The Green Innovation Premium*

Markus Leippold† Tingyu Yu‡

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Abstract

This paper introduces a novel firm-level green innovation measure utilizing ClimateBERT and GPT-3 models to analyze green patent abstracts and earnings call transcripts. Firms with higher green innovation measures experienced lower expected returns: a long-short portfolio generates an average annual return of 6%, which remains significant after accounting for common risk factors. However, these firms began to outperform in the last two years, attributed to a sharp increase in attention towards green innovation. Green innovators experience a notable value increase in response to the enforcement of more stringent environmental regulations. They also exhibit reduced carbon emissions and fewer climate incidents.

JEL Codes: G12, G14, O34, Q55

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†Department of Banking and Finance, University of Zurich, and Swiss Finance Institute (SFI). markus.leippold@bf.uzh.ch

‡Department of Banking and Finance, University of Zurich. tingyu.yu@bf.uzh.ch

1 Introduction

As the global community strives for net-zero emission targets, green technology emerges as an essential tool for both mitigating climate change and adapting to its adverse consequences. Catalyzed by the Inflation Reduction Act (IRA) under President Biden's administration, an era of incentives encouraging businesses and investors to engage with climate technologies across various sectors has begun. Such technologies offer firms the capacity to diminish their carbon emissions through renewable resources and energy efficiency, lessening their susceptibility to transition risk. Additionally, adaptation technologies, such as seawalls and drought-resistant crops, equip firms with resilience against the physical impacts of climate change. However, despite the indispensable role of green innovation, our understanding of its pricing effects on stock markets, which is a crucial guide for shaping policy incentives and regulations to stimulate clean technology, remains inadequately explored.[1] This paper aims to bridge this gap by examining the empirical relationship between green innovation and cross-sectional stock returns.

One challenge in this investigation is the absence of a comprehensive and real-time measure of firms' green innovation activities. Green patents owned by firms are often utilized in current literature. Although it provides a tangible assessment of a company's inventive endeavors, this measure carries inherent limitations. It fails to account for non-patentable innovative strategies that can notably enhance the environmental footprint. This omission is especially relevant in green innovation, where the entities inventing and adopting a technology often diverge, with the latter usually being major carbon emitters who bear a larger responsibility to reduce emissions by applying existing technologies in new contexts and at a large scale. Such a process necessitates creative thinking and innovative sourcing – elements that are integral to green innovation but typically unrepresented in green patent records. Additionally, the diverse carbon mitigation effects of various green technologies often go unrecognized in green patent proxies, which tend to treat these technologies uniformly. The lengthy patent application process further causes this measure to reflect outdated green innovation practices of firms. Taken together, green patents do not wholly capture a firm's active, strategic, and commercially relevant green innovation activities.

[1] Existing research suggests that green stocks have lower expected returns relative to their brown counterparts. These works primarily focus on metrics related to firms' brown activities, such as carbon emissions and industrial pollution. Bolton and Kacperczyk (2021) indicates that U.S. stocks with higher carbon emissions generate higher returns, a pattern also identified globally by Bolton and Kacperczyk (2022), which is more pronounced in countries with larger energy sectors and stricter domestic climate policies. Hsu et al. (2022) reveals that a long-short portfolio based on firms' toxic emission intensity generates a positive return spread and attributes it to risk related to environmental policy uncertainty.

In this paper, we introduce a new text-based green innovation measure at the firm level that alleviates restrictions on patent data. This measure is quantified as the percentage of sentences within earnings conference calls that pertain to green innovation. Earnings calls, wherein corporate managers report on company performance and future plans, furnish valuable insights into a firm's focus on green innovation and dedication to sustainable practices, irrespective of whether these activities result in patentable outputs. Given the time constraints, earnings calls tend to concentrate on the most critical actions, downplaying strategies that do not directly or not substantially address climate change issues. This selective focus thus paints a more accurate picture of firms' green innovation activities. Furthermore, the regular quarterly occurrence of earnings calls ensures timely updates on a company's strategic direction, facilitating the identification of emerging trends or changes in corporate priorities and investor interests.

While strongly correlating with green patents, our measure substantially expands the identification of firms involved in green innovation, capturing twice as many observations as those recognized by green patents alone. This underscores that many firms combat climate change through innovative adoption, rather than invention, of green techniques via supply chains and technology spillover. Firms that participate in green innovation discussions show an effective reduction in carbon emissions and negative climate incident involvement in subsequent years, even without holding green patents. Conversely, firms owning green patents but not discussing them in their earnings calls show no notable improvements in their environmental footprint. Without pertinent discussions, the presence of green patents might not considerably influence firms' operational processes. Overall, our measure, rooted in soft information from earnings calls, not only provides more comprehensive coverage of firms' green innovation activities but also more accurately reflects the diverse impact of these activities on climate mitigation.

In addition, the time-series variation of our measure reveals a sharp rise over the recent two years, indicative of an intensified focus on green innovation from firms and investors. This trend, which significantly reverses the financial performance of green innovative firms – a topic we will delve into further - goes undetected by green patent measures, exemplifying the advantages of our measure in tracking real-time shifts in investor attention.

Utilizing our new measure, we scrutinize how financial markets integrate green technology and observe a negative premium, implying that firms emphasizing green innovation have lower expected returns. Specifically, we construct quintile portfolios sorted on green innovation measures relative to their industry peers and compute each portfolio's post-formation average stock returns in the subsequent year. A value-weighted High-minus-Low portfolio that takes a long (short) position in the portfolio with the highest (lowest) greenness generates a statistically significant and negative return of 6% per annum. Similar results exist for equal-weighted portfolios. The time-series regressions of portfolios' excess returns on known factors indicate that risk-adjusted returns remain significant, suggesting that common risk factors cannot account for the cross-sectional return spread across portfolios sorted on green innovation measures.

Being substantial carbon emitters with an imperative to reduce emissions, industries like Chemicals, Metal Mining, and Coal are actively involved in green innovation activities. This makes it crucial to assess whether our return pattern is linked to carbon emissions. Accordingly, we incorporate carbon emissions as a control variable and consistently observe a strong negative coefficient on the green innovation measure: our negative return premium cannot be simply ascribed to carbon emission risk. Furthermore, by conducting independent double portfolio sorting and Fama-MacBeth cross-sectional regressions on various firm characteristics, we reconfirm the robustness of the negative premium across a majority of subsamples and alleviate potential concerns that our measures may inadvertently capture other effects.

The negative premium is primarily evident in the years up to 2019, after which green firms begin to exceed their less innovative counterparts in performance. Echoing the insights from Pastor et al. (2022), we posit that this recent outperformance by green innovators does not signify a change in expected returns. Instead, this reversal is closely tied to the marked escalation in attention to green innovation. This significantly alters investors' preferences, fueling demand for green innovating stocks and inflating their prices, especially among institutional investors. When this unexpected spike in attention is factored in, the signs of adjusted returns in the recent two years switch from positive to negative, unmasking a persistently negative pattern throughout our sample. Contrary to Pastor et al. (2022) that uses ESG scores to assess firms' management of broader climate issues like land use - resulting in positive green returns mainly driven by brown firms' underperformance and significantly weakened within industries - our focus on green innovation detects a return effect primarily originates from green firms when compared to their brown counterparts within the same industry.

The lower expected returns of green innovators stem from a better capability to hedge against climate risks. The preparedness to navigate stringent climate regulations and seize new market opportunities positions them at an advantage. On the contrary, firms less committed to green practices may face more significant negative impacts from such regulations, potentially leading to stranded assets or obsolete products. We explore stock price reactions to four key events that served as shocks to climate action in the U.S. Green firms experienced a stock price drop relative to their less environmentally focused peers following the election of Donald Trump, which was perceived as positive for carbon-intensive firms due to expected relaxed environmental regulations. Conversely, these firms performed notably better following events that underscored climate actions, including Biden's election win, the Russia-Ukraine war disruption, and the IRA announcement. Overall, the negative green innovation premium is linked to investors' concerns about potential climate policy shifts.

Our asset pricing implications of green innovation persist even within the subgroup that does not possess green patents. Thus, green innovation activities beyond patents are also priced in stock markets and seen as a buffer against tighter climate regulations. In contrast, in firms absent green innovation discussions, green patents yield insignificant coefficients in both Fama-MacBeth regressions and event studies. This implies that if green patents do not provoke related discussions during earnings calls, they might not be viewed as innovative enough within the green context to serve as a hedge against transition risks.

The construction of our textual measures capitalizes on state-of-art natural language processing techniques to identify sentences centered on green innovation in earning calls. Specifically, we fine-tune ClimateBERT, a deep-neural language model pre-trained on climate-related texts, to pinpoint pertinent sentences and categorize the particular topic being discussed.[2] We leverage information extracted from green patent abstracts that concisely describe green technologies to create training sentences required for ClimateBERT to perform classification tasks. However, the technical language of patent abstracts often differs from earnings calls' communication style. To overcome this disparity, we ask GPT-3, a cutting-edge large language model known for its ability to generate human-like text, to distill each green patent abstract into a single sentence that investors and other market participants can easily understand. As a result, these generated sentences not only contain green technology information but also emulate the language used in earnings calls, thereby enhancing ClimateBERT's ability to detect green innovation-related sentences.

Moreover, our ClimateBERT model can classify green innovation-related sentences into distinct topics, shedding light on the types of green innovation most attractive to investors. This is possible as each GPT-generated sentence can be assigned to one of the six categories based on the corresponding patent's CPC/IPC classification code. The findings reveal that pricing effects primarily originate from energy-based technologies such as clean energy and electric power techniques, which most effectively decrease firms' carbon footprints. While innovations in buildings significantly cut carbon emissions and climate incidents, they are

[2]All the fine-tuned models and the green innovation measures will be made available and open-sourced upon publication.

not priced into the stock markets, signaling a need for increased investor attention in this area.

Literature review: Our paper builds upon existing literature on the pricing effects for green versus brown firms in the equity market. Pastor et al. (2022) demonstrate that high-ESG firms, despite having lower implied capital costs, have strongly outperformed brown stocks.[3] Yang (2021) document a negative risk premium for stocks with high environmental scores and find that green stocks appreciate after climate-related disasters. Our paper distinguishes itself from current works by examining the return effect of green innovation discussions in earnings calls - a direct measure of firms' dedication to developing green technology and combating climate change.[4]

Several studies explore the relationship between firms' climate actions and financial performance.[5] Hege et al. (2023) use the patent examiners' leniency to instrument firms' newly issued green patents and show that firms with more lucky climate-related patents display higher positive cumulative abnormal stock returns. Andriosopoulos et al. (2022) analyze the impact of firms' green patent numbers on three-day abnormal returns after the patent announcement date. Their findings indicate that stock markets do not react to the announcements of green patents but respond positively to non-green patents. Compared to their works, we show that green innovation actions, including those that are not patentable, are priced into the stock markets and exhibit lower expected returns.

Our analysis contributes to works exploring market reactions to shocks that may change investors' perceptions of climate regulations.[6] Ramelli et al. (2021) present that the 2016 U.S. election boosted both carbon-intensive and climate-responsible firms. They explain the

[3]Ardia et al. (2022) confirm their results and show that the stock prices of green firms increase, while those of brown firms decrease, on days with an unexpected rise in the news-based climate index.

[4]Gibson et al. (2021) and Berg et al. (2023) argue that ESG measures are noisy and divergent across different data vendors, making it less reliable to examine their relation with stock returns.

[5]Kruse et al. (2020a) argue that an increase in revenue share generated through green goods and services boosts operational profit margins. Still, this positive effect does not translate into a higher return on investments and firm values, except in the utility sectors. Dechezlepretre et al. (2017) illustrate that clean technologies result in larger knowledge spillovers and carry greater monetary value than their dirty counterparts. Hao et al. (2022) find a positive relation between green innovation and enterprise value in China's A-share market. Kuang and Liang (2022) and Reza and Wu (2023) discover that climate innovations generate significant economic value.

[6]Kruse et al. (2020b) show that firms with higher green revenue shares or more clean patents significantly outperformed in the week following the Paris Agreement. They only observe a marginal negative reaction for carbon-intensive firms in the oil and gas extraction sectors. Similarly, Monasterolo and de Angelis (2020) find the overall systematic risk for the low-carbon stock indices decreased consistently after the Paris Agreement, while markets' reactions were mild for most carbon-intensive indices. Sen and von Schickfus (2020) exploit the gradual development of a German climate policy proposal aimed at reducing electricity production from coal and observe a negative effect on the valuation of energy utilities.

return effects for carbon-responsible firms as investors' considerations of a strong reversal in the distant future, confirmed by their soaring value after the 2020 U.S. election. Deng et al. (2022) explore the international divergence in the pace of energy transition and show that stocks in the U.S. with higher regulatory risk exposures performed better during the Russia-Ukraine war disruption, suggesting that investors expect an overall slowdown in this transition. Our paper studies the same events and shows that firms with stronger green innovation commitments outperform (underperform) in the period with potentially stringent (loosened) climate regulations.

We also add to the literature examining the effect of green technology on firms' future environmental performance. Cohen et al. (2021) document that traditional energy firms utilize their green patents to produce more kilowatts of alternative energy and invest more in low-carbon products.[7] Using a different definition of green patents, Bolton et al. (2023) show firms with green innovations do not significantly decrease their future direct emissions.[8] We enhance this discussion by uncovering a carbon reduction effect for firms that emphasize green innovation in earnings calls. The different results highlight the necessity of considering a wider scope of green innovation activities beyond patents to better comprehend the role of green technology in addressing climate change.

Our research is part of a burgeoning field of literature focusing on constructing firm-level climate exposure measures using textual analysis. Sautner et al. (2023) adapt a keyword-based method to capture firms' exposures to opportunity, physical, and regulatory shocks associated with climate change. Li et al. (2020) manually construct dictionaries measuring physical and transition climate risks. Bingler et al. (2023) apply a deep learning approach to analyze annual reports and use the ratio of specific to non-specific commitments as an indicator of cheap talk in corporate climate disclosures. Hu et al. (2022) employ an unsupervised learning approach to identify diverse strategies firms adopt that align well with the greenhouse gas emission mitigation hierarchy. Distinguishing our work, we harness information from green patent abstracts and extract firms' discussions on green innovations during their earnings calls.

The rest of this paper is organized as follows. Section 2 introduces our data sources and explains the construction of firm-level green innovation measures. In section 3, we outline the stock return patterns for firms with varying shares of green innovation discussions. Section

[7]They discover that oil, gas, and energy firms are key green innovators in the U.S. and produce significantly higher quality green patents with more citations, despite often having lower ESG scores and being excluded from ESG funds' investment universe.

[8]They report that firms with higher carbon emissions have more brown efficiency-improving patents and fewer green patents.

4 delves into the contrasting return effects after 2020 and examines their relation to the unexpected increase in green innovation attention. Section 5 conducts event studies on four shocks related to climate risks. Section 6 compares our textual measures with green patent proxies in terms of information breadth and empirical implications. We conclude our paper in Section 7.

2 Firm-level green innovation measure

In this section, we delve into the specifics of how we build our green innovation measures and the data employed in the process. We validate our text-derived measures using green patent proxies and also elucidate the distinguishing characteristics between the two.

2.1 Data sources

Our NLP methodology principally relies on two textual data sources. The first dataset consists of patent abstracts obtained from the United States Patent and Trademark Office (USPTO), including publication numbers, grant dates, and CPC/IPC codes for each patent.[9] Patents provide patentees with exclusive rights to their inventions for a limited period, serving as a tangible, quantifiable representation of a firm's innovation efforts. The abstracts concisely describe the unique aspects and intended applications of the patented technology, enabling us to effectively capture a firm's green technological advancements. By employing the CPC/IPC codes assigned during the application process, we systematically identify green patents and sort them into six categories, as delineated in Table IA1.[10]

Specifically, patents under the *Energy* category encompass technologies related to renewable energy generation, hydrogen technology, and fossil fuel efficiency enhancement. Patents

[9] https://patentsview.org/download/data-download-tables

[10] Our categorization predominantly adopts strategies proposed by the OECD and Lanzi et al. (2011). While Bolton et al. (2023) classify green patents into *non-fossil*-green and brown efficiency-improving categories, we opted for the traditional OECD strategy due to the current importance of both patent types. Despite the potential rebound effects of brown efficiency-improving patents and their less favorable status compared to *non-fossil*-green patents, they retain crucial importance, particularly during early transition stages, as they can contribute to immediate emissions reductions. Given our existing global infrastructure's reliance on fossil fuels, brown efficiency improvements are paramount in mitigating continuous environmental damage as we navigate toward a transition. Rather than concentrating on *non-fossil*-green and brown efficiency-improving categories, we adopt the approach that underscores the areas or industries where these patents can be applied, providing more direct information on the functions of related patents. However, we believe that examining the return effects of patents under Bolton et al. (2023)'s categorization could also provide valuable insights, potentially helping to identify whether investors apply different capital costs to firms with these distinct climate technologies. We propose to explore this aspect in future work.

classified under *Production* pertain to industries like metal production, chemical, oil refining, and mineral processing. The *Transportation* category involves technologies related to road, rail, air, and waterway transport, such as hybrid and electric vehicles. *Buildings* patents aim to improve the energy efficiency and thermal performance of buildings through advancements in lighting, heating, and ventilation. *Adaptation* patents focus on areas like coastal zone management, human health protection, water conservation, and agricultural or forestry improvements. Lastly, *Environment* patents concentrate on pollution abatement, waste management, and carbon capture technologies.

Our green innovation measures are derived from earnings call transcripts obtained from Refinitiv Company Events Coverage (formerly Thomson Reuters StreetEvents). These calls, wherein corporate managers report on company performance and respond to participant inquiries, offer valuable insights into a firm's focus on green innovation and commitment to sustainable practices. Furthermore, interactions with analysts and investors illuminate market perceptions of a firm's green technologies and their potential influence on financial performance.

In addition, we investigate the return patterns based on monthly returns from the Center for Research in Security Prices (CRSP) for firms traded on NYSE, AMEX, and NASDAQ. Firm-level accounting data is obtained from the Compustat North America Fundamentals Annually database via Wharton Research Data Services (WRDS).

2.2 ClimateBERT and GPT-3: quantifying green innovation

We employ the ClimateBERT and GPT-3 (Generative Pretrained Transformer 3) models to quantify firm-level green innovation measures, bridging the information gap from green patent abstracts to earnings call transcripts. Figure 1 depicts the methodology used to construct our text-based measures. The procedure consists of three sequential classification tasks: first, identifying sentences pertaining to climate transition topics; second, isolating sentences from the first task that signify firm green innovation activities; and third, classifying these sentences into one of six categories derived from green patent classifications.

We utilize ClimateBERT, an adaptation of the BERT (Bidirectional Encoder Representations from Transformers) model, to execute the three classification tasks. Pre-trained on an extensive corpus of general and climate-related data, ClimateBERT is optimized for environmental and climate change topics. It has produced cutting-edge results in various climate-related downstream tasks, including text classification, sentiment analysis, and fact-checking (Webersinke et al., 2021). The use of ClimateBERT for sentence classification helps to minimize false positives and negatives, thereby providing an improvement over dictionary-based methods frequently employed in finance literature. With labeled training sentences, we can fine-tune ClimateBERT for any specific downstream tasks of interest.

We leverage information from green patent abstracts to create training sentences related to green innovation detection in earnings calls. Considering the different styles of patent abstracts (technical) and earning calls (conversational), we utilize the GPT-3 model to condense each green patent abstract into a single sentence readily understandable by investors and the general public. This process increases the likelihood of these discussions being addressed during earnings conference calls. GPT-3 is a state-of-art large language model and uses machine learning to produce text that closely mirrors human writing. The 30,000 sentences it summarized in our sample from green patent abstracts provide clear explanations of green technologies and can be labeled into one of six categories in line with the associated patent's CPC/IPC codes. This enhances ClimateBERT's ability to differentiate between various green innovation discussions. We detail the technical aspects of our green innovation classifiers further in Internet Appendix IA.2.

A firm's green innovation measure, or *Greenness*, is determined by the fraction of sentences related to green innovation to the total sentences within each earnings call transcript:

$$Greenness_{i,t} = \frac{N_{i,t}^{GreenInnov}}{N_{i,t}}.$$

Here, $N_{i,t}^{GreenInnov}$ represents the number of sentences related to green innovation, and $N_{i,t}$ signifies the total number of sentences in the transcript of firm i at time t.

Our total sample comprises 297,691 quarterly earnings calls. Out of these, 33,264 calls feature discussions on green innovation and contain roughly two sentences specifically focusing on green innovation out of a total of 382 sentences on average. We average the quarterly measures within the same year, obtaining 51,818 firm-year observations from 2006 to 2021. Table 1 presents summary statistics for the textual measures constructed in this study. The mean value for *Greenness* stands at 0.068%. Correlation matrix analysis reveals that discussions related to *Energy* (0.77), *Transportation* (0.65), and *Environment* (0.53) exhibit a strong correlation with the overall green innovation measure.

2.3 Time-series and industry distribution

Figure 2 traces the time-series variation in quarterly green innovation measures. From 2006 to 2011, there was a discernible upward trend, with the mean value rising from 0.06% to

0.08%. Attention subsequently decreases until 2018. In the following years, a notable surge to 0.12% occurred, likely driven by heightened climate awareness due to natural disasters and the 2020 election of President Joe Biden. Figure IA1 displays the temporal evolution of distinct green innovation discussions. Among the six categories, *Energy* dominates the conversation, while the recent increase in attention is mostly due to *Energy*, *Transportation*, and *Environment* related innovation.

