patent applications among all patent ap-

plications assigned to that examiner during the year of a climatic disaster. Panel B of Table 2 presents the regressions of *Green Patent Ratio* on *Disaster*. The coefficient estimate on *Disaster* is statistically insignificant, indicating no increase in the proportion of green patent applications assigned to disaster-exposed examiners. This result suggests that the observed increase in green patent grants is driven by shifts in examiners' beliefs regarding climate change rather than by an increase in green patent applications assigned to these examiners.

3.1.3 Adaptation versus Mitigation Technologies

Green patents can be categorized into two groups based on their technological purpose: mitigation and adaptation. Adaptation technologies focus on helping societies cope with the adverse effects of climate change, such as flood control systems or hurricane monitoring solutions. Mitigation technologies aim to reduce or prevent climate change itself, such as methods for greenhouse gas capture and non-fossil fuel alternatives in aviation and other industries. Mitigation technologies dominate green innovation, representing approximately 92.8% of green patents.

If climatic disasters strengthen examiners' beliefs about the importance of climate change, we would expect their increased propensity to grant green patents to apply to both technology types, as disaster experience highlights the need for both adaptation and mitigation. To test this conjecture, we separately analyze these two types of green patents. We define *Green Adaptation Ratio* as the percentage of green adaptation patents among all patents granted by an examiner in a given year. *Green Mitigation Ratio* is defined similarly using green mitigation patents. Panel C of Table 2 reports the regressions of these two measures, which show that the climatic disaster exposure increases examiners' propensity to grant green patents for both technology types, supporting our prediction.

3.2 Additional Robustness and Placebo Tests

We conduct a series of additional robustness tests to further validate our baseline analysis. First, the assignments of patent applications across art units are not random. To further filter out confounding factors at the art-unit level, we conduct a robustness test and report the results in Panel A of Table 3 by matching each disaster-exposed examiner with non-disaster-exposed examiners in the same art unit. If more than one examiner is matched, we either keep all matched examiners as the control group (Column (1)) or keep the matched examiner whose pay level is closest to the shocked examiner (Column (2)). The sample size drops sharply, as this approach includes only the art units with disaster-exposed examiners. Panel A of Table 3 shows that, despite the much smaller sample size, the coefficient estimate on *Disaster* remains almost the same as that in the baseline analysis.

Second, geographical proximity between patent firms and examiners could increase the chance of success in patent applications, either due to an information advantage or familiarity (Jia and Tian, 2018). If firms closer to the examiners recognize their higher tendency to grant green patents, they might file more green patent applications. Approximately 1.2% of patents in our sample are granted by examiners in the same states as applicants. We conduct a robustness test by removing applicant firms located in the same state as the examiners. As shown in Panel B of Table 3, our results remain robust after this exclusion.[9]

Third, we conduct a placebo test by replacing climatic disasters with other types of natural disasters. If non-climatic disasters similarly influence examiners' green patent granting behavior, our findings would reflect general disaster effects rather than specifically capturing climate change salience. In Panel C of Table 3, we repeat our baseline analysis, replacing climatic disasters with other disasters (as detailed in the Internet Appendix IA). The coefficient estimates on non-climatic disasters are statistically insignificant across both specifications,

[9]The USPTO operates its headquarters in Alexandria (Virginia) and four regional outreach offices in Dallas (Texas), Denver (Colorado), Detroit (Michigan), and San Jose (California). We also conduct an additional robustness test by excluding examiners residing in the same county as the USPTO headquarters and regional outreach offices, and the results hold in the untabulated analysis.

highlighting that climatic disasters uniquely affect examiners' climate change beliefs and their subsequent patent review decisions.[10]

Fourth, to further validate and generalize our findings, we use temperature exposure as an alternative proxy for climatic shocks to examine whether another major climatic anomaly, extreme temperature events, similarly influences examiners' patent review behavior.[11] This analysis not only serves as a robustness check for our main findings, but also broadens our understanding of how climatic shocks may shape examiner decision-making. Panel C of Table IC1 presents the regressions of *Green Patent Ratio* on measures of extreme temperature exposure.[12] We find that the coefficient estimate on *Extreme Heat* is significantly positive (Column (1)), while the coefficient estimate on *Extreme Cold* is statistically insignificant (Column (2)). The coefficient estimate on *Extreme Temperature* is also significantly positive (Column (3)). These results suggest that exposure to extreme temperatures increases examiners' propensity to grant green patents. Furthermore, this effect is uniquely driven by exposure to abnormally high temperatures rather than abnormally low temperatures, likely because extreme heat is more directly associated with global warming concerns than extreme cold in the perception of examiners.

Finally, since our focus is climate-related green patents, our definition of green patents follows the CPC Y02 classification from the most recent OECD (2023) report. Cohen,

[10]We also conduct a robustness test that excludes two less frequent climatic disaster types, wind and hail, which occur only a few times in our sample and, therefore, may be less relevant to shaping beliefs about climate change. Panel B of Table IC1 in Internet Appendix IC shows that our results hold with this alternative classification of climatic disasters.

[11]A growing literature demonstrates that extreme heat—a salient consequence of climate change—significantly impacts human cognition, decision-making, and productivity (e.g., Graff Zivin and Neidell, 2014; Heal and Park, 2016). Recent finance literature further shows that exposure to elevated temperatures strengthens investors' climate beliefs (Di Giuli et al., 2025).

[12]We follow Addoum, Ng, and Ortiz-Bobea (2020) and use daily temperature data from the PRISM Climate Group, the official climatological database of the U.S. Department of Agriculture. The PRISM dataset provides daily average, minimum, and maximum temperatures for grid cells across the continental United States. We classify a county-day observation as experiencing an extremely hot (cold) day if the county's maximum (minimum) temperature exceeds (falls below) the 90th (10th) percentile of the maximum (minimum) temperature across all counties on that day. Then, we define a dummy variable at the county-year level, *Extreme Heat*, which equals one if the number of extremely hot days for a county-year is above the median of all counties in that year, and zero otherwise. Similarly, we construct *Extreme Cold* and *Extreme Temperature* by using the number of extremely cold days and the total number of extremely hot and extremely cold days, respectively.

Gurun, and Nguyen (2025) follow the OECD (2015) classification (Hascic and Migotto, 2015), which includes a small number of non-climate-related green patents (e.g., addressing pollution or water scarcity).[13] We conduct a robustness test following this broader definition of green patents, and the coefficient estimate remains significantly positive, as reported in Panel D of Table IC1 (Column (1)). In Column (2), we replace the independent variable with the non-climate-related green patent ratio, and the coefficient estimate is close to zero and statistically insignificant. This contrast demonstrates that the increase in green patent ratio is driven by examiners' stronger propensity to grant climate-related green patents induced by climatic disaster exposure.

Taken together, these results validate our previous findings based on climatic disasters and provide further evidence that shocks to examiners' climate change beliefs significantly influence their green patent review decisions.

4 What Drives the Increased Grant Share of Green Patents: Examiner Leniency vs. Effort

4.1 Climate-Disaster Experience and Quality of Granted Green Patents

Our findings so far indicate that patent examiners are more likely to grant green patents following exposure to climatic disasters, suggesting a shift in their attitudes toward green innovation. We then investigate plausible underlying mechanisms through which the effect occurs and their implications for patent quality, exploring two competing plausible mechanisms. On one hand, disaster-affected examiners may apply more lenient evaluation standards for green patents due to strengthened climate change beliefs, resulting in lower-quality granted green patents (the leniency explanation). On the other hand, enhanced climate change awareness could instead motivate examiners to devote greater effort to reviewing

[13] Cohen, Gurun, and Nguyen (2025) also use the most recent Y02 categorization scheme for identifying climate-related patents, while their approach also includes a small number of patents from other environmentally oriented categories. Green patents classified under our definition constitute approximately 85% of the broader set of green patents identified using their approach.

green patent applications. By conducting more thorough reviews, examiners may improve both the quantity and quality of green patents (the effort explanation). This mechanism is illustrated by Chen, Chen, and Yang (2025), who show that open justice reform motivates judges to exert greater effort, leading to both increased support for female plaintiffs' claims and higher-quality decisions.[14]

To test these competing mechanisms, we estimate Equation (1) and replace the dependent variable with *Green Patent Quality*, which is measured as the natural logarithm of one plus the average truncation-adjusted citation (Hall, Jaffe, and Trajtenberg, 2001) for green patents granted by each examiner annually. In Column (1) of Table 4, the coefficient estimate on *Disaster* is significantly positive, suggesting that examiners' exposure to climatic disasters significantly increases the quality of their granted green patents by 7.4% relative to the mean (0.0222/0.30).[15]

