Market Implications for Industry Greenness Shocks and Climate Information Transfer

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. We construct an industry innovation index, *II Index*, to capture monthly industry wide GHG innovation shocks. In the strong information environment, 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 the weak information environment, we find a negative relationship between market returns and the *II Index*. Furthermore, the effect triples in the strong information environment in industries with lower product differentiation.

Key words: greenhouse gas emissions; carbon risk; climate disclosure, product differentiation.

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 greenhouse gas (GHG) emissions, and its associated climate risks, are incorporated into firm equity prices, municipal bond prices, and housing prices has been studied by economic, finance, and accounting researchers extensively.[1] However, when it comes to climate risk associated with carbon emissions, prior research focuses mostly on the market reactions to firms' direct carbon performance, the emissions of their upstream and downstream production (Bolton and Kacperczyk 2021), their subsidiaries (Duchin, Gao and Xu 2022), or the overall market sentiment on climate news (Engle, Giglio, Kelly and Lee 2020). However, little is known on how firms' equity returns respond to industry peers' carbon emissions, and whether the responses vary with different climate disclosure regimes.

Our references herein to the Paris Agreement era are essentially references to an era of increased interest in 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) which was being discussed around the same time as the Paris Agreement, and made effective in 2018, 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 strongly encouraged to publish climate information in a stand-alone or integrated report comprising both financial and non-financial information, more so than before this era.

Accompanying this worldwide trend is the debate on whether such disclosure would be required of US public firms. 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 was not taken.[2] Built upon this momentum, in early 2021, the acting SEC

[1] A recent review of studies on climate risk, climate change, and stock returns risks was done by Venturini (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, 79: 101934.
[2] https://www.sec.gov/rules/concept/2016/33-10064.pdf

Chair and Division of Corporations began to consider environmental disclosure requirements and solicit comments on environment impact disclosures. Sitting at the center of the debate is an apparent battle between an investor-focused versus stakeholder-focused disclosure regime and a better understanding of whether the market has sufficient ability to "collect, process, disseminate, and respond to" environmental metrics without "boxing them in government-articulated metrics."[3]

Using an information transfer framework this study examines how demanded returns on firm equity vary with the GHG emission innovations of their industry peers, in both a stronger and weaker climate information environment, holding firms' own carbon emissions constant. 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 on a daily basis.[4] 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 change in 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 daily GHG emissions innovations in a month by industry to construct an industry innovation index, *II Index*. The *II Index* is computed as the sum product of firms' daily GHG emission innovations and its media coverage on the same day, across all firms in a given industry in the month. This *II 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."

The *II Index* reflects aggregate industry wide GHG innovation shocks on firms and the climate de-risking pressure they face from investors, especially investors focused on ESG risks and climate related issues. There are two hypotheses in which one would expect *II Index* to affect firm equity pricing. First, a positive GHG emissions innovation within the industry imposes an adverse shock

[3] https://www.sec.gov/news/public-statement/rethinking-global-esg-metrics

[4] 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.

on silent firms, whose carbon risk is increased as they lag their industry 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 2022; Kolbel, Heeb, Paetzold, Busch 2020). Investors with interests in 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 (i.e., browner) to ESG investors, the innovation incentivizes a marginal deviation of ESG investors away from silent firms and toward innovative firms, and demand on silent firms' equity decreases. Forward looking investors may require higher returns for holding the stocks of silent firms to bear the relatively higher carbon risk, giving rise to a positive cross-sectional relationship of higher *II Index* – higher returns. We refer to this as the relative brown hypothesis.

Second, one might expect the dissemination of a positive industry innovation from innovative firms to silent firms. Firms' carbon footprints are the product of the nature of their own business and the industry they belong to. GHG emission innovations by one firm could update investors' belief on firms without innovations. With high demand on green stocks, ESG investors may extrapolate the innovation from innovative firms to silent firms, expect the silent firms to adopt similar technology breakthroughs or firm policies to become greener, and thus demand on silent firms' equity increases. Forward looking investors thus may require lower returns for holding their stocks, giving rise to the negative cross-sectional relationship of higher *II Index* – lower returns. We refer to this as the green transfer hypothesis.