Table IA2 averages green innovation measures across firms within the same industry based on the Fama-French 49 industry classifications. Panel A ranks industries by aggregate discussions, with the top five values for each category highlighted in bold.[11] Firms in the Electrical Equipment industry exhibit the highest engagement in green innovation discussions (0.73%) across most categories, followed by Automobiles (0.34%), which predominantly emphasize *Transportation* innovations. Moreover, carbon-intensive industries like Chemicals, Metal Mining, and Coal are actively involved in developing climate technology. Panel B enumerates industries with the lowest green innovation measures, such as Communication, Apparel, Entertainment, and Banking.

In Table IA3, we collect the top twenty firms sorted on the mean value of *Greenness*. These firms are primarily associated with the Electrical Equipment, Automobiles, and Chemical industries.

2.4 Validation with green patents

In the following subsection, we aim to validate our measures using green patent proxies, which serve as tangible indicators of a firm's dedication to climate technologies. A robust correlation between these two measurements can alleviate concerns that our textual measures are subject to biases in management's communication or the potential of greenwashing, whereby firms overstate their green initiatives without substantial actions backing their claims.

Firstly, we compare green patent abstracts with the detected sentences from earnings calls discussing the same topics in Panel A of Table 2. The substantial semantic relatedness between the two suggests that the level of greenness is a reliable indicator of a firm's commitment to green innovation.

[11]Certain types, such as *Production*, *Adaptation*, and *Environment*, feature fewer than five bold numbers because some of their top-5 industries are not included in the top-15 industries for the overall green innovation discussion.

We then construct several proxies based on patent data, as outlined below:

$$Green^{s}_{i,t} = \frac{Num^{green\ patents}_{i,t}}{Num^{patents}_{i,t}},$$

$$Green^{s,value}_{i,t} = \frac{\sum_j value_{i,j,t} \cdot 1^{green}_{j}}{\sum_j value_{i,j,t}},$$

where 1^{green}_{j} is a dummy variable that equals one if patent j is classified as a green patent. The value-weighted shares consider KPSS-economic value from Kogan et al. (2017), which is based on stock market reactions to patent grants, and scientific value measured by forward citations, denoting the frequency of citations in subsequent works.[12] The numerator constitutes the summation of values associated with green patents, while the denominator aggregates the values of all patents awarded to firm i in the year t.

Table 3 carries out a regression of our green innovation measures on equal/value-weighted green patent shares. Panel A features the overall green innovation textual measure as the dependent variable. Six different green patent proxies are introduced as independent variables, with each column representing one. $Green^n/Green^s$ is the number/share of green patents for firm i in year t. Columns (3)-(4) consider the number/share of green patents weighted by economic value, while the final two columns focus on numbers/shares based on forward citations. All patent measures demonstrate positive and significant coefficients, indicating that firms with a larger number of green patents are more likely to engage in discussions around green innovation during their earnings calls. Panel B extends the regression to different types of green innovation discussions against the corresponding types of green patent numbers. The consistently positive and significant coefficients across all categories demonstrate that textual measures accurately capture information in the respective innovation domains.

Despite the strong correlations, our textual measures exhibit several differences from patent proxies. First, the two show different variations across both time and industries. Figure IA2 displays the time-series variation for different types of green patent shares. A consistent increase can be observed from 2010 to 2018. However, unlike the trend in the green innovation textual measure, there hasn't been a significant uptick in green patent shares in recent years. Additionally, while *Production* and *Adaptation* patents constitute a significant portion and exhibit a rising trend, they are discussed less frequently by managers and investors. Table IA11 unveils that Utility firms, despite being fourth in green innovation

[12]Data is obtained from https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data spanning the period from 2006 to 2020. We appreciate the authors making their data publicly available.

discussions, hold the highest percentage of green patents (38.77%). The top firms based on the two measures also differ. Table IA12 lists the top firms according to the average value of yearly green patent numbers. Transportation firms, including Toyota Motor Corp, United Technologies Corp, and Ford Motor Company, take the top three spots, in contrast to Electrical Equipment firms exhibiting the highest green innovation discussions.

We will further elaborate on comparing our measures with green patent shares in Section 6, where we discuss the different sample coverage and empirical implications derived from observations with the two measures in greater detail.

3 The negative green innovation premium

In this section, we investigate the empirical relationship between green innovations and cross-sectional stock returns. Firstly, we employ univariate portfolio sorting to analyze the return spread of firms with varying greenness levels and then conduct asset pricing factor tests on the High-minus-Low (HML) portfolios. Subsequently, we utilize independent double sorting to scrutinize whether other effects influence the return pattern. Lastly, we execute Fama-MacBeth regressions to control for additional firm characteristics that predict returns in the cross-section.

3.1 Univariate portfolio sorting

We construct quintile portfolios based on greenness and compute each portfolio's average post-formation stock returns. At the end of each year $t-1$, five portfolios are created, with the low (high) portfolios containing firms with the bottom (top) proportion of green innovation discussion. We match greenness with returns from July of year t to June of year $t+1$, holding the portfolio for 12 months. Each month, we form a High-minus-Low portfolio that takes a long position in the high-greenness portfolio and a short position in the low-greenness portfolio. Our sample spans from July 2007 to December 2019.[13]

Panel A of Table 4 reports the value-weighted and equal-weighted monthly excess returns on the portfolios in percentage. The returns decrease from 1.03% to 0.57% across portfolios from low to high greenness, leading to a return spread of -0.46% with a t-statistics of 2.88 for

[13] We exclude stock returns after 2019 in this part for two reasons. First, to reduce the impact of COVID-19 on the stock markets, especially in early 2020. Second, due to the significant increase in climate attention in 2020. Many investors anticipated Democrats controlling Congress in the US election and expected stringent climate policies. Green stocks outperform brown stocks when climate concerns strengthen (Pastor et al., 2022). In the next section, we will discuss the return pattern after 2019 in more detail.

value-weighted portfolios. The return spread is further amplified for equal-weighted portfolios, reaching -0.77% with a t-statistics of 5.51, which is both economically and statistically significant. Thus, the firm-level green innovation measure can significantly predict future returns.

Next, we implement asset pricing factor tests and perform time-series regressions of portfolios' excess returns on the Fama-French three factors (market factor MKT, size factor SMB, value factor HML) plus Carhart momentum factor (MOM) in Panel B, the Fama-French five (FF5) factors (MKT, SMB, HML, profitability factor RMW, and the investment factor CMA) in Panel C, and the Hou-Xue-Zhang q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE) in Panel D. Columns (1) to (5) display intercepts for five long-only portfolios' returns. The last column corresponds to the estimation for our greenness-based long-short portfolio return. All alphas (risk-adjusted returns) persist in significance. For example, the FF5 alpha is -0.53% (-0.67%) per month with a t-statistics of 2.50 (3.81) for the value-weighted (equal-weighted) portfolios. Consequently, common risk factors cannot explain the cross-sectional return spread across portfolios sorted on greenness.

Table IA4 presents portfolio-level characteristic summaries. On average, firms in the low portfolio allocate 0.06% of earnings call transcripts to green innovation discussions, whereas the mean values increase more than tenfold to 0.87% for the high portfolios. Firms engaging in a higher proportion of green discussions exhibit smaller sizes, higher book-to-market ratios, lower profitability, and higher WW indices.

3.2 Double portfolio sorting

We then conduct independent double sorting on greenness and other firm characteristics. Specifically, at the end of June in year t, we also sort firms into top (T) and bottom (B) groups based on the median value of the following variables: market capital (size), book-to-market ratio (B/M), return on assets (ROA), investment rate, leverage, tangibility, and WW index with the fiscal year ending in year $t-1$. The intersection of the two-way sorts yields ten portfolios (5×2). We track the performance of the portfolios from July of year t to June of year $t+1$ and compute the return spread of greenness-HML portfolios in both the T and B subsamples for different firm characteristics. If the return predictability is attributed to other effects, we should not observe a significant return spread in any subgroups. Table 5 lists monthly returns in each subgroup and adjusts them by the FF5+MOM factors. The first and last two columns report the results for value-weighted and equal-weighted portfolios, respectively, which show that both raw and risk-adjusted returns are significant in most subgroups.

3.3 Fama-MacBeth regressions

Lastly, we run Fama-MacBeth cross-sectional regressions of stock returns on the greenness and control for firm characteristics to examine whether other predictors drive the negative greenness-return relation. Controls include the natural logarithm of market capitalization, book-to-market ratio, ROA, investment rate, WW index, leverage, tangibility, and industry dummies based on the Fama-French 49 classifications. We normalize variables to a zero mean and one standard deviation and compute standard errors using the Newey-West correction for 12 lags. Column (1) in Table 6 includes only green innovation measure as the independent variable and gets a coefficient of -0.16% with a t-statistics of 3.29. Column (2) accounts for the industry fixed effect and reveals consistent findings: A one-standard-deviation increase in greenness predicts 0.16% lower future returns each month. Incorporating control variables in column (3) reduces the coefficient, yet it remains significant at the 5% level.

In addition, we categorize green innovation discussions and scrutinize their individual effects. The negative return pattern mainly stems from *Energy*-related innovation, which frequently discusses renewable energy and electrical power efficiency. Conversely, technologies in *Production* and *Buildings* have yet to garner sufficient attention from investors and are not priced in the stock markets.

3.4 Robustness check

This subsection investigates whether the identified relationship between greenness and returns remains consistent for alternative green innovation measures or if it can be attributed to other variables we omit.

3.4.1 Alternative measures for greenness

We explore whether the return pattern would disappear if we use green patent shares as a proxy for a firm's commitment to green technology. Table IA13 collects the returns for univariate portfolio sorting based on the three patent measures. Panel A shows the results for green patent shares, displaying a return spread of -0.64%(-0.58%) for value-weighted (equal-weighted) High-minus-Low portfolios. We also compute the risk-adjusted returns by regressing each portfolio's excess returns on the Fama-French five factors along with the Carhart momentum factor. Alphas remain significant with similar magnitude, regardless of value or equal-weighted portfolios. Panel B shows the results for KPSS-weighted green patent shares. The returns decrease from 1.00% (1.33%) to 0.59% (0.67%) from low to high portfolios, yielding a return spread of -0.40% (-0.66%) with a t-statistics of 1.74 (3.47) for value-weighted (equal-weighted) portfolios. The returns magnitudes remain comparable after adjusting for risk factors. Panel C reports the results for the citation-weighted measure and obtains similar return patterns.

Table IA14 rerun the Fama-MacBeth regressions using green patent shares. Columns (1)-(3) use the equal/economic value/scientific value-weighted green patent shares as the independent variables, all significant at the 1% level. A one-standard-deviation rise in green patent share correlates with a 0.13% decrease in expected monthly returns. Columns (4)-(6) replace the independent variables with disaggregate green patent shares, showing that the pricing effect arises from patents associated with energy and environmental management.

In short, green patent shares based on economic and scientific values negatively predict future returns. This suggests a robust negative premium for green innovative firms.[14]

3.4.2 Carbon emission intensity

Cohen et al. (2021) noted that firms in the oil, gas, and energy sectors, which are significant greenhouse gas emitters, play a leading role in green patent production. Therefore, it is critical to assess whether the negative greenness-return pattern can be ascribed to risks related to carbon emissions.

Columns (1)-(2) in Table IA6 perform our Fama-MacBeth regressions and include firms without carbon emission data from Trucost. Over half of the observations remain in this group, with coefficients nearly identical to those from the complete sample. A one-standard-deviation decrease in *Energy* discussions is associated with a 0.11% monthly increase in excess returns. The last five columns consider carbon intensity as another independent variable. Column (3) uses Scope 1 carbon emission intensity as the sole independent variable and obtains an insignificantly positive coefficient.[15] The coefficients of green innovation measures

[14]It should be noted that as Section 6 will illustrate, this negative premium is predominantly sustained by firms that not only hold green patents but also engage in green innovation discussions. Conversely, firms that possess green patents but do not engage in green innovation discussions may not significantly alter their green innovation strategies. Hence they do not experience a lower cost of capital. This indicates the more accurate information captured by our textual measure. We should also be cautious about the return spread for these value-weighted patent measures as they contain information that is challenging for investors to collect. The forward citations of patents keep increasing over time and may have a look-ahead bias if we use it to measure greenness. Nevertheless, our observed return pattern is not driven by patents lacking economic or scientific importance.

[15]Bolton and Kacperczyk (2021) show that firms with higher CO2 emissions earn higher returns. The

remain negative and significant after controlling for carbon intensity, while *Environment*-related innovations account for most of the negative return effects.

4 Shift in green innovation returns

The negative green innovation premium we identified predominantly existed prior to 2020, contrasted by a marked outperformance from green innovating firms in the last two years. The blue line in Figure 3a depicts the cumulative returns of the High-minus-Low portfolios sorted on greenness. From 2007 to 2019, green firms demonstrated underperformance, with the portfolio steadily producing a negative return spread over this period. Conversely, a substantial escalation in portfolio returns was noted in 2020. Drawing inspiration from Pastor et al. (2022), we propose that this recent outperformance by green innovators does not represent a change in expected returns. Instead, we attribute it to a growth in demand triggered by an unexpected surge in attention towards green innovation from investors and companies.

This section aims to verify the aforementioned hypothesis. We start by describing our method for quantifying this unexpected attention. Following this, we assess how much of this unanticipated shift could justify the superior performance of green firms. Lastly, we examine changes in the preferences of institutional investors for green stocks. Our results highlight the crucial role that attention towards green innovation plays in driving the amplified demand for and subsequent superior performance of green innovators in the recent two-year period.

4.1 Unexpected green innovation attention

We develop a monthly green innovation attention index rooted in our textual measures. Earnings calls, serving as one of the key communication channels between a company's management and its shareholders, analysts, and the wider investment community, offer an immediate and insightful perspective into the area of interest for investors. This makes them an ideal data source for tracking and gauging attention toward green innovation. Specifically, we associate firms' quarterly greenness to the current and the two preceding months, as discussed in the corresponding earnings calls. We then compute the three-month moving average to

differences can result from the different empirical settings we use. Our sample focuses on firms with at least one earnings conference call, while Bolton and Kacperczyk (2021) considers all US firms with data from Trucost. In addition, we use stock returns over the next year to regress on carbon intensity and leave six months for investors before holding stocks to avoid look-ahead bias.

reduce volatility.[16]

Our monthly attention index is illustrated through the red line in Figure 3a. It shows an upward trajectory from 2008 to 2011, coinciding with the time of the Copenhagen and Doha UN Climate Change Conferences. Subsequently, a mild decreasing trend is observed until 2017. A notable dip in attention occurred in early 2020, likely attributable to the COVID-19 pandemic. However, later in 2020, a significant surge became apparent, catalyzed by Biden's election victory. This increase closely parallels the remarkable performance of stocks related to green innovation.

We compute unexpected changes in green innovation attention by employing prediction errors from AR(1) models applied to the attention index. We estimate the equation on a monthly basis using a rolling window of 60 months.[17]

$$GreenInnovAttention_t = \mu + \rho \cdot GreenInnovAttention_{t-1} + \epsilon_t.$$

For robustness, we also utilize the Media Climate Change Concerns (MCCC) index from Ardia et al. (2022) as an alternative proxy to estimate unexpected investor attention. This score, derived from ten highly circulated U.S. newspapers and two major newswires, combine the negativity and risk expressed in articles discussing climate change. While our index focuses on the perspective of green innovation, MCCC also includes concerns about climate regulations, ecosystems, and disasters. We follow the above equation to generate unexpected media climate change concerns (UMC) and examine its relationship with our returns spread as well.

4.2 Interpreting the reversed return pattern

Table 7 relates the monthly returns of the High-minus-Low portfolio with the unexpected green innovation attention index. Specifically, we carry out time-series regressions of portfolio returns on the unexpected attention index as well as common risk factors. Panel A reports the outcomes using data from April 2020 to December 2021, a period intentionally omitted from the preceding asset pricing test. Column (1) indicates that the raw return spread for value-weighted portfolios is 1.59% per month, with a t-statistic of 1.84. The magnitude of this coefficient is more than triple that of the absolute value of the monthly return spread

[16] We also experimented with using the monthly value, as opposed to the three-month moving average, for the index, and found similar results in our empirical analysis, as demonstrated in Internet Appendix IA.1.

[17] Similar outcomes are obtained when we execute the AR(1) models utilizing data from the preceding 24, 36, or 48 months.

prior to 2019 (-0.46%). After adjusting for the Fama-French five factors and the momentum factor in column (2), the coefficient diminishes to 0.31%. This decrease is attributable to significant loadings on market, value, and investment factors, suggesting that green firms are more often characterized as growth firms.

Column (5) incorporates unexpected attention as a factor. This new factor exhibits a positive coefficient with a t-statistics of 4.79, indicating that investor attention significantly contributes to explaining the positive return spreads. Columns (3) and (4) concentrate separately on the brown and green components. While the coefficient for the brown component is negative and statistically insignificant, the green component exhibits a positive coefficient, achieving statistical significance at the 1% level. Notably, when accounting for unexpected attention, the adjusted returns switch sign, becoming -0.69% monthly. These observations collectively imply that the recent escalation in green innovation attention has inflated prices for companies engaging in substantial green innovation discussions, thereby resulting in the superior performance of the High-minus-Low portfolio.

Panel B carries out similar regressions but reports estimations for the entire sample from 2007 to 2021. Including returns from the most recent two years renders the formerly negative return premium insignificant. After making adjustments for six common factors, the intercept gains significance at the 10% level. More importantly, the unexpected attention factor showcases a significant positive correlation with the returns of the High-minus-Low portfolio across the entire sample period. This relationship amplifies both the magnitude and statistical significance of the negative alpha.

Figure 3 provides a visual illustration of the results. Panel (b) presents the cumulative returns of the High-minus-Low portfolios post-2020 and reveals a positive trend. We then cumulate the adjusted returns, which are calculated by subtracting the products of the factors and their respective coefficients from the raw returns. Once we account for common risk factors and the unexpected attention surge, green innovative firms deliver lower returns compared to their brown counterparts. Panel (c) demonstrates that the contrasting effect vanishes after unexpected attention is factored in, displaying a consistent negative pattern throughout the sample.[18]

The asset pricing factor test using UMC is presented in Table IA9, demonstrating that unexpected changes in climate concerns based on news articles can also account for the positive return spread of High-minus-Low portfolios. This arises from both the underperformance of

[18] Figure IA3 employs the monthly average green innovation measure as the green innovation attention index instead of the three-month moving average and calculates the corresponding attention-adjusted returns. The results are similar.

brown firms and the outperformance of green ones. The MCCC index captures broader concern information predominantly of negative sentiment, thereby further reducing the demand for brown companies compared to our green innovation attention index.

In short, investor concerns about climate change interpret the positive return spread in the recent two years, with attention to green innovation playing the most pivotal role in bolstering the stock prices of green innovating companies.

4.3 Institutional investor preferences

Has the sudden rise in green innovation attention altered investors' preferences for green firms? We assess the impact of green innovation discussions on institutional investors' portfolio holdings and summarize the results in Table IA5. The dependent variables include overall institutional ownership, mutual fund ownership, and equity mutual fund ownership for firm i in year t. Control variables include the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. We account for firm and year-fixed effects in all regressions. The coefficient on greenness signifies the degree of institutional investors' preference for firms involved in green innovation.

Columns (1)-(3) provide estimations for the entire sample. While institutional ownership reveals a negative coefficient, mutual funds show an insignificant increase in their holdings in green firms. Columns (4)-(6) report results for observations after 2019, with all coefficients turning positive and significant. In summary, the heightened attention to green innovation has increased institutional investors' demand for green innovating firms.

Our findings resonate with those of Pastor et al. (2022), who suggest that the superior performance of green companies mirrors the unexpectedly strong increases in environmental concerns. While they observe high returns from green assets starting in 2013, we only begin to see this outperformance post-2019. The discrepancy may stem from the different measures we use. Their assessment of a firm's greenness relies on the MSCI ESG rating, which evaluates the firm's management of land use, pollution, waste, and environmental opportunities. In contrast, our study primarily targets firms' endeavors in green innovation. Furthermore, while their findings indicate that the return effects are more pronounced in brown stocks and significantly weaken within industries, our observed return premium mainly originates from green firms and persists within industries.

5 Hedging against transition risks

Green innovators exhibit lower expected returns due to their better ability to hedge against climate risks. Their preparedness to tackle stringent climate regulations and seize new market opportunities places them in an advantageous position. In this section, we aim to investigate whether firms engaged in green innovation practices indeed showcase enhanced environmental performance and demonstrate superior resilience during adverse climate shocks.

5.1 Future environmental performance

We explore the influence of green innovations on a firm's environmental outcomes, focusing on carbon emissions and climate-related negative incidents in the future.

$$Envir\ performance_{i,t} = \alpha + \sum_{0 \leq j \leq 3} \beta_j \cdot Greenness_{i,t-j} + \gamma X_{i,t} + a_i + b_t + \epsilon_{i,t}.$$

Green technology plays a vital role in reducing carbon emissions. One example is that renewable energy sources such as solar and wind power can serve as alternatives to carbon-intensive fossil fuels in electricity generation. We employ the Scope 1 carbon emission levels of firm i in year t as the dependent variable. The primary independent variables include the green innovation discussions from the previous four years. We control for variables including the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. Firm and year-fixed effects are also considered in our analysis.