For comparison, we examine how climate-disaster exposure affects the quality of non-green patents. We construct *Non-Green Patent Quality* as the natural logarithm of one plus the average truncation-adjusted citation of non-green patents granted by each examiner annually. Column (2) of Table 4 shows an insignificant coefficient estimate on *Disaster*, suggesting that examiners' experience of climatic disasters has no discernible effect on the quality of non-green patents. This null effect persists when we replace the dependent variable

[14]For a simple numerical example in the setting of green patent review, consider a patent examiner who reviews 20 green patent applications, with application quality uniformly distributed on $[0, 1]$. Before a local climatic disaster, the examiner approves an application if its quality is at least 0.6. The examiner exerts effort $e = 0.5$, meaning that she carefully reviews 50% applications and makes approval decisions on the remaining 50% without screening. For simplicity, assume that among the applications she does not screen, she approves the same fraction as under the threshold rule, i.e., 40%, but these approvals are effectively random with respect to quality. As a result, 8 green patents are granted, and the average quality of approved patents is 0.65 ($= 0.5 \times 0.8 + 0.5 \times 0.5$). After experiencing a climatic disaster, the examiner updates her beliefs about climate change and exerts more effort. The approval threshold is lowered to 0.5, and effort increases to 0.8. This implies that the examiner carefully reviews 80% of green patent applications. As a result, 10 green patents are granted, and the average quality of granted green patents rises to 0.70 ($= 0.8 \times 0.75 + 0.2 \times 0.5$). This example illustrates how a climatic disaster can simultaneously increase both the quantity and quality of granted green patents through heightened examiner effort. A simple model underlying this example is detailed in Internet Appendix IB.

[15]Note that the average truncation-adjusted citation is a continuous rather than a discrete variable, which justifies the log transformation. We also conduct robustness tests using Poisson regressions, and our results remain unchanged (Table IC2 in Internet Appendix IC).

with *All Patent Quality* (Column (3)), defined similarly using all patents granted by the examiner. The absence of a significant change in overall patent quality is not surprising, given that green patents account for only 8% of total patents granted (Table 1). The results in Table 4 collectively support the effort explanation, suggesting that climatic disasters motivate examiners to conduct more careful evaluations, specifically of green patent applications.

4.2 Additional Analyses: Examiner Effort Proxies

To provide direct evidence for the effort explanation, we analyze how examiners' exposure to climatic disasters affects observable proxies of examiner effort. Following Harhoff and Wagner (2009), we first measure examiner effort using the number of claims reviewed per patent, since examining patents with more claims requires a greater time investment as each claim must be thoroughly reviewed to determine the patent's legal boundaries. We construct *Green Claims* as the average number of claims in green patents reviewed by an examiner in a given year. We further define *Non-Green Claims* and *All Claims* similarly for non-green patents and all patents granted by the examiner, respectively.

Panel A of Table 5 reports the results from regressions of examiner effort proxies on *Disaster*. The coefficient estimate on *Disaster* is significantly positive in the regression with *Green Claims* as the dependent variable (Column (1)) but insignificant in the regressions with *Non-Green Claims* and *All Claims* (Columns (2) and (3)) as the dependent variables, respectively. These findings are consistent with the patent quality results (Table 4), providing further evidence that examiners increase their effort specifically for green patent reviews following disaster exposure, while maintaining their usual examination effort for other technologies.

For robustness, we consider two additional measures of examiner effort. Our first alternative effort proxy relies on the total number of backward citations (prior art references) that examiners require applicants to include. This measure captures examiner effort because identifying prior art demands substantial effort in searching and evaluating existing patents.

We define *Green References* as the average number of backward citations required for green patents by an examiner in a given year. We similarly define *Non-Green References* and *All References* for non-green patents and all patents, respectively.[16] Our second alternative effort proxy is based on patent rejections. Specifically, we examine whether examiners, when rejecting patent applications for art-based reasons, including Section 102 (lack of novelty) or Section 103 (obviousness), cite at least one prior art reference.[17] If examiners reject green patents for art-based reasons and cite at least one prior art reference after experiencing climatic disasters, this indicates that they devote greater effort to reviewing these applications. We define *Green Rejection Effort*, for each examiner in each year, as the ratio of the number of green patent rejections based on art-based reasons that include at least one prior art citation to the total number of green patent rejections based on art-based reasons. Similarly, we define *Non-Green Rejection Effort* and *All Rejection Effort* for non-green patent rejections and all patent rejections, respectively.

Panels B and C of Table 5 present the results using the citation-based effort measure and the rejection-based effort measure, respectively. These results consistently demonstrate that examiners increase effort for green patent reviews after climatic disasters, while maintaining similar effort for non-green patent reviews. This pattern mirrors the results using the claims-based measure (Panel A of Table 5). Taken together, the results in Table 5 provide direct evidence supporting the effort explanation.

[16] To construct the claims- and references-based effort measures, we focus on patents without review actions before the patent grant year. This filter ensures that the backward citations do not result from reviews from earlier rounds. We also use this sample to conduct a robustness test for our baseline analysis, and our baseline findings hold in Table IC3 of Internet Appendix IC.

[17] Frakes and Wasserman (2017) show that examiners can easily use non-art-based rejection, such as subject matter eligibility (Section 101 rejections) or written description (Section 112 rejections), to reject applications on the basis that the inventions are not useful, or that the application fails to satisfy the disclosure requirements. However, it is difficult to argue that the specific grounds for rejection directly correspond to examiners' effort, since an application may be rejected for multiple reasons. Instead, we assess examiner effort by examining whether prior art is cited in art-based rejections, as this requires a thorough search and careful comparison between the claimed invention and existing prior art.

5 Climate-Disaster Experience and Examiners' Climate Change Beliefs

A key assumption of our findings is that examiners' exposure to climatic disasters shapes their beliefs about climate change, which in turn influences their behavior when reviewing green patents. In this section, we examine whether exposure to climatic disasters indeed strengthens examiners' climate change beliefs.

5.1 Climate-Disaster Exposure and Examiners' Political Donations

We use examiners' political donations as a proxy for their beliefs in climate change. If exposure to climatic disasters strengthens examiners' beliefs in climate change, we expect this to be reflected in a higher likelihood of donating to the Democratic Party. This expectation aligns with the Democratic Party's emphasis on climate change-related issues and its active advocacy for ESG initiatives, including environmental protection (Di Giuli and Kostovetsky, 2014; Bernstein et al., 2022).

We collect data on examiners' political donations from two sources. First, we use the Federal Election Commission (FEC) database, following prior studies (e.g., Hong and Kostovetsky, 2012; Di Giuli and Kostovetsky, 2014; Babenko, Fedaseyeu, and Zhang, 2020; Dasgupta et al., 2025). The FEC database provides detailed records of political contributions to federal candidates and parties since 1979, including donor names, addresses, occupations, and donation amounts. Second, we supplement the FEC data with the Database on Ideology, Money in Politics, and Elections (DIME) from Stanford University (Bonica, 2024), which covers over 130 million donation records across local, state, and federal elections. To identify patent examiners' political donations, we match their names and affiliations in the FEC database and use the DIME database to fill any gaps.

Our final sample consists of 514 examiner donations, approximately 89% of which are donated to the Democratic Party, suggesting that the majority may hold concerns about

climate change.[18] Table 6 presents regressions of examiners' political donations on *Disaster*. The coefficient estimate on *Disaster* is significantly positive in both models, revealing a significant increase in donations to the Democratic Party following climatic disasters. For example, the coefficient estimate reported in Column (2) indicates that examiners' donations to the Democratic Party rise by 8.9% relative to the mean (0.4456/4.98) after experiencing climatic disasters. This finding provides evidence that exposure to climatic disasters may reshape examiners' beliefs about climate change, as reflected by a notable change in their political views. This result is consistent with Bernard, Tzamourani, and Weber (2025), who show that individuals increase their willingness to pay (WTP) for CO_2 emission offsets after receiving relevant information.

5.2 Cross-Sectional Analyses

If exposure to climatic disasters strengthens examiners' beliefs about climate change, we expect this effect to be stronger among examiners who are more sensitive to environmental concerns and when the disaster experience is more salient. We test these conjectures by conducting cross-sectional analyses.

5.2.1 Examiner Locations

We begin by conducting cross-sectional analyses using several examiner location characteristics that serve as proxies for examiners' sensitivity to climate change concerns. First, regions governed by the Democratic Party or states that have joined the U.S. Climate Alliance are known to prioritize climate-related issues, as evidenced by their policies and election outcomes. These areas foster an environment that emphasizes climate action, which may influence or reflect the views of examiners working there. Therefore, we construct two proxies for regional political ideology or attitudes toward climate change. The first variable, *Dem County*, is a dummy variable that equals one if the examiner's county is governed

[18] This composition is in line with Shu et al. (2025), who document that Democratic patent examiners outnumber Republican examiners by a factor of 2.5.

by the Democratic Party, and zero otherwise. The second variable, *Climate Alliance*, is a dummy variable that equals one if the examiner's state has joined the U.S. Climate Alliance, and zero otherwise.

