Green Patent Signaling: Evidence from Voluntary Climate Disclosures

September 14, 2024

Abstract

We investigate how green patents signal the credibility of firms' voluntary climate disclosures, using exogenous variation in green patent issuance arising from the random assignment of patent applications to examiners of varying leniency. Consistent with the credibility-enhancement explanation, we find that firms with more green patents (i) are more likely to issue voluntary climate disclosures, (ii) experience higher stock returns around these disclosures, and (iii) see a greater subsequent increase in institutional ownership, particularly from climate-conscious investors. Additionally, (iv) the impact of green patents is less pronounced when climate disclosures are externally assured, report bad news, or when reporting firms have high reputational capital.

JEL Classification: D80, M14, O33;

Keywords: Green Patents, Voluntary Climate Disclosure, Disclosure Credibility, Climate Risk

1. Introduction

Since 2000, the US patent office has granted over 300,000 Green Patents, which we define as those covering climate change mitigation (of greenhouse gas emissions) technologies. Public firms contribute to over a third of this total. While patents are crucial for protecting valuable innovations, they can also serve as important signaling tools—a concept first introduced by Long (2002) and subsequently supported by various empirical studies.[1] Despite the large and growing number of green patents filed by US firms, the signaling function of these green patents is not well understood.

In this study, we argue that firms' green patents signal their commitment to reducing their climate impact, which is usually unobservable to investors. Two features of green patents are important for this signaling function. First, innovations underlying green patents represent one of the most tangible climate actions firms can undertake. Due to the complexity of climate challenges, existing technologies may prove either too costly or insufficient to address these challenges (Popp, Newell, and Jaffe, 2010). Similar views are shared by government agencies and climate experts, who recognize technological innovation as a crucial component in the path to achieving the targets set in the Paris Agreement.[2] Given this, the innovation activities underlying green patents are highly relevant to firms' climate commitments.

Second, green patents provide investors a *credible* proxy to gauge firms' green innovation activities.[3] Important for credibility, patents are public information. They are less prone to firms' manipulation due to the patent examination process. Obtaining patents is also costly. The substantial cost of innovation, a pre-condition for patenting, also deters firms without a genuine commitment to mitigating climate impact from engaging in green patenting (Spence,

[1]See, for example, Conti, Thursby, and Thursby (2013); Farre-Mensa, Hegde, and Ljungqvist (2020); Hoenen, Kolympiris, Schoenmakers, and Kalaitzandonakes (2014); Hottenrott, Hall, and Czarnitzki (2016); Useche (2014)

[2]For example, the government of Japan emphasizes that "Achieving net-zero by 2050 requires more ambitious attempts for innovation than ever" in its long-term strategy under the Paris Agreement. Furthermore, Figueres et al. (2023) states that "The technology-driven transition to low-carbon energy is well under way, a trend that made the 2015 Paris climate agreement possible".

[3]Actual green innovation activities are unobservable to investors. Green patents are the best proxy available to investors to gauge firms' green innovation activities.

1973). In sum, green patents provide a valuable signal about firms' climate commitment to reducing their climate impact because of the underlying green innovations as well as the credibility of the signal conveyed by these patents.

To analyze the signaling function of green patents, we use firms' voluntary climate disclosures as the laboratory. Voluntary climate disclosures are particularly suited for the analysis because they are often considered non-credible due to discretionary reporting standards and absent verification processes (Christensen, Hail, and Leuz, 2021). As a result, assessing the truthfulness of these disclosures relies on investors' perception of firms' commitment to addressing their climate impact, where the signaling value of green patents becomes especially pertinent. Given this, our main hypothesis posits that green patents certify firms' commitment to reducing their climate impact, thereby bolstering the perceived credibility of firms' voluntary climate disclosures. The increased credibility, in turn, incentivizes firms' disclosure decisions.

Consistent with this hypothesis, we find that firms with more green patents are indeed more likely to engage in voluntary climate disclosures. These disclosures are perceived as more credible by stock market investors, as evidenced by higher stock market returns around the disclosure dates and increased institutional ownership following disclosures from climate-conscious investors. A set of cross-sectional analyses also supports the hypothesis.

To undertake the analysis, we collect green patents related to climate impact mitigation filed by US public firms during 2002-2020, as categorized by experts in the World Intellectual Property Organization. To measure whether a firm provides voluntary climate disclosures, we follow Bolton and Kacperczyk (2021) and Ilhan, Krueger, Sautner, and Starks (2023) by using the availability of Scope 1 carbon emissions data, as carbon emissions are the most important component of a climate disclosure. We focus on Scope 1 emissions because the required data is entirely under a firm's control, whereas Scope 2 and Scope 3 emissions involve data from customers and suppliers, which may limit a firm's control over the decision to disclose.

Identifying the signaling effect of green patents is challenging due to the potential conflation between the value of underlying innovations and the incremental signaling effect of these patents. The former, for example, can cause a major confounding effect when firms with superior green technologies also demonstrate better environmental performance, which, in turn, can influence their climate disclosure decisions. This confounding effect is implied by adverse selection theory (Grossman and Hart, 1980; Grossman, 1981; Milgrom, 1981) and has nothing to do with patent signaling. To address the endogeneity issue, an ideal experiment would involve comparing two firms that submit equal green patent applications but receive different numbers of grants due to factors exogenous to the quality of their innovations. We find a setting that closely mirrors this ideal experiment.

Specifically, we use an instrumental variable based on the leniency of patent examiners, which relies on two key features of the US patent examination process as documented in Farre-Mensa et al. (2020), Feng and Jaravel (2020), and Sampat and Williams (2019). First, patent applications are randomly assigned to examiners within specific technology sectors, or 'art units', at the US Patent and Trademark Office (USPTO). Second, there is a significant variation in the leniency of granting patents across patent examiners. These features imply that the chance of encountering lenient examiners or 'luck' can significantly influence the number of patents granted to a firm.

Leveraging the unique examination process in USPTO, our instrumental variable can effectively isolate green patents granted due to 'luck' from those truly merited by the innovations. Importantly, for our identification strategy, the patent applications identified by examiner leniency are typically those that either barely miss or barely meet the minimum requirements for patenting. Consequently, the additional green patents granted due to lenient examiners are among the lowest-quality patents issued by the USPTO and are likely to contribute minimally to a firm's technological capabilities, thereby reducing the potential for the earlier mentioned confounding effect.

To construct this instrumental variable, we use the Patent Examination Research Dataset from the USPTO. We begin by calculating the leniency of each examiner based on the examiner's overall grant rate from patent applications that the examiner has ever reviewed. We then average the examiner leniency across all of a firm's green patent applications that receive grant decisions in a given year. This firm-level average examiner leniency measure constitutes our instrumental variable.

We use a 2SLS model. In the first stage, we show that this firm-level instrumental variable of average examiner leniency has a statistically and economically significant impact on the number of green patents granted to a firm. Specifically, a one-standard deviation increase in the average leniency of examiners dealt with by a firm leads to a 4.7% increase in the number of green patents, demonstrating the effectiveness of the instrumental variable in influencing green patents.

The second-stage regression explores the relationship between a firm's green patents and its decision to provide voluntary climate disclosures. We note that a firm's disclosure decision is determined not just by the current year's green patents but also by green patents from previous years. To account for this, following Hombert and Matray (2018) and Bloom, Schankerman, and Van Reenen (2013), we aggregate the predicted increase in a firm's green patents obtained in the first-stage regression across all previous years since the beginning of our sample period. Then, in the second stage, we relate this cumulative measure, termed "green patent stock", to the firm's climate disclosure decision. We show that an addition of one green patent corresponds to a 2.8-percentage-point (or 21.5%) increase in the likelihood of issuing climate disclosures and a 1.1-percentage-point (or 55.0%) in the propensity to initiate climate disclosures. These results are consistent with our main hypothesis that green patents incentivize firms to issue voluntary climate disclosures.

Next, we explore the credibility mechanisms. Disclosure credibility is difficult to observe. We rely on stock returns around the disclosure date to measure disclosure credibility. A more credible disclosure is usually associated with higher stock returns (Stocken, 2000; Teoh and Wong, 1993). Following these studies, we predict and find that voluntary climate disclosures from firms with more green patents are associated with significantly higher stock returns, supporting that green patents contribute to the perceived credibility of these disclosures.

To further substantiate the changes in investors' perception of climate disclosure credibility, we analyze changes in institutional ownership. Institutional investors prefer better disclosures, which reduce the monitoring cost (Bushee and Noe, 2000). Thus, provided that green patents make climate disclosures perceived to be more credible, we predict and find a greater increase in institutional ownership following climate disclosures for firms with more green patents. Additionally, following Cohen, Kadach, and Ormazabal (2023), we distinguish investors by their climate attitudes and find that this ownership increase is predominantly among climate-conscious investors. The results on institutional ownership suggest that green patents indeed alter investors' perception on climate disclosures, consistent with the credibility-enhancement hypothesis.

Additionally, we examine the heterogeneous effects of green patents by analyzing the *existing* credibility of climate disclosures. The rationale is that if green patents indeed enhance disclosure credibility, this effect tends to diminish when the disclosures are already perceived as credible. First, we differentiate (i) between externally assured disclosures and non-assured ones, and (ii) between disclosures conveying bad news (i.e., increased carbon emissions) and those conveying good news. Studies show that bad news disclosures are generally more believable than good news disclosures (Hutton, Miller, and Skinner, 2003; Kasznik, 1999; Williams, 1996). Our findings indicate that the influence of green patents is less pronounced for externally assured disclosures and for those disclosures reporting increased emissions, suggesting that high existing credibility can limit the incremental credibility enhancement provided by green patents. Second, we explore how firms' reputational capital, which enhances the credibility of their disclosures, influences the impact of green patents. We measure firms' reputational capital through (i) prior financial misconduct, which is linked to significant reputation damage that is hard to recover (Amiram, Bozanic, Cox, Dupont, Karpoff, and Sloan, 2018; Chakravarthy, DeHaan, and Rajgopal, 2014), and (ii) local social capital, which generally deters opportunistic behaviors and thus bolsters a firm's reputation (Guiso, Sapienza, and Zingales, 2004; Hasan, Hoi, Wu, and Zhang, 2017). Our results confirm that the effect of green patents is more pronounced for firms previously engaged in financial misconduct and those located in counties with lower social capital, aligning with our expectations.