Table 8 Panel A presents the estimation results for the equation. The first column, accounting for overall green innovation, identifies significant carbon reduction effects. Columns (2)-(7) run the regression on disaggregate discussions, finding that innovation related to *Energy*, *Building*, and *Adaptation* contributes the most to emission reductions. Table IA7 shows a comparable negative correlation with Scope 1 carbon intensity, while the reduction effects on Scope 2 carbon emission levels and intensity appear to be limited.

We then probe whether firms with a higher degree of greenness are less prone to climate-related incidents, such as oil spills and greenwashing. We replace the dependent variable with the logarithm of the number of incidents for firm i in year t, sourcing data from RepRisk.[19] Table 8 Panel B suggests that firms deeply engaged in green technology discussions are involved in fewer negative climate incidents, particularly those referencing technologies asso-

[19] RepRisk screens over 100,000 public sources, including print, online, and social media in 23 languages daily. It monitors ESG violations that could impact a company's reputation and financial status.

ciated with *Production* and *Adaptation*. Table IA7 estimates the regression using alternative measures from RepRisk and validates the robustness of our results. Here, *severity* indicates the extent of incidents' consequences and ranges from one to three, with three representing a severe impact. *Reach* measures the popularity of information sources based on their readership and circulation, and *novelty* denotes whether a company is exposed to a particular issue for the first time.

In summary, firms with a higher degree of greenness demonstrate improved environmental performance. They effectively reduce their carbon emissions in subsequent years and are less often involved in negative climate incidents, thus successfully mitigating potential risks to their reputation.

5.2 Event study

We hypothesize that these green firms with improved environmental footprints will exhibit superior performance compared to their less innovative counterparts during events signaling heightened climate concerns and stricter environmental regulations. Conversely, they may underperform when these concerns diminish or environmental regulations are loosened. We analyze the stock price reactions to four major events related to climate risks in the U.S.:

- Donald Trump's presidential election victory on November 8, 2016.
- Joe Biden's presidential election victory on December 14, 2020.[20]
- The Russia-Ukraine war disruption on February 24, 2022.
- The IRA announcement on July 28, 2022.[21]

5.2.1 Selected events

Our analysis begins with the 2016 U.S. presidential election, marked by Trump's unexpected victory. The two campaigns showcased starkly different attitudes toward climate change during the election cycle. Hillary Clinton put forth a comprehensive plan to address climate

[20] On December 14, the Electoral College formally voted for the president and vice president. Biden officially received 306 total electoral votes, and Trump got 232. Pham et al. (2023) use the same event date for Biden's election.

[21] On July 27, Senator Joe Manchin and Senate Majority Leader Chuck Schumer suddenly released a statement announcing the Inflation Reduction Act of 2022, which was a shock given that Democrats had previously expressed little hope for a revival of their climate and tax priorities and Manchin was rather pessimistic about the aggressive climate bill.

issues, while Trump, in contrast, labeled human-induced climate change a "hoax." He pledged to withdraw from the Paris Agreement, dismantle the Clean Power Plan, and expand fossil-fuel explorations. Given the widespread expectation of Hillary's victory, Trump's win posed a significant shock for carbon-intensive firms, suggesting a likely easing of environmental regulations.

Conversely, Biden's climate change plan in the 2020 election was described as the most ambitious yet from a presidential candidate. Amidst a year that tied the record for the highest number of billion-dollar weather and climate disasters in the U.S., Biden placed reducing greenhouse-gas emissions close to the center of his presidency. He proposed immediate reentry into the Paris Agreement upon taking office, aimed to achieve carbon-free electricity production by 2035, and targeted net-zero emissions by 2050. His election victory undoubtedly brought encouraging news to companies heavily invested in advanced green technologies.

The third event, the Russian invasion of Ukraine on February 24, 2022, presents a complex scenario regarding climate change. On one side, the U.S. imposed a ban on energy imports from Russia - the world's largest gas exporter and the second-largest oil exporter. This action led to a spike in domestic gas prices and triggered the Biden Administration to relax restrictions on oil and gas drilling to expand fossil fuel production.[22] These immediate effects seem to erase decades of progress in combating climate change, implying the need for more extensive long-term strategies to combat the climate crisis. A consensus has emerged, emphasizing the acceleration of the green transition as the optimal response to the energy crisis and increasing emissions. Thus, the conflict, while initially detrimental to climate change efforts, has ultimately underscored the urgency of investing in renewable energy sources and reducing reliance on globally traded fossil fuels, which could catalyze more decisive climate actions in the long run.

President Biden enacted the IRA on August 16, 2022, marking the U.S.'s most ambitious and comprehensive climate change legislation to date, serving as the final event for our analysis. The IRA commits an unprecedented $370 billion towards climate-related expenditures and tax credits, targeting a 41% reduction in U.S. greenhouse gas emissions by 2030, compared to 2020 levels. The legislation prioritizes the encouragement of innovation via research and development in clean technology, while also stimulating demand for low-carbon products in the building construction and transportation sectors. In short, the law defines a clear path for the U.S. to address climate change and provides opportunities for companies across multiple industries to fulfill their carbon reduction goals.

[22] Moreover, large amounts of greenhouse gases were released into the atmosphere during the war due to oil burns and forest destruction.

5.2.2 Stock price reactions

To analyze the impact of these events on stock prices, we implement a regression model with cumulative abnormal returns (CAR) as our dependent variable to isolate the effects of new information on stock prices:

$$CAR_i = \alpha + \beta \cdot Greenness_i + \gamma X_i + \epsilon_i,$$

CAR[0,1]/CAR[0,5]/CAR[0,10] corresponds to the CARs from the event date to one/five/ten days subsequent to the event. The abnormal returns are computed as the return in excess of CRSP value-weighted market returns.[23] The control variables include those used in the Fama-MacBeth regressions. We consider Fama-French 49 industry fixed effects and cluster standard errors by industry.

Table 9 Panel A reports the equation estimations for Trump's election. The first three columns show results for the sample with earnings calls, while the latter three consider only observations with non-zero green innovation discussions. Firms with a standard deviation increase in green innovation discussions underperform their industry peers by 0.4% in one-day CARs and 0.8% in five-day CARs. Figure 4 displays the evolution of coefficients on greenness from five days prior to the event up to twenty days afterward. The coefficients, significantly negative and decreasing with the event window, signify a continued decline in stock prices following the event date. Figure IA4 plots the coefficients for disaggregate green innovation measures. The negative reaction mainly comes from firms with discussions related to *Energy*, *Transportation*, and *Production*. Interestingly, firms with more discussion in *Adaptation* technology experience price increases after the election. The potential worsening of climate issues due to relaxed climate regulations in the short term may benefit firms with strong adaptation capabilities in the near future.

Table 9 Panel B presents the opposite results for Biden's election. An increase of one standard deviation in greenness correlates with a 0.3% rise in abnormal returns on the first trading day following the election. These CARs accumulate to 1.5% by the tenth day, maintaining significance at the 1% level. Panel C illustrates the coefficients for the Russia-Ukraine war. The positive coefficients indicate that firms boasting more green innovations fare better in the long run due to their enhanced ability to mitigate climate change. The CARs escalated from 0.4% to 1.2% by the fifth trading day, yielding an additional 1.2% in abnormal returns over the next five trading days. Similar coefficients are observed when observations lacking

[23] Following the literature, we adopt a 250-trading day estimation window endings 25 days prior to the event day. We require a minimum of 40 non-missing observations within the estimation window and then calculate the market-adjusted CAR for each stock.

green innovation discussions are excluded. Panel D collects the results for the IRA announcement. Firms with a higher proportion of green discussions significantly outperform, aligned with the immense opportunities the Act offers for firms engaged in clean technologies. A one standard deviation increase in greenness correspondents to 1% higher abnormal returns within the first ten trading days, significant at the 1% level.

Figure 4 demonstrates a clear upward pattern for coefficients following the three events, with innovations related to *Energy* always playing a vital role. Overall, the findings show that green innovating firms exhibit greater resilience and adaptability in the face of potential changes in environmental policies and escalating concerns about climate change.

5.2.3 Robustness check

In a bid to ensure that the observed price reactions are not driven by carbon emissions, we further scrutinize the CARs of the four events relative to greenness and carbon intensity as outlined in Table IA15, serving as a robustness check. In Panel A, we observe negative coefficients for greenness during Trump's election.[24] Panel B reveals that the inclusion of carbon intensity does not affect the estimations of greenness for Biden's election. In addition, we notice negative coefficients for carbon intensity after the election, which is consistent with the presumption that the potentially stringent climate regulations during Biden's administration would negatively impact carbon-intensive firms. Lastly, carbon intensity shows little impact on the performance of green stocks during both the Russia-Ukraine war and the IRA announcement.

6 Comparison with green patents

Despite its strong correlation with patent proxies, our text-based green innovation measure offers distinct perspectives on firms' green innovation actions. This section compares the two types of measures in terms of information breadth, sample coverage, and empirical implications. Table 10 summarizes the comparison. As we explain next, it shows that our text-based measures capture more comprehensive and precise information on firms' green innovation activities and are more informative for identifying the asset pricing implications.

[24] These results are less significant than those presented in Table 9, likely due to the reduced sample size resulting from limited data availability from Trucost.

6.1 Transcending patent limitations

Green patents, while valuable for indicating a company's inventive activity in the environmental field, may not fully reflect a firm's active, strategic, and commercially relevant green innovation endeavors due to the inherent limitations of patent data. Our text-based measure, grounded in the unique insights from earnings call transcripts, helps alleviate these constraints.

Firstly, patent data do not account for innovative strategies that significantly improve a company's environmental footprint but are not patentable. A case in point is Renovare Environmental Inc., a firm that provides a cost-effective path to ecological sustainability. Despite not having patents, the firm consistently engages in green innovation, as evidenced by its activities to transform waste into renewable fuels and partnerships to educate students about waste management solutions. Their application of existing technologies in new contexts and on a large scale requires creative thinking and innovative sourcing, effectively reducing carbon footprint and exemplifying green innovation. Such behaviors are not recorded in green patents but are extensively discussed in the firm's earnings calls. Hence the textual measure based on this "soft" information provides a broader overview of green innovation activities.

Secondly, the equal treatment of patents in calculating green patent shares overlooks the varying climate mitigation potential of different clean technologies. In contrast, due to their time limitation, earnings calls only focus on the most pivotal green innovation actions, painting a more accurate picture of commitment. For example, Codexis Inc., a leader in protein engineering, has consistently produced more than 20 green patents annually - over 70% of their portfolio - since 2015. These patents primarily enhance the precision and abundance of therapeutic compound production processes, which are classified as green due to their indirect energy-saving characteristics. Codexis seldom discusses green innovation in their earnings calls, possibly because these patents' "green" aspect emerges as a secondary outcome of these innovations rather than their primary focus.

Finally, due to the lengthy approval process, patents may represent firms' commitments that began years ago. Conversely, the quarterly frequency of earnings calls offers timely company updates, often highlighting green initiatives years before patent approval. For instance, Workhorse Group Inc., an electric vehicle manufacturer, has continuously emphasized green innovation in its earnings calls since 2016, ranking among the top 1% of all companies. However, this firm only holds a few green patents, having received its first in 2018 and another in 2021. This discrepancy illustrates the outdated nature of patent data and the real-time value of earnings call discussions.

6.2 Sample coverage

To better understand the relation between green innovation discussions and green patent shares, we categorize observations into three groups: one with positive values for both measures and the other two with positive values for only one of the measures. We then plot Venn diagrams and histogram distributions for these subgroups to examine their sample coverage.

First, Venn diagrams indicate that firms with general green innovation activities outnumber those possessing green patents by a factor of two. This can be visually depicted in Table 10. Among the 51,818 firm-year observations, 11,540 display positive engagement in green innovation discussions. Of these, 9,266 (or 75.46%) were not granted any green patents within the same fiscal year. On the other hand, of the 5,410 observations that do hold green patents, 3,136 (or 57.97%) do not participate in green innovation discussions. As such, the textual measures considerably widen the scope of the sample demonstrating green innovation activities. This disparity further escalates when contrasting the number of unique firms that exhibit at least one positive value for each of these variables. Within our sample of 5,887 unique firms, 766 demonstrate positive values for both measures. In comparison, 2,286 firms, despite never being awarded a green patent, have addressed the subject of green innovation at least once during their earnings calls. In contrast, only 246 firms that possess at least one green patent never raised the topic of green innovation in their earnings calls.

We then analyze their histogram distributions in Figure 5. Panel A displays the distribution of green innovation discussions amongst firms with or without green patents. Consistent with the results in Venn diagrams, many firms, despite lacking green patents, actively engage in green innovation discussions. Some firms without green patents even have a higher proportion of discussions than those with green patents.

Panel B portrays the distribution of green patent shares amongst firms, categorized by their participation or lack thereof in green innovation discussions. Generally, firms involved in green discussions tend to possess larger shares of green patents. Yet, some firms that do not engage in green discussions still maintain sizable shares of green patents. These patents may not substantially influence the firms' strategies, as evidenced by the absence of such topics in their earnings calls.

Panels C and D center around observations displaying positive values for both measures, demonstrating the distribution of green innovation discussions among firms with different economic values or forward citations for their green patents. On average, firms with higher green patent values or citations participate more extensively in green innovation discussions. Interestingly, some firms with lower values or citations exhibit more discussions than their counterparts. This can be attributed to the fact that while citations denote scientific importance, they do not necessarily assure commercial relevancy. Additionally, the economic value of a patent, reflected in the stock market's response on the patent grant announcement day, may not entirely capture the intrinsic value of a green patent. It is plausible that a considerable part of the value has already been incorporated into the stock price during the patent review process.

We evaluate the characteristics of these groups in IA16. Firms with positive values in both measures manifest larger values for each measure individually than firms that only score positively in one measure. This highlights the strong correlation between the two. On the other hand, firms owning green patents are generally larger than those engaged in green innovation discussions. This suggests that compared to broader green innovation activities, patent applications require more research investments and are more commonly seen in large firms.

In short, text-based measures offer a holistic view of green innovation activities, extending beyond patentable technologies. They also furnish a more precise interpretation of a patent's economic worth by considering the proportion of discussions devoted to related technology, which not only mirrors the immediate attention given by firms and investors but also tracks the evolution of their perceptions over time.

6.3 Empirical implications

In this subsection, we conduct previous empirical tests on various subgroups and illustrate that the unique information captured by our textual measures makes them more efficient in detecting the asset pricing implications of green innovation.

We first re-perform Fama-MacBeth regressions in Table IA17. Intriguingly, even for firms without green patents, the negative return premium and recent outperformance continue to be present. This indicates that the stock markets also price green innovation activities beyond the realm of patents. In contrast, green patent shares cannot predict future returns in the subgroup without green innovation discussions, suggesting that these patents may not hold considerable significance in green innovation or are not frequently utilized by firms. We observe significant coefficients for the subgroup possessing both measures, denoting that these measures contain unique and mutually beneficial information.

Further, we investigate the ability of the three groups to hedge against transition risks by examining their environmental improvement effects and event studies. Table IA18 reveals that only groups with positive green innovation discussions can effectively reduce future carbon emissions and negative incident involvement. Table IA19 displays that these firms, including those without green patents, perform better during events like Biden's election and the Russia-Ukraine war and underperform during Trump's election. Conversely, green patents yield insignificant coefficients in almost all regressions for firms lacking green innovation discussions. This suggests that broader green innovation activities are viewed as a hedge against stricter climate regulations. In contrast, in the absence of green discussions, green patents might not significantly affect operational processes and are not considered sufficiently innovative in the green context.

7 Conclusion

Our study provides an empirical investigation into the impact of firms' green innovation activities on asset pricing. Using patent abstracts and earnings call transcripts, we construct a firm-level measure to capture firms' dedication to climate technology development and investors' attention to green innovation. This approach captures a broader spectrum of green innovation activities compared to green patents alone. Also, it places a greater emphasis on the actions that most significantly influence a firm's sustainability strategies. Such unique insights enable us to discern the asset pricing implication of green innovation more accurately.

A portfolio that is long on firms with low greenness and short on those with high greenness generates an average return of about 6% per year. The negative association is confirmed through Fama-MacBeth cross-sectional regressions that control for various firm characteristics. This indicates that investors require lower returns from firms demonstrating substantial green innovation endeavors. Additionally, we noted a surge in investors' attention to green innovation over the past two years, resulting in increased demand and realized returns for green innovating stocks.

Firms' investments in green technology development and adoption equip them to reduce carbon emissions and minimize involvement in climate incidents. This positions them to better hedge against transition risks. Following Trump's election victory, firms with a higher degree of greenness underperformed, likely due to the expectations of loosening environmental regulations. Conversely, these firms demonstrated positive performance in response to Biden's election win, the Russia-Ukraine war disruption, and the IRA's announcement. These events signal a possible tightening of regulations and a shift to a more climate-conscious economy, which bodes well for firms heavily invested in green innovation.

References

Andriosopoulos, D., Czarnowski, P., and Marshall, A. P. (2022). Does green innovation increase shareholder wealth? (september 26, 2022). *Available at SSRN: https://ssrn.com/abstract=4012633*.

Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2022). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 0(0):null.

Berg, F., Kölbel, J., Pavlova, A., and Rigobon, R. (2023). Esg confusion and stock returns: Tackling the problem of noise. *Available at SSRN: https://ssrn.com/abstract=3941514*.

Bingler, J. A., Kraus, M., Leippold, M., and Webersinke, N. (2023). How cheap talk in climate disclosures relates to climate initiatives, corporate emissions, and reputation risk. *Swiss Finance Institute Research Paper No. 22-01*.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2022). Global pricing of carbon-transition risk (august 5, 2022). *Journal of Finance, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3550233*.

Bolton, P., Kacperczyk, M. T., and Wiedemann, M. (2023). The co2 question: Technical progress and the climate crisis (january 9, 2023). *Available at SSRN: http://dx.doi.org/10.2139/ssrn.4212567*.

Cohen, L., Gurun, U. G., and Nguyen, Q. (2021). The esg - innovation disconnect: Evidence from green patenting (june 3, 2021). *Available at SSRN: http://dx.doi.org/10.2139/ssrn.3718682*.

Dechezlepretre, A., Martin, R., and Mohnen, M. (2017). Knowledge Spillovers from clean and dirty technologies. GRI Working Papers 135, Grantham Research Institute on Climate Change and the Environment.

Deng, M., Leippold, M., Wagner, A. F., and Wang, Q. (2022). The net-zero transition and firm value: Insights from the russia-ukraine war, repowereu, and the us inflation reduction act (october 4, 2022). *Swiss Finance Institute Research Paper No. 22-29, Available at SSRN: https://ssrn.com/abstract=4080181*.

Gibson, R., Krueger, P., and Schmidt, P. S. (2021). Esg rating disagreement and stock returns. *Financial Analyst Journal, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3433728*.

Hao, X., Chen, F., and Chen, Z. (2022). Does green innovation increase enterprise value? *Business Strategy and the Environment*, 31(3):1232–1247.

Hege, U., Pouget, S., and Zhang, Y. (2023). The impact of corporate climate action on financial markets: Evidence from climate-related patents. *Available at SSRN: https://ssrn.com/abstract=4170774*.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2022). The pollution premium. *The Journal of Finance*.

Hu, W., Li, K., and Yu, T. (2022). A machine learning-based anatomy of firm-level climate risk exposure (february 4, 2022). *Available at SSRN: http://dx.doi.org/10.2139/ssrn.4025598*.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth*. *The Quarterly Journal of Economics*, 132(2):665–712.

Kruse, T., Mohnen, M., Pope, P., and Sato, M. (2020a). Green revenues, profitability and market valuation: Evidence from a global firm level dataset. *Available at https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2020/01/working-paper-331-Kruse-et-al-2.pdf*.

Kruse, T., Mohnen, M., and Sato, M. (2020b). Are financial markets aligned with climate action? new evidence from the paris agreement. *Available at https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2020/02/working-paper-333-Kruse-et-al.pdf*.

Kuang, H. and Liang, B. (2022). Climate-related innovations: Economic value and risk mitigation. *Available at SSRN: https://ssrn.com/abstract=4150960*.

Lanzi, E., Verdolini, E., and Haščič, I. (2011). Efficiency-improving fossil fuel technologies for electricity generation: Data selection and trends. *Energy Policy*, 39(11):7000–7014. Asian Energy Security.

Li, Q., Shan, H., Tang, Y., and Yao, V. (2020). Corporate Climate Risk: Measurements and Responses. *Available at SSRN: 3433728*.

Monasterolo, I. and de Angelis, L. (2020). Blind to carbon risk? an analysis of stock market reaction to the paris agreement. *Ecological Economics*, 170:106571.

Pastor, L., Stambaugh, R. F., and Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424.

Pham, L., Hao, W., Truong, H., and Trinh, H. H. (2023). The impact of climate policy on u.s. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. *Energy Economics*, 119:106564.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., and Ziegler, A. (2021). Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections. *The Review of Corporate Finance Studies*, 10(4):748–787.

Reza, S. W. and Wu, Y. (2023). Green innovation. *Available at SSRN: https://ssrn.com/abstract=4212739*.

Sautner, Z., van Lent, L., Vilkov, G., and Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance*, n/a(n/a).

Sen, S. and von Schickfus, M.-T. (2020). Climate policy, stranded assets, and investors' expectations. *Journal of Environmental Economics and Management*, 100:102277.

Webersinke, N., Kraus, M., Bingler, J. A., and Leippold, M. (2021). Climatebert: A pretrained language model for climate-related text. *CoRR*, abs/2110.12010.