Second, we examine two proxies for examiners' attention towards climate change using Google Search Volume Index (SVI) data from Google Trends. Specifically, we collect SVI data for the search term "climate change" at both the national (annual) and state-year levels.[19] Prior studies have shown that SVI effectively captures public attention (e.g., Da, Engelberg, and Gao, 2011). The index ranges from 0 to 100, with higher values indicating greater search interest. We construct two proxies for examiners' attention. The first proxy, *High Attention*, is a dummy variable that equals one if the national-level SVI in the year of climatic disaster exceeds the sample median, and zero otherwise. The second proxy, *High State Attention*, is a dummy variable that equals one if the SVI of the examiner's state in the disaster year is above the median of all states that year, and zero otherwise.

Panel A of Table 7 presents the baseline regressions that include interaction terms of *Disaster* and the four climate-sensitivity proxies discussed above. The coefficient estimates on these interaction terms are significantly positive across all four regressions. These findings suggest that climatic disasters have a more pronounced effect on examiners who exhibit greater sensitivity to climate change concerns, consistent with the posited mechanism of belief updating among examiners.

5.2.2 Salience of Climatic Disasters

Previous studies demonstrate that more salient experiences exert stronger influences on economic agents' belief formation and subsequent behaviors (e.g., Malmendier and Nagel, 2011; Gallagher, 2014; Dessaint and Matray, 2017). Building on this literature, we hypothesize that examiners exposed to more salient climatic disasters exhibit more pronounced belief up-

[19]Google search volume can be obtained from Google Trends (https://trends.google.com/trends/?geo=US). We also consider the search volume of "climate natural disaster" and "natural disaster" and the results are similar.

dating regarding climate change, which consequently manifests in their evaluation of green patent applications.

To test this conjecture, we consider four dimensions of climate-disaster damage as proxies for disaster salience. Specifically, we define *Large Loss* as a dummy variable that equals one if the monetary loss from a disaster is above the sample median, and zero otherwise. We similarly construct three additional dummy variables for the duration of a disaster (*Long Duration*), whether a disaster causes fatality (*Fatality*), and whether an examiner experiences climatic disasters in two consecutive years (*Consecutive*).[20] Panel B of Table 7 presents the baseline regressions that include interactions of *Disaster* and these salience proxies. Consistent with our conjecture, we find that the interaction terms have positive and statistically significant coefficient estimates across all four regressions. These findings suggest that the effect of climatic disasters on examiner behavior is magnified when disasters are more salient.

6 Impacts on Firm Outcomes

Our findings show that examiners grant higher-quality green patents following exposure to climatic disasters. In this section, we investigate whether this improvement in green patent quality impacts firms, specifically their greenhouse gas (GHG) emissions and performance.

We first examine whether the disaster-induced increase in green patent quality affects firm-level greenhouse gas (GHG) emissions. We match patents in our sample to U.S. publicly listed firms using the patent-firm linkage file developed by Kogan et al. (2017). Our key explanatory variable, *Disaster Green Ratio*, is a measure at the firm-year level defined as the proportion of a firm's green patents granted by examiners exposed to climatic disasters

[20] *Long Duration* is a dummy variable that equals one if the total duration of the corresponding disasters is higher than the median, and zero otherwise. *Fatality* is a dummy variable that equals one if the corresponding disasters have caused fatality, and zero otherwise. *Consecutive* is a dummy variable that equals one if the examiners experience climatic disasters in the previous two consecutive years, and zero otherwise.

in year $t-1$.[21] For our outcome variable, we obtain GHG emission data from the Trucost database. *GHG* is the natural logarithm of the sum of the Scope 1, Scope 2, and Scope 3 greenhouse gas emission intensity provided by the Trucost database for year t.[22]

Our regression sample includes 482 unique publicly traded firms across 1,914 firm-years from 2012 to 2020 with available measures. Table 8 presents the summary statistics for our regression sample. *Disaster Green Ratio* has a mean of 1%, indicating that, on average, 1% of a firm's green patents granted in a given year are awarded by disaster-exposed examiners. The standard deviation of *Disaster Green Ratio* is 6%, suggesting substantial variation. Moreover, *GHG* has a mean of 5.76 and a standard deviation of 1.16. We conduct a firm-year panel regression analysis with *GHG* as the dependent variable and *Disaster Green Ratio* as the independent variable. We control for firm characteristics in the disaster year, including book-to-market, asset size, leverage, dividend-to-income ratio, institutional ownership, cash holdings, and firms' exposure to climatic disasters.

Table 9 presents the regression results. Consistent with our conjecture, we find significantly negative coefficient estimates on *Disaster Green Ratio*, suggesting that high-quality green patents granted by disaster-affected examiners help reduce firms' greenhouse gas emissions.[23] In Column (1), the magnitude of the coefficient estimate, -0.6841, suggests that a one-standard-deviation increase in *Disaster Green Ratio* is associated with a 0.041 (0.6841×0.06) decrease in *GHG*, corresponding to approximately 4% (0.041/1.16) of the standard deviation. These findings indicate that green patents granted by disaster-affected examiners are not only of higher quality, but also more effective in reducing firms' GHG emissions. The observed declines in greenhouse gas emission intensity suggest that emis-

[21] We require firms to have at least one green patent granted in the measurement year to calculate this variable.

[22] Scope 1 emissions refer to direct emissions from a company's own production activities. Scope 2 emissions are indirect emissions resulting from the consumption of purchased electricity, heat, or steam. Scope 3 emissions include all other indirect emissions that occur across the supply chain. GHG emission intensity is calculated as the amount of greenhouse gas emissions for each scope divided by a company's revenue.

[23] In the untabulated analysis, we also find that the effect persists over the subsequent two years. Additionally, we decompose *Disaster Green Ratio* into two components for GHG-related and non-GHG-related green patents and find that the effect is driven by high-quality GHG-related green patents rather than non-GHG-related green patents.

sion reductions are achieved through improvements in energy efficiency rather than cutting production.

To complement the analysis of GHG emissions, we construct an *Exposure Risk* measure using the carbon emissions exposure score from the MSCI database for year t, which reflects the degree to which a company's business is vulnerable to carbon-emission risks in a given year. Higher scores indicate greater exposure to carbon-emission risks. In Column (2) of Table 9, we find a negative relation between *Disaster Green Ratio* and *Exposure Risk*, providing evidence that the increased quality of green patents helps mitigate firms' environmental risk.

Our findings offer novel insights into the effect of green innovation on GHG emissions. While existing studies (Bolton, Kacperczyk, and Wiedemann, 2025; Hege, Pouget, and Zhang, 2025) find that green patents do not necessarily reduce firms' carbon emissions, we extend this literature by examining whether patent quality matters conditional on firms having green patents. By exploring the exogenous variation in patent quality induced by examiners' climatic-disaster exposure, we provide suggestive evidence that high-quality green patents significantly reduce GHG emissions.

In addition to emission outcomes, we further investigate whether high-quality green patents granted by disaster-affected examiners enhance firm performance. To proxy for firm performance, we construct *Sales Growth*, which is defined as the annual sales growth rate for each firm in year t, sourced from the Compustat database. We conduct a firm-year panel regression analysis with *Sales Growth* as the dependent variable and *Disaster Green Ratio* as the independent variable. In Column (3) of Table 9, the result shows an increase in firms' sales growth. Specifically, the coefficient estimate of 0.3130 suggests that a one-standard-deviation increase in *Disaster Green Ratio* is associated with a 0.019 (0.3130×0.06) increase in firms' *Sales Growth*, corresponding to approximately 8% (0.019/0.23) of the standard deviation.

Overall, these results highlight the real impact of high-quality green patents granted by disaster-exposed examiners. By fostering innovation and signaling sustainability, these patents not only reduce firms' greenhouse gas emissions but also improve firms' performance. These findings suggest that green patents serve as both a practical tool for firms to address environmental challenges and a signal of their commitment to forward-looking, sustainable business practices.

7 Conclusion

This paper provides novel evidence at the intersection of climate finance and technology innovation by demonstrating how the beliefs of key market gatekeepers shape green innovation. Leveraging climatic disasters as exogenous shocks, we show that when U.S. patent examiners experience salient climate events, they grant more green patents of higher quality—an outcome driven by a measurable increase in examiner effort. We find no comparable effects for either non-green patents or non-climatic natural disasters, highlighting that examiners' climate change beliefs exclusively influence green innovation outcomes. The resulting high-quality patents are not merely symbolic; they are associated with tangible environmental and economic outcomes, including significant reductions in corporate carbon emissions and improved firm performance.