Lastly, we investigate the robustness of our identification strategy. We first examine whether the exclusion restriction is satisfied. A violation of this restriction would imply that examiner leniency might affect other variables, besides green patents, that determine firms' decisions to disclose. To address this, we first review the determinants of climate disclosure decisions documented in the literature. We then provide analyses and discussion demonstrating that these determinants are unlikely to correlate with the average leniency of the examiners a firm encounters, alleviating concerns about a violation of the exclusion restriction in our study. Additionally, recent studies by Righi and Simcoe (2019) and Barber and Diestre (2022) raise the issue that the assignment of patent applications within some art units might not be random. To address this, we focus on a subset of art units identified by Feng and Jaravel (2020), where the assignment of applications is likely to be determined by the last digit of the patent application number. Our main results remain robust when the analysis is restricted to these art units, thereby reinforcing the strength of our identification.

As we have already discussed in the part for identification, a possible endogeneity issue is that firms with more green patents generally exhibit superior climate performance, which prompts voluntary climate disclosures. While our identification strategy can mitigate this issue, we note that, different from the prediction of adverse selection theory, research on ESG disclosures has consistently found that firms with poorer ESG performance are more inclined to issue ESG disclosures (Deegan, 2002; Cho and Patten, 2007; Deegan, 2010). Recognizing that these studies are prone to endogeneity concerns, Huang and Lu (2022) uses a better identification based on the regulatory change in the UK and confirms that higher ESG performance decreases the likelihood of ESG disclosures. All these findings suggest that our results cannot be fully explained by this alternative interpretation.

Our study contributes to the literature on voluntary climate disclosures by helping to reconcile seemingly conflicting findings from previous studies. Several studies show that voluntary climate disclosures are uninformative to investors because of the credibility concerns (Christensen et al., 2021). For example, research indicates that climate disclosure manipulation occurs through cherry-picking items to disclose or by obfuscating the disclosure language.[4] Additionally, Cho and Patten (2007); Cho, Laine, Roberts, and Rodrigue (2015) discuss how some firms exploit environmental disclosure flexibility to engage in 'greenwashing.' This concern is echoed by regulators, with the SEC recently having mandated climate disclosures in an effort to provide investors with reliable information.[5] However, this line of research appears to be at odds with asset pricing studies showing that climate disclosures have a significant influence on stock price movement (Ilhan, Sautner, and Vilkov, 2021; Bolton and Kacperczyk, 2023; Griffin, Lont, and Sun, 2017). These studies suggest that investors are capable of discerning the credibility of climate disclosures. However, there has been scant research on how this evaluation is conducted. Our study bridges this gap by demonstrating that green patents serve as a valuable signal for investors to gauge the reliability of firms' climate disclosures.

Our study extends the existing literature that underscores the signaling role of patents. Building on Long (2002)'s work, research has shown the signaling effect of patents in facilitating external financing for established firms (Hottenrott et al., 2016), IPO firms (Useche, 2014), as well as startups (Conti et al., 2013; Hoenen et al., 2014). Moreover, Gong, Li, Manova, and Sun (2023) finds that obtaining a US patent also signals exporters' product quality and credibility to fulfill contracts. Interestingly, the research on the signaling role of patents extends even to historical contexts in the US. Swanson (2024) illustrate how Black people and women use their patents as evidence to advocate for their voting rights, as owning

[4]For academic evidence of disclosure manipulation, see Bingler, Kraus, Leippold, and Webersinke (2022); Fabrizio and Kim (2019); Kim and Lyon (2015); Marquis, Toffel, and Zhou (2016).

[5]The rationale for mandating climate disclosures is available at `https://www.sec.gov/files/rules/proposed/2022/33-11042.pdf.`

patents serves as certification of one's originality and independence of thought. However, the specific signaling role of green patents has not been systematically investigated, especially considering the significant stock of green patents in the United States. Our study fills this gap.

This study contributes to the literature by revealing firms' green patenting activities as an important determinant for voluntary climate disclosures. Despite the importance of these disclosures, the apparent reluctance by US firms to voluntarily disclose climate-related information highlights the need to better understand what drives these disclosure decisions, which is important for informing the ongoing debates regarding mandates for climate disclosures.

Our paper contributes more broadly to the body of research investigating the credibility of voluntary disclosures. For instance, Mercer (2004) categorizes potential factors that influence the credibility of management disclosures. Rogers and Stocken (2005) demonstrates that the credibility of management earnings forecasts varies with the market's ability to assess their truthfulness. Gu and Li (2007) finds that insider purchase transactions tend to enhance the credibility of subsequent innovation disclosures. Ng, Tuna, and Verdi (2013) reveals a general market underreaction to management earnings forecasts and attributes variations in this underreaction to differences in disclosure credibility. Our study extends this literature by focusing on voluntary climate disclosures, which face more acute credibility issues than voluntary financial disclosures due to the absence of ex-post verification mechanisms and a lack of penalties for misreporting.[6] Importantly, our research explores how firms can enhance the credibility of their climate disclosures, shedding light on a relatively understudied aspect of the climate disclosure literature.

It's worth noting that, in March 2024, the US Securities and Exchange (SEC) approved rules mandating climate-related disclosures. However, this regulatory shift does not diminish the relevance of our findings. Green patents will continue to serve as a valuable signal of

[6]As demonstrated in Stocken (2000), subsequent financial reports serve to verify the content of earlier voluntary financial disclosures, thereby deterring incentives to misrepresent these disclosures.

firms' climate commitments, and this signal will remain important to investors. In fact, our study suggests that as investors increasingly prioritize climate-related risks, understanding firms' environmental commitments will become even more crucial. Therefore, our findings remain pertinent and valuable despite the recent change in climate disclosure regime.

2. Hypothesis Development

2.1. Disclosure Credibility

The adverse selection theory suggests that firms operating in an environment of asymmetric information should voluntarily disclose their private information. This is because withholding such information will cause investors to discount firm value to the point that the benefit of disclosure outweighs that of withholding (Grossman and Hart, 1980; Grossman, 1981; Milgrom, 1981). Verrecchia (1983) further develops the model by arguing that withholding certain information (i.e., proprietary information) might actually enhance firm value, offering an explanation as to why not all firms voluntarily disclose their private information.

An important premise underpinning the theory is that investors are capable of verifying the information conveyed in voluntary disclosures. This may indeed be the case for voluntary financial disclosures. Periodic mandatory financial statements (e.g., 10-K) provide investors with a means to verify the accuracy of voluntary disclosures, thereby increasing their credibility (Stocken, 2000). Also, the high litigation threat from misreporting, which deters potential misreporting behaviors, adds credibility to voluntary financial disclosures (Fischer and Verrecchia, 2000; Beyer, Guttman, and Marinovic, 2019).

By contrast, voluntary climate disclosures, in general, lack uniform reporting standards or proper verification processes. These features, together with the modest consequences from misreporting, reduce the credibility of these disclosures (Christensen et al., 2021; Greenstone, Leuz, and Breuer, 2023). Therefore, understanding firms' commitment to reducing their climate impact becomes more important in assessing the credibility of climate disclosures.

2.2. The Signaling Function of Green Patents

Firms' climate commitments are usually unobservable to investors. This information asymmetry can increase transaction costs in identifying firms genuinely wanting to mitigate climate change impact (Akerlof, 1970; Williamson, 1985).

The role of patents in signaling some desirable attributes of firms was first proposed by Long (2002). In her analytical framework, innovation activities, which are usually unobservable to investors, are important for evaluating certain desirable attributes of firms. Patents, which correlate with innovation activities, can convey these attributes to investors, thus serving an important signaling function. This function can be observed in various contexts. For example, patents are crucial for startup financing and reputation building. As Mark Lemley notes, "Venture capitalists use client patents [...] as evidence that the company is well managed, is at a certain stage in development, and has defined and carved out a market niche". Additionally, Gong et al. (2023) show that Chinese companies with US patent grants are more likely to export to the US because US patents signal product quality and the ability to honor contracts.

In this study, we argue that green patents can credibly signal a firm's commitment to reducing climate impact, which is important for investors to assess the credibility of firms' voluntary climate disclosures. First, green innovations underlying green patents are critical to addressing climate challenges. Radical innovations are required to upgrade products or adjust supply chains in order to reduce carbon emissions. Second, the signal conveyed by green patents is credible because patents, which usually need to go through a thorough examination process, are less subject to firms' manipulation. Also, the credibility of green patents stems from the substantial cost in R&D investments, which would be costly for firms without a genuine commitment to reducing climate impacts (Riley, 1979; Spence, 1973). Besides direct investments involved in R&D, in terms of time and money, firms also incur substantial indirect costs related to these investments. For example, the R&D expense pressures current earnings, which can adversely impact stock-based compensation plans, or even heighten the risk of hostile acquisitions (Bushee, 1998; Geng, Zhang, and Zhou, 2023).

In summary, green patents provide credible and relevant signals about firms' commitments to reducing their climate impact. This signaling function builds trust with external investors, enhancing the credibility of firms' climate disclosures. The increased disclosure credibility is more likely to reduce information asymmetry and the cost of capital, thereby increasing the likelihood that firms will provide voluntary climate disclosures.

Hypothesis: *Green patents are associated with an increased likelihood of voluntary climate disclosures.*

3. Institutional Background and Empirical Design

3.1. Patent Application Process

After the submission of a new patent application to the USPTO, the new application is distributed to one of its nine technical centers. Each technical center then allocates the patent application to an appropriate art unit, each representing a more refined technology field. Supervisory patent examiners within these art units assign each patent application to an examiner, who then determines whether to grant the patent. In the biggest patent examination sample available to us, there are over 15,070 patent examiners across 768 art units.

Within each art unit, the assignment of patent applications follows a quasi-random process. In some units, applications are randomly allocated based on the last digit of the application series number, while in others, assignments are based on the caseload of examiners. Patent applicants have little control over which examiner handles their application. According to US patent law, patent grant decisions should be based on the standards of novelty and non-obviousness of technologies embedded in patent applications. However, in reality, patent examiners vary considerably in applying these legal standards. This variation in the leniency of patent examiners markedly affects the likelihood of a patent being granted.

Figure 1 plots the grant rates across all USPTO patent examiners. The top 10% most lenient examiners demonstrate a grant rate as high as 92.48%, whereas the top 10% strictest examiners have a grant rate of 35.72%. Even after accounting for any effect specific to each art unit, the difference in the grant rate between the most lenient and the strictest examiners is still highly significant. This randomness in encountering patent examiners of vast variation in examiner leniency is vividly described as a "patent lottery" by Farre-Mensa et al. (2020). Patent attorneys also understand this "lottery". In her testimony for patent examiner statistic data service provided by Patent Bots, Lisa Geary from Dentons states, "The examiner statistics are helpful for managing client expectations. Patent Bots enables me to show my clients the likelihood of getting applications allowed given the assigned examiner."[7]

An important observation is that there is a significant variation in patent grant rates across different art units. As shown in Figure 2, the top 10% art units with the highest grant rates approve, on average, 88.5% of the applications they review, whereas those with the lowest rates approve only 45.2%. This variation may stem from the different maturity levels of technology fields for which each art unit is responsible. For instance, emerging technology fields, which are often characterized by frequent breakthroughs, tend to receive more high-quality patent applications, resulting in higher grant rates. In contrast, more mature fields, where technological advancements are much harder, typically see lower grant rates. Additionally, the variation in grant rates could reflect differences in how examiners within an art unit collectively apply patenting standards. Our analysis does not seek to distinguish these underlying factors explicitly but adjusts for the general grant rate within each art unit to standardize the leniency measure for each patent examiner.

