Market Implications for Industry Greenness and Climate Information Transfer

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Abstract

This study examines whether firm equity returns are differentially affected by the greenhouse gas (GHG) emission innovations of their industry peers based on the information environment and disclosure regime. In the post-Paris Agreement era, when climate disclosures are more prevalent and detailed, we find a positive relationship between industry GHG emission innovations and firm equity returns, holding firms' own emissions constant. In contrast, prior to the Paris Agreement, when firm climate disclosures are sparce, we find a negative relationship between the two. We also document a decrease in firms' climate reporting in the forthcoming 10-Q in post-Paris era in response to peer GHG emission innovations.

Key words: greenhouse gas emissions; carbon risk; climate-related disclosure, information environment.

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I. Introduction

There has been increasing financial attention to climate risk, with global temperatures rising and increasing temperature variation causing widespread weather events (Fabris 2020). This financial attention has accelerated even more so after the Paris Agreement became effective in November 2016. How climate risk and its associated risks are incorporated into firm equity prices, municipal bond prices, and housing prices has been studied by economic, finance, and accounting researchers extensively.[3] However, when it comes to climate risk associated with carbon emissions, prior research focuses mostly on the market reactions to firms' direct carbon performance and the emissions of their upstream and downstream production (Bolton and Kacperczyk 2021), as well as their subsidiaries (Duchin, Gao and Xu 2022). However, little is known on how firms' equity returns respond to industry peers' carbon emission innovations.

Our references herein to the Paris Agreement are essentially references to an era of increased interest and disclosure on climate issues. For example, some of our inferences may be due to the EU's (EU) 2014/95/EU Non-Financial Reporting Directive (NFRD), effective in 2018, which required specific companies to provide disclosures on sustainability. Furthermore, the UN directly addressed firms as the key actors to ensure 'Responsible consumption and production' (cf. Sustainable Development Goal (SDG) 12, United Nations, 2015a) around about the same time and explicitly called for firms' transparency on their financial and non-financial environmental, social and governance (ESG) performance via sustainability reporting (cf. Target 12.6 "Sustainable practices in companies", United Nations, 2015a)., Thus, during this era firms were sometimes required and sometimes encouraged to publish the information in a stand-alone or integrated report

[3] A recent review of studies on climate risk, climate change, and stock returns risks was done by Venturini (2021). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, 79: 101934.

comprising both financial and non-financial information, more so than before this era. Finally, the increasing disclosure on environmental sustainability based on the Security and Exchange Commission's (SEC's) attention to these issues in the US aligns with the Paris Agreement. That is, in the 2016 concept release No. 10064, the SEC called attention to potential future disclosure requirements on environmental and other matters of social concerns, though immediate action has not been taken.[4] Built upon this momentum, in early 2021, the acting SEC Chair and Division of Corporations began to consider environmental disclosure requirements and solicit comments on environment impact of disclosures. Sitting at the center of the debate is an apparent battle between an investor-focused versus stakeholder-focused disclosure regime. As well as whether the market has the sufficient ability to "collect, process, disseminate, and respond to" environmental metrics without "boxing them in government-articulated metrics."[5]

To answer these questions, this study examines whether firm equity returns are differentially affected by the greenhouse gas (GHG) emission innovations of their industry peers, based particularly on information availability and the disclosure regime. Also, we examine whether the strong disclosure environment is associated with the market's collection of and reactions to competitors' GHG innovations and firms' own carbon disclosures, in a way different from in the weak disclosure environment. The motivation of this study lies on the multidimensionality of investment objectives, particularly those of ESG investors, and the impact of evolving environmental disclosure environment. Market prices are a product of a balance between ESG and non-ESG investors' targeted holdings, as well as other institutional ownership priorities and implications.

[4] https://www.sec.gov/rules/concept/2016/33-10064.pdf
[5] https://www.sec.gov/news/public-statement/rethinking-global-esg-metrics

Evaluating the GHG emission innovation shocks from industry peers is empirically challenging. We utilize FactSet Truvalue Labs Dataset which collects short-term and long-term performance and momentum across the 26 Sustainability Accounting Standards Board (SASB) categories and collect firms' real-time GHG performance from their Pulse Score variable "ghg_emissions_pulse" and "ghg_emissions_catvol" on a daily frequency from the database.[6] For a given firm, its GHG emissions innovation is defined as the change in its GHG emissions pulse score from the prior day, and its media coverage is defined as the unique number of articles on its GHG emissions from the prior day if nonnegative.

Innovations in an industry tend to cluster and overlap, preventing short window event studies. To address this issue, we aggregate all innovations by industry to construct a monthly industry index on GHG emissions. The monthly industry index is the sum product of firms' pulse score innovations and their unique article numbers in GHG emissions category, across all firms in a given industry in the month. The monthly industry GHG emissions innovation index reflects the aggregate real-time impact of GHG innovation by industry and the exposure of firms to industry level green competition and climate de-risking. This monthly industry GHG emissions innovation index is our variable of interest, nevertheless, our results are robust to alternative constructions of the index. For brevity, we call firms with GHG non-zero innovations in the month "innovative firms," and firms with zero innovations, but in the same industry, "silent firms."

There are two ways in which one would expect industry peer GHG emission innovations to affect firm equity pricing. First, one might expect a positive industry innovation on GHG emissions to impose an adverse shock on silent firms, whose carbon risk is increased as they lag their industry

[6] Variable ghg_emissions_pulse in the database is to reflect a daily Pulse Score that aggregates the GHG Emissions category for each company using a running sum average. Variable ghg_emissions_catvol variable in the database is to reflect the number of unique articles on GHG Emissions category for each company over a trailing twelve-month period of time.

peers. The intuition is that ESG investors, facing a portfolio of ESG assets and non-ESG assets, have a higher demand on firms with good GHG emission performance, driving up the price of ESG assets. (Pastor, Stambaugh and Taylor 2021; Wang and Wu 2023; Heeb, Kolbel, Paetzold, Zeisberger 2022) Investors with interests on both returns and ESG improvements will demand higher returns for the loss of the ESG surplus when holding equities of silent firms. As silent firms now look less desirable and browner to ESG investors, the innovation incentivizes a marginal deviation of ESG investors away from silent firms and toward innovative firms, and demands on silent firms decrease. Forward looking investors may require higher returns for holding their stocks to bear the relatively higher carbon risk, giving rise to the positive cross-section relationship of higher industry GHG innovation – higher returns. We refer to this as the relative brown hypothesis.

Second, one might expect a positive industry innovation on GHG emissions to impose a positive shock on silent firms. With high demand on green stocks, ESG investors may extrapolate the innovation from peers to silent firms, expect the silent firms to adopt similar technology breakthroughs or firm policies to become greener, and demands on silent firms increase. Forward looking investors thus may require lower returns for holding their stocks, giving rise to the negative cross-section relationship of higher industry GHG innovation– lower returns. We refer to this as the green transfer hypothesis.

Does environmental disclosure and information environment matter in these scenarios? We further hypothesize that the choice between these two competing hypotheses by the market lies heavily on the information transfer environment and disclosure regime. In the weak disclosure environment, facing the lack of wide-spread and reliable firm specific carbon emission information, especially due to the lack of material disclosure, investors need to infer information from peers to meet their strong green demands. However, in the strong disclosure environment, facing copious carbon emissions information, investor demand could be satisfied with firms making such disclosures, without the need to infer or guess with respect to silent firms' action and behavior. Thus, we expect to see the relative brown hypothesis in the strong disclosure environment, and the green transfer hypothesis in the weak disclosure environment.

In this study, as noted earlier, the strong disclosure environment is defined as years starting from 2017, with weak disclosure environment defined as years prior to 2017, for a couple of reasons: the Paris Agreement was signed in April 2016 and effective in Nov 2016. Following the Agreement, a range of disclosure framework and standards were developed. Starting from 2017, the Task Force on Climate-Related Financial Disclosures (TCFD) led by the UN environment program (UNEP) finance initiative (FI) work with over 100 banks, insurers, and investors to create numerous framework to accelerate climate risk management in the finance sector. The Global Reporting Initiative (GRI) led by Global Sustainability Standards Board (GSSB) published its Foundation 2016 to set out the basic process and materiality standards for sustainability reporting by corporations. In 2017, Carbon Disclosure Project (CDP) for North America launched Climetrics, the world's first climate rating for investment funds, calling into the attention of institutional investors on carbon emission disclosure.[7]

The transition to a lower carbon economy will be costly and investors have various strategies on dealing with these costs. Investors likely expect firms to behave in a manner similar to their industry peers and adopt industry standards with respect to climate risk issues. Firms must manage the expectations of capital providers and align their behaviors and actions with the various investment strategies available to investors. However, firms must also acknowledge that climate risk information from their peers is likely to influence investors seeking to align their investment

[7] https://www.cdp.net/en/info/about-us/20th-anniversary

portfolios with a low carbon, more climate resilient economy. Research shows, for example, during an earnings season, industry-wide trends and performance details can be implied from the earnings news of other firms in the same industry (Ramnath 2002; Thomas and Zhang 2008; deHaan, Shevlin, and Thornock 2015). Thus, it is probable that increasingly value relevant GHG related disclosures by industry peers will affect the climate risk related information set and the expectation of the investors, and the ensuing market prices of firms' equity.

However, the nature of the disclosure regime is likely to affect the level to which investors are willing to rely on peer information. That is, non-financial information on GHG emissions is a relatively new disclosure item and whether investors can reasonably rely on the disclosures as credible, especially when made by an industry peer, is somewhat unclear. For example, previous research finds mixed results when examining the effects of CSR disclosures on stock price (Rowbottom and Lymer 2010; Campbell and Slack 2011), which may be due to the view that public CSR disclosures are inadequate (Solomon and Solomon 2006) and the fact that investors face many impediments in making socially responsible investments (Juravle and Lewis 2008). Prior to the Paris Agreement era (i.e., pre-2017) voluntary disclosures of environmental information through the Carbon Disclosure Project (CDP) were relatively scarce (Ramadorai and Zeni 2022) and research shows that only after did climate change issues became price and risk relevant (Kölbel et al. 2020). Furthermore, both Ilhan, Sautner, Vilkov (2021) and Delis, Greiff and Ongena (2019) find that the Paris Agreement was pivotal in changing the nature and the reliance on these disclosures.

We ask three research questions in this study. Our first research question is whether firms' equity returns respond to their industry GHG emission innovations in the strong disclosure environment, though their own GHG emission performance does not change? Firms' carbon footprints are the product of the nature of their business and the industry they belong to. GHG emissions innovations by one firm could bring industry wide shocks and belief updates which have impact on firms without innovations. If ESG investors balance their portfolios by paying close attention to industry GHG emissions, the relative "greenness and brownness" changes of peer firms could change the market's perception of firm specific climate risks and the level of their institutional holdings as well. We expect the Paris Agreement era to play an increasingly important facilitating and monitoring role for firms' ESG behaviors and thus would improve information collection on carbon emissions by institutional investors. That is, post-Paris the costs associated with the awareness, acquisition, and integration of peer information (Blankespoor et al. 2020) are significantly attenuated and, therefore, when a GHG innovation shock occurs, it updates investors' beliefs and results in an ESG rebalancing of sorts.

Indeed, the findings support relative brown hypothesis in the strong information environment. We find demanded returns on silent firms increase with positive industry GHG emissions innovations in the Paris Agreement era. Specifically, a one standard deviation increase in the GHG innovation index is associated with 0.106% higher monthly returns, significant at 1% level, after controlling for other firm characteristics and their own GHG emissions scores. We further find the higher carbon risks are associated with 3-factor and 4-factor adjusted alphas (Fama and French 1993; Carhart 1997).

Next, we turn attention to the weak disclosure environment - pre-Paris Agreement era of 2007-2016 and ask whether firm equity returns respond to industry wide GHG innovation shocks in the same manner as in 2017-2021? Contrary to the post-Paris agreement period, voluntary pre-Paris disclosures were more scarce (Ramadorai and Zeni 2022) and harder for investors to find. Thus, while in the post-Paris era GHG disclosures from firms were somewhat expected and draw more attention from fund managers and other institutional investors, in the pre-Paris Agreement era GHG disclosures were more scarce. This scarcity brings about an issue for an investor. They can either take the time to find a disclosure by a target firm, or when presented with a disclosure from a peer, pass on that information to the target firm assuming that peers within an industry behave similarly. Indeed, the findings support the green transfer hypothesis. We find one standard deviation increase in GHG innovation index is associated with 0.148% lower monthly returns, significant at 10% level, after controlling for other firm characteristics and their own GHG emissions scores. Consistent with the strong information environment, the negative cross-section relationship cannot be explained away by common risk factors – size, book-to-market, and momentum (Fama and French 1993; Carhart 1997). Therefore, as disclosures in the earlier years of 2007-2016 GHG are more scarce, ESG investors transfer this positive shock to the peer firm.