Our findings underscore that the transition to a green economy is not solely a technological or capital allocation problem, but also a behavioral one. The beliefs of intermediaries, shaped by personal experience, act as a non-regulatory channel that can accelerate the screening and certification of impactful climate solutions, such as green innovation. For policymakers and regulatory authorities, this suggests that enhancing the salience of climate change information could be a lever to meaningful actions in addressing these socioeconomic challenges.

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Figure 1. Examiner Distribution across U.S. Counties

This figure presents an overview of patent examiner distribution in 2020. No. of examiners represents the number of examiners in each county.

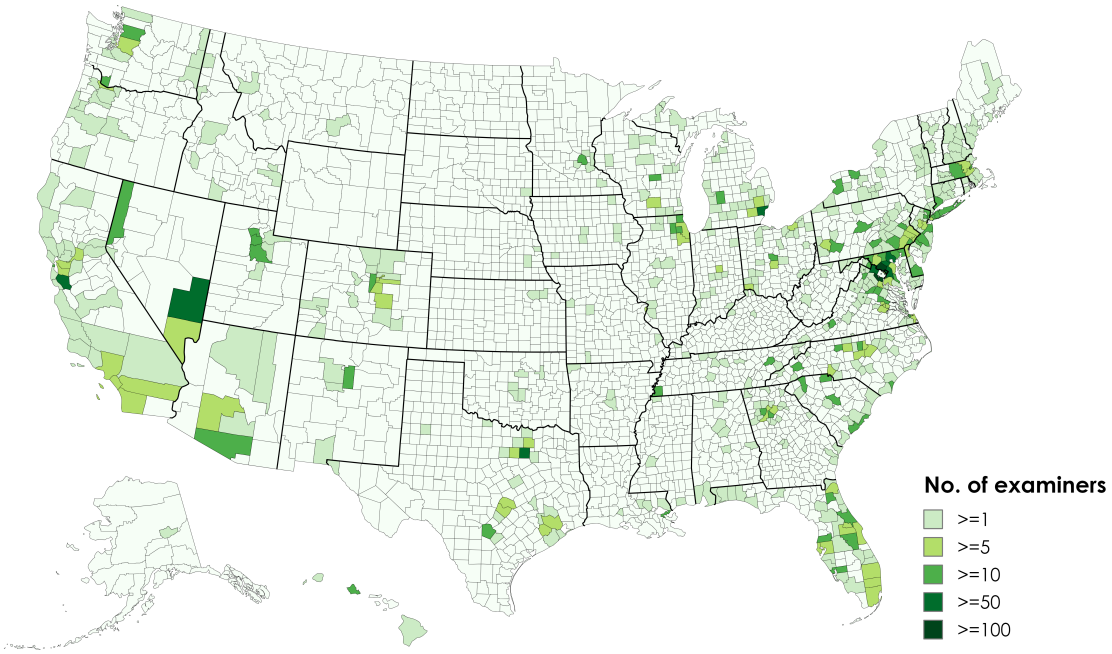


Figure 2. Dynamic Effects of Climate-Disaster Exposure on Grant Share of Green Patents

This figure shows the dynamic effects of climatic disasters on examiner decisions. Year 0 is the year in which the disasters occurred. Year "1" refers to the year following the disasters, while Year "2+" refers to the years after Year 1. Year "-1" refers to the year before the disasters, while Year "-2+" refers to the years before Year "-1". Examiner and year fixed effects are included, and standard errors are double-clustered at the county and year levels. Capped spikes indicate statistical significance at the 10% level.

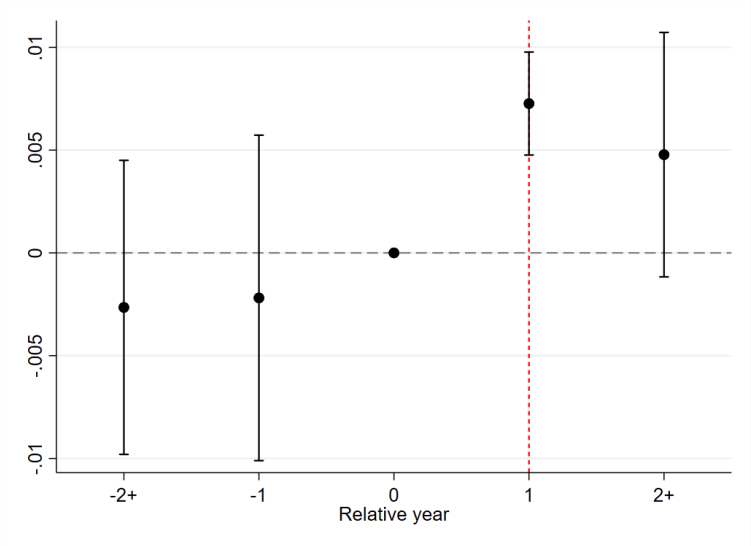


Table 1. Summary Statistics

This table shows summary statistics in our sample. Panel A reports summary statistics for climatic natural disasters in the U.S. that affected patent examiners in our sample. Reported damage is in $10 million adjusted to 2020 dollars. Panel B reports the summary statistics of examiner-year level variables from 2012 to 2020. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. *Green Patent Ratio* is defined as the percentage of green patents granted out of all granted patents for each examiner in a given year. *Green Application Ratio* is defined as the percentage of green patent applications in all patent applications received by each examiner in a given year. *Green Adaptation Ratio* is the percentage of green patents related to technologies for adaptation to climate change in all granted patents for each examiner each year. *Green Mitigation Ratio* is the percentage of green patents related to technologies for climate change mitigation in all granted patents for each examiner each year. *Green Patent Quality* is defined as the logarithm of one plus the average truncation-adjusted citation of green patents for each examiner in a given year. *Non-Green Patent Quality* is defined as the logarithm of one plus the average truncation-adjusted citation of non-green patents for each examiner in a given year. *All Patent Quality* is defined as the logarithm of one plus the average truncation-adjusted citation of all patents for each examiner in a given year. *Dem Donation* (USD) is the total annual dollar amount of donations contributed to the Democratic Party by each examiner. *Log*(*Dem Donation*) is the logarithm of the total annual dollar amount of donations to the Democratic Party for each examiner. *Green Claims* is defined as the average number of claims from green patents reviewed by each examiner in a given year. *Non-Green Claims* is defined as the average number of claims from non-green patents reviewed by each examiner in a given year. *All Claims* is defined as the average number of claims from all patents reviewed by each examiner in a given year. *Green References* is the average number of references to green patents cited by each examiner each year. *Non-Green References* is the average number of references to non-green patents cited by each examiner each year. *All References* is the average number of references to all patents cited by each examiner each year. *Green Rejection Effort* is the proportion of green rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year. *Non-Green Rejection Effort* is the proportion of non-green rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year. and *All Rejection Effort* is the proportion of all rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year. All continuous variables that are not bounded between 0 and 1 are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Appendix A.

Panel A: Summary Statistics for Climatic Natural Disasters

Disasters	Average Damage ($10M)	Average Duration (Days)	Average Injuries & Fatalities	No. of Disasters
Flooding	245.08	2.96	6.87	23
Hurricane/Tropical Storm	264.97	2.87	4.20	15
Tornado	39.02	1.00	109.80	10
Wildfire	160.33	14.33	10.03	6
Wind	105.61	1.50	1.50	2
Hail	130.38	1.00	1.00	1

Panel B: Summary Statistics for Patent Examiners

Variable	Obs	Mean	STD	P1	P25	Med	P75	P99
Examiner-year panel								
No. of Patents	58,161	43.02	26.17	1.00	23.00	40.00	59.00	114.00
No. of Green Patents	58,161	3.79	7.99	0.00	0.00	1.00	4.00	41.00
Disaster	58,161	0.01	0.08	0.00	0.00	0.00	0.00	0.00
Green Patent Ratio	58,161	0.08	0.16	0.00	0.00	0.03	0.09	0.96
Green Application Ratio	57,191	0.09	0.16	0.00	0.00	0.03	0.10	0.93
Green Adaptation Ratio	58,161	0.01	0.03	0.00	0.00	0.00	0.00	0.15
Green Mitigation Ratio	58,161	0.08	0.16	0.00	0.00	0.02	0.08	0.96
Green Patent Quality	35,450	0.30	0.32	0.00	0.00	0.22	0.48	1.42
Non-Green Patent Quality	57,735	0.32	0.21	0.00	0.15	0.32	0.47	0.89
All Patent Quality	58,161	0.33	0.21	0.00	0.16	0.33	0.48	0.88
Dem Donation (USD)	514	311.28	598.53	0.00	38.50	120.50	300.00	3000.00
Log(Dem Donation)	458	4.98	1.37	1.61	4.13	5.02	5.77	8.02
Green Claims	22,345	16.16	6.66	3.00	12.00	16.00	20.00	42.00
Non-Green Claims	54,701	16.40	4.11	6.00	13.86	16.29	18.73	30.43
All Claims	55,459	16.39	4.03	6.00	13.88	16.25	18.67	30.08
Green References	22,345	2.86	4.02	0.00	0.33	1.50	3.67	23.00
Non-Green References	54,701	3.28	3.86	0.00	0.82	2.00	4.22	21.25
All References	55,459	3.25	3.82	0.00	0.80	2.00	4.16	21.20
Green Rejection Effort	44,117	0.88	0.24	0.00	0.86	1.00	1.00	1.00
Non-Green Rejection Effort	62,630	0.87	0.16	0.23	0.82	0.92	0.98	1.00
All Rejection Effort	62,955	0.87	0.16	0.25	0.83	0.92	0.97	1.00