These features of the patent examination process allow us to use patent examiner leniency as the instrumental variable for the likelihood that a company receives a green patent grant,

[7]Patent Bots is a company that provides patent examiner statistics to patent attorneys. See the quote for Lisa Geary at https://www.patentbots.com/about-examiner-statistics, last accessed in June 2024.

as described in the following section.

3.2. Empirical Design

We use patent examiner leniency as the instrumental variable for a firm's green patents, relying on the comprehensive patent examination data released by USPTO. We construct the instrumental variable in two steps, following the procedures in Hege, Pouget, and Zhang (2024). First, for a green patent application p, we calculate the leniency of its reviewing examiner by taking the difference between the examiner's patent grant rate and the average grant rate of the corresponding art unit that administers the examiner. Doing so ensures that variations in examiners' grant rates do not reflect differences specific to their corresponding art units. We employ a leave-one-out approach, excluding the granting decision with respect to application p when calculating these grant rates. Second, we aggregate this leniency measure at the firm level by averaging the calculated leniency scores across all of a firm's green patent applications with granting decisions made in a year. Formally, our firm-level average examiner leniency measure, $Avg\_Leniency_{i,t}$, is defined as follows:

$$Avg\_Leniency_{i,t} = \frac{1}{N(P)_{i,t}} \sum_{p \in P} [\underbrace{\frac{N\_Granted_e - I(Granted)_p}{N\_Examined_e - 1}}_{\text{Examiner } e\text{'s grant rate excluding } p} - \underbrace{\frac{N\_Granted_u - I(Granted)_p}{N\_Examined_u - 1}}_{\text{Art unit } u\text{'s grant rate excluding } p}], \tag{1}$$

where p is a green patent application, e is patent examiner within art unit u, and i is application p's filing firm (i.e., assignee). $N\_Granted_e$ and $N\_Examined_e$ respectively represent the total number of patent applications that are granted and examined by examiner e. Similarly, $N\_Granted_u$ and $N\_Examined_u$ separately denote the number of applications that are granted and examined within art unit u. $I(Granted)_p$ equals 1 if application p is approved, and zero otherwise. $N(P)_{i,t}$ is the number of firm i's green patent applications with granting decisions made in year t. $Avg\_Leniency_{i,t}$ is the instrumental variable in our analysis.

To test the relevancy of this instrumental variable, we regress a firm's green patents on the average examiner leniency using the following model,

$$GreenPatGranted_{i,t} = \alpha + \beta Avg\_Leniency_{i,t} + \sigma_i + \theta_{j,t} + \eta + \epsilon_{i,t}, \tag{2}$$

where $GreenPatGranted_{i,t}$ stands for the number of green patents granted to firm i in year t. A firm would receive more green patent grants if it makes more patent applications. To align the number of patent applications, we follow Hege et al. (2024) and include the green patent application number fixed effects (η). The fixed effects comprise a set of dummies, each representing a specific count of green patent applications for a firm-year.[8] The inclusion of these fixed effects ensures that our comparisons are restricted to firms that have filed the exact same number of green patents, but have had their applications reviewed by examiners with varying levels of leniency. The regression also includes firm fixed effects (σ_i) to control for any permanent effect at the firm level and industry-by-year fixed effects ($\theta_{j,t}$) to account for time-variant heterogeneities within an industry. The industry is defined based on the two-digit SIC classification.

The decision to voluntarily disclose climate information may be influenced not only by the current year's green patents but also by the accumulation of green patents from previous years. To account for this, following the approach in Hombert and Matray (2018) and Bloom et al. (2013), we accumulate the predicted green patents obtained in the first stage, creating the predicted green patent stock, $\widehat{GreenPat\_Stk}_{i,t}$.[9] Formally,

$$\widehat{GreenPat\_Stk}_{i,t} = \widehat{GreenPatGranted}_{i,t} + (1-\delta)\widehat{GreenPat\_Stk}_{i,t-1}, \tag{3}$$

where $\widehat{GreenPatGranted}_{i,t}$ is the predicted green patents obtained from Equation 2. δ is

[8] The stringent fixed effects require at least two observations with the same number of green patent applications. These observations account for 99.5% of the observations in our sample

[9] In Hombert and Matray (2018)'s model, where R&D expenditure is instrumented, the authors create an R&D stock measure by accumulating the predicted R&D expenditure from the first stage. This R&D stock measure is used in the second stage to account for the effect of historical R&D on the outcome variable. A similar approach is also used in Bloom et al. (2013).

the depreciation rate of knowledge capital with a constant value of 15%. We initialize the green patent stock at zero in the first year the firm appears in Compustat or 2001, whichever comes last. While we adopt the conventional practice of using 15% depreciation rate (Hall, Jaffe, and Trajtenberg, 2005; Aghion, Van Reenen, and Zingales, 2013), this choice remains arbitrary.[10] We confirm that our results are not sensitive to alternative depreciation rates of 25%, 20%, 10%, or 5% in robustness analyses.

Accumulating green patents as described by Equation 3 introduces a concern: the resulting green patent stock might correlate with firm age, potentially confounding our analysis if older, more mature firms are more inclined to provide voluntary climate disclosures. To mitigate this, we include firm age as a control variable in all regression models.

Next, we estimate whether green patenting activities can influence firms' decision to disclose climate information using the following specification,

$$Disclosure_{i,t} = \alpha + \beta Green\widehat{Pat\_Stk}_{i,t-1} + Controls + \sigma_i + \theta_{j,t-1} + \epsilon_{i,t}, \tag{4}$$

where $Disclosure_{i,t}$ is a one-year forwarded dummy variable indicating if a firm makes a voluntary climate disclosure in a year. The dummy variable $Disclosure_{i,t}$ takes a value of one if self-reported Scope 1 emissions are available and zero otherwise. We also include a range of control variables which include firm size ($ln(Assets)$), measured by the natural logarithm of total assets, $Book\text{-}to\text{-}Market\ Ratio$, measured by the book value of assets divided by the market value of assets, return on asset (ROA), and firm age ($ln(FirmAge)$), measured by the natural logarithm of firm age since IPO. We also control for the natural logarithm of R&D stock.[11]

Because we use the predicted green patent stock as an explanatory variable, we need to

[10] Hall (2007) emphasize the challenge of selecting the appropriate depreciation rate, stating, "the measurement of the depreciation of R&D assets is the central unsolved problem in the measurement of the returns to R&D."

[11] R&D stock is calculated following the specification $R\&D\ Stk_{s,t} = R\&D\ Exp_{s,t} + (1 - 15\%) \times R\&D\ Stk_{s,t-1}$, assuming a depreciation rate of 15% for R&D capital following Hall et al. (2005). We replace the missing value for R&D expenditure with zero. The initial value for $R\&D\ Stk$ is set to zero in the first year the firm appears in Compustat.

adjust the standard errors to account for these predicted regressors. Following Hombert and Matray (2018), the standard errors are bootstrapped and clustered at the firm level for all second-stage regressions.[12]

4. Data and Sample Selection

4.1. Patent Examination Data

Patent examination data is sourced from the USPTO Patent Examination Research Dataset (2022 version), which includes over 13 million patent applications. For each application, the dataset provides details about the patent examiner, art unit, and application status as of the dataset's creation date, among other information. A comprehensive dataset description is provided in Graham, Marco, and Miller (2018).

Our data cleaning procedures largely follow those outlined by Lemley and Sampat (2008) and Sampat and Lemley (2010). We retain only utility patent applications, excluding design, plant, re-issue, re-examination, and Patent Cooperation Treaty (PCT) applications directed at foreign filing. Also, we exclude provisional applications, as these require the applicants to file a corresponding nonprovisional application within 12 months, which become utility patent applications included in our analysis. We limit our analysis to applications filed from January 2001 onward. This cutoff is due to the American Inventor's Protection Act of 1999, which mandates that patent applications be published 18 months after the filing date. Lemley and Sampat (2008) consider January 2001 the first month applications would reliably be published since the Act.

[12] We draw a random sample with replacement from the pool of firm-years used for estimating the second-stage regression. Notably, to maintain the correlation structure of the sample, we opt to draw from a pool of firm-years, rather than individual firms when assembling our random sample. Then, we use the random sample to perform the second-stage regression analysis. This entire process is iterated for 500 times. The standard errors reported in our study are bootstrapped and correspond to the empirical distribution of the coefficients estimated across these 500 iterations.

4.2. Green Patents

The green patent data used in this study are identified based on a list of patent classes that experts in the World Intellectual Property Organization (WIPO) consider to be related to environmentally sound technologies, which are listed by by the United Nations Framework Convention on Climate Change.[13] Given the focus of our paper on climate disclosure, we exclude patent classes that do not closely relate to carbon emission reduction. These excluded classes include waste management, water pollution control, forestry techniques (e.g., tree pruning), alternative irrigation methods, and pesticide alternatives.

WIPO green patent classes are based on the International Patent Classification (IPC) system, which is distinct from the Coordinated Patent Classification (CPC) system applied to US patents. Using a concordance for CPC to IPC conversions supplied by the European Patent Office, we delineate the CPC patent classes corresponding to IPC green patent classes. After this, we identify the green patents held by US public firms using a firm-level patent dataset generated by Kogan, Papanikolaou, Seru, and Stoffman (2017). While the patent data is available till 2021, we do not consider patents filed after 2018 to address the patent data truncation issue discussed in Lerner and Seru (2022).

4.3. Voluntary Climate Disclosure

Following Bolton and Kacperczyk (2021) and Ilhan et al. (2023), we identify whether a firm provides voluntary climate disclosure in a given year based on the availability of self-reported Scope 1 carbon emissions.[14] This choice is based on two rationales. First, carbon emissions are considered the most critical metric for assessing a firm's climate transition risk. Second, Scope 1 emissions are directly controlled by the disclosing firms, making their

[13] Details about the list of patent classes can be found at `https://www.wipo.int/classifications/ipc/green-inventory/home`

[14] The disclosure of carbon emissions is typically classified into three categories: direct emissions, which are owned or controlled by the firm, such as emissions from fossil fuels combustion (Scope 1); indirect emissions from consumption of purchased energy (Scope 2); and other indirect emissions from upstream or downstream operations (Scope 3).

reporting independent of information from suppliers and customers, unlike Scope 2 and 3 emissions.