We then ask whether firms' carbon emission and climate risk disclosures vary with their industry GHG innovation shocks? That is, do silent firms change their behavior when they become relatively greener or browner because of the activity of innovative firms and the different interpretation of the market? We also examine this question separately in the pre- and post-Paris Agreement eras. Particularly in the post-Paris Agreement era, we expect firms with exposure to positive industry GHG emissions innovations to talk less about carbon emissions and climate risk in their own forthcoming reports, as doing so weakens their links to their peers' innovations and improvements. We view this as a strategy for firms to distance themselves from the greener firms. Consistent with this expectation, we find that firms change their carbon and climate disclosure in response to their peers' GHG emission innovations. Specifically, a one standard deviation increase in positive peer GHG emission innovations is associated with a decrease in firms' climate disclosure by 0.2 to 0.5 percent. Moreover, when the industry GHG innovations are more prominent, the firms in the industry are more likely to respond by decreasing their disclosure. Combined with our first finding, decreased climate disclosure is not enough to shield these firms from the scrutiny of institutional investors.

Lastly, to provide more validity to the results on the industry GHG innovation index, we examine whether the impact on silent firms weakens when the operational distance between innovative firms and silent firms increases. The intuition is that, for a given silent firm, if its GHG emission performance is closer to the innovative firms, it may draw more attention of investors, its green image may be more severely damaged, and marginal investors may be more likely to leave and decrease their holdings since the silent firm and innovative firm are close substitutes for each other prior to the innovation. We indeed find that, in the post-Paris Agreement era, the impact of industry GHG innovation index decays with increasing operational distance between silent firms and innovative firms.

The main insight we bring to literature is that firm climate risks are incorporated into price on their competitors carbon emission innovations depending on the relevance of the information, complementary to the prior literature that firms' own carbon emissions are priced systematic risk factors. Prior studies ask whether carbon risks are underpriced and confirm some level of underpricing. This study addresses a potential explanation for the underpricing. With growing attention and growing data on greenhouse gas emissions, investors more readily price carbon risks associated with firms' own activities. However, it takes significant efforts to find out, if one can, the risks are associated with competitors' continuing efforts to become greener. This study provides the first empirical evidence on peer firm effects and the estimation of the underpriced risks. Moreover, this study helps value maximizing firms internalize externalities from their peers' green efforts, so as to make better and more informed decisions on improving GHG emission performance and emission disclosures in the post-Paris disclosure regime. Firms must carefully consider the impact of falling behind on green initiatives in the long run and realize that silence on these matters is unwittingly another kind of disclosure.

The remainder of the paper is organized as follows. Section II is literature review. In Section III we describe the data and construction of the industry innovation index. Section IV develops hypothesis and in Section V we discuss empirical results. Section VI concludes.

II. Literature Review

This study contributes to three strands of finance and accounting literatures. First, our study contributes to the growing literature on environmental risk and asset pricing. Bolton and Kacperczyk (2021) find firms with higher carbon dioxide emissions are demanded higher returns. They find institutional investors divest away from firms with high direct emissions from production (Scope 1). Wang and Wu (2022) examine the pricing and subscription of green bonds, and find the green bonds' lower offering spread is fully driven by its oversubscription by investors. Ilhan, Sautner and Vilkov (2021) find that the carbon policy uncertainty is priced in the option market. Carbon-intense firms incur higher costs of protection against the downside carbon tail risks, especially when public attention spikes. Monasterolo and Angelis (2020) analyzes systematic carbon risks in the stock market after the Paris Agreement, through examining the low-carbon and carbon-intensive indices in EU, US, and global stock markets. They provide evidence suggesting that stock market investors have started to consider low-carbon assets as an appealing investment opportunity in the post-Paris Agreement era but have not penalized yet carbon-intensive assets. Gorgen, Jacob, Nerlinger, Riordan, Rohleder and Wilkens (2020) also examines the relationships between carbon risks and equity prices in the global equity market and examines different geographic regions. They find brown firms are associated with higher average returns, while decreases in the greenness of firms are associated with lower announcement returns. Painter (2020) finds higher issuance costs on municipal bonds associated with counties with higher sea-level risk and global warming risks. Hsu, Li and Tsou (2021) examine the asset pricing implications of industrial pollution and find a pollution premium which cannot be explained by several explanations, including existing systematic risks, investors' preferences, market sentiment, political connections, and corporate governance.

Second, this study contributes to the growing literature on disclosures on climate change and environmental risk. Duchin, Gao and Xu (2023) examine the real market for firm pollution and green washing, especially when firms engage in reallocation of pollution through mergers, acquisitions and divestures. They provide evidence that current regulation and rating agencies reward such greenwash activities. The closest study to ours in this strand is Engle, Giglio, Kelly, Lee and Stroebel (2020), which examines market wide climate risk as captured by news media and provides a parsimonious way to hedge climate risk through textual analysis on major news articles. More specifically, they construct two indices to hedge climate risk. The first, Wall Street Journal climate change news index, is constructed as the correlation between WSJ text content and a fixed climate change library. The second, Crimson Hexagon's negative sentiment climate change news index, focuses solely on negative news about climate change. The main differences between their study and ours is that our GHG innovation indices are constructed from real-time industry specific innovations, different from their market-wide climate change news. Our results are robust to controls for time fixed effects which capture time trends in climate change news coverage and investor attention. Furthermore, we provide evidence that how peer carbon emission information is priced into equity can be reversed when disclosure regime evolves.

Third, our study contributes to the impact investing literature. Pastor, Stambaugh, and Taylor (2021) assume that investors' utility functions explicitly include preferences for green and brown stocks. A general equilibrium model in the study documents that greener firms have lower costs of capital due to the financial and real effects that arise from these preferences. Pedersen, Fitzgibbons, and Pomorski (2020) assume there exist three types of investors in the economy, those wanting green stocks, those wanting brown stocks, and those that are unaware of whether the stocks are green or brown. They explicitly assume that investors have ESG preferences in their utility functions and show that the green stocks' costs of capital depend on the wealth of the unaware investors. Krueger, Sautner, and Starks (2020) surveyed institutional investors about their climate risk perceptions, especially regulatory risks, to understand how institutional investors respond to climate risks in their portfolio constructions. Barber, Morse and Yasuda (2021) analyze impact investors who derive nonpecuniary utility from investing in dual-objective venture capital funds despite their lower returns. They find investors with social conscious are willing to pay more for impact investing while investors subject to legal restrictions exhibit lower willingness to pay. Heeb, Kolbel, Paetzold and Zeisberger (2023) utilize a framed field experiment to study investors' willing-to-pay for sustainable investments and find such willing-to-pay is driven by an emotional valuation of impact, or "warm glow."

III. Data and Sample

3.1 Data on Greenhouse Gas Emissions

We collect Greenhouse gas (GHG) emission data from Factset Truvalue dataset, which issues scores and unique article numbers for securities daily across the 26 SASB categories. For this study, we focus on GHG emission scores as they reflect firm GHG emission performance and media coverage. For the GHG emission category, Truvalue issues three daily scores for each category:

an insight score, a momentum score, and a pulse score. Pulse scores reflect the short-term, real-time performance, insight scores the long-term performance[8], and momentum scores the trend of each company by measuring the slope or trajectory of their insight score over a trailing 12-month period. We use the real-time innovation reflected in the pulse scores to the immediate and short-run market pricing, avoiding other explanations in the long-run that may affect carbon risk pricing. Positive innovations in GHG emission pulse scores reflect firm GHG emission improvements, while negative innovations reflect worsening performance. Our results are robust to use GHG emissions insight scores and momentum scores as well.

The Truvalue dataset also provides two measures on unique article coverage for each GHG emissions category, also at a daily frequency. Variable *catvol* measures the number of unique articles over a trailing 12-month period, and *volume_pctl* measures the percentage of unique of the 26 SASB categories over a trailing 12-month period. For this study, we use the daily change in GHG emissions *catvol* when the change is nonnegative, as it reflects the number of unique articles covered on this category on the given day.

Our full sample period is from Jan 2007 to Nov 2021. The sample includes US common equities with a share code of 10 or 11, publicly traded at major exchanges of NYSE, Nasdaq or Amex. We require distinct match between FactSet ID and PERMNO to ensure correct matching.

<Insert Table I Here >

Table I reports the summary statistics of firm daily GHG emissions innovations in the post Paris Agreement period. Panel A focuses on GHG emissions pulse scores, and reports on the number of days that a given firm has positive and negative real-time score change in a year. On

[8] Insight scores are derived from the pulse score using an exponential weighted moving average, with a six-month half-life (from Truvalue).

average, firms have 3.00 positive and 3.05 negative innovations in a year and the standard deviation is 10.96 and 11.00, respectively. Among the 56,400 firm-day pulse score observations, the median firm has no innovations. At the 75th percentile, firms have 1 positive and 1 negative innovations in a year. At the 90th percentile, firms have 15 positive and 15 negative innovations in a year. For the most innovative firms, they have 189 positive innovations in a year, in sharp contrast to worst performing firms with 176 negative innovations. The distribution is highly skewed, with the majority remaining silent and influenced by a few active ones. We also report the summary statistics in the 2007 – 2016 and 2017 – Nov 2021 sub-sample periods, and find the daily innovations in GHG pulse scores to be more volatile in the latter period.

Panel B focuses on the unique number of GHG emissions articles, and reports on the number of days that a given firm has climate news article coverage in a year. With a similar pattern to Panel A, a median firm does not have any news article coverage on GHG emissions in a year. At the 75th percentile, firms have 3 unique articles and at the 95th percentile, firms have 29 unique articles. Thus, a majority of the sample firms are not directly covered by news articles, though within the scope of directly covered firms. We also report the summary statistics in the 2007-2016 and 2017-2021 sub-sample periods. Unsurprisingly, there are more firms which are not covered by the media in the earlier sample period.

Panel C reports the number, percentage distribution, and cumulative percentages of GHG emission innovations by year after aggregating both positive and negative innovations. It complements Panels A and B, showing a pattern of increasing innovation over the years. That is, 2.02% of the daily innovations come from 2007 while 17.81% of the innovations come from 2021.[9]

[9] In Appendix Table AII we break down Panel A by year and report the number of days that a given firm has positive and negative GHG emissions innovations from 2007 through 2021. We find significant variation in both the average positive and negative innovation days from 2007 to 2021. Standard deviations increase over the years,

<Insert Table II Here >

Table II reports the percentage distribution of GHG emission innovations in representative industries. Industries are defined using the first two digits of the firms' primary SIC code. We rank all industries by the number of industry innovations as a percentage of total innovations, and report the industries with the highest percentage, the lowest percentage and some median percentage industries as well. The complete industry representation table can be found in Appendix Table AIII. Different industries have different representations for their carbon emission innovations, consistent with Bolton and Kacperczyk (2021) that carbon emissions intensity is a product of industry. There are several industries experiencing stronger innovations. Electricity, gas and sanitary services (49), business services (73), transportation equipment (37), oil and gas extraction (13), electronic and other electrical equipment and components (36) and chemical & allied products (28) are the industries with the highest number of innovative days. The observations are consistent with intuition, that the most pollutive industries have the largest room to improve its carbon emissions, are more incentivized to improve, and are under the spotlight to make green initiatives. The industries with lowest carbon emissions innovations are leather and leather goods (31), services, not elsewhere classified (8), agricultural production – livestock (2) and miscellaneous repair services (76).

We draw three conclusions from Table I and Table II. One, GHG emission innovations vary by industry. Industries making an extraordinary number of innovations are more than 10 times more active than industries making few innovations. Second, carbon emission disclosures are highly skewed and concentrate on a small group of firms. Third, GHG emission innovations appear

except for a period from 2016 to 2018, which may suggest an increasing effort to cut carbon emissions by firms, and an increasing efforts to collect and aggregate such information by the market.

to have a monotonic increase over time, consistent with increasing attention from banks, insurance companies, mutual funds, other institutional investors and likely society in general. Thus, our research question on how investors of silent firms update the GHG emission premiums required from these firms, especially in different disclosure regimes, is at the forefront of investigating the effect of carbon emission disclosures on firms' equity prices. That is, with no direct new information on firm GHG emissions, it is hard for investors to price their carbon emissions, and require appropriate compensation for higher carbon risks.

3.2 Construction of Industry GHG Emissions Innovation Index

This study focuses on whether carbon risks are priced for peers which experience the same industry GHG emission innovation shocks but do not have innovations themselves, controlling for firms' own GHG emissions. Firms must have at least one non-zero innovation in the month accompanying media coverage to be considered innovative firms, otherwise these firms are considered to have no innovation and labeled "silent firms." Industry is defined by the first two digits of firm SIC code as in Table II.

$$Innovation_{i,d,m}$$

$$= GHG\ emissions\ pulse\ score_{i,d,m} - GHG\ emissions\ pulse\ score_{i,d-1,m}$$

$$= \begin{cases} > 0 & Positive\ Innovation \\ 0 & No\ innovation \\ < 0 & Negative\ Innovation \end{cases}$$

Where i denotes firm, m denotes year-month, d denotes days in the year-month. Here $d \epsilon m$.