Table 2. Climate-Disaster Experience and Grant Share of Green Patents

This table presents examiner-year level regressions of examiners' propensity to grant green patents on climate-disaster exposures. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. Panel A shows the baseline results. *Green Patent Ratio* is defined as the percentage of green patents granted out of all granted patents for each examiner in a given year. Panel B presents the results of climatic disasters on the share of green applications assigned to examiners. *Green Application Ratio* is defined as the percentage of green patent applications in all patent applications received by each examiner in a given year. Panel C shows the impact on different green patent categories. *Green Adaptation Ratio* is the percentage of green patents related to technologies for adaptation to climate change in all granted patents for each examiner each year. *Green Mitigation Ratio* is the percentage of green patents related to technologies for climate change mitigation in all granted patents for each examiner each year. The baseline model includes examiner and year fixed effects. Standard errors are double-clustered at the county and year levels, and reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Regressions of Green Patent Ratio		
	Dependent Variable: Green Patent Ratio	
	(1)	(2)
Disaster	0.0079***	0.0079***
	(0.0020)	(0.0024)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	58,161	58,161
Adj. R^2	0.852	0.852
Panel B: Regressions of Green Application Ratio		
	Dependent Variable: Green Application Ratio	
	(1)	(2)
Disaster	0.0002	0.0002
	(0.0030)	(0.0031)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	57,191	57,191
Adj. R^2	0.883	0.883
Panel C: Climate Change Adaptation Patents vs. Mitigation Patents		
	Green Adaptation Ratio	Green Mitigation Ratio
	(1)	(2)
Disaster	0.0014*	0.0062***
	(0.0008)	(0.0014)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
# Obs.	58,161	58,161
Adj. R^2	0.547	0.864

Table 3. Robustness Tests and Placebo Tests

This table shows the results of robustness and placebo tests. Panel A presents examiner-year level regressions of examiners' propensity to grant green patents on climate-disaster exposures using matched samples. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. *Green Patent Ratio* is the percentage of green patents granted in all granted patents for each examiner in a given year. Column (1) uses a sample with matched examiners of the same art units, while column (2) uses a sample that only keeps one matched examiner whose pay level is closest to the shocked examiner. In Panel B, we exclude patents filed by companies located in the same state as the examiners. Panel C presents examiner-year level regressions of examiners' propensity to grant green patents on non-climate-disaster exposures. *Non-Climatic Disaster* is a dummy variable that equals one if the examiner experiences non-climatic disasters in the previous year, and zero otherwise. The baseline model includes examiner and year fixed effects. Standard errors are double-clustered at the county and year levels, and reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Matched Examiners within Art Units		
	Dependent Variable: Green Patent Ratio	
	Art unit matching	
	1:m	1:1
	(1)	(2)
Disaster	0.0076***	0.0077***
	(0.0016)	(0.0015)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
# Obs.	9,402	3,128
Adj. R^2	0.827	0.865

Panel B: Excluding Firms in the Same State as Examiners		
	Dependent Variable: Green Patent Ratio	
	(1)	(2)
Disaster	0.0081***	0.0081***
	(0.0017)	(0.0025)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	58,142	58,142
Adj. R^2	0.851	0.851

Panel C: Placebo Test Using Non-Climatic Disasters		
	Dependent Variable: Green Patent Ratio	
	(1)	(2)
Non-Climatic Disaster	0.0003	0.0003
	(0.0017)	(0.0019)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	58,161	58,161
Adj. R^2	0.852	0.852

Table 4. Climate-Disaster Experience and Quality of Granted Green Patents

This table presents examiner-year level regressions of green patent quality on climate-disaster exposures. *Green Patent Quality* is defined as the logarithm of one plus the average truncation-adjusted citation of green patents for each examiner in a given year. *Non-Green Patent Quality* is defined as the logarithm of one plus the average truncation-adjusted citation of non-green patents for each examiner in a given year. *All Patent Quality* is defined as the logarithm of one plus the average truncation-adjusted citation of all patents for each examiner in a given year. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. Examiner and year fixed effects are included. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Green Patent Quality	Non-Green Patent Quality	All Patent Quality
	(1)	(2)	(3)
Disaster	0.0222**	-0.0034	-0.0013
	(0.0111)	(0.0061)	(0.0060)
Examiner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	35,450	57,735	58,161
Adj. R^2	0.322	0.661	0.677

Table 5. Climate-Disaster Experience and Examiners' Efforts in Green Patent Reviews

This table presents examiner-year level regressions of examiners' efforts for green patents on climate-disaster exposures. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. In Panel A, we focus on the data related to patent claims. *Green Claims* is defined as the average number of claims from green patents reviewed by each examiner in a given year. *Non-Green Claims* is defined as the average number of claims from non-green patents reviewed by each examiner in a given year. *All Claims* is defined as the average number of claims from all patents reviewed by each examiner in a given year. In Panel B, we focus on the data related to patent references. *Green References* is the average number of references to green patents cited by each examiner each year. *Non-Green References* is the average number of references to non-green patents cited by each examiner each year. *All References* is the average number of references to all patents cited by each examiner each year. In Panel C, we focus on the sample with all the rejection applications. *Green Rejection Effort* represents the proportion of green rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year. *Non-Green Rejection Effort* represents the proportion of non-green rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year. *All Rejection Effort* represents the proportion of all rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year. Examiner and year fixed effects are included. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Claims of Patents Reviewed by Examiners			
	Green Claims	Non-Green Claims	All Claims
	(1)	(2)	(3)
Disaster	1.1476***	0.0292	0.2098
	(0.3576)	(0.1628)	(0.1809)
Examiner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	22,345	54,701	55,459
Adj. R^2	0.176	0.320	0.330
Panel B: References Cited by Examiners in the Review Process			
	Green References	Non-Green References	All References
	(1)	(2)	(3)
Disaster	0.3124**	-0.0990	-0.0294
	(0.1414)	(0.0762)	(0.0400)
Examiner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	22,345	54,701	55,459
Adj. R^2	0.584	0.744	0.749
Panel C: Examiners' Rejection Effort			
	Green Rejection Effort	Non-Green Rejection Effort	All Rejection Effort
	(1)	(2)	(3)
Disaster	0.0296**	0.0033	0.0036
	(0.0142)	(0.0068)	(0.0065)
Examiner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	44,117	62,630	62,955
Adj. R^2	0.329	0.649	0.659

Table 6. Climate-Disaster Experience and Examiners' Political Donations

This table presents examiner-year level regressions of examiners' political donations on climate-disaster exposures. *Dem Donation* (*USD*) is the total annual dollar amount of donations contributed to the Democratic Party by each examiner. *Log*(*Dem Donation*) is the logarithm of the total annual dollar amount of donations to the Democratic Party for each examiner. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. Examiner and year fixed effects are included. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dem Donation (USD)	Log(Dem Donation)
	(1)	(2)
Disaster	204.8644***	0.4456***
	(52.1659)	(0.1156)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
# Obs.	514	458
Adj. R^2	0.238	0.495

Table 7. Climate-Disaster Experience and Grant Share of Green Patents: Cross-Sectional Analyses