Does the climate disclosure regime matter in these scenarios? We further hypothesize that the choice between these two competing hypotheses by the market relies heavily on the information availability and the quality of information inherent in the environment at the time. Non-financial information on GHG emissions is a relatively new disclosure and how investors can reasonably rely on the disclosures as credible, especially when made by an industry peer, is an empirical question. In the weak disclosure environment, facing the lack of wide-spread and reliable firm specific carbon emission information, especially due to the lack of (required) material disclosures, investors likely must infer information from peers to meet their strong climate information demands. However, in the strong disclosure environment, facing increasingly available carbon emissions information, investor demand could be satisfied by innovative firms, without the need to infer or guess with respect to silent firms' actions and behaviors. 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 the 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. 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 2023) and research shows that only after the Paris Agreement did climate change issues became price and risk relevant (Kölbel et al. 2020). 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) worked with over 100 banks, insurers, and investors to create numerous frameworks 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, drawing the attention of institutional investors towards carbon emission disclosure.[5] 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. That is, after 2016, the costs associated with the awareness, acquisition, and integration of peer information (Blankespoor et al. 2020) are significantly attenuated.

Our findings support relative brown hypothesis in the strong information environment, in that demanded returns on silent firms increase with *II Index*. Specifically, a one-standard-deviation increase in the *II Index* is associated with 0.106% higher monthly returns, significant at 1% level, 0.078% higher 3-factor adjusted alpha, and 0.088% higher 4-factor adjusted alpha, significant at 5% level, after controlling for firms' own GHG emissions scores and other firm characteristics.

Our finding also supports the green transfer hypothesis in the weak information environment, in that when GHG emissions information is scarcer, positive GHG emission shocks are transferred to peer (silent) firms. A one-standard-deviation increase in *II Index* is associated with 0.148% lower monthly returns, significant at 10% level, after controlling for firms' own GHG emissions

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

scores and other firm characteristics. Consistent with the strong information environment, the negative cross-sectional relationship cannot be explained away by common risk factors – size, book-to-market, and momentum (Fama and French 1993; Carhart 1997).

Do silent firms change their carbon emission and climate risk disclosures in their quarterly reporting after the *II Index* shocks? In the strong information environment where the relative brown hypothesis dominates, we expect firms with exposure to positive industry GHG emissions innovations to talk less about carbon emissions and climate risk in their own forthcoming 10-Q 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 a one-standard-deviation increase in *II Index* is associated with a 0.2 to 0.5 percent decrease in the number of climate-related words in firms' forthcoming 10-Q reports. However, combined with our main finding, decreased climate disclosure is not enough to shield these firms from the intense scrutiny of institutional investors. Our results are consistent with the theoretical model in Bond and Zeng (2022) that firms remain silent in equilibrium when they face voluntary disclosure decisions on ESG.

Lastly, to provide more validity to the *II Index*, we examine whether the impact on silent firms strengthens when products in a given industry are more similar and firms' differentiation is weaker. The intuition is that, for firms in a given industry, if the products are more similar and the operations are closer to each other, the equity in the silent firms could be more substitutable by the equity in the innovative firms. The marginal investors would be more likely to leave and substitute their holdings on silent firms with holdings on the innovative firms. The demand for the equities from the more similar industries are thus expected to be more elastic. Indeed, we find that in the strong information environment the correlation between *II Index* and the demand returns of silent firms triples in industries where the total similarity scores are above median and products are less differentiable. Such an effect is muted in the weak information environment.

The main insights we bring to literature is that climate risk as a systematic risk factor not only reflects firms' own carbon footprint (Bolton and Kacperczyk 2021), but also their industry peers' carbon emission innovations, which is another unique channel for carbon emissions and "the greenium" to be priced. Industry peers' innovations are interpreted and incorporated into equity prices in the opposite ways depending on the strength or weakness of the climate information environment. Prior studies confirm some level of underpricing and ask why carbon risks are underpriced. This study provides novel empirical evidence on peer firm effects and an explanation for the underpricing puzzle. Lastly, this study helps value maximizing firms carefully consider the impact of falling behind on green initiatives and realize that silence on carbon risks is unwittingly another kind of (negative) disclosure (in today's increasingly strong climate disclosure environment).

This study contributes to three strands of the finance and accounting literatures. First, our study contributes to the growing literature on the asset pricing of carbon risk. 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 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, and suggests 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 relationship between carbon risks and equity prices in the global equity market and examines different geographic regions. Our study documents the effects of information transfer, depending on the disclosure regime, on the asset pricing of carbon risk.