Yang, B. (2021). Explaining greenium in a macro-finance integrated assessment model (may 27, 2021). *Available at SSRN: https://ssrn.com/abstract=3854432*.

Figure 1: **NLP Methodology**

This figure outlines our approach to developing firm-level green innovation measures from earnings call transcripts. We leverage the capabilities of the ClimateBERT model to execute three classification tasks: identifying sentences related to transition, ascertaining whether they pertain to green innovation, and categorizing the specific type of green innovation discussions. To generate training sentences for the ClimateBERT model, we harness GPT-3 to condense each green patent abstract into a single investor-friendly sentence.

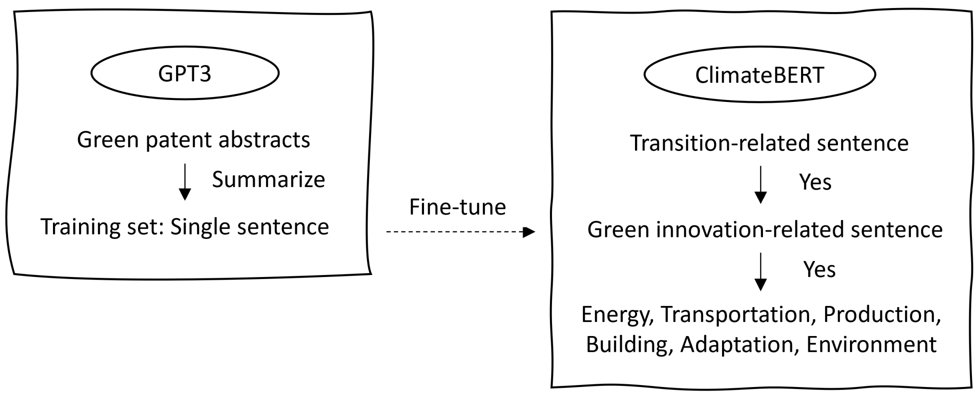


Figure 2: **Time-Series Variation of Greenness**

This figure depicts the mean value of quarterly green innovation measures across firms over time.

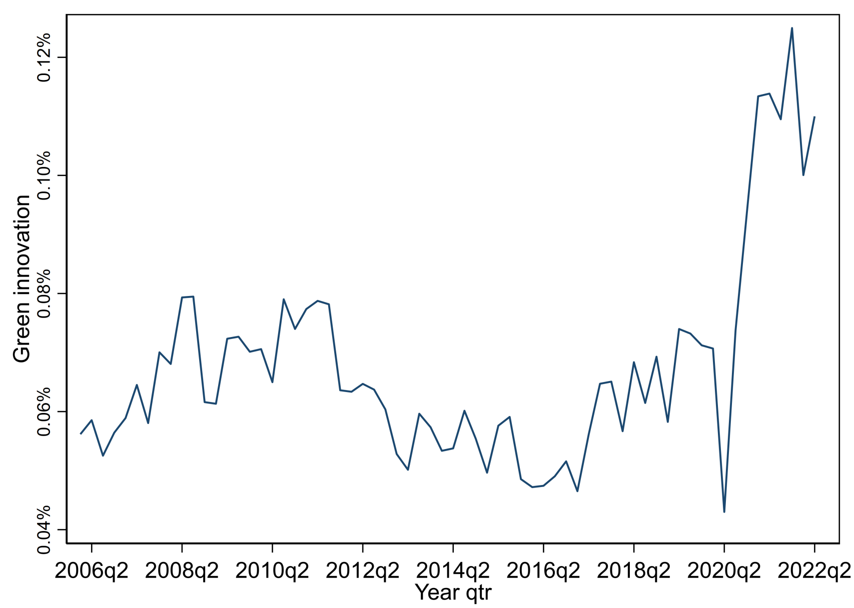
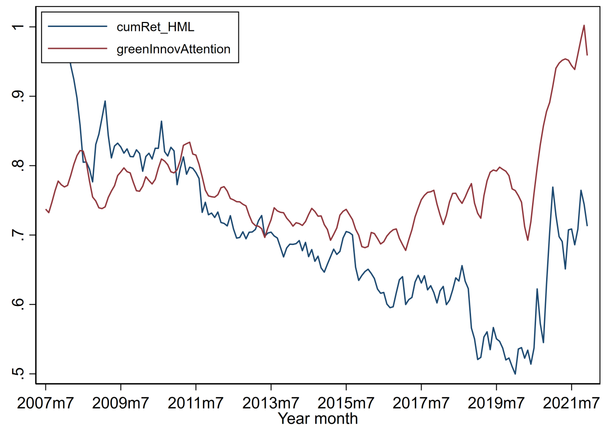
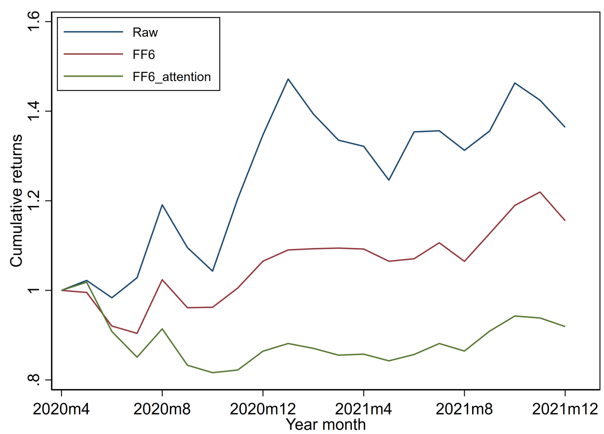


Figure 3: **Unexpected Green Innovation Attention**

This figure examines the relationship between the return patterns and the level of unexpected attention towards green innovation. Panel (a) compares the time series of the green innovation attention index with the cumulative returns of the High-minus-Low portfolios, sorted based on greenness. Panel (b) illustrates the cumulative raw returns, returns adjusted for Fama-French five factors and momentum factor, and returns further adjusted for unexpected attention to green innovation for High-minus-Low portfolios for the period from April 2020 to December 2021. Panel (c) extends the timeline and shows the cumulative returns of High-minus-Low portfolios for the entire period spanning from July 2007 to December 2021.



(a)



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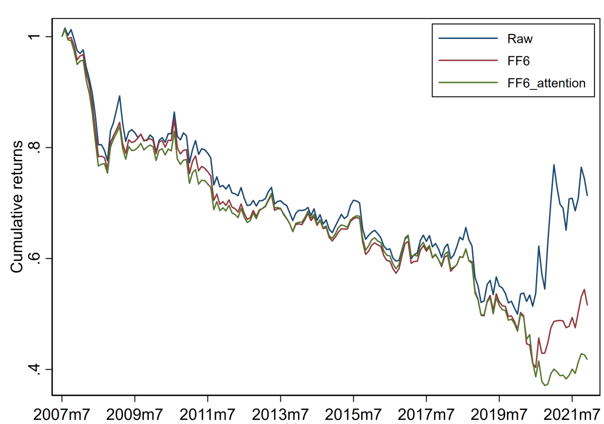
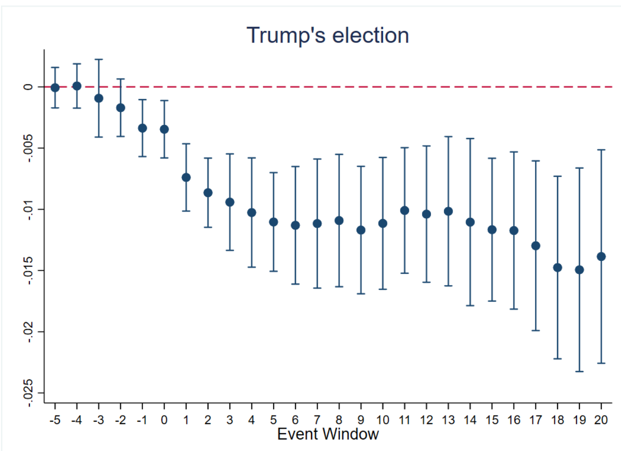


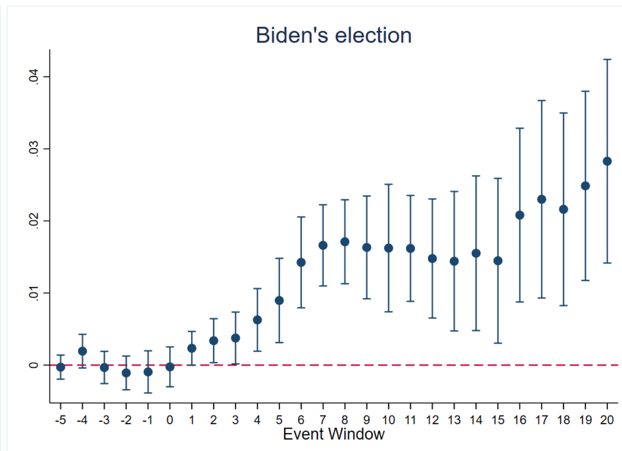
(c)

Figure 4: **Event Study**

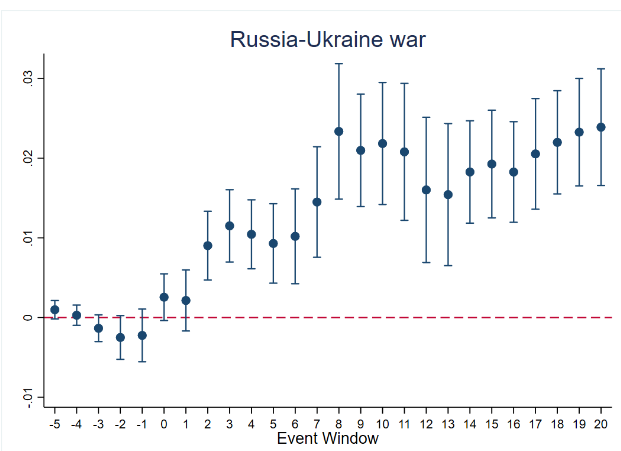
This figure illustrates the trajectory of coefficients along with 90% confidence intervals derived from cross-sectional regression analysis. These regressions use market-adjusted cumulative abnormal returns as the dependent variable, with a focus on key events, including Trump's electoral victory on November 8, 2016, Biden's election triumph on December 14, 2020, the outbreak of the Russia-Ukraine war on February 24, 2022, and the announcement of the Inflation Reduction Act on July 28, 2022. As control variables, we incorporate the natural logarithm of firm size, book-to-market ratio, Return on Assets (ROA), investment rate, the WW Index, leverage, and industry controls based on the Fama-French 49 industry classifications. All variables are normalized to a zero mean and one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The standard errors are clustered by industry.



(a)



(b)



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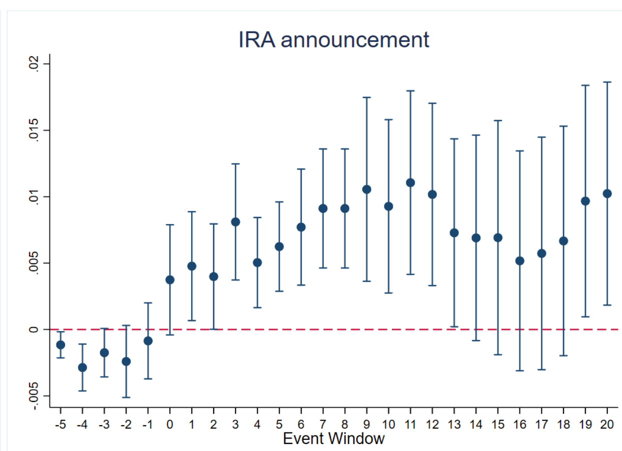
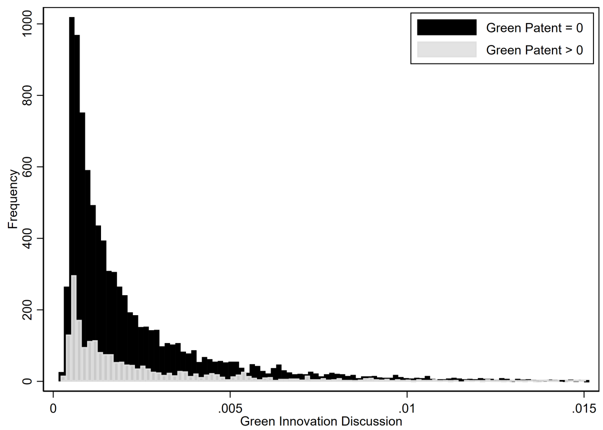


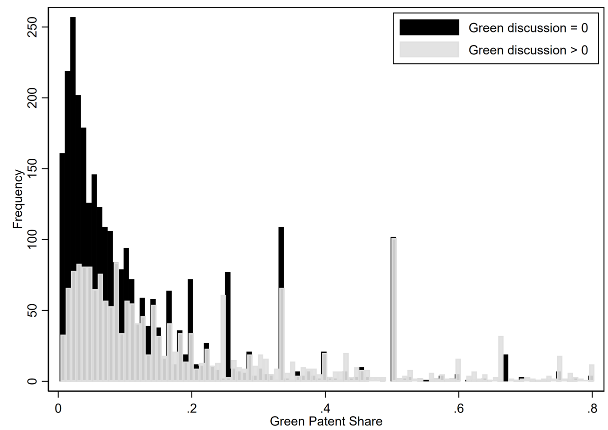
(d)

Figure 5: **Comparison with Green Patents: Histogram Distributions**

This figure presents histogram distributions representing the relationship between green innovation discussions and green patent shares. Panel (a) depicts the distribution of green innovation discussions among firms with and without green patents. Panel (b) shows the distribution of green patents among firms with and without green innovation discussions. Panel (c) and (d) portray the distribution of green innovation discussions among firms with high and low KPSS value-weighted and citation-weighted green patent shares.



(a)



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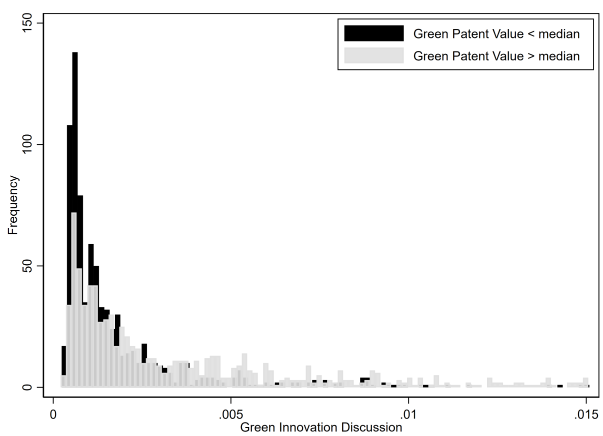

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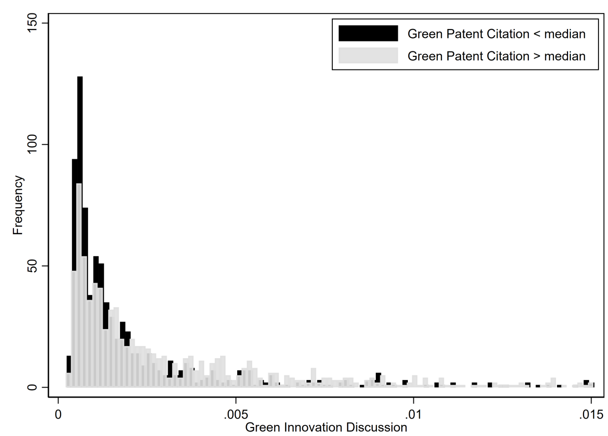


(d)

Table 1: **Summary Statistics**

This table presents summary statistics for variables used in this paper. *Greenness* is the annual proportion of green innovation discussions. *Energy/Production/Transportation/Buildings/Adaptation/Environment* reflect the discussion proportions in their respective areas. $Green^n/Green^s$ denote the count and share of green patents, respectively. $Green^{s,e}$ represents the KPSS-economic value-weighted share of green patents, whereas $Green^{s,c}$ corresponds to the forward citation-weighted shares.

Variable	**Mean**	**N**	**std**	**p5**	**p50**	**p95**
Green innovation measures from earnings calls						
Greenness	0.068%	51818	0.255%	0	0	0.357%
Energy	0.021%	51818	0.125%	0	0	0.099%
Transportation	0.018%	51818	0.101%	0	0	0.090%
Production	0.005%	51818	0.031%	0	0	0
Building	0.005%	51818	0.041%	0	0	0
Adaptation	0.006%	51818	0.034%	0	0	0
Environment	0.012%	51818	0.065%	0	0	0.068%
Green patent measures from USPTO						
$Green^n$	4.035	15512	15.269	0	0	19
$Green^s$	8.190%	15512	19.969%	0	0	50%
$Green^{s,e}$	8.233%	11954	20.002%	0	0	50.649%
$Green^{s,c}$	7.196%	11954	19.884%	0	0	50%

Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Greenness	1										
(2) Energy	0.77	1									
(3) Transportation	0.65	0.29	1								
(4) Production	0.37	0.20	0.11	1							
(5) Building	0.35	0.20	0.08	0.11	1						
(6) Adaptation	0.27	0.08	0.04	0.09	0.03	1					
(7) Environment	0.53	0.21	0.18	0.24	0.07	0.16	1				
(8) $Green^n$	0.05	0.02	0.09	0.01	0.01	-0.01	0.01	1			
(9) $Green^s$	0.38	0.35	0.22	0.14	0.10	0.08	0.23	0.18	1		
(10) $Green^{s,e}$	0.38	0.34	0.24	0.14	0.10	0.07	0.24	0.18	0.96	1	
(11) $Green^{s,c}$	0.29	0.27	0.16	0.11	0.09	0.05	0.18	0.20	0.73	0.75	1

Table 2: **Excerpts from Patent Abstracts and Earnings Calls**

This table compares the titles, abstracts, and GPT-3 summarized abstracts of green patents with sentences detected in earnings calls that pertain to relevant patent categories.

Panel A: Firms with green patents

Fuelcell Energy Inc.
Patent: [Energy] Gas flow control assembly for use with fuel cell systems operating on fuels with varying fuel composition.
Abstract: A gas flow control assembly for use in a fuel cell system comprising an airflow control assembly for adjusting flow of air to a cathode side of the fuel cell system based on content variations in an exhaust gas leaving an anode side of the system and a fuel flow control assembly for controlling flow of fuel to the anode side based on adjustment to the airflow by the airflow control assembly.
GPT-3 summarization: This gas flow control assembly is designed to help fuel cell systems use energy more efficiently by adjusting the flow of air and fuel based on the exhaust gas content.
Detected sentences in an earnings call:
(2010-09-02) Our fuel cell technology helps South Korea achieve its low carbon, green energy goals, allows agricultural and municipal customers to transform waste problems into renewable energy solutions, and generates reliable secure power for commercial and government facilities.

Baidu Inc.
Patent: [Transportation] Method and apparatus for operating FPGA board in driverless vehicle.
Abstract: The present application discloses a method and apparatus for operating a field-programmable gate array (FPGA) board in a driverless vehicle. The method according to a specific embodiment includes: collecting driving scenario information on a driving scenario of the driverless vehicle; determining, based on the driving scenario information, a speed at which the driverless vehicle executes a computing operation in the driving scenario; comparing the speed with a speed threshold; switching a working mode of the FPGA board in the driverless vehicle executing the computing operation to reduce power consumption of the FPGA board, in response to the speed being lower than the speed threshold. This embodiment implements the adaptive adjustment of the working mode of the FPGA board, thereby reducing the overall power consumption.
GPT-3 summarization: This application is about a method and apparatus for using an FPGA board in a driverless vehicle to help reduce power consumption by changing its working mode depending on the speed of the vehicle.
Detected sentences in an earnings call:
(2021-05-18) AI platforms that power smart transportation, autonomous driving, and in-vehicle infotainment, working in tandem, can bring incredible operating efficiencies and convenience as well as improved traffic safety, and reduced carbon emission for the transportation sector.

Super Micro Computer Inc.
Patent: [Production] Disaggregated computer system.
Abstract: A computer system includes a processor and a memory. The processor is located on a first circuit board having a first connector. The memory is located on a second circuit board having a second connector. The first circuit board and the second board are physically separated from each other but connect to each other through the connector. The processor and the memory are communicated to each other based on a differential signaling scheme.
GPT-3 summarization: The computer system is designed so that the main brain of the computer (processor) and the part that holds information (memory) are on separate boards that can talk to each other, even though they aren't physically connected.
Detected sentences in an earnings call:
(2018-05-03) Furthermore, resource-saving systems are capable of achieving 1.5 PUE in data centers to save millions of dollars in energy costs, while significantly reducing waste. So green computing and resource savings solutions not only save customers' energy costs, and initial hardware acquisition costs but also make their deployment easier and help our mother earth from its pollution.

Echelon Corp.
Patent: [Building] Systems, apparatuses, and methods for detecting problems in air.
Abstract: The combination of LED lighting and particulate detectors are enhanced by exploiting the light degradation/reflection/wavelengths detected, absorbed or frequency shift seen in lighting due to the presence of smoke, gas or other molecules (such as explosives) in the air can be detected. The use of LEDs is expanded well beyond simple lighting and energy savings to include not only smoke and fire detection by also to scan for gases and particulates found based in the usage environment.
GPT-3 summarization: This technology uses LED lights to detect problems in the air, like smoke, fire, gases, and particulates, to make buildings safer.
Detected sentences in an earnings call:
(2014-11-06) Smart Controls is focused on monitoring indoor temperature, humidity, CO2, and VoC levels. This is in addition to the numerous safety benefits and the significant energy and cost savings of as much as 90% over their old lighting system.