This table presents the results from the cross-sectional analyses. *Green Patent Ratio* is defined as the percentage of green patents granted in all granted patents for each examiner in a given year. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. Panel A is based on the role of regional-level characteristics. *Dem County* is a dummy variable that equals one if the county where the examiner is located is governed by the Democratic Party in the previous year, and zero otherwise. *Disaster* × *Dem County* is an interaction term between *Disaster* and *Dem County*. *Climate Alliance* is a dummy variable that equals one if the state where the examiner is located has joined the United States Climate Alliance in the previous year, and zero otherwise. *Disaster* × *Climate Alliance* is an interaction term between *Disaster* and *Climate Alliance*. *High Attention* is a dummy variable that equals one if the total Google search volume in the previous year is higher than the median, and zero otherwise. *Disaster* × *High Attention* is an interaction term between *Disaster* and *High Attention*. *High State Attention* is a dummy variable that equals one if the state's Google search volume in the previous year is higher than the median of all states for that year, and zero otherwise. *Disaster* × *High State Attention* is an interaction term between *Disaster* and *High Attention*. Panel B is based on the role of disaster-level characteristics. *Large Loss* is a dummy variable that equals one if the monetary loss of a disaster is above the median, and zero otherwise. *Disaster* × *Large Loss* is an interaction term between *Disaster* and *Large Loss*. *Long Duration* is a dummy variable that equals one if the total duration of the corresponding disasters is higher than the median, and zero otherwise. *Disaster* × *Long Duration* is an interaction term between *Disaster* and *Long Duration*. *Fatality* is a dummy variable that equals one if the corresponding disasters have caused fatality, and zero otherwise. *Disaster* × *Fatality* is an interaction term between *Disaster* and *Fatality*. *Consecutive* is a dummy variable that equals one if the examiners experience climatic disasters in the previous two consecutive years, and zero otherwise. *Disaster* × *Consecutive* is an interaction term between *Disaster* and *Consecutive*. Examiner and year fixed effects are included. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Regional-level Characteristics				
	Dependent Variable: Green Patent Ratio			
	(1)	(2)	(3)	(4)
Disaster	0.0048**	0.0067***	0.0015	0.0071***
	(0.0022)	(0.0017)	(0.0013)	(0.0017)
Dem County	0.0001			
	(0.0001)			
Disaster × Dem County	0.0021**			
	(0.0009)			
Climate Alliance		-0.0013		
		(0.0009)		
Disaster × Climate Alliance		0.0101***		
		(0.0028)		
Disaster × High Attention			0.0086***	
			(0.0017)	
High State Attention				-0.0004
				(0.0009)
Disaster × High State Attention				0.0048**
				(0.0021)
Examiner FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# Obs.	58,161	58,161	58,161	58,161
Adj. R^2	0.852	0.852	0.852	0.852

Panel B: Disaster-level Characteristics				
	Dependent Variable: Green Patent Ratio			
	(1)	(2)	(3)	(4)
Disaster	0.0051***	0.0058***	-0.0015	0.0069***
	(0.0008)	(0.0022)	(0.0044)	(0.0015)
Disaster × Large Loss	0.0074*			
	(0.0039)			
Disaster × Long Duration		0.0090**		
		(0.0057)		
Disaster × Fatality			0.0115**	
			(0.0052)	
Disaster × Consecutive				0.0108**
				(0.0051)
Examiner FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# Obs.	58,161	58,161	58,161	54,815
Adj. R^2	0.852	0.852	0.852	0.857

Table 8. Summary Statistics for the Firm Regression Sample

This table shows the statistics for firm-year level variables in our sample. *Disaster Green Ratio* is, for each firm, the percentage of green patents granted by examiners who experienced the disaster in the previous year. *GHG* is the natural logarithm of the sum of the Scope 1 greenhouse gas emission intensity, the Scope 2 greenhouse gas emission intensity, and the Scope 3 greenhouse gas emission intensity provided by the Trucost database for each firm each year. *Exposure Risk* is the extent to which a company's business is vulnerable to carbon emission risks each year. *Sales Growth* is the annual sales growth rate for each firm. *Firm Disaster* is a dummy variable that equals one if the county where the firm's headquarters is located experienced a climatic disaster in the previous year, and zero otherwise. *Book-to-market* is the difference between common equity and preferred stock capital divided by the equity market value at the end of the previous year. *Log*(*Assets*) is the logarithm of total assets at the end of the previous year. *Div*/*Inc* is dividends at the end of the year divided by net income at the end of the year. *Leverage* is long-term debt plus current liabilities divided by total assets in US dollars (millions) at the end of the previous year. *Cash Holding* is the ratio of current assets to total assets at the end of the previous year. *Institutional Ownership* is the fraction of outstanding shares owned by institutional investors at the end of the previous year. The sample period is from 2012 to 2020. All continuous variables that are not bounded between 0 and 1 are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Appendix A.

Variable	Obs	Mean	STD	P1	P25	Med	P75	P99
Firm-year panel								
GHG	1,914	5.76	1.16	3.61	4.90	5.70	6.36	9.10
Disaster Green Ratio	1,914	0.01	0.06	0.00	0.00	0.00	0.00	0.20
Sales Growth	1,914	0.05	0.23	-0.74	-0.04	0.04	0.12	1.08
Exposure Risk	1,465	3.21	1.70	0.71	2.26	2.60	3.90	8.80
Firm Disaster	1,914	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Book-to-market	1,914	0.37	0.28	0.01	0.19	0.31	0.48	1.46
Log(Assets)	1,914	8.76	2.04	4.09	7.41	8.69	10.26	13.22
Div/Inc	1,914	0.27	0.50	-1.34	0.00	0.17	0.40	3.09
Leverage	1,914	0.24	0.16	0.00	0.12	0.23	0.34	0.62
Cash Holding	1,914	0.77	0.20	0.02	0.69	0.81	0.90	1.00
Institutional Ownership	1,914	0.77	0.20	0.02	0.69	0.81	0.90	1.00

Table 9. Climatic-Disaster Exposure, Patent Quality, and Firm Outcomes

This table presents firm-year level regressions of firm outcomes on selected green patents by event examiners. *Disaster Green Ratio* is, for each firm, the percentage of green patents granted by examiners who experienced the disaster in the previous year. *GHG* is the natural logarithm of the sum of the Scope 1, Scope 2, and Scope 3 greenhouse gas emission intensity provided by the Trucost database for each firm each year. *Exposure Risk* is the extent to which a company's business is vulnerable to carbon emission risks each year. *Sales Growth* is the annual sales growth rate for each firm. We control for firm-level variables, including *Book-to-market*, *Log*(*Assets*), *Div*/*Inc*, *Leverage*, *Cash Holding*, *Institutional Ownership*, and *Firm Disaster*. Industry, county, and year fixed effects are included. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

	GHG	Exposure Risk	Sales Growth
	(1)	(2)	(3)
Disaster Green Ratio	-0.6841***	-0.6605***	0.3130**
	(0.1918)	(0.2079)	(0.1542)
Firm Disaster	-0.0487	0.0239	0.0246
	(0.1157)	(0.0675)	(0.0347)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	1,914	1,465	1,914
Adj. R^2	0.728	0.803	0.192

Appendix A: Variable Definitions

Variables	Definitions
Examiner-year level	
Disaster	Disaster is a dummy variable, which equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise.
Green Patent Ratio	Green Patent Ratio is the percentage of green patents granted in all granted patents for each examiner in a given year.
Green Application Ratio	Green Application Ratio is defined as the percentage of green patent applications received by the examiner, in all patent applications received by the examiner in the previous year.
Green Adaptation Ratio	Green Adaptation Ratio is the percentage of green patents related to technologies for adaptation to climate change in all granted patents for each examiner each year.
Green Mitigation Ratio	Green Mitigation Ratio is the percentage of green patents related to technologies for climate change mitigation in all granted patents for each examiner each year.
Non-Climatic Disaster	Non-Climatic Disaster is a dummy variable that equals one if the examiner experiences non-climatic disasters in the previous year, and zero otherwise.
Green Patent Quality	Green Patent Quality is defined as the logarithm of one plus the average truncation-adjusted citation of green patents for each examiner in a given year.
Non-Green Patent Quality	Non-Green Patent Quality is defined as the logarithm of one plus the average truncation-adjusted citation of non-green patents for each examiner in a given year.
All Patent Quality	All Patent Quality is defined as the logarithm of one plus the average truncation-adjusted citation of all patents for each examiner in a given year.
Dem Donation (USD)	Dem Donation (USD) is the total annual dollar amount of donations contributed to the Democratic Party by each examiner.
Log(Dem Donation)	Log(Dem Donation) is the logarithm of the total annual dollar amount of donations to the Democratic Party for each examiner.
Green Claims	Green Claims is defined as the average number of claims from green patents reviewed by each examiner in a given year.
Non-Green Claims	Non-Green Claims is defined as the average number of claims from non-green patents reviewed by each examiner in a given year.
All Claims	All Claims is defined as the average number of claims from all patents reviewed by each examiner in a given year.
Green References	Green References is the average number of references to green patents cited by each examiner each year.
Non-Green References	Non-Green References is the average number of references to non-green patents cited by each examiner each year.
All References	All References is the average number of references to all patents cited by each examiner each year.