We collect firms' Scope 1 emission data from Refinitiv, formerly known as Thomson Reuters, which has carbon emission data dating back to 2002. Multiple vendors offer carbon emission data (e.g., Refinitiv, Bloomberg, Trucost, Sustainalytics, and MSCI). A recent study by Busch, Johnson, and Pioch (2022) evaluates carbon emission data provided by several data vendors, including Refinitiv. They concluded that self-reported Scope 1 data demonstrates high consistency across data vendors with an average Pearson correlation of 0.98 (See their Table 6). As for the scope of coverage, Busch et al. (2022) show that Refinitiv covers 12,677 firms for the self-reported Scope 1 emission, slightly higher than 11,761 firms covered by Trucost, which is used in several other studies (e.g., Bolton and Kacperczyk, 2021).

4.4. Sample Selection

Our regression sample combines information from Compustat, the green patent dataset, the patent examination dataset, and Refinitiv. The regression sample begins in 2002, when Refinitiv carbon emission data were first available, and extends through 2018, the last year for which green patent data are available after accounting for patent truncation issues.

We further exclude financial and government-related firms (i.e., SIC code starting with "6" and "9") since firms in these industries usually operate under different regulatory rules. We remove firm-years with negative total assets, for which we consider the accounting data unreliable. We require all firms to have at least one green patent throughout the sample period to avoid bias stemming from firms self-selecting to pursue green innovation.

[Insert Table 1 about here.]

Table 1 reports the summary statistics for the main variables used. The baseline sample contains 1,020 distinct public firms in the US, with 14,166 firm-year observations holding

48,184 granted green patents from 2002 to 2018. On average, a firm receives 3.40 green patents each year. 13% of sample firm-years issue voluntary climate disclosures. All continuous control variables used in the study are winsorized at a 1% level to reduce the effect of outliers. Appendix Table A.1 provides a detailed description of all the variables used in our analysis.

[Insert Table 2 about here.]

Table 2 tabulates the yearly distribution of firms issuing voluntary climate disclosures as well as firms receiving green patent grants. The number of firms receiving green patent grants increases from 90 in 2002 to 583 in 2018. Similarly, the number of firms providing voluntary climate disclosures also shows a rising trend over the same period, growing from 13 to 427.

5. Main Results

5.1. *Green Patents and Patent Examiner Leniency*

In this section, we report the first-stage regression relating average examiner leniency to the number of green patents granted to a firm, as specified in Equation 2. As shown in Table 3, the average leniency of examiners encountered by a firm, *Avg_Leniency*, exhibits a statistically significant and positive effect on the number of green patents granted to a firm. The results remain robust after the inclusion of control variables. In Column (1), a one-standard-deviation increase in *Avg_Leniency* is associated with a 4.7% increase in the number of green patents. More importantly, the F-statistics exceeding 10 alleviate the weak instrument concerns. These results suggest that average examiner leniency, *Avg_Leniency*, serves as an effective instrumental variable for the number of green patents granted to a firm, satisfying the relevancy assumption required for the instrumental variable approach.

[Insert Table 3 about here.]

5.2. *Corporate Climate Disclosure and Green Patents*

The second-stage regression investigates the impact of green patents on a firm's climate disclosure decision. To account for the possibility that the disclosure decision may depend on both current and past green patents, we generate a measure for the green patent stock by accumulating the green patents induced by examiner leniency using the method detailed in Equation 3. Then, we estimate Equation 4 to examine the relation between the green patent stock and firms' decisions to issue voluntary climate disclosures.

Regression results are reported in Column (3) of Table 3. We find that the green patent stock, denoted by $\widehat{GreenPat\_Stk}$, has a statistically significant and positive effect on a firm's decision to provide voluntary climate disclosure. The results are also economically meaningful. An addition of one green patent leads to an increase in the likelihood of voluntary climate disclosure by 2.8 percentage points or 21.5%. We also examine the initiation of voluntary climate disclosures, as represented by the variable $InitialDisclosure$. This dummy is set to one in the year a firm first discloses, and to zero for years preceding the first disclosure and for firms that never disclose during the sample period. The years following the initial disclosure are excluded from the regression analysis, resulting in fewer observations. The result in Column (4) implies that an addition of one green patent increases the likelihood of initiating voluntary climate disclosures by 1.1 percentage points or 55%. The findings are consistent with the hypothesis that green patents enhance disclosure credibility, which in turn increases firms' incentives to provide voluntary climate disclosures.

Our main analysis uses a depreciation rate of 15% in accumulating green patent stocks as in Equation 4. While this rate is commonly used in the literature, we examine if our findings are sensitive to this choice. To do so, we separately replace the depreciation rate with 25%, 20%, 10%, or 5% and repeat our analyses. Results in Table 4 indicate that the choice of depreciation rate does not significantly vary our results.

[Insert Table 4 about here.]

Lastly, it is useful to report OLS counterparts to our 2SLS estimates. As shown in Table A.3, the coefficients for $GreenPat\_Stk$ from the OLS regressions are smaller than those from 2SLS regressions. The discrepancy is likely due to the fact that the instrumental variable primarily identifies a local average treatment effect (LATE) stemming from a subset of green patent applications that are sensitive to examiners' leniency. Specifically, applications substantially below the patenting standards will be rejected even by lenient examiners. Likewise, applications well above the standards will be approved by strict examiners. Thus, only those applications that are marginally above or below the patenting requirement will respond to examiner leniency and constitute the source of identification.

Therefore, our 2SLS estimates, being local average treatment effects, reflect the signaling effect for a subset of *compliant* firms for which most of inventions hover around the threshold of patenting requirements. *Non-compliant firms*, comprising firms with many great inventions ("always takers") and firms with many bad inventions ("never takers"), are less likely to respond to examiner leniency and thus do not contribute to 2SLS estimates. However, both non-compliant and compliant firms are included in estimating the average treatment effect (ATE) for OLS regressions. The relatively smaller OLS estimates may suggest that the ATE among non-compliant firms is substantially lower than the LATE. Specifically, for always takers with a lot of highly successful green patents, they may perform so well environmentally so that investors perceive their climate commitments already (e.g., from media reports or high-profile awards). For never takers with very few green patents, they have neither enough green patents nor alternative means to signal their climate commitments to outsiders.

6. The Credibility Channel

6.1. Stock Market Return Around Voluntary Climate Disclosures

While disclosure credibility is difficult to measure empirically, investors' trading of disclosing firms' shares may reveal their perception on the credibility of disclosed information (Teoh and Wong, 1993). Following this logic, we examine firms' cumulative abnormal returns around voluntary climate disclosures. If green patents increase climate disclosures' credibility, we expect to observe higher stock returns for firms with more green patents.

US firms usually disclose climate information in their annual reports (10-K). As a result, we use the 10-K filing date as the date for firms' climate disclosures. We perform the following regression,

$$CAR_{i,t} = \beta_0 + \beta_1 Disclosure_{i,t} \times \widehat{GreenPat\_Stk}_{i,t} + \beta_2 Disclosure_{i,t} + \beta_3 \widehat{GreenPat\_Stk}_{i,t} + Controls + \epsilon_{i,t}. \tag{5}$$

The outcome variable CAR measures the cumulative abnormal return in an eleven-day-event window (CAR[-5,5]) or a twenty-one-day-event window (CAR[-10,10]) around the disclosure dates. The abnormal return is calculated using the market and Fama-French 3-factor Model. Because 10-K filings also reveal firms' earnings news, we measure earnings surprise by standard unexpected earnings (SUE) and control it in the regression.[15] Other control variables are the same as in the previous tables.

As reported in Table 5, the interaction term $Disclosure_{i,t} \times \widehat{GreenPat\_Stk}_{i,t}$ is statistically significant and positive, suggesting that the stock market return is higher for voluntary climate disclosures for firms with more green patents. The coefficient estimate appears robust and remains stable across different models used to calculate the abnormal stock returns.

[15] SUE is calculated based on the difference between actual earnings per share and the median estimated earnings per share by stock analyses.

These results support our hypothesis that green patents increase the credibility of voluntary climate disclosures.

[Insert Table 5 about here.]

6.2. *Institutional Ownership and Voluntary Climate Disclosures*

To further demonstrate shifts in investors' perceptions of climate disclosures, we examine changes in institutional ownership following these disclosures. Bushee and Noe (2000) show that investors prefer firms with better disclosures because of reduced monitoring costs. We expect that voluntary climate disclosures by firms with more green patents, if perceived to be more informative, are more likely to draw increased institutional ownership.

To test this hypothesis, we estimate the following regression:

$$\begin{aligned} InstOwn_{i,t} = \beta_0 + \beta_1 Disclosure_{i,t-1} \times Green\widehat{Pat\_Stk}_{i,t-1} + \beta_2 Disclosure_{i,t-1} \\ + \beta_3 Green\widehat{Pat\_Stk}_{i,t-1} + Controls + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where $InstOwn_{i,t}$ is institutional ownership, calculated as total equity shares held by institutional investors relative to total shares outstanding. Table 6, Columns (1) reports the regression results. The significant and positive coefficient for $Disclosure_{i,t-1} \times Green\widehat{Pat\_Stk}_{i,t-1}$ suggests that voluntary climate disclosures are associated with a greater increase in institutional ownership for firms with more green patents, consistent with our expectation.

Additionally, by separating investors by their climate attitude, we analyze which institutional investors primarily contribute to the change in institutional ownership documented earlier. To do so, following Cohen et al. (2023), we delineate investors' climate attitude by their affiliation with the CDP (formerly known as the Carbon Disclosure Project). The affiliated investors, the CDP signatories, are more interested in their portfolio firms' climate information and thus should be more sensitive to firms' climate disclosures. As illustrated in Columns (2) and (3) of Table 6, the increase in ownership documented in Column (1) is predominantly attributed to CDP signatories, with non-signatories showing little response, reinforcing that green patents significantly enhance investors' perception of firms' voluntary climate disclosures.

[Insert Table 6 about here.]

6.3. Distinguishing the Credibility of Climate Disclosures

This section focuses on the heterogeneous credibility of climate disclosures and examines how the credibility-enhancing effect of green patents interacts with this heterogeneity. We predict that green patents have a moderated credibility enhancement effect on climate disclosures that are already considered credible. Our analysis focuses on the variation in climate disclosure credibility arising from the nature of the news (good or bad) reported, the presence of external ESG assurance, and the reputation of the companies making the disclosures.