Panel B: Firms without green patents

Tetra Tech Inc. Main topic: [Adaptation].
Detected sentences in an earnings call:
(2016-11-10) For example, here in Southern California, the groundwater reliability improvement project's design, often referred to as the GRIP project, provides a recharge of groundwater supplies with treated wastewater. And we are treating this water and returning both to the groundwater or reusing it for irrigation.

Star Bulk Carriers Corp. Main topic: [Environment].
Detected sentences in an earnings call:
(2018-11-21) Scrubbers not only remove sulfur, but they also remove inhalable particulate matter emissions and reduce those by approximately 80%, being most effective with the smaller particulates as well as the black carbon. So scrubbers are one of the options on hand to meet the IMO's regulatory requirements, alleviating the air pollution caused by sulfur without having any proven negative effect on seawater.

Table 3: **Validation Test**

This table validates the text-based green innovation measures through several green patent proxies. In Panel A, the dependent variable is the green innovation measure. The independent variables across the six columns are green patent number/share, economic value-weighted green patent number/share, and citation-weighted green patent number/share, respectively. Panel B presents regression analyses of the disaggregated green innovation discussions on the corresponding types of green patent counts. The control variables encompass the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. We consider the year and industry fixed effects. t-statistics based on standard errors clustered by industry are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Aggregate green innovation						
	Green^{n}	**Green**^{s}	**Green**^{n,e}	**Green**^{s,e}	**Green**^{n,c}	**Green**^{s,c}
Patent	0.46***	0.88***	0.25***	0.93***	0.24**	0.61***
	(3.68)	(2.77)	(3.07)	(3.06)	(2.47)	(3.23)
Observations	12,760	12,760	10,447	10,447	10,447	10,447
R-squared	0.23	0.28	0.23	0.28	0.22	0.25
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Disaggregate green innovation						
	Energy	**Prod**	**Transp**	**Build**	**Adapt**	**Envir**
Patent	0.46**	0.03***	0.40***	0.17***	0.03*	0.12***
	(2.17)	(3.27)	(3.07)	(3.42)	(1.91)	(3.77)
Observations	12,760	12,760	12,760	12,760	12,760	12,760
R-squared	0.23	0.05	0.18	0.10	0.04	0.08
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: **Univariate Portfolio Sorting**

This table presents the raw and adjusted returns for five portfolios sorted on greenness relative to their industry peers, for which we use the Fama-French 49 industry classifications. We rebalance portfolios at the end of every June on the basis of the green innovation measure of year $t-1$ and track the performance of the five portfolios from July of year t to June of year $t+1$. Portfolio returns are equal-weighted (ew) or value-weighted by firms' market capitalization (vw). Panel A shows the average excess returns for the five portfolios as well as the High-minus-Low (HML) portfolios. We perform time-series regressions of greenness-sorted portfolios' excess returns on the Fama-French three factors plus Carhart momentum factor in Panel B, on the Fama-French five factors in Panel C, on the Hou-Xue-Zhang q-factors in Panel D. The sample period spans from July 2007 to December 2019. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		(1) **Low**	(2) **2**	(3) **3**	(4) **4**	(5) **High**	(6) **HML**
Panel A: Excess returns							
Raw	vw	1.03**	0.90***	0.45	0.70*	0.57	-0.46***
		(2.38)	(2.63)	(0.94)	(1.74)	(1.15)	(-2.88)
	ew	0.85*	0.68	0.54	0.59	0.09	-0.77***
		(1.77)	(1.19)	(0.97)	(1.24)	(0.16)	(-5.51)
Panel B: Fama-French three factors + Momentum factor							
α	vw	0.22	0.17	-0.33**	-0.08	-0.30*	-0.52***
		(1.42)	(1.09)	(-2.06)	(-0.46)	(-1.67)	(-2.67)
	ew	0.03	-0.12	-0.28**	-0.17	-0.74***	-0.77***
		(0.22)	(-0.82)	(-1.99)	(-1.01)	(-3.68)	(-4.76)
Panel C: Fama-French five factors							
α	vw	0.16	-0.01	-0.43**	-0.12	-0.37*	-0.53**
		(0.95)	(-0.06)	(-2.23)	(-0.68)	(-1.68)	(-2.50)
	ew	-0.02	-0.16	-0.33*	-0.17	-0.70***	-0.67***
		(-0.15)	(-0.91)	(-1.92)	(-0.91)	(-3.08)	(-3.81)
Panel D: Hou-Xue-Zhang q factors							
α	vw	0.23	0.12	-0.22	-0.02	-0.24	-0.46**
		(1.42)	(0.75)	(-1.54)	(-0.15)	(-1.53)	(-2.32)
	ew	0.14	-0.05	-0.17	-0.13	-0.59***	-0.73***
		(0.87)	(-0.31)	(-1.01)	(-0.75)	(-2.90)	(-4.11)

Table 5: **Double Portfolio Sorting**

This table presents the excess returns and Fama-French five factors, plus Momentum factor-adjusted returns, for portfolios that are independently two-way sorted based on greenness and other firm characteristics relative to their industry peers, for which we use the Fama-French 49 industry classifications. We rebalance portfolios at the end of every June on the basis of the sorted variables in year $t-1$ and track the performance of the portfolios from July of year t to June of year $t+1$. Portfolio returns are equal-weighted (ew) or value-weighted by firms' market capitalization (vw). The sample starts from July 2007 to December 2019. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		(1)	(2)	(3)	(4)
		Greenness-sorted HML portfolio			
		vw		**ew**	
		Excess return	**FF5+Mom α**	**Excess return**	**FF5+Mom α**
Size	T	-0.44**	-0.50**	-0.43**	-0.42**
		(-2.37)	(-2.16)	(-2.09)	(-2.44)
	B	-0.04	-0.01	-0.87***	-0.74***
		(-0.16)	(-0.05)	(-3.79)	(-2.92)
B/M	T	-0.94***	-0.92**	-0.87***	-0.73***
		(-2.85)	(-2.40)	(-3.74)	(-2.84)
	B	-0.01	-0.05	-0.67***	-0.59**
		(-0.06)	(-0.21)	(-3.15)	(-2.30)
ROA	T	-0.47*	-0.66**	-0.17	-0.19
		(-1.95)	(-2.32)	(-1.02)	(-1.10)
	B	-0.33	-0.25	-0.99***	-0.82***
		(-1.16)	(-0.81)	(-3.76)	(-2.62)
Investment	T	-0.60**	-0.51*	-0.78***	-0.76***
		(-2.46)	(-1.73)	(-3.83)	(-2.95)
	B	-0.25	-0.39	-0.67***	-0.50**
		(-0.91)	(-1.26)	(-4.00)	(-2.49)
WW	T	0.25	0.42	-0.62**	-0.45
		(0.80)	(1.24)	(-2.41)	(-1.52)
	B	-0.57***	-0.64***	-0.44**	-0.41**
		(-3.37)	(-2.83)	(-2.07)	(-2.18)
Leverage	T	-0.50*	-0.50	-1.02***	-0.92***
		(-1.95)	(-1.42)	(-4.78)	(-3.82)
	B	-0.48**	-0.59***	-0.47***	-0.40**
		(-2.15)	(-2.84)	(-2.69)	(-1.98)
Tangibility	T	-0.29	-0.31	-0.61***	-0.48**
		(-1.38)	(-1.26)	(-3.27)	(-2.06)
	B	-0.61*	-0.78**	-0.89***	-0.83***
		(-1.74)	(-2.05)	(-4.27)	(-3.30)

Table 6: **Fama-MacBeth Regressions**

This table reports Fama-MacBeth regressions of individual stock returns on green innovation measures as well as proportions of different categories of green innovation discussions related to energy use, production, transportation, building, adaptation, and environment management. We conduct cross-sectional regressions of monthly returns from July of year t to June of year $t+1$ on the greenness of year $t-1$. Control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. All variables are normalized to a zero mean and one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample starts from July 2007 to December 2019. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)
	Excess return				
Greenness	-0.16***	-0.16***	-0.09**		
	(-3.29)	(-3.91)	(-2.34)		
Energy				-0.11***	-0.07**
				(-2.94)	(-1.98)
Transportation				0.03	0.05
				(1.00)	(1.37)
Production				-0.04	-0.01
				(-1.46)	(-0.60)
Environment				-0.06*	-0.03
				(-1.79)	(-0.95)
Adaptation				-0.05*	-0.02
				(-1.73)	(-0.70)
Building				-0.02	-0.01
				(-0.98)	(-0.36)
Size			0.15		0.15
			(1.05)		(1.01)
B/M			0.04		0.04
			(0.54)		(0.54)
ROA			0.38***		0.39***
			(3.46)		(3.49)
Investment			-0.12***		-0.12**
			(-2.64)		(-2.58)
WW			0.17		0.17
			(0.78)		(0.74)
Leverage			0.01		0.01
			(0.08)		(0.07)
Tangibility			-0.16**		-0.16**
			(-2.11)		(-2.11)
Observations	380,058	374,361	319,681	374,361	319,681
R-squared	0.00	0.09	0.11	0.09	0.12
Number of groups	138	138	138	138	138
Industry FE	No	Yes	Yes	Yes	Yes

Table 7: **Unexpected Attention Factor**

This table presents asset pricing factor tests for the sample including observations after 2020. The dependent variable is the value-weighted return of High-minus-Low portfolios sorted on greenness. The analysis considers the Fama-French five factors and the momentum factor, with the addition of unexpected attention as an extra factor. Unexpected attention is derived from the prediction errors of AR(1) models applied to the time-series green innovation attention index. Panel A includes the sample ranging from April 2020 to December 2021, with the exclusion of the first three months of 2020 to minimize the impact of COVID-19 on earnings call discussions. Panel B considers the entire sample, spanning from July 2007 to December 2021. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) **HML**	(2) **HML**	(3) **L**	(4) **H**	(5) **HML**
Panel A: 2020-2021					
Unexpected attention			-0.07	0.39***	0.47***
			(-0.96)	(5.91)	(4.79)
MKT		0.76**	0.70***	1.53***	0.83***
		(2.69)	(7.12)	(9.02)	(3.64)
SMB		-0.05	0.15	-0.00	-0.15
		(-0.10)	(0.56)	(-0.01)	(-0.19)
HML_{value}		-0.66**	-0.13	-0.90***	-0.77***
		(-2.86)	(-0.97)	(-6.55)	(-3.32)
RMW		-0.89	0.28	-0.40	-0.68
		(-1.65)	(1.12)	(-0.73)	(-0.89)
CMA		1.18**	0.03	1.43***	1.40***
		(2.88)	(0.20)	(4.81)	(3.39)
Mom		0.02	-0.12	-0.26	-0.15
		(0.06)	(-1.30)	(-1.35)	(-0.54)
α	1.59*	0.31	0.45	-0.24	-0.69
	(1.84)	(0.17)	(0.34)	(-0.15)	(-0.24)
Observations	21	21	21	21	21
Panel B: 2007-2021					
Unexpected attention			-0.04	0.17**	0.21***
			(-0.69)	(2.54)	(2.68)
MKT		0.13	1.05***	1.17***	0.12
		(1.19)	(19.59)	(14.50)	(1.12)
SMB		0.22*	-0.01	0.21*	0.21*
		(1.67)	(-0.14)	(1.89)	(1.75)
HML_{value}		-0.40**	-0.01	-0.43**	-0.42**
		(-1.99)	(-0.22)	(-2.40)	(-2.02)
RMW		-0.09	0.11	0.07	-0.04
		(-0.59)	(1.26)	(0.66)	(-0.27)
CMA		0.30	0.04	0.38	0.34
		(0.89)	(0.40)	(1.29)	(1.00)
Mom		0.04	0.01	0.04	0.03
		(0.73)	(0.17)	(0.71)	(0.44)
α	-0.17	-0.38*	0.15	-0.28	-0.43**
	(-0.67)	(-1.97)	(0.88)	(-1.47)	(-2.20)
Observations	174	174	174	174	174

Table 8: **Future Environmental Performances**

This table presents the regression results of firms' environmental performance on various categories of green innovation discussions in the current and previous three years. The dependent variable in Panel A is the Scope 1 carbon emission level, while Panel B focuses on the number of negative climate incidents. Column (1) uses the overall green innovation discussions as the independent variables, and columns (2)-(7) employ one of the six disaggregated innovation types. Control variables include the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. We consider year and firm fixed effects. t-statistics based on standard errors clustered by firm are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) **Green**	(2) **Energy**	(3) **Transp**	(4) **Prod**	(5) **Build**	(6) **Adapt**	(7) **Envir**
Panel A: Scope 1 carbon emission level							
$\text{Innovation}_{i,t}$	-0.28***	-0.25**	-0.10	-0.07*	-0.07**	-0.15**	0.12*
	(-2.72)	(-2.45)	(-1.28)	(-1.76)	(-2.18)	(-2.25)	(1.69)
$\text{Innovation}_{i,t-1}$	-0.27***	-0.28***	-0.06	-0.05	-0.14***	-0.13**	0.09
	(-2.84)	(-2.77)	(-1.03)	(-1.48)	(-2.83)	(-2.10)	(1.49)
$\text{Innovation}_{i,t-2}$	-0.09	-0.16*	-0.05	-0.02	-0.11**	-0.07	0.10*
	(-1.00)	(-1.75)	(-0.57)	(-0.66)	(-2.23)	(-1.40)	(1.79)
$\text{Innovation}_{i,t-3}$	-0.21*	-0.24**	-0.09	-0.06	-0.06	-0.04	0.01
	(-1.76)	(-2.25)	(-1.09)	(-1.57)	(-1.07)	(-0.97)	(0.15)
Observations	16,790	16,790	16,790	16,790	16,790	16,790	16,790
R-squared	0.88	0.88	0.87	0.87	0.87	0.87	0.87
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Number of negative climate incidents							
$\text{Innovation}_{i,t}$	0.00	-0.02*	0.01	0.00	-0.00	0.00	0.02*
	(0.23)	(-1.80)	(0.30)	(0.09)	(-0.08)	(0.25)	(1.84)
$\text{Innovation}_{i,t-1}$	-0.04***	-0.01	-0.02	-0.04***	-0.03**	-0.04***	0.01
	(-2.60)	(-1.07)	(-1.20)	(-3.13)	(-2.50)	(-3.42)	(0.98)
$\text{Innovation}_{i,t-2}$	-0.02	-0.01	-0.03	-0.00	-0.02*	-0.02	0.02
	(-0.80)	(-0.40)	(-1.48)	(-0.09)	(-1.80)	(-1.38)	(1.32)
$\text{Innovation}_{i,t-3}$	0.01	0.01	-0.02	0.01	-0.00	0.00	0.01
	(0.37)	(0.41)	(-1.09)	(0.85)	(-0.41)	(0.11)	(1.01)
Observations	2,177	2,177	2,177	2,177	2,177	2,177	2,177
R-squared	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

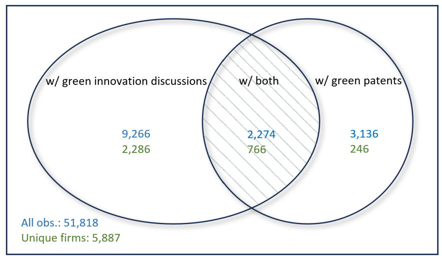
Table 9: **Event Study**

This table regresses the cumulative abnormal returns (CARs) around four events on the greenness. The dependent variables are cumulative market-adjusted abnormal returns over a one-day/five-day/ten-day window from the event date. We conduct event studies for Trump's election victory on November 8th, 2016 in Panel A, Biden's election victory on December 14th, 2020 in Panel B, the Russia-Ukraine war on February 24th, 2022 in Panel C, and the Inflation Reduction Act (IRA) announcement on July 28th, 2022 in Panel D. Control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. The first three columns are based on samples with earnings calls while the second three columns contain observations with non-zero green innovation discussions. All variables are normalized to a zero mean and one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The standard errors are clustered by industry and t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	w/ earnings calls			**w/ green innovation**		
	CAR[0,1]	**CAR[0,5]**	**CAR[0,10]**	**CAR[0,1]**	**CAR[0,5]**	**CAR[0,10]**
Panel A: Trump's election						
Greenness	-0.004***	-0.008***	-0.008***	-0.004**	-0.009***	-0.011***
	(-3.839)	(-4.027)	(-3.248)	(-2.158)	(-3.413)	(-4.328)
Observations	2,418	2,418	2,418	508	508	508
Panel B: Biden's election						
Greenness	0.003**	0.009***	0.015***	0.003**	0.010***	0.015***
	(2.337)	(4.254)	(7.161)	(2.093)	(4.630)	(5.412)
Observations	2,601	2,601	2,601	614	614	614
Panel C: Russia-Ukraine war						
Greenness	0.004***	0.012***	0.024***	0.004***	0.011***	0.021***
	(3.412)	(6.843)	(7.084)	(2.742)	(4.854)	(5.255)
Observations	2,549	2,549	2,549	821	821	821
Panel D: IRA announcement						
Greenness	0.005***	0.007***	0.010***	0.004***	0.005**	0.008**
	(4.337)	(4.325)	(3.262)	(3.535)	(2.578)	(2.155)
Observations	2,494	2,494	2,494	809	809	809
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: **Comparison with Green Patents**

This table compares observations from three groups: one with positive values for both green innovation discussions and green patent shares, and two with positive values for one of the two measures. The comparison focuses on the interpretation, sample coverage, and empirical implications. The figure in the first row portrays Venn diagrams for the two measures. The numbers of observations are represented by blue digits, while the green digits illustrate the numbers of distinct firms. There are 2,286 (246) firms that have at least one observation of positive green discussions (green patents) but have never possessed green patents (engaged in green innovation discussions). Meanwhile, 766 firms have recorded at least one observation with positive scores for both measures within our sample.

<table>
<tr><th></th><th>Only w/ green innovation discussions</th><th>w/ both</th><th>Only w/ green patents</th></tr>
<tr><td>Sample coverage</td><td colspan="3">
</td></tr>
<tr><td>Interpretation</td><td>1. Nonpatentable innovative activities including implementation of novel strategies based on existing technology in new contexts or at larger scales or faster speeds.
2. Long-term green technology dedication before the patents get granted.</td><td>Green innovation supported by green patents.</td><td>Inventions that are not primarily targeted at climate mitigation and may not substantially impact firms' green innovation strategies.</td></tr>
<tr><td>Negative premium</td><td>Yes</td><td>Yes</td><td>No</td></tr>
<tr><td>Environment improvement</td><td>Yes</td><td>Yes</td><td>No</td></tr>
<tr><td>Hedging against events</td><td>Yes</td><td>Yes</td><td>No</td></tr>
</table>

Internet Appendix

In this Internet Appendix, we provide supplementary material for our study. Section IA.1 contains additional figures and tables for empirical analysis. Section IA.2 presents a detailed description of our green innovation classifier.

IA.1 Additional figures and tables for empirical analysis

Figure IA1: **Time-Series Variation of Disaggregated Greenness**
This figure depicts the mean value of disaggregated green innovation measures across firms over time.

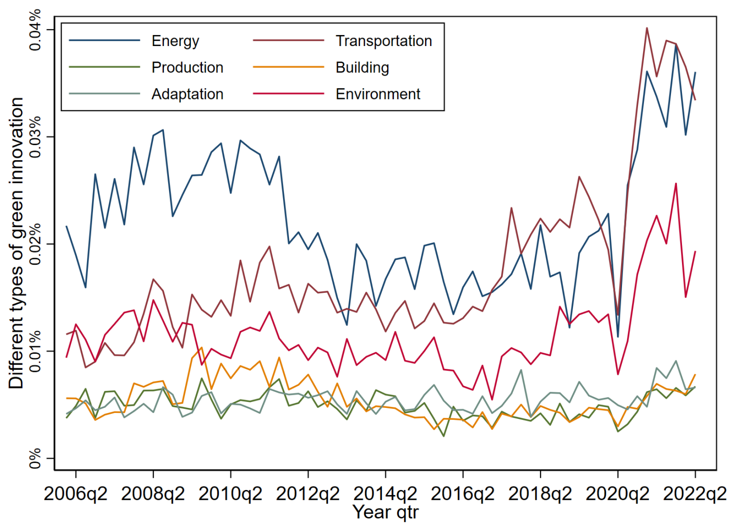


Figure IA2: **Time-Series Variation of Green Patent Shares**

This figure displays the average of overall green patent shares (left axis) as well as disaggregate shares (right axis) in different areas.