To aggregate the impact of all innovations by industry, we construct a monthly industry GHG innovation index ("Industry Innovation Index" afterwards), computed as the sum product of the GHG emission pulse score change and unique article numbers each day, across all days in the month, and all innovative firms in the industry. The constructed index is by industry, year, and month.

$$Industry\ Innovation\ Index_{j,m} = \sum_{i,d} Innovations_{i,d,m} * Unique\ Article\ Number_{i,d,m}$$

Where i denotes firm, m denotes year-month, d denotes day. Here $i \epsilon j\ and\ d \in\ m$.

We also separately examine the equity pricing impact of positive industry innovations and negative ones, to alleviate the concern that they may have asymmetric impact on firm equity, by building two corresponding industry innovation indices. The positive industry GHG innovation index ("Positive Innovation Index" afterwards) is constructed using positive firm-day innovations only, computed as the sum product of positive GHG emission pulse score changes and unique article numbers each day, across all days in the month, and all positive innovative firms in the industry. In a similar manner, we construct the negative industry GHG innovation index ("Negative Innovation Index" afterwards) using negative firm-day innovations only. For ease of interpretation, we add a negative sign to the Negative Innovation Index. Formally, we have:

$$Positive\ Innovation\ Index_{j,m} = \sum_{i,d} Innovation_{i,d} * Unique\ Article\ Number_{i,d}$$

$$where\ Innovation_{i,d} > 0$$

$$Negative\ Innovation\ Index_{jm} = -\sum_{i,d} Innovation_{i,d} * Unique\ Article\ Number_{i,d}$$

$where\ Innovation_{i,d} > 0$ denotes firm, m denotes year-month, d denotes days in the year-month, and j denotes industry. Here $i \in j$ and $d \epsilon m$.

Overall, the Industry Innovation Index aggregates shocks coming from firms both getting greener and browner, and reflects the industry level green efforts. A higher index level thus suggests an aggregate improvement in carbon emissions by industry peers. Positive (Negative) Industry Index aggregates positive (negative) shocks and reflects industry level green (brown) choices and results. A higher positive index level suggests an aggregate improvement in controlling carbon emission intensity through various green initiatives and technology development, while a higher negative index level suggests worsening of the situation and lack of control in carbon emissions for the industry.

<Insert Table III Here >

Table III reports the summary statistics on the indices constructed in our study. Panel A reports over the entire sample period 2007 – 2021. Panel B breaks down the summary statistics into two sub-sample periods 2007 – 2016 and 2017 – 2021. We make three observations. First, from Panel A, though innovations are highly skewed, the Industry Innovation Index is not. The mean industry innovation level is 2.85, with a median of 1.17. Its 25th percentile is -20.68 and its 75th percentile is 24.15, reflecting a distribution close to normal distribution. We thus do not expect the findings to be driven by outliers. Second, we observe balanced Positive and Negative Innovation Index levels. The Positive (Negative) Innovation Index is non-negative by construction, has a mean of 63.25 (60.40) and a median of 26.00 (24.93). We thus do not expect the findings to be driven by censored coverage, that is, media coverage only on good (bad) news. Third, from Panel B, a time trend in the Industry Innovation Index level can be observed. In the latter sample period from 2017 to 2021, all three industry innovation indices become more volatile with higher standard deviation, when compared to the sample period from 2007 to 2016. The three industry innovation indices are also at a higher level in the latter sample period, with larger means and medians.[10]

<Insert Figure I Here >

[10] We also test the robustness of the innovation index using GHG emissions insight scores and momentum scores in the regressions. Findings are qualitatively similar to using GHG emissions pulse scores.

How volatile is the industry innovation index? Are the most volatile industries for positive innovation index also the most volatile industries for negative index? To give readers an idea of the volatility of these indexes for some industries, in Figure I, we graph the monthly index for the most volatile industries, captured by the volatility of the index from 2017 to 2021, in the post Paris Agreement sample period. As in Panel A, industries with the most volatile innovation index are oil and gas extraction (13), food and kindred products (20), chemicals and allied products (28), electronic and other electrical equipment and components (36) and business service (73). As in Panel B, industries with the most volatile positive or negative index are oil and gas extraction (13), chemicals and allied products (28), electronic and other electrical equipment and components (36), transportation equipment (37), electric, gas and sanitary services (49), and business service (73)

We make two observations from Figure I. First, what's captured by the innovation index is the change in GHG emissions, not the level of GHG emissions. That's why we don't observe that the most volatile positive innovation industries fall into clean industries while most volatile negative innovation industries fall into brown industries. Instead, industries with positive innovations are more likely to have negative innovations, which could be explained by more investor attention drawn to the industry. This observation is consistent with our hypothesis that GHG emission innovations make an impact through industry membership and are priced not only for firms with innovations but could be also priced for firms without innovations but in the same industry. Second, volatility of the indices increases over the years. This could be explained by more green initiatives in recent years, stronger media attention and investor attention to firm carbon emissions, and a clustering of events driven by competition for the green image.

3.3 Other Variables

We collect monthly stock returns, shares outstanding, prices and other variables from CRSP. Monthly market risk premium, SMB, HML and momentum factors are downloaded from WRDS contributed (ff) data. To estimate Fama French 3-factor adjusted alpha and Carhart 4-factor adjusted alpha, we use the rolling 60 months' return to estimate the beta loadings and then calculate the alpha (Fama and French 1993; Carhart 1997). More specifically, to estimate Fama French 3-factor adjusted alpha in a given month t, we use the monthly stock returns and three factor returns from month $t-61$ to month $t-1$, to find out beta loadings on market risk premium, small minus big (SMB) and high minus low (HML) factors in month t, and lastly calculate the 3-factor predicted return as well as the factor adjusted alpha in month t. We also keep the coefficient on market excess returns as market beta from this time-series regression as the control variable in the Section V pooled regressions. We repeat the similar exercise using the prior 60 months' stock returns, market risk premiums, SMB, HML and momentum (MOM) factor returns to estimate Carhart 4-factor adjusted alpha in month t.

<Insert Table IV Here >

For control variables, market capitalization is estimated as the product of the stock closing price and shares outstanding at the end of month. The book-to-market ratio is estimated as book value to share holders' equity following Daniel and Titman (2006). Momentum is the cumulative returns in the prior 12 months. Profitability is total revenue minus cost of goods sold, scaled by total assets, following Novy-Marx (2013). Amihud illiquidity is the absolute daily return divided by trading volume in millions of dollars, following Amihud (2002). Furthermore, we take natural log of market cap, book-to-market and Amihud illiquidity to address the skewness of these variables. All control variables are winsorized at 1% on each tail. Summary statistics are reported to Table IV.

IV. Hypothesis development

Pastor, Stambaugh and Taylor (2021) model an equilibrium expected return of green and brown assets, when investors not only have returns but also ESG investors enjoy a surplus for holding green assets. Following their model, demands from ESG investors drive lower equilibrium expected returns on green stocks. Motivated by this logic, we posit that silent firms become browner and carry relatively higher carbon risk in the eyes of ESG investors, presuming that investors are assuming no changes have been made on their own GHG emissions due to the lack of an innovation. Thus, the first testable hypothesis of this study is *relative brown hypothesis*, formally:

H1 Relative Brown Hypothesis: Cross-sectional stock returns of firms experiencing aggregately positive industry innovation shocks are returns.

Bolton and Kacperczyk (2021) find that stocks of firms with higher carbon dioxide emissions and higher changes in carbon dioxide emissions earn higher returns cross-sectionally, after controlling for other risk factors. They further use time-series regression to confirm that the carbon premium is an independent premium which cannot be explained by existing well known risk factors. Motivated by this logic, we posit that information on carbon risk is collected and evaluated more broadly, not only from firms' direct production, but also from their industry peers. When the industry peers improve their carbon emissions and lower their carbon risks, investors project the improvements to those have not yet, expecting other firms in the same industry to decreasing carbon emission in the foreseeable future, thus lowing the carbon risks of the silent firms as well. The most natural alternative hypothesis to the relative brown hypothesis is *green transfer hypothesis*, formally:

H2 Green Transfer Hypothesis: Cross-sectional stock returns of firms experiencing aggregately positive industry innovation shocks are lower.

To disentangle these two competing hypotheses, we examine when the investors, especially ESG investors, are more likely to transfer carbon emission improvements in the industry from one peer to another. We argue the disclosure regime and the copiousness of carbon emissions information disclosed by firms are important for investors to decide how to make use of peer carbon emission information. In a strong information environment, when firms are more likely to make carbon emissions disclosures and when institutional investors put stronger efforts in requesting and seeking such information, we expect the relative brown hypothesis to dominate. However, in the weak information environment, when firms make scarce carbon emissions disclosures, we expect the green transfer hypothesis to dominate. We refer to this conjecture as the *disclosure regime hypothesis*, and formally:

H3 Disclosure Regime Hypothesis: Relative brown hypothesis dominates in the strong environmental information environment, while green transfer hypothesis dominates in the weak environmental information environment.

A natural extension of the disclosure regime hypothesis is *the operational distance hypothesis*. When socially conscious investors decide to rebalance their portfolio from silent firms to their innovative industry peers, whose equities are going to be affected the most? When these investors decide to transfer green shocks in the industry from one to another, how far do they extrapolate? We posit that operational distance is an important deciding factor for investors. When investors decide to extrapolate positive green shocks, they are more likely to extrapolate to silent firms closer in operating proximity. Similarly, if they are dropping relatively brown stocks from their holdings, firms in close proximity are the first to be dropped. We proxy proximity using GHG emissions pulse scores, and close in the pulse scores suggest they are more likely the supplementary in ESG investors' portfolio holdings. Formally:

H4: Cross-sectional stock returns of firms in response to industry innovation shocks decay with operational distance from innovative firms in the industry.

How do firms in different disclosure regime respond to the industry GHG emissions innovation? Public firms are regulated from actively misleading investors or making untruthful material disclosures. So, firms cannot correct the updated belief of ESG investors when they become relatively brown in their eyes, by falsely claiming carbon emissions improvement. Thus, they must speak less on carbon related topics or remain indifferent to the industry shocks, despite the change to their equity returns. A natural hypothesis following the disclosure regime hypothesis and the operational distance hypothesis is that firms have significant incentive to speak less on climate topics, following a positive industry shock, expecting to increase their distance from innovative firms. Formally:

H5: In response to aggregately positive industry innovation shocks, firms decrease their disclosure on carbon emission issues in the forthcoming quarterly reports.

V. Model Specification and Empirical Results

This section uses regression models to examine the hypotheses developed in Section IV and discusses empirical evidence in support of or rejecting the hypotheses. For regressions in this section, the Industry Innovation Index and its variations, firm GHG emission pulse scores, market beta, market capitalization, book-to-market, momentum, profitability, and Amihud illiquidity are all winsorized by 1% on both tails and then standardized, for ease of interpretation of regression results.

Our full sample period is from Jan 2007 through Nov 2021, with the Paris Agreement signed into effect during the sample period. Following the Paris Agreement, the Climate-Related Financial Disclosures (TCFD) led by the UN environment program (UNEP) finance initiative (FI), the Global Reporting Initiative (GRI) led by Global Sustainability Standards Board (GSSB) and the Carbon Disclosure Project (CDP) for North America launched Climetrics, the world's first climate rating for investment funds. Furthermore, the CDP developed various frameworks and led various initiatives to improve firm carbon emissions disclosures. We thus use the post Paris Agreement period, 2017 – 2021, to proxy for the strong climate related information environment, and the prior Paris Agreement period, 2007 – 2016, to proxy for the weak climate information environment.

5.1 Strong climate information environment

We first formally test H1 and H2 in the strong information environment using the sample period 2017 - 2021. We use pooled regressions to test H1 and H2 and specify the model in (1) and (2) below. The dependent variable in both models is percentage monthly stock returns. The independent variables of main interest in model (1) are the Positive and Negative Innovation Index, and in model (2) is Industry Innovation Index. H1 is supported if α_1 is significantly positive, α_2 significant negative, or δ_1 significantly positive. Otherwise, H1 is rejected.

$$RET_{i,t} = \alpha_0 + \alpha_1 * Positve\ Innovation\ Index_{ind,t} + a_2 * Negative\ Innovation\ Index\ _{ind,t} + \alpha_3 * GHG\ emission\ pulse\ score_{i,t-1} + \sum \alpha_k * control_{i,t-1} + \gamma_{ind} + \mu_t + \varepsilon_{i,t} \quad (1)$$

$$RET_{i,t} = \delta_0 + \delta_1 * Industry\ Innovation\ Index_{ind,t} + \delta_2 * GHG\ emission\ pulse\ score_{i,t-1} + \sum \delta_k * control_{i,t-1} + \gamma_{ind} + \mu_t + \varepsilon_{i,t} \quad (2)$$

Where $RET_{i,t}$ is monthly stock returns for firm i in month t.