First, we distinguish the credibility of voluntary climate disclosures by categorizing the disclosed information as either good or bad news. Existing studies suggest that bad news disclosures are perceived as more credible than good news disclosures because managers have limited incentives to falsely disseminate negative information (Hutton et al., 2003; Kasznik, 1999; Williams, 1996). Empirically, we split the climate disclosure dummy $Disclosure$ into (i) a good news disclosure dummy ($Disclosure^{GN}$), which identifies climate disclosures with reduced Scope 1 emission intensity, and (ii) a bad news disclosure dummy ($Disclosure^{BN}$), which marks climate disclosures with increased Scope 1 emission intensity. We measure emission intensity in two ways: as self-reported Scope 1 emissions divided by total assets, and by sales. The regression results in Columns (1)-(4) of Table 7 show that the effect of green patents is less pronounced for bad news disclosures for both emission intensity measures chosen. The diminished impact of green patents on voluntary climate disclosures of high credibility further substantiates our hypothesis about the credibility-enhancement effect of green patents on climate disclosures.

Second, we distinguish disclosure credibility based on the presence of external ESG assurance, which refers to the verification of a firm's ESG-related information by third-party agencies. Voluntary climate disclosures with external assurance should be more reliable than those without such verification. We collect data on external ESG assurance from Refinitiv DataStream, using the variable "CGVSDP030." We separate climate disclosures with external ESG assurance and mark these disclosures with a dummy variable $Disclosure^{Assured}$. The dummy $Disclosure^{NonAssured}$ represents the remaining climate disclosures without such assurance. In Columns (5)-(6) of Table 7, where we separately tabulate the results for $Disclosure^{Assured}$ and $Disclosure^{NonAssured}$, we find a more pronounced effect of green patents on climate disclosures without external assurance ($Disclosure^{NonAssured}$), but the difference in coefficients appears to be statistically insignificant. This finding may be explained by concerns about the quality of external assurance. As highlighted by Christensen et al. (2021): "the experiences with auditing for financial reporting and with many high-profile accounting scandals suggest that voluntary private assurance is unlikely to result in effective enforcement [of reporting standards]."

[Insert Table 7 about here.]

Next, we turn to firms' reputational capital, as a high reputation can enhance the credibility of their voluntary climate disclosures. The first proxy for reputational capital is a firm's involvement in financial misconduct. Studies suggest that the revelations of financial misconduct can generate long-lasting damage to a firm's reputational capital (Amiram et al., 2018; Chakravarthy et al., 2014). To identify instances of financial misconduct, we search for all securities class action lawsuits from the Securities Class Action Clearinghouse maintained by Stanford University. Since financial misconduct typically leads to securities class action lawsuits, this approach should enable us to capture most revealed cases of financial misconduct in the United States.

Our second proxy for reputational capital is local social capital. Social capital, characterized by the strength of cooperative norms and the density of social networks, can significantly influence local firms' behavior in ways that constrain opportunistic actions (Guiso, Sapienza, and Zingales, 2011; Hasan et al., 2017). Consequently, we expect firms headquartered in areas with high social capital to be perceived as less likely to manipulate their climate information, thereby enhancing the credibility of their climate disclosures. We retrieve data on US county-level social capital scores from a database maintained by Penn State University. The data is available for 1990, 1997, 2005, 2009, and 2014.[16] We average social capital scores over the five years for each county and label firms in counties with below-median scores using a dummy variable $LowSocialCap$.

As shown in Table 8, the significantly positive coefficients for the interaction terms $Misconduct \times Green\widehat{Pat\_Stk}_{i,t}$ and $LowSocialCap \times Green\widehat{Pat\_Stk}_{i,t}$ suggest that the impact of green patents is more pronounced among firms with a history of financial misconduct and those located in low social capital counties, supporting our expectation that the credibility-enhancing effect of green patents is less pronounced for firms with strong reputational capital. The attenuated effect of green patents on high-credibility disclosures reinforces our hypothesis that green patents improve the credibility of voluntary climate disclosures.

[Insert Table 8 about here.]

7. Other Identification Issues

We explore several issues that may render our identification invalid. First, we analyze whether the exclusion restriction is satisfied for our IV identification. Then, we address concerns relating to the random allocations of patent applications within the USPTO's art units.

[16]The data can be accessed at https://nercrd.psu.edu/data-resources/county-level-measure-of-social-capital. Rupasingha, Goetz, and Freshwater (2006, with updates) provides a detailed description of how the social capital score for each county is calculated. The database has been periodically updated, with the latest available data covering the year 2014.

7.1. Exclusion Restriction

To test whether the exclusion restriction is violated, we perform a range of analyses that relate important firm characteristics to average examiner leniency (*Avg_Leniency*). Specifically, we focus on the determinants of voluntary climate disclosures, as these deterministic variables potentially present a higher risk for violating exclusion restriction if they are related to *Avg_Leniency*.

We rely on the literature review by Christensen et al. (2021). This review comprehensively summarizes the determinants of voluntary CSR disclosures, which encompass voluntary climate disclosures. These deterministic variables include market capitalization, profitability, ownership structure, and the quality of corporate governance. Empirically, we set up regressions relating average examiner leniency to the log of market capitalization, return on assets (profitability), a corporate governance index developed by Gompers, Ishii, and Metrick (2003) reflecting governance quality, and dual-class share structure (*DualClass*), which is a dummy indicating if a firm adopts a dual-class share structure.[17] As shown in Table 9, none of these variables correlates with *Avg_Leniency* significantly, reinforcing the exogeneity of our identification.

[Insert Table 9 about here.]

The review by Christensen et al. (2021) also underscores the importance of managerial characteristics such as education, ethnicity, and the gender of their child, in shaping firms' disclosure practices. However, to the extent that managers' characteristics do not vary much over time, incorporating firm fixed effects into our analyses allows us to account for much of the effect attributable to these characteristics. Furthermore, it appears implausible that these managerial attitudes should feature any correlation with the leniency of patent

[17] As discussed in Christensen et al. (2021), studies focusing on non-US firms indicate that ownership structure is a determinant for environmental disclosures. Here, the ownership structure of firms encompasses 1) whether a firm has a dominant shareholder and 2) the amount of foreign ownership from the US and UK. To address 1), we use a dummy indicating if a firm adopts a dual-class share structure. 2) is less relevant and not considered in our analysis.

examiners.

Industry affiliation is another important determinant for climate disclosure behaviors. For instance, the oil and gas sectors, often subject to greater societal pressure, are more likely to engage in climate disclosures. Yet, the potential impact of industry-specific variations on our findings appears minimal, due to the inclusion of industry-by-year fixed effects in our regression analyses.

Another possible determinant for voluntary climate disclosures is external pressures from stakeholders and societies. Empirically measuring the external pressures is difficult. To address this concern, we perform a cross-sectional analysis by industry emission intensity. Industries with higher emission intensities are presumed to be under greater external pressures. However, as shown in Table A.2, our findings show no variation in disclosure propensity based on the emission intensity of industries, alleviating the concern that our results are driven by stakeholder and societal pressures.

7.2. Random Allocation of Patent Applications

The validity of our identification strategy is predicated on the premise that patent applications are randomly assigned to patent examiners. While this is supported by the interviews with patent examiners separately conducted by Lemley and Sampat (2012) and Cockburn, Kortum, and Stern (2002), recent studies by Righi and Simcoe (2019) and Barber and Diestre (2022) raise the concern that the assignment of patent applications in some art units might not be random. Specifically, Righi and Simcoe (2019) argues that, in some art units, patent application assignment follows examiners' specialization. Meanwhile, Barber and Diestre (2022) presents statistical evidence suggesting that some firms may influence the assignment process to have their applications examined by more lenient examiners.

To address these concerns, we follow the approach by Feng and Jaravel (2020), which identify a subset of art units where the assignment to examiners is likely determined by the last digit of the patent application number. We restrict our analysis to patent examiners within these specific art units and adjust our instrumental variable as follows:

$$Adj\_Avg\_Leniency_{i,t} = \frac{1}{N(P')_{i,t}} \sum_{p \in P'} [\underbrace{\frac{N\_Granted_e - I(Granted)_p}{N\_Examined_e - 1}}_{\text{Examiner } e\text{'s grant rate excluding } p} - \underbrace{\frac{N\_Granted_u - I(Granted)_p}{N\_Examined_u - 1}}_{\text{Art unit } u\text{'s grant rate excluding } p}], \tag{7}$$

where P' is the set of green patent applications assigned with those art units identified by Feng and Jaravel (2020). $N(P')_{i,t}$ is the number of i's green patent applications in P' with outcomes determined in year t.

In Table 10, we first demonstrate that the revised instrumental variable remains highly effective. Subsequent regression analysis in the second stage confirms that green patents continue to have a significant, positive effect on climate disclosures, thus reinforcing the causal interpretation of our results.

[Insert Table 10 about here.]

8. Conclusion

In March 2024, the US Securities and Exchange (SEC) approved rules mandating climate-related disclosures. An important rationale underlying the SEC's decision is to provide more useful climate-related information to assist investors' decision-making. This followed a decade in which this agenda was pursued, globally, through the Taskforce for Climate-Related Disclosures (TCFD). This development of mandatory rather than voluntary disclosures, is partly motivated by the realization that the current voluntary climate disclosures regime may lack credibility. However, despite the concern, it is surprising that many firms still choose to disclose voluntarily and that these disclosures have observable impacts on their stock price.

We posit that green patents serve as an important signaling tool that demonstrates firms' commitment to reducing their climate impact. We argue that these patents enhance the credibility of climate disclosures, thereby increasing firms' propensity to disclose climate-related information voluntarily. To discern the causal impact of green patents, we employ an instrumental variable approach based on the random encounters of patent examiners of various leniency. Our main finding is that green patents represent a statistically significant and positive explanatory variable for the propensity to provide voluntary climate disclosures. Adding one green patent corresponds to a 2.8-percentage-point (or 21.5%) increase in the likelihood of issuing climate disclosures and 1.1-percentage-point (or 55.0%) in the propensity to initiate climate disclosures. These results are consistent with our main hypothesis about the credibility-enhancement effect of green patents.

To provide further evidence of the credibility channel, we show that stock market returns react more strongly to voluntary climate disclosures of firms with more green patents. Also, we observe that these disclosures cause a significant increase in institutional ownership, most of which is from CDP signatories - i.e., institutional investors that are more concerned about climate issues. These findings suggest that the perceived quality of climate disclosures increases with the number of green patents held by disclosing firms, reaffirming the credibility-enhancement effect of green patents.

Furthermore, we explore the varying impact of green patents by the existing credibility of climate disclosures. Our analyses show that green patents have a less pronounced effect when climate disclosures are already highly credible—specifically, when they are externally assured, report bad news, or when the reporting firms possess high reputational capital. These results further support that the positive effect of green patents on the propensity to provide climate disclosures is due to the enhanced credibility these green patents confer.