Second, our study contributes to the growing literature on impact investing and willingness to pay for green assets. 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. Pastor, Stambaugh, and Taylor (2021) propose a general equilibrium model that greener firms have lower costs of capital due to the financial and real effects that arise from the preferences for green stocks over brown stocks, assuming the investors' utility functions that includes such 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. 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." Our study documents that the disclosure regime is associated with the greenness of company equity and the pricing of the equity.

Third, this study contributes to the broader literature on climate change and environmental risk. 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) find a pollution premium which cannot be explained by several explanations, including existing systematic risks, investors' preferences, market sentiment, political connections, and corporate governance. Duchin, Gao and Xu (2022) examine the real market for firm pollution and green washing, especially when firms engage in reallocation of pollution through mergers, acquisitions and divestures. Our study contributes to this literature by examining the effect of the disclosure regime on the views of investors with respect to climate innovations in the industry.

The closest study to ours is Engle, Giglio, Kelly, Lee and Stroebel (2020), which examines market wide climate sentiment 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, the 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 *II Index* is constructed from real-time industry-specific innovations, different from their market-wide climate news coverage. Our results are robust to controls for time fixed effects which capture time trends in climate change news and investor attention. Most importantly, we provide evidence that the asset pricing implications of *II Index* are reversed as the disclosure regime evolves.

I. Data and Sample

1.1 Data on GHG Emissions

We start with FactSet Truvalue dataset, which issues daily updates for short-term, long-term, and momentum scores generated for securities across the 26 ESG categories defined by the Sustainability Accounting Standards Board (SASB), along with an overall score and a volume score. The scores are issued based on a daily collection of the important positive and negative ESG events detected by their algorithms, including headlines and key bullet points of articles. For each category, there are three scores generated to measure a company's ESG performance: Pulse score, Insight score and Momentum score. Pulse score measures the firm's short-term and real-time performance, insight score measures long-term performance, and momentum score measures the trend by calculating the slope of the long-term scores over a trailing of 12-month time period. [6] A higher score reflects better performance in the given category.

In this study, we focus on the GHG emission category, which reflects firms' GHG emission performance and related media coverage, and on the pulse scores to avoid other compounding events in the long-run that may affect carbon risk pricing. For a given firm, GHG emission innovation is defined as the change in its GHG emissions pulse score from the prior day. Positive innovations in GHG emission pulse scores reflect GHG emission improvements, while negative innovations reflect worsening performance. Our results are robust to use GHG emissions insight scores and momentum scores. The Truvalue dataset also provides a daily measure, *catvol*, to capture the number of unique articles over a trailing 12-month period for each SASB category. For a given firm, the number of unique articles covering its GHG emissions on the given day is computed as the daily change in its GHG emissions *catvol* when the change is nonnegative. When the daily change in *catvol* is negative, we replace it with zero as it results from dropping the number of unique articles on the firm from more than 12 months ago.

Our full sample period is from Jan 2007 to Dec 2021.[7] Our 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 a distinct match between FactSet ID and PERMNO to ensure correct matching.

Table I Panel A reports the distribution of positive and negative GHG emission innovations, Panel B reports the distribution of unique daily articles on GHG emissions, and Panel C reports the distribution of non-zero GHG emission innovations by year. Panels A and B also break down

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

[7] Nov 2021 is when the subscription ends.

the summary statistics into two subperiods: 2007-2016 and 2017-2021. From Panel A, the average number of positive (negative) innovations a firm experiences is 3.00 (3.05) in a year with a standard deviation of 10.96 (11.00) and a median of 0 (0). At the 75th percentile, a firm experiences 1 (1) positive (negative) innovations in a year. At the 90th percentile, a firm experiences 15 (15) positive (negative) innovations in a year. Comparing the 2007-2016 to the 2017-2021 sample period, firms in the latter period on average experience more positive and negative innovations, suggesting a more robust information environment with respect to climate news.