<Insert Table V Here >

Regression results are reported to Table V. Columns 1 to 3 report on Industry Innovation Index, with column 1 not controlling for firms' own GHG emissions pulse scores, column 2 controlling for firms' current month GHG emissions pulse scores and column 3 controlling for firms' own GHG emissions pulse scores at the prior month end. Columns 4 to 6 examine the positive (negative) innovation index, controlling for firms' own current month and prior month end GHG emissions pulse scores in a similar manner.

H1 is supported and H2 is rejected with the evidence in Table V. Column 3 suggests that equity monthly returns increase by 10.6 bps with one standard deviation increase in the Industry Innovation Index, significant at 1% level. Similarly, Column 6 suggests that equities demand 13.9 bps higher monthly returns with a one standard deviation increase in the Positive Innovation Index, significant at 5% level. Moreover, when there is one standard deviation increase in the Negative Innovation Index, equity returns are lowered by 21.1 bps monthly, significant at 1% level. We conclude that, consistent with the relative brown hypothesis, both positive and negative industry GHG innovation shocks by peer firms are priced by the market, and carbon risk increases for firms without innovation.

As documented by other recent studies, carbon risk is likely unique information to be incorporated into equity prices . Thus, we do not expect such risk even when coming from peers in the industry, to be fully incorporated into the conventional risk factors – market risk, size risk, value risk, and momentum risk factors. Instead, we expect to find the additional carbon risk associated with industry innovations to be found in excess returns after adjusted for the conventional risk factors. More specifically, consistent with H1, we expect to find higher (lower) alpha associated with Positive (Negative) Industry Innovations and aggregate Industry Innovation Index.

<Insert Table VI Here >

We use pooled regressions and models similar to (1) and (2), except that the dependent variables are monthly Fama French 3-factor alpha and Carhart 4-factor alpha (Fama and French, 1993; Carhart 1997). As returns have already been adjusted for the market returns, size, book-to-market, and momentum, we do not control for these variables in Table VI. We still control for firms' own GHG emissions pulse scores at the end of prior month, the industry and time fixed effects as in model (1) and (2), and standard errors are clustered by industry and year. Results are reported to Table VI.

Table VI also supports Hypothesis H1 and rejects H2. Carbon risk arising from industry peer innovations is a new form of risk and a new source of equity price information, explaining excess returns that cannot be explained by conventional well known risk factors. Positive Industry Innovations increase carbon risk on silent firms, and such increased carbon risk is associated with higher alpha. From column 1 and 3, with a one standard deviation increase in the Negative Innovation Index, monthly 3-factor adjusted alpha decreases by 7.8 bps and monthly 4-factor adjusted alpha decreases by 8.8 bps. Columns 2 and 4 suggest that, on one hand, with a one standard deviation increase in the positive innovation index, monthly 3-factor adjusted alpha increases by 12.3 bps and monthly 4-factor adjusted alpha increases by 13.5 bps. On the other hand, when shocked with a GHG Negative Index Increase, firm carbon risk decreases relatively which is associated with negative alphas.

In conclusion, in the post Paris Agreement strong information environment, the relative brown hypothesis is supported while the green transfer hypothesis is rejected. Results are consistent with theory on ESG investors' portfolio holding equilibrium and utility surplus from holding green stocks (Pastor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2020). ESG investors manage a portfolio by balancing between green and brown stock holdings and maximize their utility as a function of portfolio greenness. Relative brownness is not only associated with firms' own GHG emissions, but also with their industry peers' emission innovations. When there is positive news on GHG emissions, firms in the same industry without innovations become browner for ESG investors. Vice versa for negative news on GHG emissions. ESG investors, whose green utility is sub-optimal with the arrival of innovation information, will update their portfolio holdings towards optimal green utility. Non-ESG investors also respond to the innovations on carbon risk and the lower demand by ESG investors on relatively brown stocks, by demanding higher returns. Altogether, a new equilibrium between demand and supply of silent firms is reached between ESG and non-ESG investors who have different utility functions.

5.2 Weak climate information environment

We next formally test H1 and H2 in the weak climate information environment using pooled regressions in the sample period 2007 – 2016. Our model specifications are the same as in (1) and (2) from Section 5.1. Regressions results are reported to Table VII. H2 is supported if α_1 is significantly negative, α_2 significant positive, or δ_1 significantly negative. Otherwise, H2 is rejected.

<Insert Table VII Here >

The significantly negative coefficients on the Positive Innovation Index and on Industry Innovation Index support H2 and reject H1. The coefficient on Negative Innovation Index is insignificant, supporting neither hypothesis. Column 1 (4) does not control for firms' own carbon emissions, column 2 (5) controls for firms' own carbon emissions at the end of current month, while column 3 (6) controls for firms' own carbon emissions at the end of prior month.

Evidence supports that, in the weak climate information environment, investors extrapolate Positive Industry Innovations to silent firms and lower their demanded equity returns, while not extrapolating negative news to the silent ones. Thus, green transfer hypothesis is supported in the weak information environment prior to Paris Agreement passage and the other multitude of events and regulations that led to a stronger climate information environment. Evidence from column 3 suggests that when the Industry Innovation Index increases by one standard deviation, equity returns decrease by 14.8 bps monthly, significant at 10% level. In column 6, a one-standard-deviation increase in Positive Innovation Index is associated with a decrease of monthly equity returns by 56.3 bps, significant at 1% level. Equity returns, however, do not respond significantly to the Negative Innovation Index in this pre Paris Agreement period.

<Insert Table VIII Here >

Similarly, we examine whether the presumed lowered carbon risk arising from Positive Industry Innovations in the weaker climate information environment can explain 3-factor and 4-factor adjusted excess returns, using pooled regressions on model (1) and (2) with excess returns as dependent variables. Regression results are reported in Table VIII.

Consistent with H2 and Table VII, lower 3- and 4-factor adjusted excess returns are found to be associated with positive innovation shocks, after controlling for firms' own GHG emissions at the prior month end. In column 1 and 3, with a one-standard-deviation increase in the aggregate Industry Innovation Index, stock monthly 3- and 4-factor alpha decrease by 16.7 bps and 15.8 bps, both significant at 5% level. In column 2 and 4, with a one-standard-deviation increase in the Positive GHG Innovation Index, monthly 3-factor adjusted alpha and 4-factor adjusted alphas decrease by 54.2 bps and 56.6 bps, both significant at 1% level. The findings further suggest the significance of hypothesis H2 in a weaker carbon information environment that suggests carbon risk information transfer is a priced source of information, different from conventional risk factors such as size, value, and momentum.

5.3 Disclosure regime hypothesis

Putting together the findings in Section 5.1 and Section 5.2, we find the relative brown hypothesis dominates in the post Paris Agreement era, while the green transfer hypothesis dominates in the pre Paris Agreement years. Collectively, they support H3, the disclosure regime hypothesis.

The conflicting findings supporting H1 and H2 confirm the importance of detailed and firm specific carbon emissions disclosure. Investors rely on information to understand the greenness of a firm, how it meets climate risk and carbon risk challenges, and to make predictions on firms' future emissions, without which, they cannot make ideal decisions and asset allocations. Though theory predicts environmental conscious investors holding green stocks, in practice, it is rather difficult for ESG investors to identify green firms and green stocks in information scarcity. To distinguish green stocks from brown stocks, a sufficient GHG emission information environment is a necessity.

The two competing hypothesis H1 and H2 do not differ on the utility function of ESG investors. Rather, they are both consistent with theory on ESG investors and their demand on green stocks (Pastor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2020). The two hypotheses, instead, differ on how ESG investors collect and process information in different disclosure regimes, and the path to maximize their utility, especially green utility.

5.4 Operational distance hypothesis

In this section, we examine H4, the operational distance hypothesis, as a natural extension of H3 the disclosure regime hypothesis in the strong information environment. If silent firms are adversely affected by the industry innovations in GHG emissions, we expect the adverse effect to be stronger for firms which are more likely to be replaced by the green innovative firms. We conjecture that firms that have similar carbon emission performance are better replacement for each other. To proxy the likelihood to be replacement and close proximity in carbon emission performance, we use absolute distance in carbon emission pulse scores. On the other side, when the absolute distance between firms' GHG emissions pulse scores increases, we expect the adverse impact to be weakened. For a given firm, its absolute distance is computed as the absolute differences between its GHG emission pulse score and the scores of innovative firms in the same industry in the month. If there are more than one innovative firms in the month, we use the median pulse score across all innovative firms to compute absolute distance ("distance" afterwards).

Model specification is in equation (6). Our main variables of interest are the coefficients on the interaction term between distance and positive innovation index, as well as on the interaction term between distance and industry innovation index. We control for the same set of control variables and fixed effects as in model (1) and (2), clustering all standard errors by firm and year. Results are reported to Table IX.

$$RET_{i,t} = \alpha_0 + \alpha_1 * Distance_{\ i,t}\ X\ GHG\ Index\ Positve_{i,t} + a_2 * Distance_{\ i,t}\ X\ GHG\ Index\ Negative_{i,t} + \alpha_3 * GHG\ Index\ Positve_{i,t} + a_4 * GHG\ Index\ Negative_{i,t} + \alpha_5 * GHG\ emission\ pulse\ score_{i,t-1} + \sum \alpha_k * control_{i,t-1} + \gamma_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

<Insert Table IX Here >

H4 is supported if α_1 is significantly negative or α_2 is significantly positive, or both. Column 1 and 2 report the results for the strong climate information era, with column 3 and 4 reporting the results for the weak climate information era. Column 1 and 2 confirm H4 that distance matters in the post Paris Agreement era. We observe the decay in higher carbon risk pricing when distance to innovative firms increases. In column 1 when we use industry innovation index in the regressions, the negative coefficient of -0.015 on the interaction between distance and industry innovation index suggests that, the positive industry innovation – firm equity return relationship is weakened by 10.64% (= 0.015 / 0.141) as the distance to innovation increases. Similarly, in column 2, the negative α_1 of -0.031 suggests that, with a one-standard-deviation increase in the positive innovation index, the higher equity return associated with higher carbon risk can be lowered by 14.76% (= 0.031 / 0.21) with the distance increasing by one standard deviation from innovative firms. The results are both significant at 5% level. We do not observe similar decay with increasing distance when it comes to negative innovation index.

Columns 3 and 4 suggest that, in the weak climate information environment, green transfer is not significantly associated with and sensitive to the distance to innovative firms. New information on GHG emissions is extrapolated to silent firms in the same industry in a similar manner, regardless of their proximity to firms improving their emission intensities. This is consistent with lack of detailed firm specific information in this period making it harder for investors to estimate the distance between silent firms and innovative firms in terms of their carbon emissions, and to disentangle firms based on operational distance.

In conclusion, the operational distance hypothesis is supported by Table IX. When there is a good amount of information on firm carbon emissions, firms with close emission scores are good replacements for each other and are subject to the strongest adverse shocks when one innovates.

When distance increases, these adverse shocks are weakened, and firms' equity returns are not increased as much as firms in close proximity to innovations. The contrasting results between column 1 (2) and 3 (4) also complements our conjecture that in the strong climate information environment, it is easier for investors to collect and analyze firm carbon emission performance and price firm carbon risks.

5.5 How do firms respond in their own reporting to industry innovations?

Lastly, we are interested in the interplay in disclosures made by firms with innovations and firms with innovations. When firms become aware of investors preferences, higher carbon risks and the ensuing higher equity premiums in the strong information environment, will they change their forthcoming disclosure on carbon emission and climate risks? We don't expect public firms regulated by the Exchange Act and SEC, to actively mislead investors to believe that they are making improvements. However, we still expect them to react rationally and quickly to weaken the adverse shock arising from positive industry innovations.

We focus on firm disclosure on GHG emissions as a response and start with two carbon-related and climate-related wordlists. The first is developed by Li, Shan, Tang and Yao (2021) and can be found in their Table 2. The second is developed by Matsumura, Prakash and Vera-Munoz (2022). To create our first word list (i.e., Wordlist 1) we utilize the transition climate risk list from Li, etc. (2021) which focuses on climate risks associated with fuel, gas, energy and carbon, instead of on natural climate disasters such as hurricanes and earthquakes. Next, we expand the transition climate risk list by adding the wordlist used in Matsumura et al. (2022), to catch possible omissions. This combined list is utilized as Wordlist 2. Lastly, we parse firms' 10-Q reports and count the number of times the words in each wordlist shows up in each report. We refer to the variable constructed as *wordcount*.