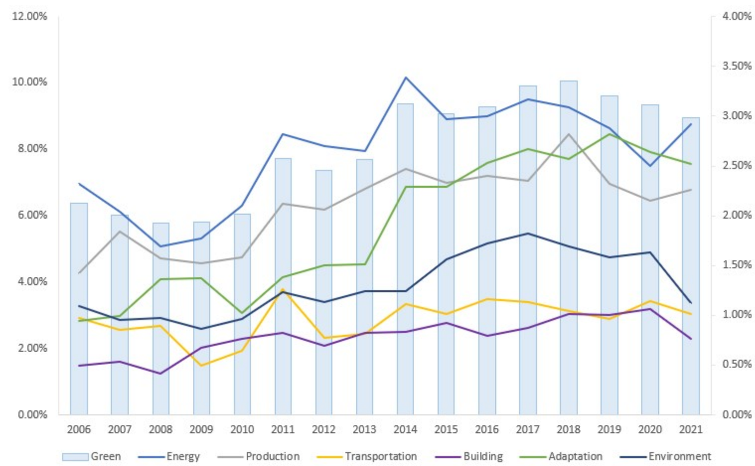
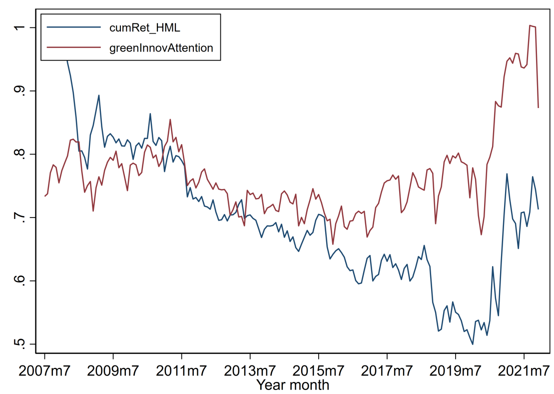
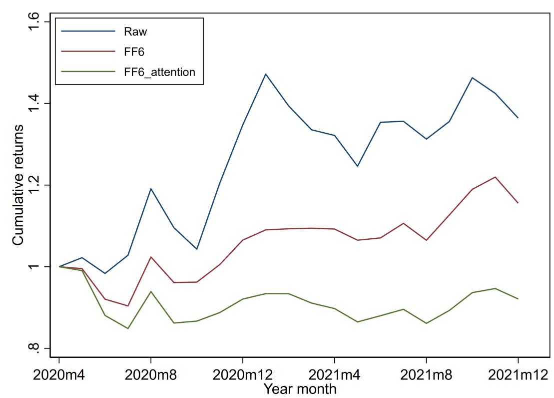


Figure IA3: **Robustness: Unexpected Green Innovation Attention**

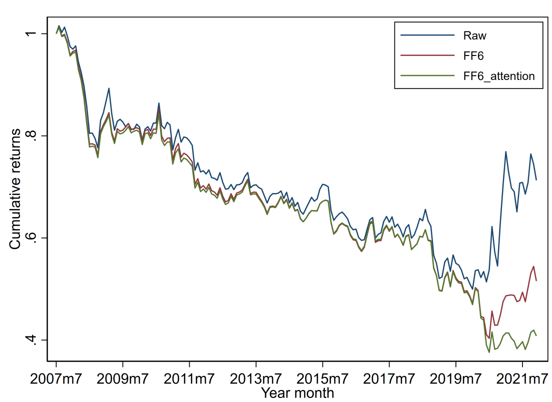
This figure replicates the analysis presented in Figure 3, with one key variation: we deploy the monthly average of green innovation measures as our attention index, in contrast to the prior usage of a three-month moving average. Panel (a) compares the time series of the green innovation attention index with the cumulative returns of the High-minus-Low portfolios, sorted based on greenness. Panel (b) illustrates the cumulative raw returns, returns adjusted for Fama-French five factors and momentum factor, and returns further adjusted for unexpected attention to green innovation for High-minus-Low portfolios, from April 2020 to December 2021. Panel (c) extends the timeline and shows the cumulative returns of High-minus-Low portfolios for the entire period spanning from July 2007 to December 2021.



(a)



(b)



(c)

Figure IA4: **Event Study for Disaggregate Greenness**

This figure illustrates the trajectory of coefficients for disaggregate green innovation measures along with 90% confidence intervals derived from cross-sectional regression analysis.

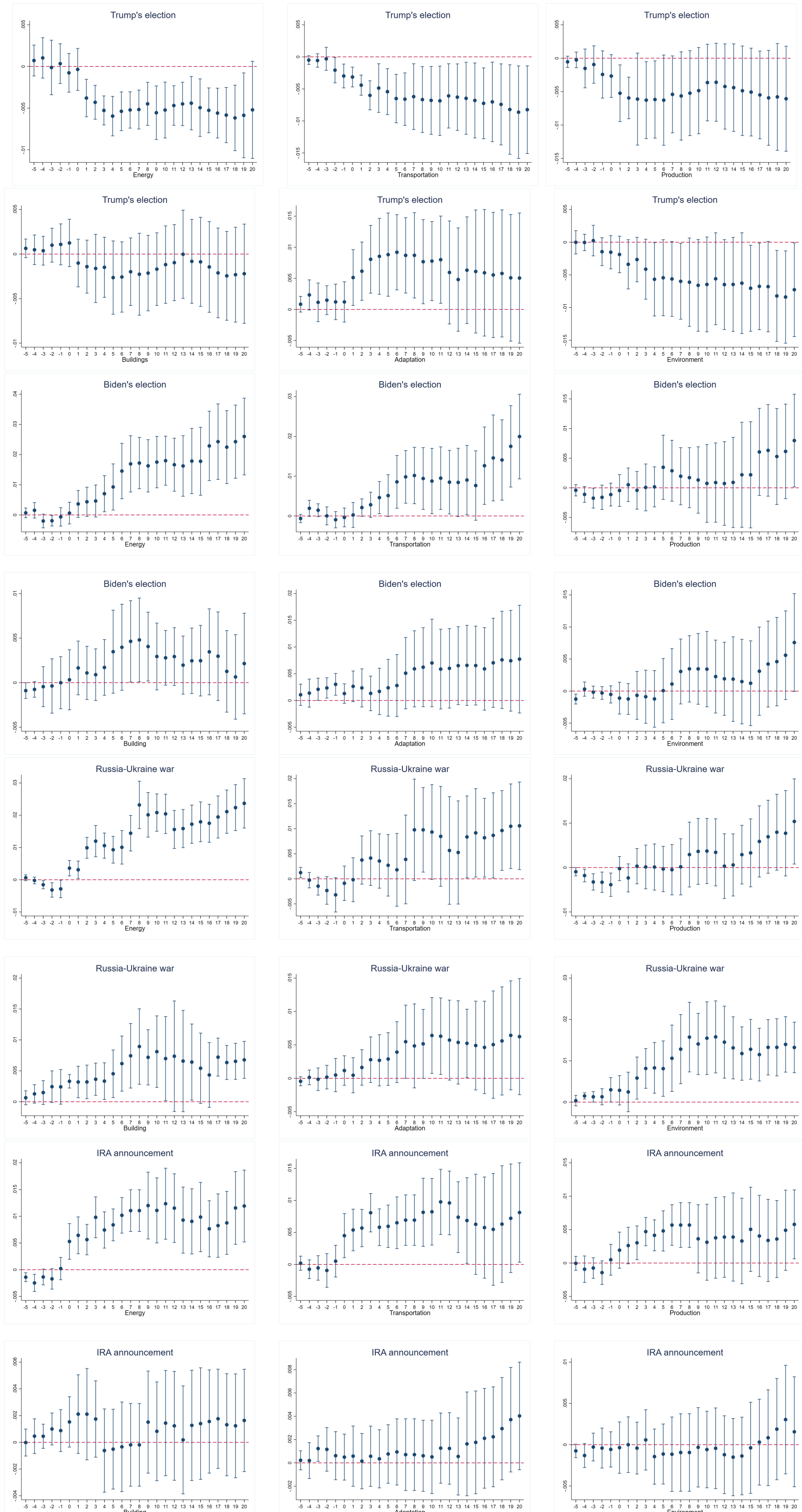


Table IA1: **Strategy to Classify Green Patent Categories**

This table lists our methodology for classifying categories of green patents, primarily based on strategies from the OECD and Lanzi et al. (2011).

Patent categories	IPC code	CPC code
Energy use	Lanzi et al. (2011)	Y02E
Transportation		Y02T
Production		Y02P, Y02D
Building		Y02B
Adaptation	OECD-ENV-TECH-2	Y02A
Environmental management	OECD-ENV-TECH-1	Y02W, Y02C

Table IA2: **Industry Distribution**

This table presents average green innovation measures across firms for the top-15 and bottom-15 industries. The highest five values for disaggregate green innovation are emphasized in bold.

FF49	Green	Energy	Trans	Prod	Build	Adapt	Envir
Panel A: Top-15 industries							
Electrical Equipment	0.731%	**0.401%**	**0.193%**	**0.019%**	**0.077%**	0.010%	**0.032%**
Automobiles	0.336%	0.037%	**0.256%**	0.005%	0.003%	0.002%	**0.033%**
Chemicals	0.260%	**0.066%**	0.029%	**0.035%**	0.008%	**0.020%**	**0.102%**
Utilities	0.241%	**0.125%**	**0.036%**	0.009%	**0.018%**	**0.023%**	0.032%
Fabricated Products	0.222%	0.029%	**0.118%**	0.008%	**0.030%**	0.007%	0.030%
Machinery	0.177%	**0.058%**	0.033%	0.009%	**0.016%**	0.014%	**0.046%**
Electronic Equipment	0.125%	**0.053%**	0.031%	**0.014%**	**0.018%**	0.005%	0.004%
Measuring Equipment	0.117%	0.041%	0.025%	0.013%	0.013%	0.008%	0.017%
Agriculture	0.101%	0.025%	0.008%	**0.019%**	0.000%	**0.041%**	0.008%
Metal Mining	0.096%	0.021%	0.026%	0.005%	0.002%	**0.014%**	0.027%
Shipbuilding	0.095%	0.015%	**0.060%**	0.003%	0.002%	0.005%	0.009%
Construction	0.092%	0.039%	0.017%	0.005%	0.013%	0.009%	0.010%
Construction Materials	0.091%	0.024%	0.010%	0.008%	0.010%	0.013%	0.024%
Coal	0.083%	0.032%	0.024%	0.006%	0.002%	0.003%	0.016%
Steel Works Etc	0.080%	0.029%	0.019%	0.007%	0.002%	0.008%	0.016%
Panel B: Bottom-15 industries							
Computer Software	0.017%	0.002%	0.007%	0.003%	0.001%	0.001%	0.002%
Medical Equipment	0.017%	0.005%	0.001%	0.001%	0.001%	0.005%	0.003%
Trading	0.016%	0.004%	0.003%	0.002%	0.003%	0.002%	0.002%
Pharmaceutical Products	0.015%	0.002%	0.001%	0.002%	0.000%	0.006%	0.005%
Real Estate	0.014%	0.003%	0.003%	0.000%	0.005%	0.003%	0.001%
Personal Services	0.013%	0.002%	0.008%	0.001%	0.001%	0.001%	0.001%
Communication	0.012%	0.002%	0.005%	0.001%	0.000%	0.003%	0.000%
Tobacco Products	0.011%	0.005%	0.002%	0.001%	0.000%	0.001%	0.002%
Restaurants, Hotels, Motels	0.009%	0.002%	0.000%	0.000%	0.002%	0.003%	0.002%
Insurance	0.009%	0.001%	0.002%	0.000%	0.000%	0.003%	0.001%
Apparel	0.008%	0.001%	0.000%	0.000%	0.000%	0.002%	0.003%
Entertainment	0.007%	0.000%	0.001%	0.000%	0.001%	0.004%	0.001%
Printing and Publishing	0.006%	0.002%	0.000%	0.000%	0.001%	0.001%	0.001%
Banking	0.003%	0.001%	0.001%	0.000%	0.000%	0.001%	0.001%
Healthcare	0.003%	0.000%	0.000%	0.000%	0.000%	0.001%	0.001%

Table IA3: **Firm with Top Green Innovation Measure**

This table presents the mean value of green innovation measures for the top 20 firms.

Company	FF49	obs	Green	Energy	Trans	Prod	Build	Adapt	Envir
MILLENNIUM CELL INC	22 ElcEq	6	5.11%	4.00%	0.82%	0.06%	0.03%	0.02%	0.17%
NIKOLA CORP	23 Autos	2	4.37%	1.68%	2.50%	0.13%	0.00%	0.07%	0.00%
AEMETIS INC	14 Chems	4	4.35%	1.03%	0.54%	0.77%	0.08%	0.13%	1.81%
HYDROGENICS CORP	22 ElcEq	8	4.02%	2.30%	1.38%	0.23%	0.03%	0.01%	0.07%
FUELCELL ENERGY INC	22 ElcEq	19	4.00%	3.25%	0.24%	0.04%	0.09%	0.02%	0.36%
IDEAL POWER INC	22 ElcEq	4	3.58%	2.40%	0.64%	0.08%	0.36%	0.00%	0.10%
SOLUNA HOLDINGS INC	38 LabEq	6	3.17%	2.68%	0.32%	0.06%	0.00%	0.01%	0.10%
ENERGY CONVERSION DEV	37 Chips	10	3.02%	1.85%	0.80%	0.04%	0.20%	0.04%	0.09%
TECOGEN INC	22 ElcEq	7	2.88%	0.69%	0.72%	0.11%	0.64%	0.13%	0.60%
GEVO INC	14 Chems	11	2.79%	0.56%	0.32%	0.74%	0.01%	0.14%	1.02%
CHINA MING YANG WIND PWR-ADR	21 Mach	6	2.79%	2.68%	0.03%	0.03%	0.00%	0.05%	0.00%
BLOOM ENERGY CORP	22 ElcEq	4	2.79%	2.05%	0.15%	0.10%	0.05%	0.05%	0.39%
BALLARD POWER SYSTEMS INC	22 ElcEq	16	2.73%	1.27%	1.42%	0.01%	0.01%	0.00%	0.02%
WORKHORSE GROUP INC	23 Autos	6	2.58%	0.22%	2.28%	0.00%	0.04%	0.02%	0.02%
ELECTROVAYA INC	22 ElcEq	7	2.50%	0.80%	1.64%	0.00%	0.01%	0.05%	0.00%
QUANTUM FUEL SYS TECH WORLDW	23 Autos	2	2.48%	0.50%	1.89%	0.00%	0.00%	0.00%	0.09%
LIGHTBRIDGE CORP	14 Chems	11	2.46%	1.80%	0.10%	0.03%	0.08%	0.06%	0.40%
MAXWELL TECHNOLOGIES INC	22 ElcEq	17	2.40%	0.89%	1.33%	0.04%	0.05%	0.01%	0.08%
ENSYNC INC	22 ElcEq	4	2.40%	1.54%	0.17%	0.22%	0.37%	0.00%	0.10%
SPIRE CORP	37 Chips	5	2.32%	2.20%	0.00%	0.03%	0.09%	0.00%	0.00%

Table IA4: **Portfolio Characteristics**

This table reports the equal-weighted average of firm characteristics for five greenness-sorted portfolios. *Energy/Transportation/Production/Building/Adaptation/Environment* is the discussion proportion in corresponding areas. logME is the logarithm of market capitalization at the end of December. B/M is the ratio of book equity to market capitalization. ROA is the return on assets and Investment is the annual change in total assets divided by one-year-lagged total assets. Leverage is the summation of current liability and long-term debt scaled by total assets. WW index is a measure of financial constraints.

	Low	2	3	4	High
Greenness	0.060%	0.106%	0.172%	0.317%	0.869%
Energy	0.013%	0.025%	0.046%	0.103%	0.332%
Transportation	0.017%	0.028%	0.044%	0.079%	0.216%
Production	0.006%	0.011%	0.014%	0.027%	0.058%
Building	0.005%	0.009%	0.017%	0.028%	0.064%
Adaptation	0.009%	0.014%	0.021%	0.030%	0.049%
Environment	0.011%	0.018%	0.031%	0.050%	0.150%
logME	14.96	14.48	14.21	13.99	13.52
B/M	0.63	0.68	0.69	0.73	0.73
ROA	0.11	0.09	0.08	0.07	0.02
Investment	0.10	0.10	0.10	0.12	0.12
Leverage	0.27	0.27	0.26	0.25	0.24
Tangibility	0.33	0.34	0.35	0.35	0.35
WW index	-0.37	-0.35	-0.33	-0.33	-0.30
Num of firms	119	107	106	107	93

Table IA5: **Green Innovation and Institutional Ownership**

This table reports panel regressions of institutional ownership on green innovation measures. The first three columns present results for the sample from 2008 to 2020, while the second three columns include observations after 2019. We consider the percentage of institutional ownership, mutual fund ownership, and equity mutual fund ownership as our dependent variables. Control variables include the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors clustered by industry are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
		All			2019-2020	
	IOR	MFOR	EMFOR	IOR	MFOR	EMFOR
Greenness	-0.20	1.11	1.44	1.23**	1.08***	0.31***
	(-1.23)	(0.10)	(0.50)	(2.01)	(2.82)	(2.86)
Size	14.21***	131.56***	38.78***	-6.33*	19.95***	3.50***
	(12.55)	(3.76)	(4.41)	(-1.81)	(2.88)	(2.78)
ROA	1.20**	33.50**	7.12**	5.12***	2.36	0.24
	(2.04)	(2.49)	(2.25)	(4.93)	(0.56)	(0.51)
Leverage	-0.95	-8.13*	-3.68***	-1.14	0.86	-0.02
	(-1.50)	(-1.84)	(-3.28)	(-0.82)	(0.55)	(-0.05)
Investment	0.32	-0.28	2.07	0.25	-1.12**	-0.19
	(1.42)	(-0.05)	(1.20)	(0.35)	(-2.20)	(-1.54)
Tangibility	-1.08	17.01	9.73	0.21	-1.37	-0.06
	(-1.25)	(0.49)	(1.36)	(0.08)	(-0.46)	(-0.11)
Sales growth	-0.12	-2.95	0.89	-0.95***	-0.20	0.00
	(-1.01)	(-0.69)	(0.97)	(-3.43)	(-0.39)	(0.04)
Employ growth	-0.06	-1.65	-0.50	1.03**	-0.54	-0.10
	(-0.38)	(-0.73)	(-0.64)	(2.47)	(-1.62)	(-1.11)
Observations	25,922	25,922	25,922	4,268	4,268	4,268
R-squared	0.80	0.30	0.29	0.89	0.75	0.91
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA6: **Robustness: Fama-MacBeth Regressions with Carbon Intensity**

This table reports Fama-MacBeth regressions of individual stock returns on greenness as well as diverse aspects related to energy use, production, transportation, building, adaptation, and environment management. We add Scope 1 carbon emission intensity as a control variable. Columns (1)-(2) consider observations lacking carbon emission data, while columns (3)-(7) incorporate observations that include this data. We conduct cross-sectional regressions of monthly returns from July of year t to June of year $t+1$ on the greenness of year $t-1$. Other control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. All control variables are normalized to a zero mean and one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2007 to December 2019. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Excess return						
	w/o emission data		w/ emission data				
Greenness	-0.08**			-0.08*	-0.08*		
	(-2.08)			(-1.81)	(-1.75)		
Carbon intensity			0.01		0.02		0.02
			(0.30)		(0.53)		(0.60)
Energy		-0.11**				-0.02	-0.02
		(-2.06)				(-0.68)	(-0.65)
Transportation		-0.01				0.02	0.01
		(-0.25)				(0.52)	(0.49)
Production		0.06				-0.02	-0.02
		(1.59)				(-0.80)	(-0.87)
Environment		0.00				-0.05**	-0.05**
		(0.07)				(-2.28)	(-2.17)
Adaptation		-0.03				-0.04	-0.04
		(-1.34)				(-0.95)	(-0.96)
Building		-0.01				0.01	0.01
		(-0.40)				(0.32)	(0.30)
Observations	185,185	185,185	164,102	164,102	164,102	164,102	164,102
R-squared	0.12	0.12	0.22	0.22	0.22	0.22	0.22
Number of groups	138	138	138	138	138	138	138
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA7: **Robustness: Future Environmental Performance**

This table presents the regression results of firms' environmental performance on green innovation discussions in the current and previous three years. In Panel A, the dependent variables are Scope 1 carbon intensity, Scope 2 carbon intensity, and Scope 2 carbon emission level in columns (1) to (3). Panel B focus on the Severity, Reach, and Novelty of firms' negative climate incidents. Control variables include the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. We consider year and firm fixed effects. t-statistics based on standard errors clustered by the firm are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Carbon emission			
	$CarbonIntensity^{scope1}$	$CarbonIntensity^{scope2}$	$CarbonEmission^{scope2}$
$Greenness_{i,t}$	-0.23**	0.00	-0.17**
	(-2.46)	(0.06)	(-2.04)
$Greenness_{i,t-1}$	-0.17*	0.07	-0.01
	(-1.67)	(1.44)	(-0.20)
$Greenness_{i,t-2}$	-0.15	0.03	0.09
	(-1.62)	(0.49)	(1.34)
$Greenness_{i,t-3}$	-0.32***	0.01	0.09
	(-2.97)	(0.15)	(1.28)
Observations	16,790	16,790	16,790
R-squared	0.91	0.82	0.83
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Panel B: Negative climate incidents			
	Severity	Reach	Novelty
$Greenness_{i,t}$	0.02	-0.01	0.01
	(1.05)	(-0.56)	(0.54)
$Greenness_{i,t-1}$	-0.05**	-0.04**	-0.03*
	(-2.49)	(-2.05)	(-1.66)
$Greenness_{i,t-2}$	-0.01	-0.03	-0.02
	(-0.27)	(-1.51)	(-0.76)
$Greenness_{i,t-3}$	-0.01	0.00	0.01
	(-0.34)	(0.17)	(0.30)
Observations	2,177	2,177	2,177
R-squared	0.67	0.67	0.61
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table IA8: **Robustness: Event Study with Carbon Intensity**