Green Rejection Effort	Green Rejection Effort represents the proportion of green rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year.
Non-Green Rejection Effort	Non-Green Rejection Effort represents the proportion of non-green rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year.
All Rejection Effort	All Rejection Effort represents the proportion of all rejections based on 102 or 103 reasons that include at least one prior art citation, relative to the total number of such rejections by each examiner each year.
Dem County	Dem County is a dummy variable that equals one if the county where the examiner is located is governed by the Democratic Party, and zero otherwise.
Climate Alliance	Climate Alliance is a dummy variable that equals one if the state where the examiner is located has joined the United States Climate Alliance and zero otherwise.
High Attention	High Attention is a dummy variable that equals one if the total Google search volume in one year is higher than the median, and zero otherwise.
High State Attention	High State Attention is a dummy variable that equals one if the state's Google search volume in one year is higher than the median of all states this year, and zero otherwise.
Large Loss	Large Loss is a dummy variable that equals one if the monetary loss from a disaster exceeds the median, and zero otherwise.
Long Duration	Long Duration is a dummy variable that equals one if the total duration of the disasters is higher than the median duration of all disasters, and zero otherwise.
Fatality	Fatality is a dummy variable that equals one if the disaster has caused at least one fatality, and zero otherwise.
Consecutive	Consecutive is a dummy variable that equals one if the examiners experience climatic disasters in two consecutive years, and zero otherwise.
Extreme Heat	Extreme Heat is a dummy variable that equals one if the total number of days in a year when the maximum temperature in the examiner's county exceeds the 90th percentile across all counties is greater than the median of all counties for that year, and zero otherwise.
Extreme Cold	Extreme Cold is a dummy variable that equals one if the total number of days in a year when the minimum temperature in the examiner's county is below the 10th percentile across all counties is greater than the median of all counties for that year, and zero otherwise.

Extreme Temperature	Extreme Temperature is a dummy variable that equals one if the total number of days when the maximum temperature in the examiner's county exceeds the 90th percentile plus the total number of days when the minimum temperature falls below the 10th percentile across all counties is greater than the median of all counties for that year, and zero otherwise.
Green Patent Ratio (OECD15)	Green Patent Ratio (OECD15) is the percentage of green patents identified by the OECD 2015 classification in all granted patents for each examiner each year.
Non-Climate-Related Green Patent Ratio	Non-Climate-Related Green Patent Ratio is the percentage of green patents that fall within the OECD 2015 classification but do not include the OECD 2023 classification in all granted patents for each examiner each year.
Firm-year level	
Disaster Green Ratio	Disaster Green Ratio is, for each firm, the percentage of green patents granted by examiners who experienced the disaster in the previous year.
GHG	GHG is the natural logarithm of the sum of the Scope 1 greenhouse gas emission intensity, the Scope 2 greenhouse gas emission intensity, and the Scope 3 greenhouse gas emission intensity provided by the Trucost database for each year.
Sales Growth	Sales Growth is the annual sales growth rate for each firm.
Exposure Risk	Exposure Risk is the extent to which a company's business is vulnerable to carbon emission risks each year, according to the MSCI database.
Book-to-market	Book-to-market is the difference between common equity and preferred stock capital divided by the equity market value at the end of the previous year.
Firm Disaster	Firm Disaster is a dummy variable that equals one if the county where the firm's headquarters is located experienced a climatic disaster in the previous year, and zero otherwise.
Log(Assets)	Log(Assets) is the logarithm of total assets at the end of the previous year.
Div/Inc	Div/Inc is dividends at the end of the year divided by net income at the end of the year.
Leverage	Leverage is long-term debt plus current liabilities divided by total assets in US dollars (millions) at the end of the previous year.
Cash Holding	Cash Holding is the ratio of current assets to total assets at the end of the previous year.
Institutional Ownership	Institutional Ownership is the fraction of outstanding shares owned by institutional investors at the end of the year.

Internet Appendix (not to be published)

Appendix IA: Classification of Climatic Natural Disasters

This appendix provides details for our classification of climatic natural disasters. The Spatial Hazard and Loss Database for the United States (SHELDUS) includes eighteen types of natural disasters. In our study, we focus on identifying natural disasters more closely linked to climate change, referred to as *climatic natural disasters*. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (2022) highlights extreme climate events, including flooding, drought, wind, tornadoes, and storms (including thunderstorms, hail, and hurricanes/tropical storms).[24] Additionally, Alok, Kumar, and Wermers (2020) and Kim, Wang, and Wu (2023) provide broader definitions of climatic disasters based on SHELDUS, though their categorizations differ slightly.

Building on previous studies and classifications generated with the assistance of ChatGPT, we identify ten climate-related disaster types: drought, flooding, coastal, heat, hurricane/tropical storm, severe thunderstorm, wildfire, wind, tornado, and hail. We exclude the remaining eight disaster types: fog, avalanche, landslide, lightning, winter weather, earthquake, tsunamis/seiche, and volcanic, as these are either not directly linked to climate change or are geologically driven. Figure IA1 presents ChatGPT's classification process, while Table IA1 draws on existing scientific research to detail the relationships between the six selected climatic disaster types in our final sample and climate change, providing a solid foundation for our classification and analysis.

Overall, these references collectively support our classification of events in the sample as climatic natural disasters and establish their connection to climate change. This ensures that our analysis is grounded in established scientific and empirical research, thereby strengthening the validity of our findings.

[24] See https://www.ipcc.ch/report/ar6/wg2/.

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Figure IA1. Climatic Disasters Classified by ChatGPT

This figure demonstrates how ChatGPT classifies climatic disasters that are highly related to climate change.