We formally test H5 on firm disclosure as a response to industry innovations using pooled regressions on model specification (4). The dependent variable is *wordcount* in the forthcoming 10-Q reporting. We control for the same set of control variables as in Table V, industry and time fixed effects, and cluster standard errors by firm. Regression results are reported to Table X. Panel A reports on the strong climate information environment while Panel B reports on the weak climate information environment. In both panels, columns 1 and 2 report wordcounts using Wordlist 1, the transition climate risk list by Li, etc. (2021) and columns 3 and 4 report the wordcounts using Wordlist 2, the combined wordlist.

$$WordCount_{i,t} = \beta_0 + \beta_1 * GHG\ Index\ Positve_{ind,t} + \beta_2 * GHG\ Index\ Negative_{ind,t} + \beta_3 * GHG\ emission\ pulse\ score_{i,t} + \sum \beta_k * control_{i,t} + \gamma_{ind} + \mu_t + \varepsilon_{i,t} \quad (4)$$

<Insert Table X Here >

If β_1 is significantly negative, H5 is supported: In response to positive industry innovation shocks, firms decrease their disclosure on carbon emission issues in the forthcoming quarterly reports. Otherwise, H5 is rejected. Panel A supports H5 in the strong climate information environment, suggesting that firms use fewer words related to carbon emission and climate change, following a positive industry innovation shock. From column 1 and 3, with a one-standard-deviation increase in the industry innovation index, firms decrease their climate disclosure by 0.2% based on wordlist 1 and 2, respectively, both significant at 5% level. Similarly, from columns 2 and 4, with a one-standard-deviation increase in the positive innovation index, firms decrease the number of climate words used by 0.5% and 0.3% based on wordlist 1 and 2, respectively. The finding is significant at the 5% level. Indeed, firms respond quickly to positive industry innovation shocks by talking less, disclosing less, and distancing themselves from innovative firms.

Panel B rejects H5 in the weak climate information environment, suggesting that firms do not change the number of times they discuss carbon emission and climate change in the forthcoming quarter, following a positive industry innovation shock. Consistent with lack of sensitivity of the market to firm GHG emission levels in this period, firms may be less reactionary and do not change their disclosure as their industry peers have positive (negative) climate news.

In all, we find firms change their climate disclosure and the use of climate words in their reporting, as a rational response to increased investor scrutiny in more recent years after 2017. Through speaking less, firms may decrease information accuracy on their emissions, increase their distance to innovative firms, or make it harder to approximate the distance, decrease investor attention, and attempt to alleviate the carbon risk premium associated with the innovation. This is enabled by the flexibility of the voluntary environment of climate related disclosures and the non-standardized disclosure framework.

5.6 Robustness checks using Hoberg Phillips Industry Classification

As a robustness check, we classify industry following the Hoberg and Phillips Text-based Network Industry Classifications (TNIC-2 and TNIC – 3 afterwards), derived from firm annual 10 - K filings (Hoberg and Phillips 2010, 2016). The level of coarseness of TNIC-3 matches that of a three digit SIC code as "both classifications result in the same number of firm pairs being deeded related." The level of coarseness of TNIC-2 matches that of a two digit SIC code, which is the industry classification used in the main body of our study. We use both TNIC-2 and TNIC-3 in this section, and expect to see carbon risk premium associated with positive industry innovations when industry is defined in either way.

Since TNIC – 2 and TNIC – 3 industry classifications cater to each firm, unique industry classification and industry peers, the industry innovation index is also unique to each firm. More specifically, for a given firm, we find its TNIC – 2 industry peers, excluding itself, and compute the TNIC-2 industry innovation index as the sum product of GHG emission pulse score innovations and the number of unique articles on the same day across all firms in the same TNIC industry. Similarly, we compute TNIC-2 positive (negative) innovation index as the sum product of positive (negative) GHG emission innovations and the number of unique articles on the same day across all firms in the same TNIC – 2 industry peer group. TNIC-3 Industry Innovation Index and TNIC-3 Positive (Negative) Industry Index are constructed in a similar manner, with industry defined following TNIC-3 classification.

We use the TNIC-2 and TNIC-3 classification to formally test H1 – the relative brown hypothesis, using pooled regressions on the model specification (5) and (6). Any firm with GHG emission innovations, in the current, prior, or next month, is excluded from our regression. We control for the same set of control variables as in Table V, firm fixed effects γ_i and time-fixed effects μ_t, and cluster standard errors by firm and year. Results are reported to Table XI. Column 1 and 2 focus on TNIC-2 innovation index and column 3 and 4 focus on TNIC-3 innovation index.

$$RET_{i,t} = \alpha_0 + \alpha_1 * Industry\ Innovation\ Index_{i,t} + \alpha_2 * GHG\ emission\ pulse\ score_{i,t} + \sum \alpha_k * control_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t} \quad (5)$$

$$RET_{i,t} = \beta_0 + \beta_1 * GHG\ Index\ Positve_{i,t} + \beta_2 * GHG\ Index\ Negative_{i,t} + \beta_3 * GHG\ emission\ pulse\ score_{i,t} + \sum \beta_k * control_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t} \quad (6)$$

<Insert Table XI Here >

H1 is supported if α_1 is significantly positive, β_1 is significantly positive, or β_2 significantly negative. In Table X column 1 and 3, α_1 of 0.152 for TNIC-2 industry classification and of 0.105 for TNIC-3 classification are both significantly positive, supporting H1 and providing evidence to carbon risk premium in the strong information environment associated with industry innovation. In column 2, a one-standard-deviation increase in the Positive Innovation Index following TNIC – 2 classification is associated with 26.3 bps higher monthly returns. And in column 4, a one-standard-deviation increase in the Positive Innovation Index following TNIC – 3 classification is associated with 13.1 bps higher monthly returns. In both column 2 and 4, the coefficient on Industry Innovation Index is significantly positive at 5% level following TNIC-2 classification and significant at 1% level following TNIC-3 classification. Moreover, β_2 is negative in both column 2 and 4, though significant only in column 2, suggesting the investors are more sensitive to positive shocks than to negative shocks. In conclusion, the relative brown hypothesis that firms' carbon risk increases in the strong climate information environment with Positive Industry Innovation shocks are robust to alternative definitions of industry.

VI. Conclusion

Motivated by the debate of whether to require mandatory environmental risk disclosure for publicly traded firms, and how such a ruling may change the landscape of environmental information processing and equity pricing, this study examines two research questions. First, how do firm equity returns and carbon risk vary with greenhouse gas emission innovations by industry peers, holding firms' own carbon emissions constant? Second, are industry peer greenhouse gas emission innovations priced in the same way with differing information environments? We propose three hypotheses to these questions. First, the relative green hypothesis that there is a positive relationship between industry GHG emission innovations and the carbon risk premium, resulting in higher equity returns. Second, the green transfer hypothesis that there is a negative relationship between them. Third, the role the information environment plays role in how investors process environmental disclosure information. In the weak climate disclosure environment, investors extrapolate green innovations from innovative firms to peers, supporting the green transfer hypothesis. In strong climate information environment, they rebalance their portfolio between the new brown and green stocks, supporting relative green hypothesis.

Empirically, we construct monthly industry innovation indices to capture GHG emission shocks in the industry, and find that firm equities are demanded higher returns and higher alpha in the post Paris Agreement period, when shocked by positive innovations in the industry. Opposite observations are made in the pre-Paris Agreement period. In response to the market sentiment to industry GHG emission innovations, firms choose to talk less on climate-related issues and use fewer climate-related words, in the post-Paris Agreement era following positive industry innovations.

Climate risk is an increasingly influential physical, environmental, and social risk. A deeper understanding of climate risk and carbon risk, as well as the channels through which they are incorporated into firm equity returns is essential for institutional investors, policy makers, regulators, and the firms themselves. With the SEC's recent focus on standardized climate-related disclosures, other standard setting bodies abroad, and an increasingly engaged generation of climate conscientious investors, future research could explore how firms' real investments on carbon risk vary with carbon emission intensity and disclosure transparency.

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Table I
Daily Greenhouse Gas (GHG) Emission Innovations

Table reports summary statistics on the number of firm-day innovations of greenhouse gas (GHG) emission pulse scores and the number of unique GHG emissions news articles in one year. The sample period is Jan 2007 – Nov 2021. We report over the whole sample period, the strong information environment from Jan 2007 to Dec 2016, and the weak information environment from Jan 2017 to Nov 2021. Panel A reports the number of firm-day non-negative and non-positive daily GHG emission pulse score innovations in a year. Panel B reports the number of unique articles for a given firm in a year, as well as the number of missing observations for unique article number *catvol*. Panel C reports the number of firm-day innovations in each year and as a percentage of all firm-day innovations over the full sample period. GHG emission pulse score and *catvol* the number of unique articles on firm GHG emissions category over a trailing of 12-month period are collected from Truvalue dataset. GHG emission pulse score reflects real time, short-term firm GHG emissions. For a given firm, daily innovation in pulse scores is computed as the pulse score change from the prior day. Daily innovation in *catvol* is computed as the change in *catvol* from the prior day, if non-negative, and captures the number of unique news articles published in the day on firm GHG emissions performance.

Panel A. Firm-day GHG pulse score innovations in a year

N = 56,400	Mean	Std Dev	Median	P75	P90	P95	Max
>= 0	3.00	10.96	0	1	6	15	189
<= 0	3.05	11.00	0	1	6	15	176

Strong information environment: 2017 – 2021

N = 23,845	Mean	Std Dev	Median	P75	P90	P95	Max
>= 0	3.37	12.90	0	1	6	17	189
<= 0	3.47	13.07	0	1	7	17	176

Weak information environment: 2007 – 2016

N = 32,555	Mean	Std Dev	Median	P75	P90	P95	Max
>= 0	2.67	8.97	0	2	6	13	157
<= 0	2.69	8.85	0	1	6	13	152

Panel B. Number of unique GHG emissions articles in a year

	Mean	Std Dev	Median	P75	P90	P95	Max
Unique Article	5.50	17.36	0	3	13	29	263

Unique Articles	Missing	Mean	Std Dev	Median	P75	P90	P95	Max
2017 - 2021	4,973	5.03	18.62	0	2	10	26	263
2007 – 2016	18,923	6.13	15.49	1	5	16	32	220

Panel C. Distribution of firm-day GHG emission innovations

Year	N	Percentage	Cumulative %	Year	N	Percentage	Cumulative %
2007	2,296	2.02	2.02	2017	5,200	4.57	52.48
2008	3,966	3.48	5.50	2018	5,907	5.19	57.67
2009	4,377	3.85	9.35	2019	10,546	9.27	66.93
2010	4,985	4.38	13.73	2020	17,365	15.26	82.19
2011	5,516	4.85	18.57	2021	20,269	17.81	100.00
2012	5,771	5.07	23.64				
2013	5,976	5.25	28.90				
2014	8,128	7.14	36.04				
2015	9,504	8.35	44.39				
2016	4,007	3.52	47.91				

Table II
Industry Representations on Firm-Day GHG Emission Innovations

Table reports industry description[1], the number of firm-day GHG emission innovations and the number as a percentage of total firm-day GHG emission innovations in the sample. The sample period is Jan 2007 – Nov 2021. We report the top 6, bottom 6 and midden 6 industries ranked by the number of firm-day innovations as representative data. The full table can be found in Appendix Table AII. Industry is defined by the first 2 digits of firm SIC code. We consider it as a GHG emission innovation if there is a non-zero change on firm GHG emission pulse score from the prior day and there is at least one unique article related to firm GHG emissions on the same day.

SIC2	Industry Description	COUNT	PERCENT
49	Electric, Gas, & Sanitary Services	32,135	28.23
73	Business Services	10,535	9.26
37	Transportation Equipment	9,706	8.53
13	Oil & Gas Extraction	8,553	7.51
36	Electronic & Other Electric Equipment	5,585	4.91
28	Chemical & Allied Products	5,068	4.45
	……		
63	Insurance Carriers	612	0.54
61	Depository Institutions	586	0.51
53	General Merchandise Store	545	0.48
87	Engineering & Management Services	524	0.46
51	Wholesale Trade – Nondurable Goods	449	0.39
55	Automotive Dealers & Service Stations	363	0.32
	……		
24	Lumber & Wood Products	10	0.01
80	Health Services	8	0.01
31	Leather & Leather Products	4	0.00
89	Services, Not Elsewhere Classified	4	0.00
2	Agricultural Production – Livestock	2	0.00
76	Miscellaneous Repair Services	1	0.00

[1]Industry 2-digit SIC codes and description can be found in: https://mckimmoncenter.ncsu.edu/2digitsiccodes-2/

Table III
Monthly Industry GHG Emission Innovation Index (*II Index*)

Table reports summary statistics on industry GHG emission innovation index (*II Index*), Positive innovation index (*II Pos Index*) and Negative innovation index (*II Neg Index*). Panel A reports over the whole sample period, and Panel B breaks it down to the strong and weak information environment. The sample period is 2007 – 2021. For a given industry, its monthly *II Index* is computed as the sum product of its GHG emission pulse score innovations and the number of unique articles on the same day, across all firms in the industry in the month. The *II Pos Index* (*II Neg Index*) is computed as the sum product of positive GHG emissions pulse score innovations and the number of unique articles on the same day, across all firms in the industry in the month.