This table regresses the cumulative abnormal returns around four events on the green innovation measures, considering Scope 1 carbon emission intensity as a control variable. The dependent variables are cumulative market-adjusted abnormal returns over a one-day/five-day/ten-day window from the event date. We conduct event studies for Trump's election on November 8th, 2016 in Panel A, Biden's election on December 14th, 2020 in Panel B, the Russia-Ukraine war on February 24th, 2022 in Panel C, and the IRA announcement on July 28th, 2022 in Panel D. Other control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. The first three columns are based on samples with earnings calls while the second three columns contain observations with non-zero green innovation discussions. All control variables are normalized to a zero mean and a one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The standard errors are clustered by industry and t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	w/ earnings calls			w/ green innovation		
	CAR[0,1]	CAR[0,5]	CAR[0,10]	CAR[0,1]	CAR[0,5]	CAR[0,10]
Panel A: Trump's election						
Greenness	-0.003*	-0.009**	-0.007*	-0.002	-0.008*	-0.006
	(-1.696)	(-2.638)	(-1.994)	(-1.116)	(-1.840)	(-1.195)
Carbon intensity	-0.002	-0.002	-0.004	-0.001	-0.002	-0.005
	(-1.105)	(-0.473)	(-0.805)	(-0.697)	(-0.685)	(-1.115)
Observations	1,696	1,696	1,696	376	376	376
Panel B: Biden's election						
Greenness	0.003***	0.010***	0.015***	0.003***	0.011***	0.016***
	(4.292)	(4.359)	(4.500)	(3.142)	(4.181)	(4.261)
Carbon intensity	-0.001	-0.004***	-0.003*	-0.001**	-0.003	-0.003
	(-1.012)	(-2.795)	(-1.868)	(-2.067)	(-1.636)	(-1.026)
Observations	2,243	2,243	2,243	545	545	545
Panel C: Russia-Ukraine war						
Greenness	0.003*	0.010***	0.023***	0.003*	0.011***	0.022***
	(1.777)	(4.150)	(5.064)	(1.863)	(3.649)	(3.731)
Carbon intensity	0.002	0.003	0.004	0.000	-0.001	-0.001
	(1.184)	(0.627)	(0.901)	(0.242)	(-0.180)	(-0.154)
Observations	2,052	2,052	2,052	666	666	666
Panel D: IRA announcement						
Greenness	0.006***	0.008***	0.009**	0.004***	0.005*	0.008
	(4.111)	(3.134)	(2.359)	(3.515)	(1.749)	(1.662)
Carbon intensity	-0.001	-0.000	-0.000	-0.002	-0.001	-0.001
	(-0.387)	(-0.094)	(-0.071)	(-0.573)	(-0.167)	(-0.290)
Observations	2,011	2,011	2,011	656	656	656

Table IA9: **Robustness: Unexpected Attention Factor - MCCC Index**

This table presents asset pricing factor tests for the sample from April 2020 to December 2021. The dependent variable is the value-weighted return of High-minus-Low portfolios sorted on greenness. The analysis considers the Fama-French five factors and the momentum factor, with the addition of unexpected attention as an extra factor. Unexpected attention is derived from the prediction errors of AR(1) models applied to the MCCC index from Ardia et al. (2022). t-statistics based on standard errors using the Newey-West correction are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) **HML**	(2) **HML**	(3) **L**	(4) **H**	(5) **HML**
UMC			-0.08*	0.10*	0.18**
			(-1.97)	(2.04)	(2.83)
MKT		0.76**	0.58***	1.66***	1.08**
		(2.69)	(4.21)	(4.27)	(2.21)
SMB		-0.05	-0.15	0.45	0.60
		(-0.10)	(-0.39)	(0.76)	(0.67)
HML_{value}		-0.66**	-0.05	-0.95***	-0.90***
		(-2.86)	(-0.33)	(-4.44)	(-3.40)
RMW		-0.89	0.19	-0.41	-0.60
		(-1.65)	(0.59)	(-0.62)	(-0.65)
CMA		1.18**	-0.05	1.40**	1.46**
		(2.88)	(-0.20)	(2.99)	(2.27)
MOM		0.02	-0.35*	0.15	0.50
		(0.06)	(-1.79)	(0.40)	(0.95)
α	1.59*	0.31	1.24	-0.69	-1.93
	(1.84)	(0.17)	(0.94)	(-0.40)	(-0.67)
Observations	21	21	21	21	21

Table IA10: **Sample Formation for Green Patents**

This table reports the formation of the patent sample. Columns (1)-(4) list the count of patents and columns(5)-(6) shows the number of firm-year observations with patents for which corresponding financial data is available from Compustat.

	(1)	(2)	(3)	(4)	(5)	(6)
	# patents		# patents by US-listed firms		# firm-year obs	
USTPO patents	8,169,776					
Utilitiy patents	7,403,434					
Granted after 2006	4,367,304		1,582,690		22,693	
Green patents	405,227		131,486		7,756	
Energy		157,757		41,664		3,344
Production		117,673		45,015		4,505
Transportation		87,447		35,977		1,643
Environment		64,495		19,568		1,972
Adaptation		40,289		10,172		2,448
Building		41,323		10,309		1,943

Table IA11: **Industry Distribution for Green Patents**

This table presents firms' green patent shares for the top-15 and bottom-15 industries. The five highest values for disaggregate green patent shares are highlighted in bold.

FF49	obs	Green	Energy	Prod	Transport	Build	Adapt	Envir
Panel A: Top-15 industries								
31 Utilities	196	38.77%	**22.38%**	4.95%	**3.75%**	**8.59%**	**4.75%**	**10.59%**
22 Elect Equipment	503	33.98%	**26.46%**	**5.96%**	2.84%	**5.97%**	0.30%	1.51%
28 Mines	71	29.58%	2.49%	**20.04%**	0.00%	**5.40%**	2.82%	3.10%
23 Automobiles	594	19.73%	5.39%	0.75%	**11.77%**	0.41%	0.97%	**7.43%**
24 Aircraft	200	19.48%	**6.82%**	2.15%	**11.41%**	0.93%	1.66%	2.06%
16 Textiles	39	15.66%	0.28%	**12.25%**	0.00%	0.00%	1.50%	**13.89%**
14 Chemicals	672	15.65%	5.68%	**5.53%**	1.67%	0.19%	1.78%	**4.64%**
18 Construction	54	14.21%	**11.42%**	2.19%	0.00%	0.40%	0.77%	4.01%
21 Machinery	1156	13.76%	5.26%	3.36%	2.04%	1.22%	0.94%	4.34%
30 Oil	573	13.14%	6.47%	**6.65%**	0.86%	0.36%	0.64%	2.83%
19 Steel	185	11.20%	2.73%	4.66%	1.07%	0.97%	1.48%	2.70%
44 Meals	35	11.05%	0.00%	0.00%	0.00%	1.72%	2.86%	**6.48%**
17 Constr Materials	418	9.74%	2.90%	3.09%	1.55%	0.56%	1.17%	3.58%
33 Personal Services	43	9.72%	**8.32%**	0.26%	3.65%	1.00%	**4.65%**	0.00%
25 Ships	55	9.62%	0.15%	0.05%	**9.49%**	0.00%	0.00%	0.08%
Panel B: Bottom-15 industries								
3 Candy & Soda	19	3.63%	0.42%	1.92%	0.00%	0.31%	0.56%	0.59%
35 Computers	851	3.27%	0.22%	2.36%	0.05%	0.70%	0.03%	0.18%
2 Food Products	187	3.09%	0.69%	1.55%	0.03%	0.00%	0.55%	0.96%
12 Medical Equipment	1624	2.61%	0.41%	0.51%	0.17%	0.07%	1.35%	0.46%
40 Shipping Containers	116	2.19%	0.93%	0.20%	0.03%	0.00%	0.61%	0.54%
36 Computer Software	2378	2.06%	0.51%	1.14%	0.05%	0.20%	0.12%	0.27%
11 Healthcare	166	2.05%	0.59%	1.40%	0.01%	0.00%	0.40%	0.19%
15 Rubber	118	1.74%	0.24%	0.52%	0.00%	0.00%	0.69%	1.09%
10 Apparel	138	1.72%	0.01%	0.93%	0.00%	0.36%	0.51%	0.09%
7 Entertainment	81	1.61%	0.00%	0.13%	0.00%	0.25%	1.23%	0.00%
45 Banking	273	1.42%	0.37%	0.31%	0.00%	0.15%	0.58%	0.00%
4 Beer & Liquor	72	1.41%	0.13%	0.21%	0.00%	0.00%	0.04%	1.10%
6 Recreation	213	1.01%	0.34%	0.40%	0.12%	0.07%	0.04%	0.12%
8 Books	92	0.78%	0.00%	0.69%	0.00%	0.00%	0.00%	0.09%
47 Real Estate	53	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table IA12: **Firm with Top Green Patent Numbers**

This table presents the mean value of green patent numbers for the top 20 firms.

Company	FF49	obs	Green	Energy	Prod	Trans	Build	Adapt	Envir
TOYOTA MOTOR CORP	23 Autos	16	690	260	76	458	9	16	198
UNITED TECHNOLOGIES CORP	24 Aero	16	471	259	21	239	15	89	14
FORD MOTOR CO	23 Autos	16	427	62	11	332	7	17	198
GENERAL MOTORS CO	23 Autos	16	339	115	24	215	2	14	108
INTEL CORP	37 Chips	16	263	11	248	1	13	0	1
HONDA MOTOR CO LTD	23 Autos	16	250	112	17	138	4	5	57
PANASONIC CORP	22 ElcEq	8	239	153	94	27	31	2	8
INTL BUSINESS MACHINES CORP	36 Softw	16	235	56	169	6	18	11	7
ELECTRONIC DATA SYSTEMS CORP	36 Softw	2	170	45	12	108	2	5	45
BOEING CO	24 Aero	16	164	43	25	104	4	4	5
QUALCOMM INC	37 Chips	16	155	4	142	7	6	1	0
SONY CORP	22 ElcEq	16	134	77	72	10	11	0	1
NISSAN MOTOR CO LTD	23 Autos	4	115	33	11	85	0	4	37
APPLE INC	37 Chips	16	114	17	94	1	12	0	1
CATERPILLAR INC	21 Mach	16	96	12	4	57	0	3	57
DU PONT (E I) DE NEMOURS	14 Chems	11	92	52	17	1	1	27	5
CUMMINS INC	21 Mach	16	88	9	1	60	0	7	68
EXXON MOBIL CORP	30 Oil	16	81	17	53	6	2	3	25
DIRECTV	32 Telcm	9	72	22	6	43	1	1	18
BROADCOM CORP	37 Chips	9	68	1	66	0	2	0	0

Table IA13: **Robustness: Univariate Portfolio Sorting on Green Patents**

This table presents the raw and adjusted returns for five portfolios sorted on green patent share relative to their industry peers, for which we use the Fama-French 49 industry classifications. Panel A reports the excess returns and asset pricing factor tests for equal-weighted green patent shares. Panels B and C show the results for KPSS-weighted and citation-weighted green patent shares respectively. We rebalance portfolios at the end of every June on the basis of the green patent share of year $t-1$ and track the performance of the five portfolios from July of year t to June of year $t+1$. Portfolio returns are equal-weighted (ew) or value-weighted by firms' market capitalization (vw). The sample period ranges from July 2007 to December 2019. t-statistics, based on standard errors using the Newey-West correction for 12 lags, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		(1) **Low**	(2) **2**	(3) **3**	(4) **4**	(5) **High**	(6) **HML**
Panel A: Green patent share							
Raw	vw	0.76**	0.88**	1.09***	0.65	0.12	-0.64*
		(2.08)	(2.52)	(2.65)	(1.56)	(0.20)	(-1.78)
	ew	0.98*	1.17*	0.81	0.48	0.40	-0.58***
		(1.74)	(1.93)	(1.54)	(0.90)	(0.75)	(-3.85)
FF5+Mom α	vw	0.04	0.13	0.22	-0.07	-0.77**	-0.81**
		(0.52)	(0.82)	(1.57)	(-0.46)	(-2.36)	(-2.30)
	ew	0.11	0.29*	-0.01	-0.34*	-0.26	-0.37**
		(1.05)	(1.90)	(-0.08)	(-1.77)	(-1.45)	(-2.28)
Panel B: KPSS-weighted green patent share							
Raw	vw	1.00***	0.89***	1.28***	0.87*	0.59	-0.40*
		(3.53)	(2.70)	(3.47)	(1.79)	(1.49)	(-1.74)
	ew	1.33***	1.30***	1.25**	0.73	0.67	-0.66***
		(2.62)	(2.67)	(2.31)	(1.43)	(1.35)	(-3.47)
FF5+Mom α	vw	0.16	-0.07	0.23	-0.19	-0.44***	-0.60***
		(1.25)	(-0.52)	(1.38)	(-0.78)	(-2.89)	(-2.86)
	ew	0.28**	0.15	0.16	-0.39**	-0.35*	-0.62***
		(2.07)	(1.20)	(0.84)	(-2.23)	(-1.78)	(-2.87)
Panel C: Citation-weighted green patent share							
Raw	vw	1.05***	0.95**	0.71*	0.85**	0.40	-0.65**
		(2.75)	(2.42)	(1.90)	(2.17)	(0.63)	(-2.01)
	ew	1.13**	1.13**	0.99*	0.68	0.54	-0.58**
		(1.99)	(2.02)	(1.76)	(1.32)	(0.95)	(-2.55)
FF5+Mom α	vw	0.36**	0.08	-0.14	0.04	-0.47*	-0.82**
		(2.25)	(0.51)	(-0.93)	(0.32)	(-1.67)	(-2.27)
	ew	0.29**	0.29**	0.16	-0.10	-0.28	-0.57**
		(2.43)	(2.21)	(0.88)	(-0.84)	(-1.24)	(-2.36)

Table IA14: **Robustness: Fama-MacBeth Regressions Using Patent Values**

This table reports Fama-MacBeth regressions of individual stock returns on overall green patent shares and proportions of various green patent categories related to energy use, production, transportation, building, adaptation, and environment management. We use KPSS-weighted green patent shares in columns (2) and (5) and citation-weighted shares in columns (3) and (6). We conduct cross-sectional regressions of monthly returns from July of year t to June of year $t+1$ on the green patent share of year $t-1$. Control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. All control variables are normalized to a zero mean and a one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is from July 2007 to December 2019. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Excess return					
	Green^{s}	Green^{s,e}	Green^{s,c}	Green^{s}	Green^{s,e}	Green^{s,c}
Green	-0.13***	-0.15***	-0.13***			
	(-3.56)	(-3.34)	(-2.82)			
Energy				-0.14**	-0.17**	-0.12**
				(-2.23)	(-2.48)	(-2.54)
Transportation				0.04	0.02	0.05
				(1.62)	(0.62)	(1.51)
Production				-0.01	-0.03	-0.04
				(-0.29)	(-0.93)	(-1.28)
Building				-0.04	0.01	-0.02
				(-1.14)	(0.11)	(-0.50)
Adaptation				0.05	0.07*	0.08*
				(0.70)	(1.78)	(1.81)
Environment				-0.08***	-0.11***	-0.09***
				(-3.10)	(-3.03)	(-2.85)
Observations	162,085	162,085	141,740	141,740	141,740	141,740
R-squared	0.10	0.11	0.11	0.11	0.11	0.11
Number of groups	138	138	138	138	138	138
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA15: **Robustness: Event Study for Green Patent Shares**

This table regresses the cumulative abnormal returns around four events on the green patent shares, considering Scope 1 carbon emission intensity as a control variable. The dependent variables are cumulative market-adjusted abnormal returns over a one-day/five-day/ten-day window from the event date. We conduct event studies for Trump's election on November 8th, 2016 in Panel A, Biden's election on December 14th, 2020 in Panel B, the Russia-Ukraine war on February 24th, 2022 in Panel C, and the IRA announcement on July 28th, 2022 in Panel D. Other control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. The first three columns are based on samples with patents while the second three columns contain observations with at least one green patent. All control variables are normalized to a zero mean and one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The standard errors are clustered by industry and t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	w/ patents			w/ green patents		
	CAR[0,1]	CAR[0,5]	CAR[0,10]	CAR[0,1]	CAR[0,5]	CAR[0,10]
Panel A: Trump's election						
$Green^s$	-0.004	-0.007**	-0.008*	-0.006	-0.010	-0.014*
	(-1.266)	(-2.040)	(-1.831)	(-1.054)	(-1.520)	(-1.858)
Carbon intensity	0.000	-0.002	-0.002	0.002*	0.000	0.001
	(0.014)	(-0.522)	(-0.461)	(2.043)	(0.069)	(0.526)
Observations	381	381	381	195	195	195
Panel B: Biden's election						
$Green^s$	0.005*	0.004	0.005**	0.006*	0.010*	0.007*
	(1.982)	(1.348)	(2.244)	(1.882)	(1.913)	(2.024)
Carbon intensity	-0.001	-0.001	-0.006	-0.006***	-0.009***	-0.008***
	(-0.974)	(-0.482)	(-1.674)	(-3.006)	(-3.853)	(-4.819)
Observations	801	801	801	338	338	338
Panel C: The Russia-Ukraine war						
$Green^s$	0.004**	0.013**	0.024**	0.008***	0.019***	0.034***
	(2.595)	(2.312)	(2.650)	(3.548)	(2.887)	(3.210)
Carbon intensity	0.004**	0.004	0.004	-0.000	0.002	0.003
	(2.043)	(0.902)	(0.796)	(-0.232)	(0.730)	(0.624)
Observations	805	805	805	323	323	323
Panel D: The IRA announcement						
$Green^s$	0.008**	0.011***	0.011**	0.011***	0.011**	0.010
	(2.473)	(3.466)	(2.114)	(2.795)	(2.618)	(0.915)
Carbon intensity	0.001	-0.003	-0.001	0.004	0.003	0.004
	(0.481)	(-0.768)	(-0.179)	(1.355)	(0.888)	(0.874)
Observations	788	788	788	319	319	319
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA16: **Comparison with Green Patents: Portfolio Characteristics**

This table presents the annual, equal-weighted averages of firm characteristics for portfolios, categorized by the presence or absence of green innovation discussions and green patents. *Num of firms* represents the annual average count of observations within the corresponding portfolios.

	w/ both	w/ green discussions	w/ green patents	w/o both
Greenness	0.41%	0.27%	0	0
$Green^n$	22	0	13	0
$Green^s$	30.64%	0	16.93%	0
$Green^{s,e}$	29.44%	0	15.07%	0
$Green^{s,c}$	25.03%	0	13.55%	0
logAsset	8.15	7.32	8.23	7.00
ROA	0.07	0.05	0.04	0.03
Leverage	0.24	0.29	0.25	0.28
Investment	0.21	0.25	0.24	0.38
Tangibility	0.24	0.38	0.16	0.21
Tobin's Q	2.23	1.87	2.74	2.08
Sales growth	0.12	0.35	0.64	0.80
WW	-0.38	-0.32	-0.21	-0.28
Num firms	152	579	209	2194

Table IA17: **Comparison with Green Patents: Fama-MacBeth Regressions**

This table presents a comparative analysis of Fama-MacBeth regressions, which use individual stock returns as the dependent variable and green innovation discussions in earnings calls, as well as green patent shares, as independent variables. Panel A focuses on observations encompassing earnings calls without green patents, while Panel B considers observations lacking of green innovation discussions. Panel C includes observations with positive values for both measures. Control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. All control variables are normalized to a zero mean and a one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. t-statistics based on standard errors using the Newey-West correction are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess returns							
	Panel A: w/o green patents				Panel B: w/o green discussions			
	2007-2019		2020		2007-2019		2020	
Greenness	-0.12***	-0.08*	0.39***	0.29*				
	(-2.62)	(-1.71)	(3.19)	(1.83)				
$Green^s$					-0.04	-0.05	0.34	0.23
					(-0.62)	(-0.71)	(1.64)	(1.15)
Observations	329,591	281,111	33,608	27,387	89,171	80,329	9,257	8,078
R-squared	0.09	0.11	0.10	0.14	0.10	0.15	0.08	0.15
Control	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel C: w/ green patents & w/ green discussions							
	2007-2019				2020			
Greenness	-0.19***		-0.12**	-0.15***	0.98**		0.66	0.52
	(-2.94)		(-2.33)	(-2.95)	(2.61)		(1.62)	(1.34)
$Green^s$		-0.35***	-0.26***	-0.25***		1.22***	0.87***	0.63*
		(-3.86)	(-3.48)	(-3.04)		(5.43)	(6.31)	(2.19)
Observations	18,315	18,315	18,315	17,612	2,014	2,014	2,014	1,888
R-squared	0.24	0.24	0.25	0.36	0.24	0.23	0.25	0.39
Control	No	No	No	Yes	No	No	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA18: **Comparison with Green Patents: Environmental Performance**