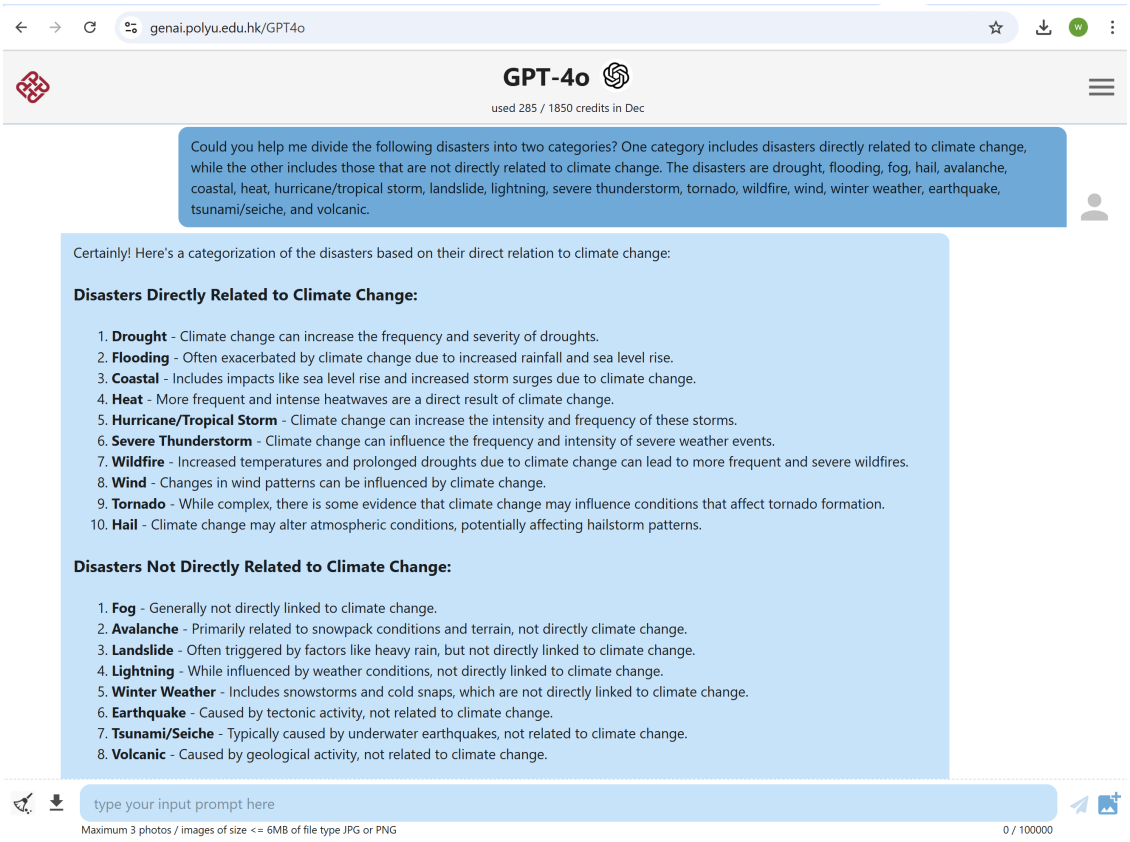


Table IA1. Supporting Evidence for Climatic Natural Disasters

Disasters	Relation to Climate Change
Flooding	Climate change increases flooding by raising the frequency and intensity of heavy precipitation and altering temperatures across the region. (e.g., Mallakpour and Villarini, 2015; Alifu et al., 2022)
Hurricane / Tropical Storm	Climate changes, such as higher sea-surface temperatures, increased atmospheric moisture, and changes in large-scale circulation, can influence factors like intensity, size, landfall angle, translation speed, and sea level, thereby contributing to hurricanes and tropical storms. (e.g., Hassanzadeh et al., 2020; Strauss et al., 2021)
Tornado	Climate change plays a significant role in modulating the annual frequency of tornadoes. In a warming climate, the frequency of environments favorable to tornadoes is expected to increase, particularly in spring, due to a rise in high wind shear values in the lowest 1 km of the atmosphere. (e.g., Brooks, Carbin, and Marsh, 2014; Nouri et al., 2021)
Wildfire	Climate changes, such as increased global temperatures, accelerate the water cycle, leading to more intense rainfall events, more severe and widespread droughts, regional humidity variations, and sea surface temperature fluctuations, which in turn increase wildfire. For example, these changes dry out vegetation, making it more flammable, and create conditions that are more favorable for wildfires, thereby increasing their frequency and severity. (e.g., Jolly et al., 2015; Gutierrez et al., 2021)
Wind	Climate change can influence wind-related natural disasters by altering variables directly linked to wind generation and propagation. For instance, increasing greenhouse gas concentrations can intensify winds that promote upwelling. This intensification is more noticeable at higher latitudes, consistent with the warming patterns associated with climate change, leading to more severe wind events. (e.g., Sydeman et al., 2014; Lobeto, Menendez, and Losada, 2021)
Hail	Climate change, such as global warming, affects low-level moisture, convective instability, microphysical processes, and vertical wind shear. These changes create conditions that increase the frequency and severity of hail by enhancing the atmospheric environment necessary for hail formation and growth. (e.g., Allen, 2017; Raupach et al., 2021)

Appendix IB: A Simple Model and Prediction

We model a simple setting to generate predictions about whether examiners' exposure to climatic disasters may simultaneously increase the quantity and quality of granted green patents.

Consider an examiner who reviews N green patent applications. Application quality q is uniformly distributed on $[0, 1]$, and the examiner is assumed to know this distribution. A green patent application is approved if its quality exceeds a threshold $Q \in [0, 1]$. The examiner exerts screening effort $e \in [0, 1]$, meaning that she carefully screens eN green applications, while the remaining $(1 - e)N$ applications are processed via random selection.

Among screened applications, a fraction $(1-Q)$ exceeds the threshold, so $(1-Q)eN$ green patents are granted, with an average quality of $\frac{1+Q}{2}$. Assuming that among the applications she does not screen, she approves the same fraction as under the threshold rule, i.e., $(1-Q)$, but these approvals are effectively random with respect to quality. Therefore, among the non-screened applications, $(1 - Q)(1 - e)N$ patents are granted, with an average quality of $\frac{1}{2}$. In total, the examiner grants $(1 - Q)N$ patents. The average quality of granted patents is a weighted average of the screened and randomly selected components:

$$\bar{q}(Q, e) = \frac{\frac{1+Q}{2} \times (1 - Q)eN + \frac{1}{2} \times (1 - Q)(1 - e)N}{(1 - Q)N} = \frac{1}{2}(1 + eQ) \tag{1}$$

Following the logic above, if before the climatic disaster, the approval threshold is Q_1 and the screening effort is e_1, then the examiner grants $(1 - Q_1)N$ green patents, with the average quality of granted patents equal to $\frac{1}{2}(1 + e_1Q_1)$.

After experiencing a climatic disaster, patent examiners become more favorable toward green patent applications and devote greater effort to reviewing them. As a result, the approval threshold decreases from Q_1 to Q_2 ($Q_2 < Q_1$), while screening effort increases from e_1 to e_2 ($e_2 > e_1$). Thus, the total number of granted patents becomes $(1 - Q_2)N$, with the average quality of granted patents equal to $\frac{1}{2}(1 + e_2Q_2)$.

Comparing the two regimes, the number of granted green patents increases after the disaster because the approval threshold is lower: $(1 - Q_2)N > (1 - Q_1)N$. The change in average quality of green patents is $\frac{1}{2}(e_2Q_2 - e_1Q_1)$. Therefore, the framework is consistent with our baseline finding that patent examiners grant more green patents after experiencing climatic disasters. Although a lower approval threshold tends to reduce the average quality of granted patents, increased screening effort works in the opposite direction by improving selection and quality. Consequently, the overall effect on green patent quality depends on the relative strength of these two forces. Specifically, when the effort effect dominates the threshold effect (i.e., $e_2Q_2 > e_1Q_1$), the average quality of granted green patents increases.

Appendix IC: Additional Results

Table IC1. Climate-Disaster Experience and Grant Share of Green Patents: Additional Tests

This table presents examiner-year level regressions of examiners' propensity to grant green patents on climatic exposures. *Green Patent Ratio* is the percentage of green patents granted out of all granted patents for each examiner in a given year. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. In Panel A, we run the regression using the Tobit model, including county and year fixed effects. In panel B, we exclude certain climatic disasters, such as hail and wind events, as they may be less directly associated with climate change compared to other climatic disasters in our sample. Panel C presents examiner-year level regressions for green patent review on extreme temperature exposures. *Extreme Heat* is a dummy variable that equals one if the total number of extremely hot days in a year exceeds the median of all counties for that year, and zero otherwise. *Extreme Cold* is a dummy variable that equals one if the total number of extremely cold days in a year exceeds the median of all counties for that year, and zero otherwise. *Extreme Temperature* is a dummy variable that equals one if the combined total of extremely hot and extremely cold days exceeds the median of all counties for that year, and zero otherwise. Panel D presents examiner-year level regressions based on an alternative green patent classification. *Green Patent Ratio* ($OECD15$) is the percentage of green patents identified by the OECD 2015 classification in all granted patents for each examiner each year. *Non-Climate-Related Green Patent Ratio* is the percentage of green patents that fall within the OECD 2015 classification but do not include the CPC Y02 classification in all granted patents for each examiner each year, where these green patents are all non-climate-change related. The baseline model includes examiner and year fixed effects. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Tobit Model		
	Dependent Variable: Green Patent Ratio	
	(1)	(2)
Disaster	0.0202***	0.0202***
	(0.0071)	(0.0074)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	58,161	58,161
Adj. R^2	0.112	0.112

Panel B: Alternative Definition of Climatic Disasters		
	Dependent Variable: Green Patent Ratio	
	(1)	(2)
Disaster	0.0084***	0.0084***
	(0.0019)	(0.0024)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	58,161	58,161
Adj. R^2	0.852	0.852

Panel C: Extreme Temperature Exposure			
	Dependent Variable: Green Patent Ratio		
	(1)	(2)	(3)
Extreme Heat	0.0022***		
	(0.0006)		
Extreme Cold		-0.0011	
		(0.0010)	
Extreme Temperature			0.0029***
			(0.0008)
Examiner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	58,141	58,141	58,141
Adj. R^2	0.852	0.852	0.852

Panel D: Alternative Classification of Green Patents		
	Green Patent Ratio (OECD15)	Non-Climate-Related Green Patent Ratio
	(1)	(2)
Disaster	0.0074***	-0.0006
	(0.0018)	(0.0010)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
# Obs.	58,161	58,161
Adj. R^2	0.868	0.819

Table IC2. Climate-Disaster Experience and Grant Share of Green Patents: Poisson Regressions

This table presents examiner-year level Poisson regressions of green patent quality on climate-disaster exposures. *Green Patent Quality* is the average number of citations received by green patents for each examiner in a given year. *Non-Green Patent Quality* is the average number of citations received by non-green patents for each examiner in a given year. *All Patent Quality* is the average number of citations received by all patents for each examiner in a given year. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. Examiner and year fixed effects are included. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Green Patent Quality	Non-Green Patent Quality	All Patent Quality
	(1)	(2)	(3)
Disaster	0.1961***	0.0032	0.0231
	(0.0723)	(0.0501)	(0.0459)
Examiner FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	35,450	57,735	58,161
Pseudo R^2	0.471	0.499	0.500

Table IC3. Climate-Disaster Experience and Grant Share of Green Patents: Patents without Prior Actions

This table presents examiner-year level regressions of examiners' propensity to grant green patents on climate-disaster exposures. *Green Patent Ratio* is the percentage of green patents granted out of all granted patents for each examiner in a given year. *Disaster* is a dummy variable that equals one if the examiner experiences climatic disasters in the previous year, and zero otherwise. We use the same sample as in Table 5. The baseline model includes examiner and year fixed effects. Standard errors are double-clustered at the county and year levels, and are reported in parentheses. The sample period is from 2012 to 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Green Patent Ratio	
	(1)	(2)
Disaster	0.0091^{***}	0.0091^{***}
	(0.0022)	(0.0029)
Examiner FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County, Year	County
# Obs.	55,682	55,682
Adj. R^2	0.874	0.874