<Insert Table I Here >

From Panel B, a firm is covered by 5.50 unique GHG emission articles on average with a standard deviation of 17.36 articles. At the 75th percentile, firms have 3 unique articles and at the 90th percentile, firms have 13 unique articles. Unsurprisingly, there are substantially more firms which are not covered by any GHG emission articles in a year in the 2007-2016 sample period than in the 2017-2021 sample period. Panel C complements Panels A and B, presenting a pattern of increasing number of innovations over the years. 2.02 percent of the firm-day innovations in the sample period come from 2007 while 17.81 percent of the firm-day innovations come from 2021.[8]

Table II breaks down the distribution of GHG emission innovations by industry and reports 15 representative industries. Industries are defined using the first two digits of firms' primary SIC code. We rank a given industry by the total number of its GHG emission innovations as a percentage of total number of GHG emission innovations, and report the industries with the highest percentages, the lowest percentages and median percentages. The complete table on distribution of innovations by industry can be found in Appendix Table AIII. Distributions of carbon emission innovations are not equal across all industries, consistent with Bolton and Kacperczyk (2021) that carbon emissions intensity is a product of industry. 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) have the largest number of GHG emission innovations. This observation is consistent with the intuition that

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

the most pollutive industries have the largest room to improve their carbon emissions, are most incentivized to make improvements, and are under the brightest spotlight to make green initiatives. In contrast, health services (80), leather and leather goods (31), services, not elsewhere classified (89), agricultural production – livestock (2) and miscellaneous repair services (76) present the lowest carbon emissions innovations.

<Insert Table II Here >

We draw two conclusions from Table I and Table II. First, GHG emission innovations are a product of industry and vary by industry. Industries making an extraordinary number of innovations are more than 10 times more active than industries making the fewest innovations. Second, GHG emission innovations almost monotonically increase over time, consistent with increasing attention from banks, insurance companies, mutual funds, other institutional investors.

1.2 Construction of Industry GHG Emissions Innovation Index

This study captures the industry wide carbon emission innovation shocks by constructing an industry innovation index, *II Index*. We first classify firms by month into innovation firms and silent firms. A given firm is an innovative firm if it has at least one non-zero innovation and is covered by at least one unique article in the month, otherwise it is a silent firm. Industry is defined by the first two digits of firm SIC code as in Table II.

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

$$= \begin{cases} > 0\ Positive\ Innovation \\ 0 \qquad No\ innovation \\ < 0\ Negative\ Innovation \end{cases} \qquad (1)$$

where i denotes firm, m denotes year-month, d denotes day in the year-month. Hence $d \epsilon m$.

Next, *II Index* is computed as the sum product of GHG emission innovation and the number of unique articles on the same day, across firms in the industry and days in the month, as follows:

$$II\ Index_{j,m} = \sum_{i,d} Innovation_{i,m,d} * Unique\ Article\ Number_{i,m,d} \qquad (2)$$

where i denotes firm, j denotes industry, m denotes year-month, d denotes day. Hence $i \epsilon j$.

As positive innovations and negative innovations may have an asymmetric spillover effect and have an asymmetric impact on firm equity pricing, we construct an alternative set of industry innovation indices which includes a positive innovation index, *II Pos Index,* and a negative innovation index, *II Neg Index*. *II Pos Index* is computed as the sum product of positive innovations and the number of unique articles on the same day, across firms in the industry and days in the month. In a similar manner, *II Neg Index* is computed as the sum product of negative innovations and the number of unique articles on the same day, across firms in the industry and days in the month. For easiness of interpretation, we add a negative sign to *II Neg Index*. All three GHG emission innovation indices are at industry-year-month frequency. Formally, we have:

$$II\ Pos\ Index_{j,m} = \sum_{i,d} Positive\ Innovation_{i,m,d} * Unique\ Article\ Number_{i,md} \quad (3)$$

$$II\ Neg\ Index_{jm} = -\sum_{i,d} Negative\ Innovation_{i,m,d} * Unique\ Article\ Number_{i,m,d} \quad (4)$$

A higher *II Index* level proxies for an aggregate improvement in carbon emissions, positive media coverage, and a greener industry for investors. A higher *II Pos Index* level proxies for stronger green initiatives and technology breakthroughs in reducing carbon emission intensity, while a higher *II Neg Index* level proxies for higher carbon emission intensity and a browner industry for investors.