Our findings should not be understood as a justification for the adequacy of the existing voluntary disclosure framework, as the high costs of innovation may not be feasible for all firms in the market. More importantly, as stated in Christensen et al. (2021), a mandatory disclosure system has the potential to reduce negative (or leads to positive) externalities, create economy-wide cost savings, reduce existing dead-weight losses or social costs, or create commitment, all of which do not exist in a voluntary disclosure regime.

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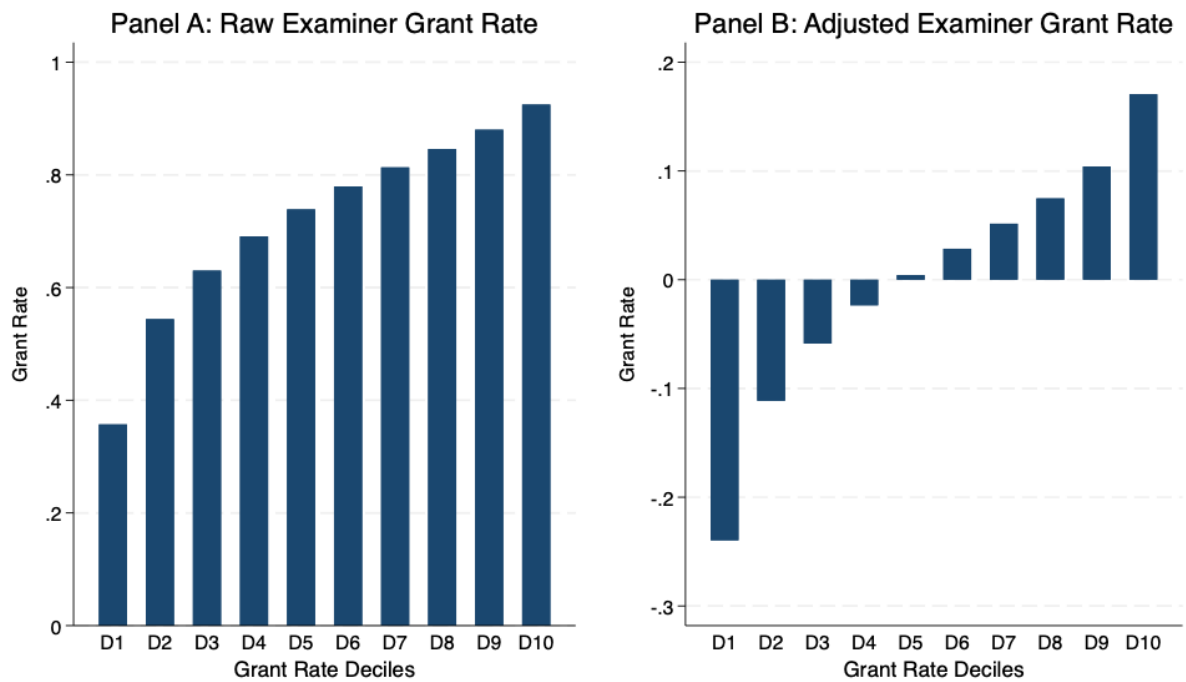

Fig. 1. **Patent Examiner's Grant Rate**

This figure displays the grant rates of all USPTO patent examiners, divided into deciles by their grant rates. Each bar represents the average grant rate across all examiners within a decile group. The left graph depicts the raw grant rates, while the right graph displays the adjusted grant rates, which represent the differences between an examiner's grant rate and the average grant rate of the examiner's respective art unit.

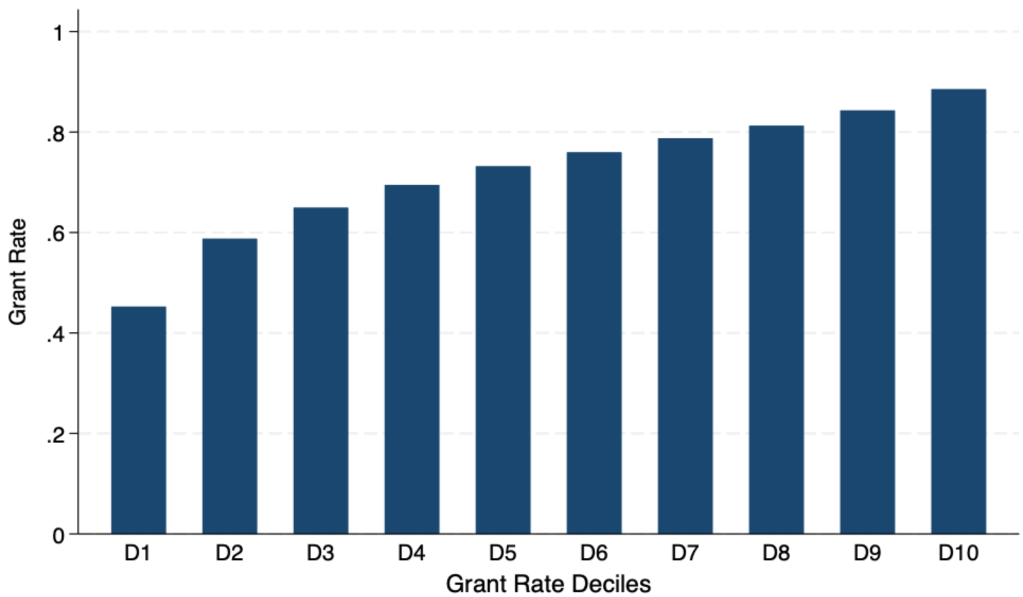

Fig. 2. **The Grant Rate of Art Units**

This figure displays the grant rates of all USPTO art units, divided into deciles by their grant rates. Each bar represents the average grant rate across all art units within a decile group.

Table 1: **Summary Statistics**

This table reports the summary statistics for the variables used in this study. *Avg_Leniency* measures the average leniency level of examiners reviewing the green patent applications filed by a firm. *GreenPatGranted* represents the number of green patents granted to a firm in a year. The voluntary climate disclosure, denoted by *Disclosure*, is a dummy variable that is one if a firm voluntarily discloses its Scope 1 carbon emissions in a year and zero otherwise. We sort *Disclosure* into good news disclosures $Disclosure^{GN}$, which identify climate disclosures with reduced Scope 1 emission intensity relative to the previous year, and bad news disclosures $Disclosure^{BN}$, which mark climate disclosures with increased Scope 1 emission intensity. Emission intensity is calculated as Scope 1 emission divided by total assets or divided by sales. We also separate the dummy *Disclosure* based on the presence of external ESG assurance, with $Disclosure^{Assured}$ representing voluntary climate disclosures with external assurance and $Disclosure^{NonAssured}$ representing those without such assurance. The dummy variable *InitialDisclosure* is one in the year a firm first makes voluntary climate disclosures, and is zero for years preceding the first disclosure and for other firms that never disclose during the sample period. The years following a firm's initial disclosure are excluded, resulting in fewer observations. $\widehat{GreenPat\_Stk}$ denotes the predicted capital stock of green innovation as per Equation 3. Financial variables include the *Book-to-Market Ratio*, the natural logarithm of total assets (*ln*(*Assets*)), the natural logarithm of R&D capital stock (*ln*(*R&D Stk*)), return on asset (*ROA*), and firm age. Other variables used in this study include *Adj_Avg_Leniency*, defined in Equation 7, which restricts our test sample to a subset of random art units. *GreenPat_Stk* represents the green patent stocks. *InstOwn* represents the institutional equity ownership, which is calculated as total equity shares held by institutional investors relative to the total share outstanding. *InstOwn* is further split into ownership by CDP signatory investors (*InstOwn_CDP*) and non-CDP signatory investors (*InstOwn_NonCDP*). We also use the natural logarithm of market capitalization (*ln*(*MarketCap*)), and Corporate Governance Index (*CGI*). *DualClass* indicates whether a firm adopts a dual-class share structure. The continuous financial variables are winsorized at the 1% level to control for extreme values.

	N	Mean	S.D.	P25	P50	P75
	(1)	(2)	(3)	(4)	(5)	(6)
Avg_Leniency	14,166	0.01	0.06	0.00	0.00	0.00
Adj_Avg_Leniency	8,740	0.01	0.06	0.00	0.00	0.00
Disclosure	14,166	0.13	0.34	0.00	0.00	0.00
$Disclosure^{GN}$ (Scope 1 Emission/Assets)	14,166	0.07	0.25	0.00	0.00	0.00
$Disclosure^{BN}$ (Scope 1 Emission/Assets)	14,166	0.04	0.20	0.00	0.00	0.00
$Disclosure^{GN}$ (Scope 1 Emission/Sales)	14,166	0.07	0.25	0.00	0.00	0.00
$Disclosure^{BN}$ (Scope 1 Emission/Sales)	14,166	0.05	0.21	0.00	0.00	0.00
$Disclosure^{Assured}$	14,166	0.04	0.19	0.00	0.00	0.00
$Disclosure^{NonAssured}$	14,166	0.09	0.29	0.00	0.00	0.00
InitialDisclosure	12,199	0.02	0.14	0.00	0.00	0.00
GreenPatGranted	14,166	3.40	20.56	0.00	0.00	1.00
GreenPat_Stk	14,166	12.04	72.59	0.00	0.52	3.03
InstOwn	12,739	0.64	0.30	0.47	0.72	0.87
InstOwn_CDP	12,739	0.21	0.13	0.10	0.22	0.31
InstOwn_NonCDP	12,739	0.43	0.21	0.31	0.46	0.57
ln(*MarketCap*)	14,166	7.65	2.23	6.07	7.69	9.31
ROA	14,166	0.09	0.14	0.06	0.12	0.17
CGI	1,097	9.10	2.65	7.00	9.00	11.00
DualClass	14,166	0.08	0.27	0.00	0.00	0.00
ln(*Assets*)	14,166	7.51	2.30	5.82	7.56	9.23
ln(*R&D Stk*)	14,166	4.78	2.82	3.16	5.16	6.71
Book-to-Market Ratio	14,166	0.90	0.80	0.41	0.68	1.12
FirmAge	14,166	26.94	18.58	12.00	21.00	41.00

Table 2: **Yearly Distribution of Voluntary Climate Disclosures and Green Patents**

This table tabulates by year the number of firms disclosing Scope 1 carbon emissions and the number of public firms that received granted decisions for green patents from 2002 to 2018.