Panel A. 2007 – 2021

N = 7,106	Mean	Std Dev	P10	P25	P50	P75	P90
II Index	2.85	71.00	-49.22	-20.68	1.17	24.15	56.67
II Pos Index	63.25	119.42	0.00	6.58	26.00	64.33	151.30
II Neg Index	60.40	112.98	0.00	6.44	24.93	63.35	144.26

Panel B. By Strong and Weak Information Environment

Strong Information Environment: 2017 - 2021							
N = 2,551	Mean	Std Dev	P10	P25	P50	P75	P90
II Index	4.88	94.98	-61.32	-23.98	1.41	27.57	76.37
II Pos Index	86.28	160.35	0.00	9.01	31.41	86.46	219.12
II Neg Index	81.40	147.16	0.00	8.86	30.58	81.52	202.53
Weak Information Environment: 2007 - 2016							
N = 4,555	Mean	Std Dev	P10	P25	P50	P75	P90
II Index	1.71	53.00	-43.85	-19.48	0.99	22.09	49.71
II Pos Index	50.35	85.97	0.00	5.37	23.36	55.61	122.00
II Neg Index	48.64	86.05	0.00	5.15	22.54	53.74	118.08

Table IV
Summary Statistics

Table reports summary statistics on variables used in this study. Our sample Period is 2007-2021. *II Index*, *II Pos Index* and *II Neg Index* are defined in Table III. Return is stock monthly returns in percentages. 3-factor alpha is Fama French 3-factor adjusted excess return and 4-factor alpha is Carhart 4-factor adjusted excess return, both represented in percentages (Fama and French 1993; Carhart 1997). We use the prior 60 month rolling window (from t-60 to t-1) to estimate the coefficients on market risk premium, size (SMB) and value (HML), to compute the 3-factor adjusted alpha in month t. We use the prior 60 month rolling window (from t-60 to t-1) to estimate the coefficients on market risk premium, size (SMB), value (HML), momentum (MOM) to compute the 4-factor adjusted alpha in month t. Market beta is the coefficient on market risk premium from the time-series regressions when using the Fama-French 3-factor model. Market capitalization is the product of shares outstanding and share price at the end of month. Book-to-market is the book value scaled by market value following Daniel and Titman (2006). Momentum is the accumulative prior 12-month stock returns. Profitability is revenue minus cost of goods sold scaled by total assets following Novy-Marx (2013). Amihud illiquidity is absolute stock daily return scaled by daily volume traded measured in million dollars, averaged by month (Amihud 2002). We take the natural log of market capitalization, book-to-market and Amihud illiquidity for their high skewness.

	N	Mean	Std Dev	P25	P50	P75
II Index	562,638	3.83	78.41	-19.38	0.00	25.16
II Pos Index	562,638	77.34	123.59	2.67	36.05	99.24
II Neg Index	562,638	73.51	115.40	2.11	34.30	95.70
Return (%)	560,858	0.86	18.06	-6.47	0.28	6.89
3-Factor Adjusted Alpha (%)	552,662	0.01	17.77	-6.79	-0.48	5.56
4-Factor Adjusted Alpha (%)	551,052	0.08	17.99	-6.74	-0.45	5.64
Market Beta	554,486	1.03	0.88	0.49	0.96	1.48
Market Capitalization	562,614	19.90	2.01	18.39	19.88	21.34
Book-to-Market	477,469	-0.63	0.90	-1.15	-0.53	-0.05
Momentum	561,089	0.10	0.53	-0.16	0.10	0.35
Profitability	499,588	0.26	0.29	0.05	0.24	0.42
Amihud Illiquidity	562,514	-4.35	3.42	-6.95	-4.82	-2.09

Table V

II Index and Stock Returns in the Strong Information Environment

Table presents the relationship between *II Index*, *II Pos Index*, *II Neg Index* and stock monthly returns in the strong information environment. The sample period is 2017 –2021. The dependent variable is stock monthly returns in percentages. *II Index II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	1	2	3	4	5	6
II Index	0.106***	0.106***	0.106***			
	(0.000)	(0.000)	(0.000)			
II Pos Index				0.139**	0.139**	0.138**
				(0.024)	(0.024)	(0.024)
II Neg Index				-0.211***	-0.211***	-0.212***
				(0.004)	(0.004)	(0.004)
GHG Emission Score L1	0.148***			0.148***		
	(0.006)			(0.006)		
GHG Emission Score		0.153***			0.152***	
		(0.006)			(0.006)	
Market Beta L1	0.337	0.337	0.347	0.336	0.335	0.346
	(0.232)	(0.232)	(0.225)	(0.233)	(0.233)	(0.225)
Market Cap L1	-0.973*	-0.974*	-0.942*	-0.975*	-0.976*	-0.943*
	(0.072)	(0.072)	(0.076)	(0.072)	(0.072)	(0.076)
Book-to-Market L1	-1.802***	-1.802***	-1.786***	-1.802***	-1.802***	-1.786***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	-0.571*	-0.571	-0.580*	-0.570	-0.570	-0.579*
	(0.100)	(0.100)	(0.098)	(0.101)	(0.101)	(0.100)
Profitability L1	0.205	0.205	0.209	0.205	0.205	0.209
	(0.125)	(0.125)	(0.115)	(0.124)	(0.124)	(0.115)
Amihud Illiquidity L1	-0.319	-0.319	-0.321	-0.320	-0.320	-0.322
	(0.172)	(0.172)	(0.172)	(0.171)	(0.171)	(0.170)
N	122569	122569	122569	122569	122569	122569
R^2	0.131	0.131	0.130	0.131	0.131	0.130

Table VI
Industry Innovations and Excess Returns in Strong Climate Information Environment

Table presents the relationship between *II Index*, *II Pos Index*, *II Neg Index* and excess returns in the strong information environment. The sample period is 2017 –2021. The dependent variables are monthly Fama-French 3-factor adjusted alpha (column 1-2) and Carhart 4-factor adjusted alpha (column 3-4), both in percentages. *II Index*, *II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	1	2	3	4
	Fama-French 3-factor Alpha		Carhart 4-factor Alpha	
II Index	0.067**		0.081***	
	(0.031)		(0.004)	
II Pos Index		0.117**		0.138***
		(0.037)		(0.001)
II Neg Index		-0.075		-0.099*
		(0.237)		(0.096)
GHG Emission Score L1	0.149*	0.149*	0.131*	0.131*
	(0.100)	(0.099)	(0.093)	(0.093)
Market Beta L1	-0.802***	-0.801***	-0.735***	-0.734***
	(0.001)	(0.001)	(0.002)	(0.002)
Market Cap L1	-0.995**	-0.994**	-0.986**	-0.986**
	(0.031)	(0.031)	(0.038)	(0.038)
Book-to-Market L1	-1.579***	-1.579***	-1.580***	-1.579***
	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	-0.638	-0.638	-0.691	-0.692
	(0.245)	(0.245)	(0.186)	(0.185)
Profitability L1	0.237*	0.237*	0.289**	0.289**
	(0.067)	(0.067)	(0.035)	(0.035)
Amihud Illiquidity L1	-0.352*	-0.352*	-0.369*	-0.369*
	(0.070)	(0.070)	(0.096)	(0.097)
N	122568	122568	122391	122391
R^2	0.014	0.014	0.014	0.014

Table VII

Industry Innovations and Stock Returns in Weak Climate Information Environment

Table presents the relationship between *II Index*, *II Pos Index*, *II Neg Index* and stock returns in the weak information environment. The sample period is 2007 – 2016. The dependent variable is monthly stock returns in percentage. *II Index*, *II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	1	2	3	4	5	6
II Index	-0.148*	-0.148*	-0.148*			
	(0.089)	(0.089)	(0.089)			
Positive Innovation Index				-0.563***	-0.563***	-0.559***
				(0.000)	(0.000)	(0.000)
Negative Innovation Index				-0.013	-0.013	-0.010
				(0.935)	(0.936)	(0.952)
GHG Emission Pulse Score		0.165*			0.168**	
		(0.051)			(0.044)	
GHG Emission Pulse Score L1	0.164*			0.167**		
	(0.054)			(0.046)		
Market Beta L1	0.345	0.345	0.348	0.344	0.344	0.348
	(0.239)	(0.239)	(0.238)	(0.240)	(0.240)	(0.239)
Market Cap L1	-0.649**	-0.650**	-0.612***	-0.651**	-0.651**	-0.613***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Book-to-Market L1	-1.766***	-1.766***	-1.758***	-1.767***	-1.767***	-1.758***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	-0.701**	-0.701**	-0.710**	-0.704**	-0.704**	-0.713**
	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)
Profitability L1	0.140**	0.141**	0.143**	0.141**	0.141**	0.143**
	(0.019)	(0.019)	(0.017)	(0.018)	(0.018)	(0.016)
Amihud Illiquidity L1	-0.162*	-0.162*	-0.156*	-0.162*	-0.162*	-0.156*
	(0.078)	(0.078)	(0.080)	(0.078)	(0.078)	(0.081)
N	344174	344174	344174	344174	344174	344174
R^2	0.148	0.148	0.148	0.148	0.148	0.148

Table VIII

Industry Innovations and Excess Returns in Weak Climate Information Environment

Table presents the relationship between *II Index*, *II Pos Index*, *II Neg Index* and stock excess returns in the weak information environment. The sample period is 2007 – 2016. The dependent variables are monthly Fama-French 3-factor adjusted alpha (column 1-2) and Carhart 4-factor adjusted alpha (column 3-4), both in percentages. *II Index*, *II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	1	2	3	4
	Fama-French 3-factor Alpha		Carhart 4-factor Alpha	
II Index	-0.185**		-0.185**	
	(0.012)		(0.015)	
II Pos Index		-0.657***		-0.693***
		(0.000)		(0.000)
II Neg Index		0.016		-0.008
		(0.871)		(0.941)
GHG Emission Score L1	0.119	0.123	0.142	0.146
	(0.158)	(0.139)	(0.120)	(0.105)
Market Beta L1	0.115	0.115	0.202	0.202
	(0.804)	(0.805)	(0.673)	(0.674)
Market Cap L1	-0.634***	-0.635***	-0.664***	-0.665***
	(0.005)	(0.005)	(0.005)	(0.005)
Book-to-Market L1	-1.725***	-1.725***	-1.723***	-1.723***
	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	-0.912**	-0.916**	-0.798**	-0.802**
	(0.032)	(0.031)	(0.033)	(0.032)
Profitability L1	0.203***	0.203***	0.155**	0.156**
	(0.001)	(0.001)	(0.027)	(0.026)
Amihud Illiquidity L1	-0.169	-0.168	-0.160	-0.159
	(0.117)	(0.118)	(0.127)	(0.127)
N	344164	344164	343192	343192
R^2	0.018	0.019	0.018	0.018

Table IX
Hoberg Phillips Total Similarity and Industry Innovation Impact

Table examines how the impact of industry innovations on equity returns varies with industry product similarities. Industry product similarity is defined as the average Hoberg Phillips total similarity score across all firms in a SIC2 industry. Above_median_similarity is a dummy variable which equals one if the industry product similarity is above median and zero otherwise. Our variables of interests are the interaction terms between above_median_similarity dummy and *II Index*, *II Pos Index*, *II Neg Index*. The sample period is 2017 – 2021 for column 1 and 2, and 2007 – 2016 for column 3 and 4. The dependent variables are monthly stock returns in percentages. *II Index*, *II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	Strong Information Environment 2017-2021		Weak Information Environment 2007 - 2016	
	1	2	3	4
Above_Median_Similarity X *II Index*	0.361**		0.073	
	(0.012)		(0.697)	
Above_Median_Similarity X *II Pos Index*		0.594**		0.022
		(0.043)		(0.945)
Above_Median_Similarity X *II Neg Index*		-0.404		0.007
		(0.378)		(0.988)
II Index	-0.139		-0.216	
	(0.287)		(0.141)	
II Pos Index		-0.278		-0.588**
		(0.233)		(0.026)
II Neg Index		0.019		-0.013
		(0.960)		(0.974)
Above_Median_Similarity	0.294	0.265	0.099	0.090
	(0.263)	(0.113)	(0.747)	(0.760)
GHG Emission Pulse Score L1	0.172***	0.171*	0.168**	0.172*
	(0.007)	(0.057)	(0.044)	(0.066)
Market Beta L1	0.348	0.347	0.344	0.344
	(0.219)	(0.289)	(0.239)	(0.270)
Market Cap L1	-0.969*	-0.970	-0.651**	-0.652**
	(0.076)	(0.150)	(0.011)	(0.031)
Book-to-Market L1	-1.860***	-1.861***	-1.767***	-1.768***
	(0.000)	(0.002)	(0.000)	(0.000)
Momentum L1	-0.549	-0.549	-0.701**	-0.704*
	(0.109)	(0.186)	(0.046)	(0.076)
Profitability L1	0.182	0.182	0.137**	0.138**
	(0.158)	(0.233)	(0.020)	(0.045)