This table displays a comparative analysis of firms' future environmental performance. The independent variables are green innovation discussions in the current and previous three years in Panel A and green patent shares in Panel B. Dependent variables encompass Scope 1 carbon intensity, Scope 1 carbon emission level, and frequency and severity of firms' negative climate incidents. Control variables contain the natural logarithm of total assets, ROA, leverage, investment rate, tangibility, sales growth, and employment growth. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. We consider year and firm fixed effects. t-statistics based on standard errors clustered by the firm are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) $\text{CarbonIntensity}^{scope1}$	(2) $\text{CarbonEmission}^{scope1}$	(3) Number	(4) Severity
Panel A: w/o green patents				
$\text{Greenness}_{i,t}$	-0.31**	-0.29**	0.01	0.02
	(-2.22)	(-2.45)	(0.35)	(0.74)
$\text{Greenness}_{i,t-1}$	-0.22	-0.30***	-0.04**	-0.05**
	(-1.51)	(-2.67)	(-2.15)	(-2.22)
$\text{Greenness}_{i,t-2}$	-0.23*	-0.13	-0.01	0.00
	(-1.72)	(-1.19)	(-0.59)	(0.01)
$\text{Greenness}_{i,t-3}$	-0.38***	-0.21*	-0.00	-0.02
	(-2.74)	(-1.72)	(-0.08)	(-0.68)
Observations	13,512	13,512	1,584	1,584
Panel B: w/o green discussions				
$\text{Green}^s_{i,t}$	0.03	0.41	-0.02	0.08
	(0.36)	(0.93)	(-0.11)	(0.48)
$\text{Green}^s_{i,t-1}$	-0.01	0.32	-0.02	0.00
	(-0.11)	(0.88)	(-0.15)	(0.02)
$\text{Green}^s_{i,t-2}$	-0.04	0.28	0.09	0.03
	(-0.64)	(0.95)	(1.14)	(0.32)
$\text{Green}^s_{i,t-3}$	-0.08*	0.25	0.02	0.14
	(-1.66)	(1.02)	(0.17)	(1.18)
Observations	3,628	3,628	423	423
Panel C: w/ green patents & w/ green discussions				
$\text{Greenness}_{i,t}$	0.09	0.09	-0.01	0.01
	(1.10)	(0.81)	(-0.26)	(0.30)
$\text{Greenness}_{i,t-1}$	0.02	0.02	-0.07	-0.11*
	(0.38)	(0.41)	(-1.41)	(-1.81)
$\text{Greenness}_{i,t-2}$	-0.03	0.00	0.02	0.05
	(-0.84)	(0.03)	(0.39)	(1.43)
$\text{Greenness}_{i,t-3}$	0.00	-0.02	0.07	0.09
	(0.04)	(-0.30)	(1.25)	(1.32)
$\text{Green}^s_{i,t}$	-0.78	-0.96	-0.20***	-0.20***
	(-1.28)	(-1.24)	(-3.00)	(-3.08)
$\text{Green}^s_{i,t-1}$	-0.69	-0.62	0.06	0.09
	(-1.30)	(-1.27)	(0.71)	(1.22)
$\text{Green}^s_{i,t-2}$	-0.15	0.13	-0.09	-0.08
	(-0.68)	(0.54)	(-1.06)	(-0.91)
$\text{Green}^s_{i,t-3}$	0.16	0.51	0.09	0.10
	(0.83)	(1.63)	(1.06)	(1.28)
Observations	818	818	216	216
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table IA19: **Comparison with Green Patents: Event Study**

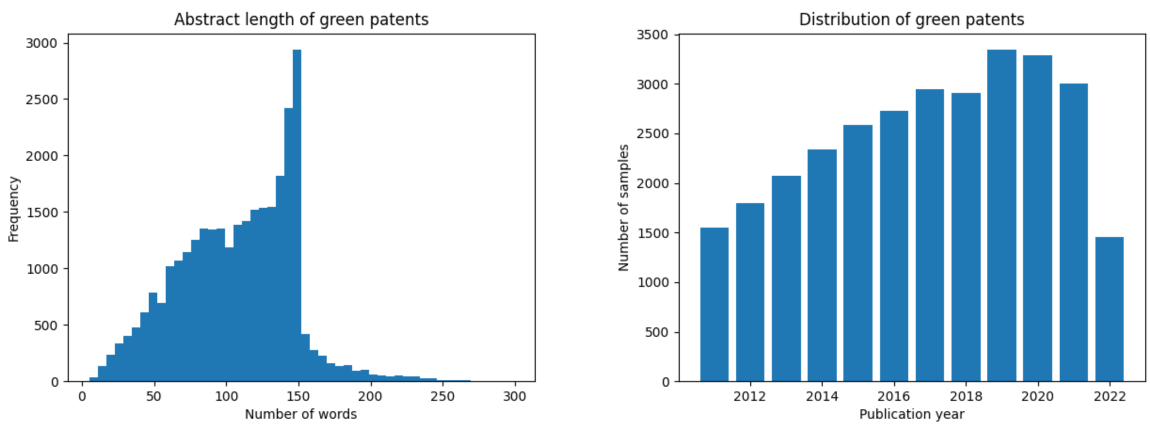
This table reports a comparative analysis of cumulative abnormal returns in response to four events, regressed on the green innovation discussions and green patent shares. Columns (1)-(3) focus on observations with green innovation discussions but without green patents, while columns (4)-(6) consider observations with green patents but lacking green innovation discussions. Columns (7)-(9) include observations with positive values for both measures. The dependent variables are cumulative market-adjusted abnormal returns over a one-day/five-day/ten-day window from the event date. We conduct event studies for Trump's election on November 8th, 2016 in Panel A, Biden's election on December 14th, 2020 in Panel B, the Russia-Ukraine war on February 24th, 2022 in Panel C, and the IRA announcement on July 28th, 2022 in Panel D. Other control variables include the natural logarithm of size, book-to-market ratio, ROA, investment rate, WW index, leverage, and industry dummies based on Fama-French 49 industry classifications. All control variables are normalized to a zero mean and one standard deviation and are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The standard errors are clustered by industry and t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	w/o green patents			w/o green discussions			w/ green patents & w/ green discussions		
	CAR[0,1]	CAR[0,5]	CAR[0,10]	CAR[0,1]	CAR[0,5]	CAR[0,10]	CAR[0,1]	CAR[0,5]	CAR[0,10]
Panel A: Trump's election									
Greenness	-0.004*	-0.007*	-0.011**				-0.004*	-0.010**	-0.009**
	(-1.929)	(-1.696)	(-2.168)				(-2.049)	(-2.713)	(-2.311)
$Green^s$				0.002	-0.007	-0.006	-0.002	-0.005	-0.011
				(0.641)	(-0.782)	(-0.581)	(-0.453)	(-1.174)	(-1.266)
Observations	378	378	378	194	194	194	120	120	120
Panel B: Biden's election									
Greenness	0.003	0.009***	0.014***				0.002	0.010***	0.015***
	(1.330)	(3.173)	(3.426)				(1.492)	(3.640)	(3.655)
$Green^s$				-0.002	0.001	-0.009	0.003	0.006	0.002
				(-0.584)	(0.166)	(-1.538)	(1.194)	(1.508)	(0.357)
Observations	461	461	461	198	198	198	137	137	137
Panel C: Russia-Ukraine war									
Greenness	0.004**	0.009***	0.018***				0.003	0.007**	0.015*
	(2.219)	(3.411)	(3.593)				(1.010)	(2.145)	(1.982)
$Green^s$				0.008**	0.007	0.003	0.004**	0.017***	0.029***
				(2.362)	(0.488)	(0.217)	(2.895)	(3.620)	(4.460)
Observations	633	633	633	176	176	176	173	173	173
Panel D: IRA announcement									
Greenness	0.000	-0.001	0.002				0.004**	0.010**	0.013*
	(0.032)	(-0.206)	(0.458)				(2.157)	(2.134)	(1.836)
$Green^s$				0.007	0.000	-0.021	0.008**	0.002	0.005
				(1.430)	(0.051)	(-1.036)	(2.476)	(0.425)	(0.840)
Observations	623	623	623	172	172	172	171	171	171

IA.2 Green innovation classifier

This section briefly outlines our classification approach employed for green innovation. Initially, we extracted a sample of 5,000 abstracts of green patents for each of the six designated categories, resulting in a total of 30,000 abstracts. Figure IA5 offers an overview of the data. The left panel illustrates the distribution of abstract lengths measured in words used, revealing that most abstracts consist of approximately 150 words. Furthermore, our data collection methodology ensures that all years within the sample are appropriately represented, however, with an emphasis on the more recent years.

Figure IA5: **Green Patent Sample**
This figure gives an overview of green patent abstracts used for training the classifier. The left panel shows the length of the abstracts in the dataset, measures in terms of the words used. The right panel shows the distribution of the patents across the different years in our sample.



IA.2.1 Transforming technical abstracts into layman's sentences

To address the challenge of identifying green innovation in earning calls, we encounter the issue of highly technical language used in patent abstracts. To mitigate this, we employ a strategy that leverages conversational artificial intelligence's eloquence. Specifically, we prompt GPT-3 (text-davinci-003) to generate a layman's summary, condensing the information from the abstract, the category, and the title into a single sentence.[1] These resultant sentences will subsequently be utilized in the classification task, employing ClimateBERT, introduced by Webersinke et al. (2022).

To complete the dataset for the classification task, we also introduce sentences unrelated to the green innovation classes but still pose a semantic challenge for the classification task.

[1]For each abstract, we prompt GPT-3 to "Write a layman summary in one sentence that optimally reflects the information from the category and the title."

For that purpose, we gather sentences from the 10K filings, specifically from Item 1A, as utilized and classified in Varini et al. (2020). We specifically retain sentences related to climate change, as they are found in the risk section (Item 1A) of the 10K filings. These sentences are typically of a general nature and, upon inspection, are not associated with the firm's innovation activities. Additionally, to further enhance the diversity of sentences unrelated to green innovation, we collect sentences from annual reports sourced from Bingler et al. (2023), ensuring that they do not pertain to climate change.

The left panel of Figure IA6 shows that by using the above method, we have successfully reduced the length of the technical abstracts to a layman's sentence of 10 to 50 words. However, we want to double-check whether our sentences generated by GPT-3 are semantically close to the abstracts.[2] For that purpose, we perform a similarity check between the abstract and the corresponding sentence using a state-of-the-art Sentence Transformer Reimers and Gurevych (2019).[3] Sentence Transformers work by fine-tuning pre-trained Transformer models, like BERT or RoBERTa, using a Siamese or triplet network architecture to generate semantically meaningful fixed-length vector representations of text inputs.[4] Once trained, Sentence Transformers can be used for various NLP tasks like semantic textual similarity and paraphrase identification, among other tasks, by simply calculating the cosine similarity or Euclidean distance between the embeddings of text inputs.

The right panel of Figure IA6 shows that semantic similarity measured using a Sentence Transformer is, on average, 0.7. Given this high cosine similarity, we are confident that our approach captures the most important information from the patent abstracts in layman's terms. However, it still remains to be seen whether fine-tuning ClimateBERT on just the sentences will perform well in classifying the patents into different categories. This is what we explore next.

IA.2.2 Fine-tuning ClimateBERT on layman's sentences

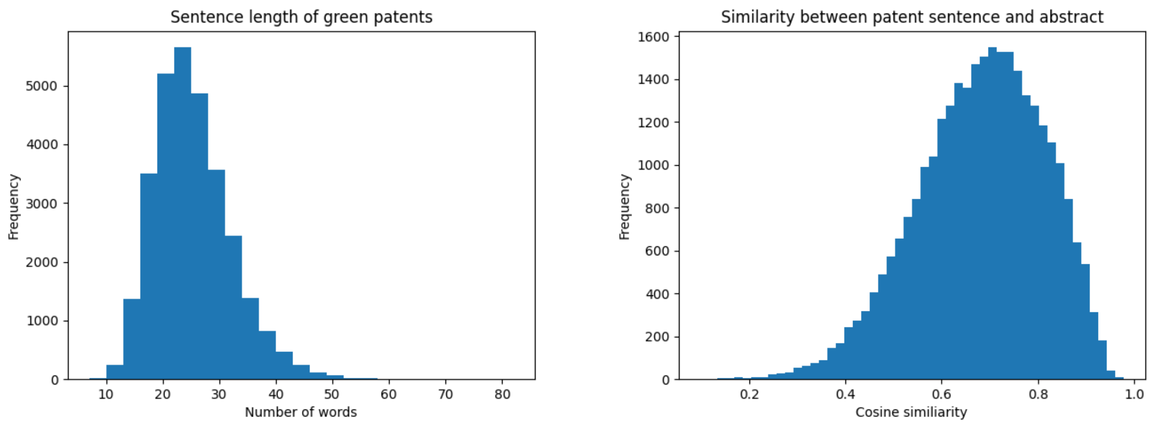
To classify the sentences into the six green innovation categories and the additional category of unrelated sentences, we use ClimateBERT introduced in Webersinke et al. (2022). ClimateBERT is a language model designed and trained to understand and analyze climate-related texts. It is based on the BERT (Bidirectional Encoder Representations from Transformers)

[2]In particular, we measure semantic similarity, which is a metric defined over a set of documents or terms, where the idea of the distance between items is based on the likeness of their meaning.

[3]In particular, we rely on the model 'all-mpnet-base-v2', which is, as of the time of writing, the best-performing sentence-transformer model.

[4]During training, these architectures compare and optimize the embeddings of semantically similar sentence pairs (or triplets), so that the embeddings are closer in the vector space.

Figure IA6: **Green Patent Sentences**
This figure shows the length, i.e., number of words, of the generated sentence-level summaries using GPT-3 (left panel) and the cosine-similarity between the generated sentences and the original abstracts of the green patents (right panel). Cosine-similarity has been calculated using a Sentence Transformer.



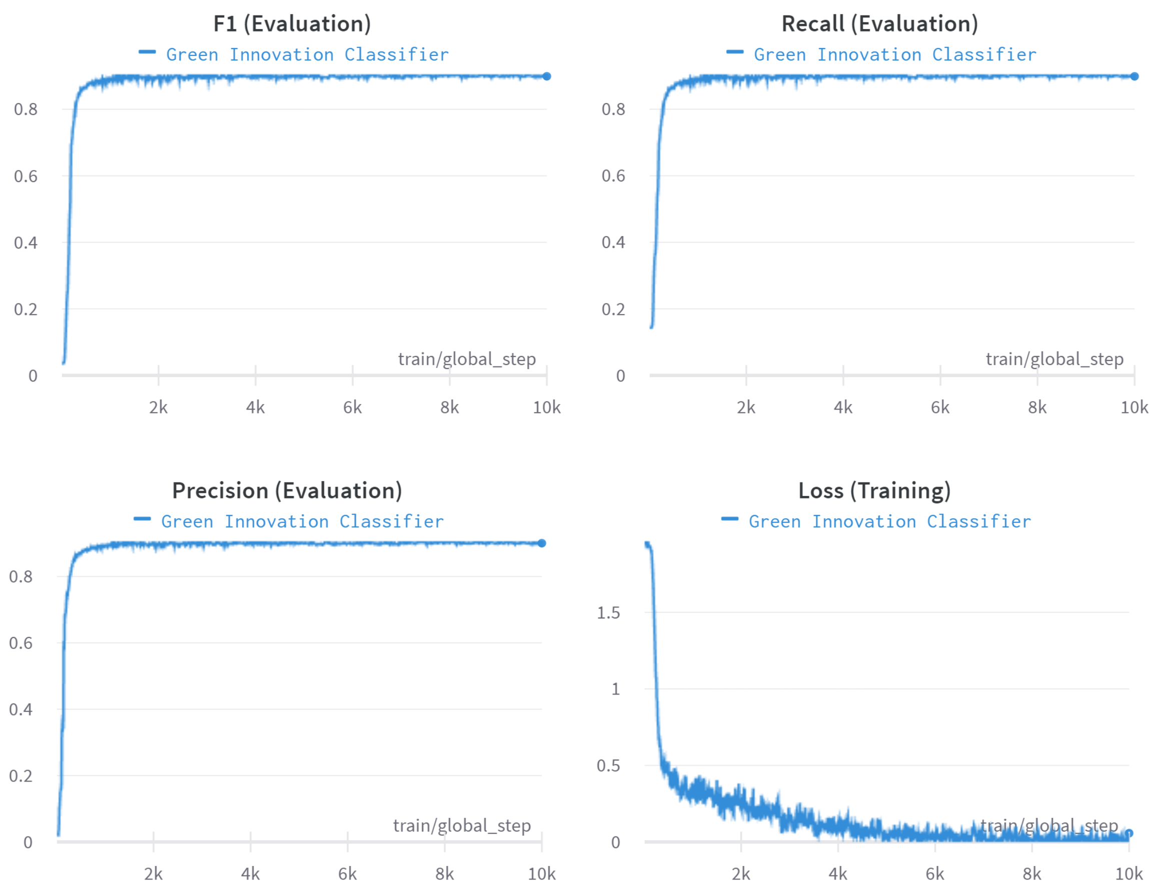
architecture, a popular neural network model for NLP tasks. ClimateBERT is pre-trained on a large corpus of climate-related documents and can be fine-tuned for various downstream tasks, such as classification, sentiment analysis, or question-answering related to climate change. Its training incorporates domain-specific knowledge and terminology related to climate science, allowing it to effectively process and comprehend climate-related texts. Adding the sentences not related to green patents, we have a sample of total of 35,054 annotated sentences.[5] We take 20% of these sentences, i.e., 7011 sentences, for the test set. For the training of ClimateBERT, We then divide the remaining sentences into a training set with 22,434 and a validation set with 5,609 sentences.

We then fine-tuned the pre-trained ClimateBERT model for our classification task.[6] The training was performed over 30 epochs, with each epoch consisting of 10 steps. The model was trained using a batch size of 16 and gradient accumulation of 2, resulting in an effective batch size of 32. The learning rate was set to 5e-5, and a linear learning rate warmup was employed, with a warmup ratio of 0.1. Additionally, a weight decay of 0.1 was applied during the optimization process. In Figure IA7, we plot the performance of the model for the different training steps and for different performance measures, like the F1, Recall, and Precision for the validation (or evaluation) set and the loss function for the training set.

[5] We have the annotations from the categorization of the patents from the data provider.

[6] In particular, we use 'climatebert/distilroberta-base-climate-f,' which is available from huggingface. For more information, see www.chatclimate.ai.

Figure IA7: **Performance**

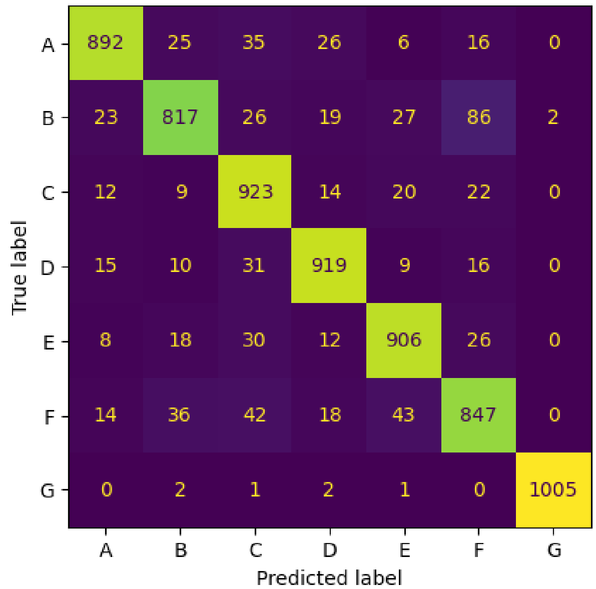


IA.2.3 Performance analysis

We can now run the model on the test set using the ClimateBERT model fine-tuned on the classification task. We present the results in Figure IA8. It depicts the performance of the fine-tuned ClimateBERT model on the test set. The left panel showcases the confusion matrix, providing insights into the model's predictions for each category. The right panel offers an overview of the model's performance across different categories. The test set comprises a balanced sample of 7,011 sentences, with each green innovation class consisting of 1,000 sentences, and the general class containing 1,011 sentences. The table accompanying Figure IA8 presents each category's precision, recall, and F1 scores. The "energy use" category achieved a precision of 0.9253, a recall of 0.8920, and an F1 score of 0.9084. Similarly, the "transportation," "production," "buildings," "adaptations," and "environments" categories demonstrated strong performance with respectable precision, recall, and F1 scores. The "general" category exhibited exceptional precision, recall, and F1 scores above 0.994.

Figure IA8: **Performance on the Test Set**

This figure presents the performance of the fine-tuned ClimateBERT model on the test set. The left panel shows the confusion matrix and the right panel gives an overview of the different performances for the different categories. The test set consists of a balanced sample of 7,011 sentences. Each green innovation class has a support of 1,000 sentences and for the general class, we are left with 1,011 sentences.



	precision	recall	F1
energy use	0.9253	0.8920	0.9084
transportation	0.8909	0.8170	0.8524
production	0.8483	0.9230	0.8841
buildings	0.9099	0.9190	0.9144
adaptations	0.8953	0.9060	0.9006
environments	0.8361	0.8470	0.8415
general	0.9980	0.9941	0.9960
accuracy			0.8999
macro avg	0.9006	0.8997	0.8996
weighted avg	0.9007	0.8999	0.8998

The model's overall accuracy on the test set was 0.8999, indicating its ability to classify sentences correctly. The macro average precision, recall, and F1 score were all approximately 0.900, while the weighted average scores were slightly higher, indicating a balanced performance across the categories. These results demonstrate the effectiveness of the fine-tuned ClimateBERT model in accurately categorizing sentences related to green innovation.

IA References

Bingler, J. A., Kraus, M., Leippold, M., and Webersinke, N. (2023). How cheap talk in climate disclosures relates to climate initiatives, corporate emissions, and reputation risk. *Swiss Finance Institute Research Paper No. 22-01*.

Reimers, N. and Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*.

Varini, F. S., Boyd-Graber, J., Ciaramita, M., and Leippold, M. (2020). Climatext: A dataset for climate change topic detection. *NeurIPS, ClimateChange AI Workshop, arXiv preprint arXiv:2012.00483*.

Webersinke, N., Kraus, M., Bingler, J., and Leippold, M. (2022). ClimateBERT: A Pretrained Language Model for Climate-Related Text. In *Proceedings of AAAI 2022 Fall Symposium: The Role of AI in Responding to Climate Challenges*.