Year	# of Compustat Firms	# of Disclosing Firms	# of Firms with Green Patents
2002	6,535	13	90
2003	6,189	17	204
2004	6,030	24	254
2005	5,794	73	278
2006	5,578	101	319
2007	5,364	115	326
2008	5,106	137	372
2009	4,921	244	456
2010	4,786	267	517
2011	4,657	289	543
2012	4,541	288	536
2013	4,531	241	559
2014	4,556	239	594
2015	4,449	285	609
2016	4,308	328	617
2017	4,202	364	579
2018	4,117	427	583

Table 3: **Patent Examiners' Leniency**

This table presents the regression results for 2SLS models using the average leniency of patent examiners (*Avg_Leniency*) as the instrumental variable. Columns (1)-(2) report the first-stage regression results where the outcome variable, denoted by *GreenPatGranted*, is the number of green patents granted to a firm in a given year. The second-stage regression results are reported in Columns (3) and (4), where the outcome variables are i) *Disclosure*, a dummy variable that is one if a firm has a voluntary climate disclosure in a year and zero otherwise, and ii) *InitialDisclosure*, a dummy variable that is one in the year a firm makes its first voluntary climate disclosure, and is zero for years preceding the first disclosure and for other firms that never disclose during the sample period. The years following a firm's initial disclosure are excluded, resulting in fewer observations. Control variables include the log of total assets (*ln*(*Assets*)), the log of R&D stock (*ln*(*R&D Stk*)), the *Book-to-Market* ratio, the log of firm age (*ln*(*FirmAge*)), and return on asset (*ROA*). Firm fixed effects and industry-year fixed effects are included for all specifications. Additionally, green patent application fixed effects are included in the first-stage regression. Industry classifications are based on 2-digit SIC industry codes. Robust standard errors are bootstrapped and clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Vars.	*GreenPatGranted*		*Disclosure*	*InitialDisclosure*
	(1)	(2)	(3)	(4)
Avg_Leniency	**2.699*****	**2.704*****		
	(9.38)	**(9.36)**		
$\boldsymbol{\widehat{GreenPat\_Stk}}$			**0.028*****	**0.011*****
			(4.77)	**(5.09)**
ln(*Assets*)	0.005	-0.003	0.014	0.009***
	(0.08)	(-0.05)	(1.50)	(2.93)
ln(*R&D Stk*)		0.014	0.036***	0.005
		(0.19)	(3.33)	(1.43)
Book-to-Market Ratio		-0.031	-0.006	-0.004*
		(-0.82)	(-1.06)	(-1.94)
ROA		0.293	0.022	0.007
		(1.64)	(0.84)	(0.80)
ln(*FirmAge*)		-0.082	-0.192***	-0.048***
		(-0.49)	(-6.19)	(-5.27)
Constant	2.280***	2.518***	0.154*	-0.036
	(4.86)	(3.31)	(1.84)	(-1.28)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
GreenPatApp FE	Yes	Yes	Yes	Yes
Observations	14,166	14,166	14,166	12,199
Adj. R^2	0.954	0.954	0.663	0.170
F Statistics	47.79	16.14		

Table 4: **Different Depreciation Rate Choices**

This table presents the second-stage regression results using various depreciation rates to account for patent value obsolescence. We compare the depreciation rates of 25%, 20%, 15% (our choice), 10%, and 5% in accumulating predicted green patents obtained in the first stage. Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, the return on assets, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. The standard errors are bootstrapped and clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Vars.	*Disclosure*				
	Depreciation Rates				
	25%	20%	15%	10%	5%
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{\widehat{GreenPat\_Stk}}$	**0.031*** **	**0.029*** **	**0.023*** **	**0.029*** **	**0.035*** **
	(4.72)	**(4.76)**	**(4.02)**	**(4.75)**	**(4.55)**
Control Vars.	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	14,166	14,166	14,166	14,166	14,166
Adj. R^2	0.663	0.663	0.662	0.663	0.663

Table 5: **Stock Market Reaction Around Voluntary Climate Disclosures**

This table presents regression analyses of cumulative abnormal returns (CAR) around the disclosure date, using two symmetric event windows: a twenty-one-day window from [-10,10] and an eleven-day window from [-5,5]. The abnormal returns are calculated based on the market model and the Fama-French 3-Factor model, respectively. *Disclosure* is a dummy variable that is equal to one if a firm provides voluntary climate disclosure in a year and zero otherwise. $\widehat{GreenPat\_Stk}$ is the predicted green patent stock, as defined in Equation 3. Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, the return on assets, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. All continuous control variables are winsorized at 1% level. The standard errors are bootstrapped and clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Market Model		Fama-French 3-factor Model	
Dependent Vars.	$CAR[-10, 10]$	$CAR[-5, 5]$	$CAR[-10, 10]$	$CAR[-5, 5]$
	(1)	(2)	(3)	(4)
$\boldsymbol{Disclosure \times \widehat{GreenPat\_Stk}}$	**0.003****	**0.002***	**0.002***	**0.002***
	(2.02)	**(1.71)**	**(1.72)**	**(1.80)**
$\widehat{GreenPat\_Stk}$	-0.002	0.001	-0.003	0.001
	(-0.42)	(0.42)	(-0.63)	(0.40)
Disclosure	-0.024	-0.021	-0.019	-0.022
	(-1.51)	(-1.43)	(-1.21)	(-1.55)
Control Vars.	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	9,241	9,241	9,241	9,241
Adj. R^2	0.0541	0.0438	0.0294	0.0290

Table 6: **Green Patents, Voluntary Climate Disclosures, and Institutional Ownership**

This table presents the regression analyses for institutional ownership, denoted as $InstOwn$, which is defined as the proportion of shares held by institutional investors relative to total shares outstanding. Institutional ownership is further split into ownership contributed by CDP signatory investors ($InstOwn\_CDP$) and non-CDP signatory investors ($InstOwn\_NonCDP$). The predicted green patent stock, $\widehat{GreenPat}\_Stk$, is defined as in Equation 3. *Disclosure* is one if a firm provides voluntary climate disclosure in a year and zero otherwise. Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, the return on assets, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. All continuous control variables are winsorized at 1% level. The standard errors are bootstrapped and clustered at the firm level. Significance levels are denoted by *, **, and *** for 10%, 5%, and 1%, respectively.

Dependent Vars.	$InstOwn$	$InstOwn\_CDP$	$InstOwn\_NonCDP$
	(1)	(2)	(3)
$\boldsymbol{Disclosure \times \widehat{GreenPat}\_Stk}$	**0.007****	**0.005*****	**0.001**
	(2.06)	**(3.34)**	**(0.52)**
$\widehat{GreenPat}\_Stk$	0.009	0.006**	0.002
	(1.40)	(2.20)	(0.50)
Disclosure	-0.020	-0.043**	0.022
	(-0.53)	(-2.19)	(0.81)
Control Vars.	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	12,739	12,739	12,739
Adj. R^2	0.678	0.670	0.603

Table 7: **Distinguishing the Credibility of Voluntary Climate Disclosures**

This table reports the regression results of voluntary climate disclosure decisions on green patents. Columns (1)-(4) sort the climate disclosure dummy ($Disclosure$) into a dummy for good news disclosure ($Discloure^{GN}$), which identifies disclosures with decreased Scope 1 emission intensity relative to the previous year, and a dummy for bad news disclosure ($Discloure^{BN}$), which marks the disclosures with increased Scope 1 emission intensity. The emission intensity is defined as reported Scope 1 emissions divided by total assets in Columns (1) and (2) and as reported Scope 1 emissions divided by sales in Columns (3) and (4). Columns (5) and (6) further distinguish climate disclosures based on the presence of external ESG assurance, with $Disclosure^{Assured}$ representing voluntary climate disclosures with external ESG assurance, and $Disclosure^{NonAssured}$ representing those without such assurance. Control variables are defined as before. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. All the continuous control variables are winsorized at 1% level. The standard errors are bootstrapped and clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Scope 1 Emission/Assets		Scope 1 Emission/Sales			
Dep. Vars.	$Disclosure^{GN}$	$Disclosure^{BN}$	$Disclosure^{GN}$	$Disclosure^{BN}$	$Disclosure^{Assured}$	$Disclosure^{NonAssured}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{\widehat{GreenPat\_Stk}}$	**0.020*** **	**0.013*** **	**0.018*** **	**0.016*** **	**0.011** **	**0.017*** **
	(4.93)	**(3.68)**	**(4.32)**	**(4.95)**	**(2.54)**	**(2.99)**
	Difference p-value: 0.001		Difference p-value: 0.007		Difference p-value: 0.188	
Control Vars.	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,166	14,166	14,166	14,166	14,166	14,166
Adj. R^2	0.385	0.233	0.364	0.242	0.507	0.490

Table 8: **Voluntary Climate Disclosures and Reputational Capital**

This table reports results for cross-sectional regressions by a firm's reputation capital. The dummy variable *Misconduct* is one if a firm is involved in financial misconduct cases before and zero otherwise. The dummy variable *LowSocialCap* is one if a firm's headquarters is located in a county with a social capital score lower than the median score across all US counties and zero otherwise. The predicted green patent stock, denoted by $\widehat{GreenPat}\_Stk$, is defined as in Equation 3. *Disclosure* is one if a firm provides voluntary climate disclosures in a year and zero otherwise. Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, the return on assets, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. All the continuous control variables are winsorized at 1% level. The standard errors are bootstrapped and clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Var.	*Disclosure*	
	(1)	(2)
$\boldsymbol{Misconduct \times \widehat{GreenPat}\_Stk}$	**0.011*****	
	(3.44)	
$\boldsymbol{LowSocialCap \times \widehat{GreenPat}\_Stk}$		**0.005****
		(2.00)
$\widehat{GreenPat}\_Stk$	0.026***	0.023***
	(4.39)	(3.19)
Misconduct	-0.132***	
	(-3.14)	
Control Vars.	Yes	Yes
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	14,141	11,862
Adj. R^2	0.667	0.661

Table 9: **Assessing the Validity of Exclusion Restriction**

This table tabulates the results for regressions relating the instrumental variable, *Avg_Leniency*, to the potential determinants for voluntary climate disclosures. These variables include the log of market capitalization ($ln(MarketCap)$, return on assets (ROA), Corporate Governance Index (CGI)), and Dual-class share structure ($DualClass$). Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, the return on assets, and the log of firm age. Column (4) excludes the return on assets (ROA) from the control variables. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. All the continuous control variables are defined as before and winsorized at 1%. The standard errors are clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Vars.	ln(MarketCap)		*ROA*		*CGI*		*DualClass*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg_Leniency	**0.130**	**0.028**	**-0.006**	**-0.009**	**0.276**	**0.172**	**0.057**	**0.056**
	(1.42)	**(0.55)**	**(-0.53)**	**(-0.88)**	**(0.74)**	**(0.50)**	**(1.26)**	**(1.25)**
Control Vars.	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,166	14,166	14,166	14,166	1,097	1,097	12,781	12,781
Adj. R^2	0.928	0.980	0.678	0.705	0.968	0.969	0.055	0.058

Table 10: **Modified Instrumental Variable**

We regenerate the instrumental variable by focusing on art units where applications are randomly assigned to examiners by the last digit of patent application number, according to Feng and Jaravel (2020). The adjusted average examiner leniency, *Adj_Avg_Leniency*, is defined as in Equation 7. Columns (1) and (2) report the results for the first-stage regression, where *GreenPatGranted* is the number of green patents granted to a firm in a year. The second-stage regression results are reported in Columns (3) and (4), where the outcome variables are i) *Disclosure*, a dummy variable that is one if a firm has a voluntary climate disclosure in a year and zero otherwise, and ii) *InitialDisclosure*, a dummy variable that is one in the year a firm makes its first voluntary climate disclosure, and is zero for years preceding the first disclosure and for other firms that never disclose during the sample period. $\widehat{GreenPat}\_Stk$ is the predicted green patent stock. Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, the return on assets, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Additionally, green patent application fixed effects are included in the first-stage regression. Industry classification is based on 2-digit SIC code. All continuous control variables are winsorized at 1% level. The standard errors are bootstrapped and clustered at the firm level. Significance levels are denoted by *, **, and *** for 10%, 5%, and 1%, respectively.