Table III reports the descriptive statistics on the three indices. Panel A reports over the entire sample period 2007 – 2021 while Panel B breaks it down by the two subperiods 2007 – 2016 and 2017 – 2021. We make three observations. First, though innovations are highly skewed, the three indices are not. *II Index* averages at 2.85, with a median of 1.17 and a standard deviation of 71.00. Its 25th percentile is -20.68 and its 75th percentile is 24.15, suggesting balanced positive and negative shocks. Second, both the positive and negative indices show a significant amount of variations. The *II Pos Index* (*II Neg Index*) is non-negative by construction, with a mean of 63.25 (60.40) and a median of 26.00 (24.93). Third, contrasting the strong information environment in 2017-2021 to the weak information environment in 2007-2016 from Panel B, all three industry innovation indices are observably more volatile with higher standard deviations, and more active with higher mean and median in the strong information environment.[9]

<Insert Table III Here >

How volatile are the three industry innovation indices over time? To provide an intuitive interpretation of our main variables, in Figure I Panel A, we graph the time series variation of the five most volatile industries with respect to the *II Index* from 2017 to 2021, which 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). In Figure I Panel B, we graph the time series variation of the six most volatile *II Pos Index* and *II Neg Index*, which are oil and gas extraction (13), chemicals and allied products (28), electronic and other electrical

[9] 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.

equipment and components (36), transportation equipment (37), electric, gas and sanitary services (49), and business service (73).

<Insert Figure I Here >

We draw two conclusions from Figure I. First, the indices reflect innovations and market attention, not just GHG emissions. Thus, as might be expected, industries with the most volatile indices include both green and brown industries. Second, volatility of all three indices increases over time. This could be explained by more green initiatives in recent years, stronger market attention, more media coverage on climate events and disasters, and stronger competition for the green image. Alternatively, it could be driven by more availability of carbon emission data through required and voluntary disclosures, and better data collection and integration by market players.

1.3 Other Variables

We collect monthly stock returns, shares outstanding, equity prices, and other variables from the CRSP dataset. We download monthly market risk premium, small minus big (SMB), high minus low (HML), and momentum (MOM) factors from WRDS Fama-French Portfolios and Factors dataset. To estimate Fama French 3-factor adjusted alpha and Carhart 4-factor adjusted alpha (Fama and French 1993; Carhart 1997), we use the rolling 60 months' return to estimate the beta loadings and then calculate the alpha in the next month. More specifically, we use the monthly stock returns and Fama French 3-factor returns from month $t-61$ to month $t-1$, to estimate beta loadings on the market risk premium, SMB, and HML factors for month t, and lastly calculate the 3-factor beta predicted returns as well as the adjusted alpha in month t. The beta loading on market excess returns estimated from the time-series regressions is the market beta used as a control variable in the Section II pooled regressions. We repeat the similar exercise using the prior 60 months' stock returns, market risk premiums, SMB, HML and MOM factor returns to estimate Carhart 4-factor adjusted alpha in month t.

For control variables used in Section II, market capitalization is the product of closing price and shares outstanding at the end of the 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). Appendix Table AI defines all variables used in the study. 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 and standardized by the strong (weak) information environment sample. Summary statistics are reported to Table IV.

<Insert Table IV Here >

II. Hypothesis development

Pastor, Stambaugh, and Taylor (2021) model an equilibrium expected return of green and brown assets, when ESG investors enjoy a utility surplus for holding green assets. Demands from ESG investors drive lower equilibrium expected returns on green stocks. Bolton and Kacperczyk (2021) confirm with empirical evidence 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 silent firms become browner relative to their industry peers, deliver less green utility, and carry higher carbon risk in the eyes of ESG investors, when their industry peers improve their GHG emission scores and are covered by favorable news articles. Lower demands from ESG investors shift the demand – supply equilibrium towards higher demanded returns by non-ESG investors. Thus, the first testable hypothesis is the *relative brown hypothesis*, formally:

H1 Relative Brown Hypothesis: Cross-sectional stock returns of silent firms increase with higher *II Index*, higher *II Pos Index*, and decrease with higher *II Neg Index.*

A number of studies have examined the effect of information extrapolation and spillover on equity returns and corporate governance. Gustafson, He, Lel and Qin (2023) document the spillover effect of natural disaster through investors' common ownership to firms without experiencing natural disasters. Firth (1976), Firth (1996), Foster (1981), Baginski (1987), Clinch and Sinclair (1987) and Bannister (1994) provide evidence on intra-industry information transfers and spillovers from earnings announcements and the corresponding impact on firm valuation. Motivated by the intra-industry information transfer literature, we posit that new information on carbon emissions is aggregated by industry and extrapolated from innovative to silent industry peers. When the innovative firms lower their carbon risk, investors project the improvements and expect to see silent firms in the same industry adopt similar green initiatives and improve their GHG emissions. Demands on the silent firms by ESG investors increase as well and demanded returns are lowered. The most natural competing hypothesis to the relative brown hypothesis is *green transfer hypothesis*, formally:

H2 Green Transfer Hypothesis: Cross-sectional stock returns of silent firms decrease with higher *II Index*, higher *II Pos Index*, and increase with higher *II Neg Index*.