	Strong Information Environment 2017-2021		Weak Information Environment 2007 - 2016	
	1	2	3	4
Amihud Illiquidity L1	-0.322	-0.323	-0.162*	-0.161
	(0.177)	(0.247)	(0.078)	(0.113)
N	120,072	120,072	344,166	344,166
R^2	0.132	0.132	0.148	0.148

Table X
Firm 10-Q Climate-Related Disclosures and *II Index*

Table presents the relationship between *II Index*, *II Pos Index*, *II Neg Index* amd the number of climate-related words used in firms' forthcoming 10-Q filings. Panel A reports on the strong information environment and Panel B on the weak information environment. Column 1 and 2 reports on Wordlist 1 and column 3 and 4 on Wordlist 2. Dependent variable is the number of climate-related words from the wordlist 1 or wordlist 2 used in firms' forthcoming 10-Q filings. Wordlist 1 is the transition climate risk wordlist used in Table 2 of Li, Shan, Tang and Yao (2021). We expand Wordlist 1 by adding the climate-related wordlist used in Matsumura, Prakash and Vero-Munoz (2022), and the expanded wordlist is Wordlist 2. *II Index*, *II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

Panel A. Strong Information Environment	Wordlist 1		Wordlist 2	
	1	2	3	4
II Index	-0.002**		-0.002**	
	(0.034)		(0.050)	
II Pos Index		-0.005**		-0.003**
		(0.017)		(0.012)
II Neg Index		-0.003		0.000
		(0.253)		(0.717)
GHG Emission Pulse Score L1	0.036*	0.036*	0.028	0.028
	(0.050)	(0.050)	(0.103)	(0.103)
Market Beta L1	0.028	0.028	0.022	0.022
	(0.241)	(0.242)	(0.304)	(0.305)
Market Cap L1	-0.004	-0.004	-0.004	-0.004
	(0.785)	(0.777)	(0.784)	(0.781)
Book-to-Market L1	0.053**	0.053**	0.059**	0.059**
	(0.021)	(0.021)	(0.014)	(0.014)
Momentum L1	0.005	0.005	0.002	0.002
	(0.398)	(0.392)	(0.760)	(0.759)
Profitability L1	-0.036**	-0.036**	-0.032**	-0.032**
	(0.026)	(0.026)	(0.042)	(0.042)
Amihud Illiquidity L1	-0.016	-0.016	-0.022*	-0.022*
	(0.125)	(0.124)	(0.065)	(0.064)
N	105367	105367	105367	105367
R^2	0.118	0.118	0.105	0.105

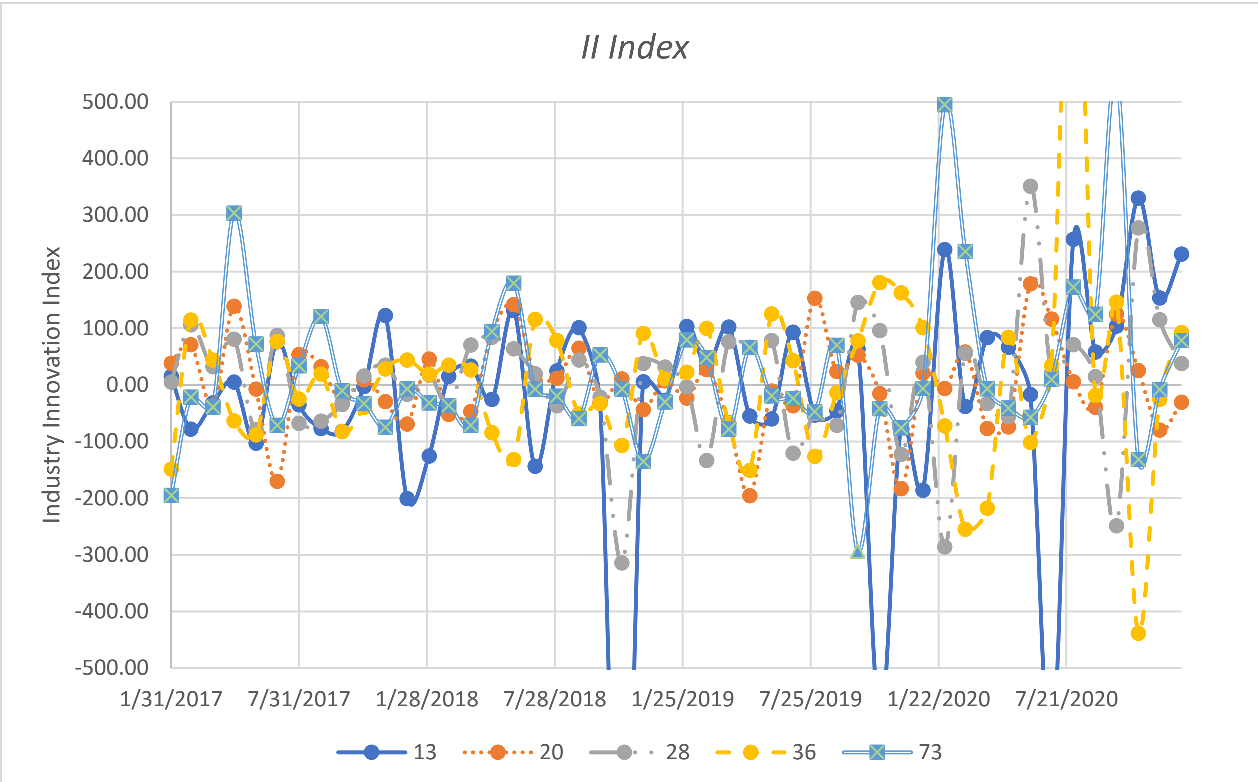
Panel B. Weak Information Environment	Wordlist 1		Wordlist 2	
	1	2	3	4
II Index	-0.002		-0.003	
	(0.544)		(0.439)	
II Pos Index		-0.005		-0.004
		(0.809)		(0.873)
II Neg Index		0.001		0.005
		(0.910)		(0.733)
GHG Emission Pulse Score L1	0.091***	0.091***	0.107***	0.107***
	(0.002)	(0.002)	(0.002)	(0.002)
Market Beta L1	0.008	0.008	0.021	0.021
	(0.524)	(0.524)	(0.149)	(0.148)
Market Cap L1	-0.018	-0.018	-0.015	-0.015
	(0.319)	(0.319)	(0.378)	(0.378)
Book-to-Market	0.075***	0.075***	0.072***	0.072***
	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	0.007	0.007	0.000	0.000
	(0.457)	(0.458)	(0.979)	(0.979)
Profitability	-0.018	-0.018	-0.021*	-0.021*
	(0.102)	(0.102)	(0.069)	(0.068)
Amihud Illiquidity L1	-0.028***	-0.028***	-0.029***	-0.029***
	(0.006)	(0.006)	(0.005)	(0.005)
N	299950	299950	299950	299950
R^2	0.191	0.191	0.198	0.198

Figure I

Time-Series Variations of Industry GHG Emission Innovation Index

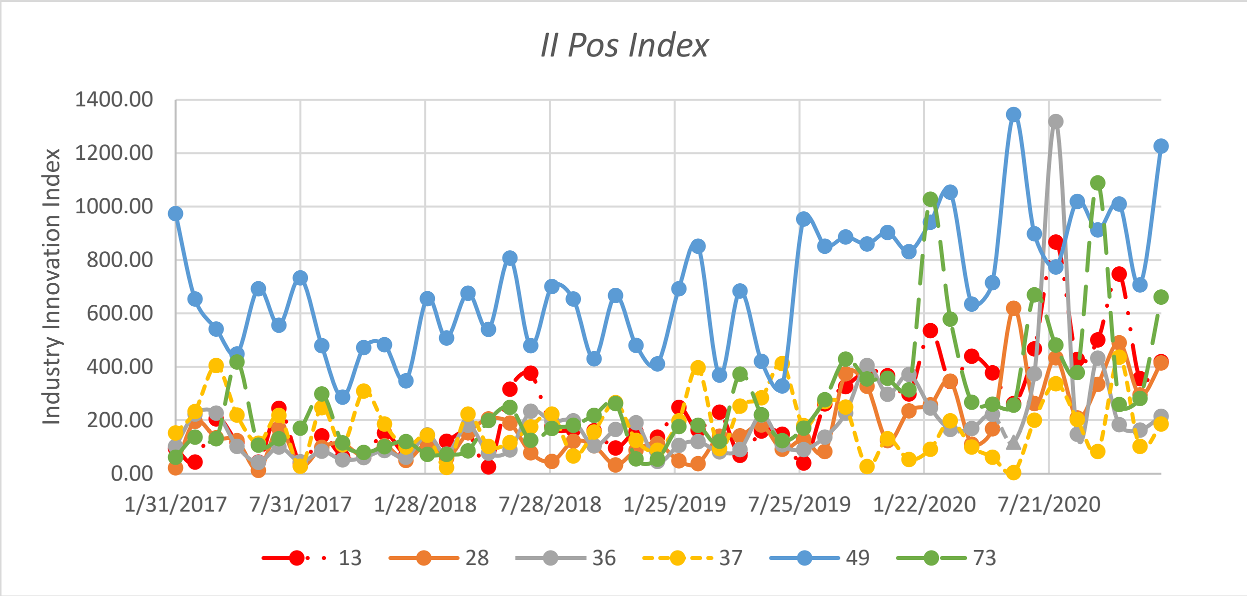
Figure plots time series variations in *II Index*, *II Pos Index* and *II Neg Index* of the most volatile industries in 2017-2021. Panel A graphs *II Index* and Panel B graphs *II Pos Index* and *II Neg Index*. Industries are defined by the first 2 digits of their SIC code. Industries with the most volatile *II Index* are 13, 28, 36, 37, 49 and 73. We also report industry descriptions for the most volatile industries below.

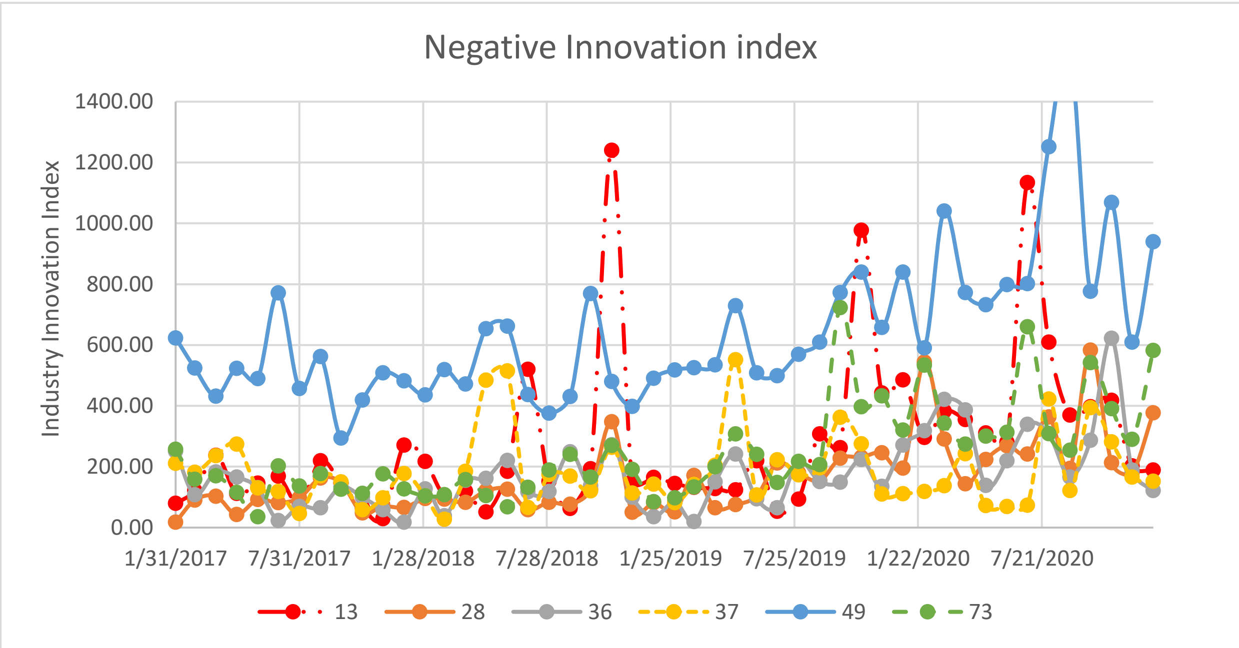
Panel A. The time-series variations of *II Index* for the most volatile industries