Dependent Vars.	*GreenPatGranted*		*Disclosure*	*InitialDisclosure*
	(1)	(2)	(3)	(4)
Adj_Avg_Leniency	**1.885******	**1.879******		
	(7.09)	**(7.04)**		
$\boldsymbol{\widehat{GreenPat}\_Stk}$			**0.046******	**0.023******
			(3.10)	**(3.84)**
Control Vars.	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
GreenPatApp FE	Yes	Yes	No	No
Observations	8,740	8,740	8,740	7,185
Adj. R^2	0.976	0.976	0.665	0.172
F Statistics	25.86	10.58		

Appendix

Table A.1: **Definitions of Variables**

Variable (ranked alphabetically)	**Definition**
Avg_Leniency	This variable measures the firm-level patent examiner leniency. To obtain this measure, we first calculate patent-level leniency. We then aggregate these values to the firm level by averaging patent-level leniency across green patent applications filed by a firm, as defined in Equation 1. (Source: USPTO Patent Examination Database)
Adj_Avg_Leniency	It represents an alternative measure of firm-level patent examiner leniency. We restrict patent examiners within a subset of random art units, where the assignment to examiners is likely determined by the last digit of the patent application number. Then we adjust our instrumental variable as defined by Equation 7. (Source: USPTO Patent Examination Database)
Book-to-Market Ratio	This variable represents the book-to-market ratio, calculated as the book value of equity divided by the market value of equity. (Source: Compustat).
CAR	This variable represents the cumulative abnormal returns in an eleven-day-event window (CAR[-5,5]) or a twenty-one-day-event window (CAR[-10,10]) or around 10-K filings date.The abnormal return is calculated using the market and Fama-French 3-factor Models, respectively. (Source: CRSP)
CGI	This variable stands for Corporate Governance Index developed by Gompers et al. (2003) reflecting governance quality. (Source: Gompers et al. (2003))
Disclosure	This is a dummy variable that takes the value of one if a firm discloses Scope 1 carbon emission in a given year, and zero otherwise. (Source: Refinitiv DataStream).
$Disclosure^{GN}$	A dummy variable indicating good news climate disclosures. It is equal to one if a firm makes voluntary climate disclosure with reduced Scope 1 carbon emission intensity relative to the previous year and zero for the remaining firms. The emission intensity is calculated as Scope 1 emission divided by total assets or sales. (Source: Refinitiv DataStream)

Continued on next page

Table A.1 – continued from previous page

Variable	Definition
$Disclosure^{BN}$	A dummy variable indicating bad news climate disclosures. It is equal to one if a firm makes voluntary climate disclosure with reduced Scope 1 carbon emission intensity relative to the previous year and zero for the remaining firms. The emission intensity is calculated as Scope 1 emission divided by total assets or sales. (Source: Refinitiv DataStream)
$Disclosure^{Assured}$	A dummy variable indicating externally assured climate disclosures. It is equal to one for firms making voluntary climate disclosures with external assurance in a year and zero for the remaining firms. (Source: Refinitiv DataStream)
$Disclosure^{NonAssured}$	A dummy variable indicating non-assured climate disclosures. It is equal to one for firms making voluntary climate disclosures without external assurance in a year and zero for the remaining firms. (Source: Refinitiv DataStream)
$DualClass$	This is a dummy variable that takes the value of one if a firm adopts a dual-class share structure at the time of its IPO, and zero otherwise. In a dual-class share structure, a company issues multiple classes of shares, typically with differing voting rights. (Source: Dual-class share structure at the time of its IPO before 2002: Gompers, Ishii, and Metrick (2010); IPO after 2002: Ritter (2024)).
$GreenPatGranted$	This variable stands for the total number of green patents granted to a firm in a year. (Source: Kogan et al. (2017) updated to 2022 and World Intellectual Property Organization (WIPO) IPC Green Inventory).
$GreenPat\_Stk$	This variable represents the accumulated green patents. We initialize the green patent stock at zero in the first year the firm appears in Compustat or in 2001, whichever comes last. We adopt the conventional practice of using a 15% annual depreciation rate. (Source: Kogan et al. (2017) updated to 2022 and World Intellectual Property Organization (WIPO) IPC Green Inventory)

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Table A.1 – continued from previous page

Variable	Definition
HighIntensity	This dummy variable identifies firms in high emission-intensity sectors, taking a value of one for sectors classified by Ilhan et al. (2021) with specific 2-digit SIC codes (13, 26, 29, 32, 33, 40, 44, 45, 49, 75), and zero otherwise. (Source: Ilhan et al. (2021))
InitialDisclosure	This is a dummy variable that takes the value of one in the year a firm first discloses its Scope 1 carbon emissions, zero for preceding years, and remains zero for firms that never disclose throughout the sample period. The years following the initial disclosure are excluded from the regression analysis, resulting in a smaller number of observations. (Source: Refinitiv DataStream).
InstOwn	Institutional Equity Ownership. This variable measures the proportion of a company's available stock owned by institutions in a given year. (Source: Backus, Conlon, and Sinkinson (2021))
InstOwn_CDP	This variable measures the proportion of institutional ownership participating in the CDP (Carbon Disclosure Project). (Source: Backus et al. (2021) and CDP)
InstOwn_NonCDP	This variable measures the proportion of institutional ownership *not* participating in the CDP. (Source: Backus et al. (2021) and CDP)
ln(*Assets*)	This variable is the natural logarithm of a firm's total assets. (Source: Compustat).
ln(*FirmAge*)	It denotes the natural logarithm of firm age, which is the difference between the current year and the IPO year. (Source: Compustat).
ln(*R&D Stk*)	This variable is the natural logarithm of one plus R&D Stock. R& D expenditure is measured using the variable 'XRD' in Compustat. Then, we constructed R&D stock by using a perpetual inventory method with a depreciation rate of 15% per year. (Source: Compustat).
ln(*MarketCap*)	It is the natural logarithm of market capitalization. (Source: Compustat).

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Table A.1 – continued from previous page

Variable	Definition
LowSocialCap	This variable is set to one if a firm's headquarters is located in a county with a social capital score lower than the median score across all US counties, and zero otherwise. We sourced social capital scores from Rupasingha et al. (2006, with updates), which provides county-level social capital scores for the years 1990, 1997, 2005, 2009, and 2014. We averaged the social capital scores for each county and determined the median score across all US counties. (Source: Rupasingha et al. (2006, with updates))
Misconduct	This time-variant dummy reflects a firm's entanglement in a financial misconduct lawsuit, switching from zero to one in the initial year of the lawsuit and remaining at one thereafter. The determination of a firm's involvement in a lawsuit is based on the "Class Period Start" date, marking when the alleged financial misconduct began. (Source: Securities Class Action Clearinghouse)
ROA	This variable is calculated as by dividing the earnings before interest, taxes, depreciation, and amortization (OPITDA) scaled by total assets. (Source: Compustat).

Table A.2: **Cross-Sectional Analysis by Carbon Intensity**

This table provides a cross-sectional analysis that differentiates firms in high emission intensity sectors from those in low emission intensity sectors. The *HighIntensity* variable is a dummy equal to one if a firm belongs to a high emission intensity sector, as classified by Ilhan et al. (2021) with specified 2-digit SIC codes (13, 26, 29, 32, 33, 40, 44, 45, 49, 75). Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. All the variables are winsorized at 1%. The standard errors are bootstrapped and clustered at the firm level. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Var.	*Disclosure*
$\boldsymbol{HighIntensity \times \widehat{GreenPat\_Stk}}$	**0.025**
	(1.32)
$\boldsymbol{\widehat{GreenPat\_Stk}}$	0.026***
	(4.45)
ln(Assets)	0.014
	(1.48)
ln(R&D Stk)	0.036***
	(3.38)
Book-to-Market Ratio	-0.006
	(-1.06)
ROA	0.023
	(0.85)
ln(FirmAge)	-0.192***
	(-6.23)
Constant	0.145*
	(1.74)
Firm FE	Yes
Industry-Year FE	Yes
Observations	14,166
Adj. R^2	0.663

Table A.3: **OLS Regression Results**

This table presents the OLS regression results analyzing the impact of voluntary climate disclosure decisions on green patent stock. The green patent stock, denoted as $GreenPat\_Stk$, represents the cumulative total of green patents granted to a firm each year, calculated using $GreenPat\_Stk_{i,t} = GreenPatGranted_{i,t} + (1 - 0.15) \times GreenPat\_Stk_{i,t-1}$. The dependent variable, *Disclosure*, is a dummy variable set to one if a firm makes voluntary climate disclosures in a given year, and zero otherwise. Control variables include the log of total assets, the log of R&D stock, the book-to-market ratio, and the log of firm age. Firm fixed effects and industry-year fixed effects are controlled in all specifications. Industry classification is based on 2-digit SIC code. Continuous control variables are winsorized at 1%. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent Vars.	*Disclosure*	
	(1)	(2)
GreenPat_Stk	**0.0002***	
	(1.69)	
ln(GreenPat_Stk)		**0.019****
		(2.46)
ln(Assets)	0.015*	-0.001
	(1.73)	(-0.09)
ln(R&D Stk)	0.036***	0.054***
	(3.55)	(2.62)
Book-to-Market Ratio	-0.006	0.000
	(-1.06)	(0.01)
ROA	0.017	0.092**
	(0.64)	(2.11)
ln(FirmAge)	-0.123***	-0.149***
	(-5.07)	(-3.01)
Constant	0.216**	0.331*
	(2.47)	(1.93)
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	14,166	7,662
Adj. R^2	0.662	0.735