SIC2	Industry Description
13	Oil & Gas Extraction
20	Food & Kindred Products
28	Chemical & Allied Products
36	Electronic & Other Electric Equipment
37	Transportation Equipment
49	Electric, Gas, & Sanitary Services
73	Business Services

Panel B. The time-series variations of *II Pos Index* and *II Neg Index* for the most volatile industries





Appendix Table AI
Variable Definitions

GHG emission innovation: for a given firm, it is the change in the firm's GHG emissions pulse score from the prior day. GHG emissions pulse score is collected from Truvalue dataset for a given firm *i* on day *d*, reflecting its short-term real-time GHG emissions performance. $GHG\ emission\ innovation_{i,d}$ can be positive, negative or zero.

$$GHG\ emission\ innovation_{i,d} = GHG\ emission\ pulse\ score_{i,d} - GHG\ emission\ pulse\ score_{i,d-1}$$

GHG emission unique article number: for a given firm, it is the change in its GHG emissions *catvol* from the prior day, if nonnegative. GHG emissions *catvol* is collected from Truvalue dataset for a given firm *i* on day *d*, reflecting the cumulative number of unique articles over a trailing 12-month period. And its daily change reflects the number of unique articles published on day *d*, if nonnegative. If the daily change is negative, it suggests articles published 12 months before are dropped from the trailing number, and we record the change as zero.

$$GHG\ emission\ unique\ article\ number_{i,d} = GHG\ emission\ catvol_{i,d} - GHG\ emission\ catvol_{i,d-1}$$

Industry innovation index (*II Index*): for industry *j* in month *m*, it is defined as the sum product of GHG emission innovation and the number of unique GHG emission articles on the same day, across all firm *i* in the industry *j* and all day *d* in the month *m*:

$$II\ Index_{j,m} = \sum_{i,d} GHG\ Emission\ Innovations_{i,d} * Unique\ Article\ Number_{i,d}$$

Where $i \in j\ and\ d\ \in m$.

Positive (Negative) innovation index (*II Pos Index, II Neg Index*): for industry *j* in month *m*, it is defined as the sum product of positive (negative) GHG emission innovation and the number of unique GHG emission articles on the same day, across all firm *i* in the industry *j* and all day *d* in the month *m*:

$$II\ Pos\ Index_{j,m} = \sum_{i,d} GHG\ emission\ innovation_{i,d} * Unique\ Article\ Number_{i,d}$$
$$where\ GHG\ emission\ innovation_{i,d} > 0, i \in j\ and\ d\ \in m.$$

$$II\ Neg\ Index_{j,m} = \sum_{i,d} GHG\ emission\ innovation_{i,d} * Unique\ Article\ Number_{i,d}$$
$$where\ GHG\ emission\ innovation_{i,d} < 0, i \in j\ and\ d\ \in m.$$

Fama French 3-factor adjusted alpha: for a given stock, we use the prior 60 month (from *t*-60 to *t*-1) rolling window to estimate the coefficients on market risk premium, size (SMB) and value (HML), to compute its 3-factor adjusted alpha in month *t* (Fama and French 1993).

Carhart 4-factor adjusted alpha: for a given stock, we use the prior 60 month (from *t*-60 to *t*-1) rolling window to estimate the coefficients on market risk premium, size (SMB), value (HML) and momentum (MOM), to compute its 4-factor adjusted alpha in month *t* (Carhart 1997).

Market Beta: for a given stock, it is the coefficient on market risk premium estimated using Fama French 3-factor model and a 60-month rolling window.

Market capitalization: is the product of shares outstanding and share price at the end of month. We take its natural log for its skewness.

Book-to-Market: is the book value scaled by market value following Daniel and Titman (2006).

Momentum: is the accumulative prior 12-month stock returns following Carhart (1997).

Profitability: for a given stock, it is revenue minus cost of goods sold scaled by total assets following Novy-Marx (2013).

Amihud illiquidity: for a given stock, it is absolute stock daily return scaled by daily volume traded measured in million dollars, averaged over all days in the given month following Amihud (2002). We take the natural log of Amihud illiquidity for their high skewness.

Appendix Table AII
Annual distribution of number of GHG pulse score innovations

Appendix Table reports the number of firm-day innovations of greenhouse gas (GHG) emission pulse scores by year for the 2007 – 2021 sample period. GHG emission pulse score is collected from Truvalue dataset. GHG emission pulse score reflects real time, short-term firm GHG emissions. For a given firm, daily innovation in pulse scores is computed as the pulse score change from the prior day.

	N	Innovation	Mean	Std Dev	P50	P75	P90	P95	Max
2007	1,712	>0	2.61	7.31	0	2	6	11	81
		<0	2.63	7.98	0	2	6	11	73
2008	2,238	>0	3.06	9.28	1	2	7	13	131
		<0	3.15	9.42	0	2	8	13	140
2009	2,645	>0	2.85	8.97	0	2	7	13	127
		<0	2.90	8.84	0	2	7	12	111
2010	2,983	>0	2.89	8.86	0	2	6	15	111
		<0	2.84	8.53	0	2	6	14	99
2011	3,256	>0	2.79	9.11	0	2	6	13	126
		<0	2.76	8.61	0	2	7	13	113
2012	3,505	>0	2.63	8.45	0	2	6	13	124
		<0	2.56	8.12	0	1	6	13	123
2013	3,728	>0	2.46	8.66	0	1	5	12	146
		<0	2.44	8.34	0	1	5	13	138
2014	3,991	>0	3.06	10.21	0	1	7	17	157
		<0	3.04	9.81	0	2	7	16	152
2015	4,194	>0	3.32	10.83	0	2	7	18	136
		<0	3.42	11.32	0	2	7	17	144
2016	4,303	>0	1.49	6.09	0	1	3	6	88
		<0	1.54	5.87	0	1	3	7	88
2017	4,429	>0	1.71	6.78	0	1	3	8	100
		<0	1.67	6.47	0	1	3	8	100
2018	4,535	>0	1.88	7.93	0	1	3	8	124
		<0	1.84	7.55	0	1	3	9	122
2019	4,676	>0	2.95	11.56	0	1	5	14	156
		<0	3.06	11.68	0	1	6	16	157
2020	5,017	>0	4.53	16.19	0	2	9	22	189
		<0	4.81	17.00	0	2	10	24	176
2021	5,188	>0	5.15	16.53	0	2	12	26	157
		<0	5.28	16.48	0	2	12	29	160

Appendix Table AIII
Industry Representations on Firm-Day GHG Emission Innovations

Table reports industry description, the number of firm-day GHG emission innovations and the number as a percentage of total firm-day GHG emission innovations in the sample. The sample period is Jan 2007 – Nov 2021. Industry is defined by the first 2 digits of firm SIC code. We consider it as a GHG emission innovation if there is a non-zero change on firm GHG emission pulse score from the prior day and there is at least one unique article related to firm GHG emissions on the same day.

SIC2	COUNT	PERCENT
49	32,135	28.23
73	10,535	9.26
37	9,706	8.53
13	8,553	7.51
36	5,585	4.91
28	5,068	4.45
35	4,486	3.94
20	4,147	3.64
45	3,923	3.45
54	2,054	1.80
62	1,906	1.67
48	1,762	1.55
59	1,643	1.44
58	1,633	1.43
60	1,510	1.33
33	1,328	1.17
42	1,209	1.06
12	1,113	0.98
70	979	0.86
67	969	0.85
29	934	0.82
38	930	0.82
75	822	0.72
32	807	0.71
26	746	0.66
23	731	0.64
34	681	0.60
30	671	0.59
40	643	0.56
63	612	0.54
61	586	0.51
53	545	0.48
87	524	0.46
51	449	0.39

SIC2	COUNT	PERCENT
55	363	0.32
47	356	0.31
10	337	0.30
56	293	0.26
25	290	0.25
52	273	0.24
57	237	0.21
50	220	0.19
65	220	0.19
44	218	0.19
16	185	0.16
39	159	0.14
22	140	0.12
27	138	0.12
15	113	0.10
21	70	0.06
72	50	0.04
79	47	0.04
17	43	0.04
46	30	0.03
78	19	0.02
64	17	0.01
14	14	0.01
82	14	0.01
1	13	0.01
24	10	0.01
80	8	0.01
31	4	0.00
89	4	0.00

Appendix Table AIV
Variation of Stock Returns on *II Index* with Within-Industry Distance

Table presents how GHG emission distances between silent firms and innovative firms within industry affect the relationship between *II Index* and firm equity returns. The sample period is 2017-2021 in column 1-2 and 2007 – 2016 in column 3-4. For a given firm in the month, GHG emission distance is computed as the absolute difference between its GHG emission pulse score and the median GHG emission pulse scores of innovative firms in the same SIC2 industry and month. The dependent variables are monthly stock returns in percentages. *II Index*, *II Pos Index*, *II Neg Index* are defined in Table III. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. *p*-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	Strong Information Environment 2017-2021		Weak Information Environment 2007 - 2016	
	1	2	3	4
Distance X *II Index*	-0.015**		-0.008	
	(0.036)		(0.833)	
Distance X *II Pos Index*		-0.031**		0.001
		(0.025)		(0.989)
Distance X *II Neg Index*		-0.006		0.017
		(0.858)		(0.741)
II Index	0.141***		-0.134	
	(0.000)		(0.285)	
II Pos Index		0.210**		-0.568**
		(0.017)		(0.021)
II Neg Index		-0.199		-0.044
		(0.173)		(0.817)
GHG Emission Pulse Score L1	0.150***	0.186**	0.164*	0.154**
	(0.007)	(0.043)	(0.051)	(0.035)
Market Beta L1	0.337	0.336	0.345	0.345
	(0.232)	(0.233)	(0.239)	(0.240)
Market Cap L1	-0.973*	-0.970*	-0.649**	-0.651**
	(0.072)	(0.071)	(0.011)	(0.010)
Book-to-Market L1	-1.802***	-1.804***	-1.766***	-1.767***
	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	-0.571*	-0.570	-0.701**	-0.704**
	(0.100)	(0.101)	(0.045)	(0.044)
Profitability L1	0.205	0.207	0.141**	0.141**
	(0.125)	(0.121)	(0.019)	(0.018)
Amihud Illiquidity L1	-0.319	-0.317	-0.162*	-0.162*
	(0.172)	(0.170)	(0.078)	(0.078)
N	122569	122569	344174	344174
R^2	0.131	0.131	0.148	0.148

Table AV

Hoberg Phillips *II Index* and Monthly Stock Returns

Table presents a robustness check on the relationship between *II Index*, *II Pos Index*, *II Neg Index* and firm equity returns, when industry is defined following Hoberg and Phillips (2010, 2016) text-based network industry classification TNIC2 (column 1-2) and TNIC3 (column 3-4). The sample period is 2017 – 2021. The dependent variable is stock monthly return in percentage. *II Index*, *II Pos Index*, *II Neg Index* are constructed using the similar manner as in Table III, except that industries peers are defined using Hoberg Phillips TNIC_2 or TNIC_3 methodology. GHG emission pulse score is defined in Table I, and all other variables are defined in Table IV. All control variables are lagged by one month, except for book-to-market and profitability which are from the last 10-K filings. All independent variables are winsorized and standardized. All regressions control for industry and time fixed effects with standard errors clustered by firm and year. p-values are reported in paratheses. ***, **, * denotes 1%, 5% and 10% significance levels.

	TNIC 2		TNIC 3	
	1	2	3	4
II Index	0.152**		0.105***	
	(0.042)		(0.004)	
II Pos Index		0.263*		0.131***
		(0.052)		(0.001)
II Neg Index		-0.163**		-0.118
		(0.029)		(0.307)
GHG Emission Pulse Score L1	0.187**	0.186**	0.173	0.173
	(0.048)	(0.049)	(0.109)	(0.110)
Market Beta L1	-0.335	-0.334	-0.207	-0.207
	(0.500)	(0.500)	(0.566)	(0.566)
Market Cap L1	-8.251***	-8.254***	-8.849***	-8.849***
	(0.000)	(0.000)	(0.000)	(0.000)
Book-to-Market L1	-5.355***	-5.357***	-5.447***	-5.447***
	(0.000)	(0.000)	(0.000)	(0.000)
Momentum L1	-0.422	-0.420	-0.524	-0.524
	(0.158)	(0.159)	(0.160)	(0.161)
Profitability L1	1.033**	1.033**	1.264**	1.264**
	(0.045)	(0.045)	(0.047)	(0.047)
Amihud Illiquidity L1	-0.534	-0.536	-0.919***	-0.919***
	(0.126)	(0.126)	(0.000)	(0.000)
N	122915	122915	84726	84726
R^2	0.164	0.164	0.198	0.198