We disentangle the two competing hypotheses by examining the disclosure and information environment within which investors interpret the innovation information. Glosten, Nallareddy and Zou (2021) document an asymmetric effect of ETF activities on information efficiency of underlying stocks in weak versus strong information environments. We adopt similar logical frameworks and argue the disclosure regime and the copiousness of carbon emissions information disclosed by firms are necessary for investors to decide how to make use of peer carbon emission information. In a stronger information environment, when firms are more likely to make carbon emissions disclosures and these disclosures are mandated or strongly encouraged, we expect the relative brown hypothesis to dominate. However, in the weaker information environment, when firms make scarce carbon emissions disclosures and the information environment is more opaque, 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 stronger environmental information environment, while green transfer hypothesis dominates in the weaker environmental information environment.

A natural extension of the disclosure regime hypothesis is *the product similarity hypothesis*. That is, in which kind of industries can ESG investors more confidently shift their demands from innovative firms to silent firms in the stronger information environment? We posit that industry product differentiation or similarity is an important deciding factor. When product differentiation in a given industry is low, when production and products are similar to each other, ESG investors incur relatively lower costs when substituting relative-brown stocks with relative-green ones. We separate industries by their total similarity scores based on their 10-K reporting given by Hoberg and Phillips (2016), and industries with above median total similarity scores are classified as low differentiation and high similarity industries. Formally:

H4 Product Similarity Hypothesis: Cross-sectional stock returns of silent firms belonging to industries with low product differentiation are more likely to increase with higher *II Index*, higher *II Pos Index*, and decrease with higher *II Neg Index*.

How do firms respond to their peers' GHG emissions innovations? Public firms are regulated from making untruthful material disclosures or falsely claiming carbon emissions improvement. Bond and Zeng (2022) find firms facing voluntary disclosure decisions choose to remain silent. Their silence is a safer choice when the audience's preferences are uncertainty. Following the same intuition, we argue that silent firms have incentives to speak less on carbon related topics and increase their distance from innovative firms, following a positive industry carbon risk shock. Formally:

H5: Silent firms speak less about carbon emissions and climate issues in the forthcoming 10-Q reports facing positive industry climate innovations.

III. Model Specification and Empirical Results

This section uses pooled regressions to examine the hypotheses developed in Section II and discusses the empirical evidence. The Paris Agreement, effective at the end of 2016, is used as the cutoff date for the two eras of climate disclosures we examine. 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, increasing the focus and prevalence of carbon risk disclosures. Furthermore, the CDP developed various frameworks and led various initiatives to improve firm carbon emissions disclosures. We thus use the post-Paris Agreement era, 2017 – 2021, to proxy for the strong climate disclosure and information environment, and the prior-to-Paris Agreement era, 2007 – 2016, to proxy for the weak climate disclosure and information environment. We report the results in the two sub-sample periods separately.

3.1 Strong information environment

We first test H1 and H2 in the strong climate information and disclosure environment using the sample from 2017 to 2021 and the model specification (3) and (4) below. The dependent variable is the percentage monthly stock returns. The independent variables of interest are *II Index* in model (3) and *II Pos Index* and *II Neg Index* in model (4). H1 is supported if δ_1 is significantly positive, α_1 is significantly positive, or α_2 is significant negative. H2 is supported if δ_1 is significantly negative, α_1 is significantly negative, or α_2 is significant positive.

$$RET_{i,m} = \delta_0 + \delta_1 * II\ Index_{i,j,m} + \sum \delta_k * control_{i,m-1} + \gamma_j + \mu_m + \varepsilon_{i,yr} \quad (3)$$

$$RET_{i,m} = \alpha_0 + \alpha_1 * II\ Pos\ Index_{i,j,m} + a_2 * II\ Neg\ Index_{i,j,m} + \sum \alpha_k * control_{i,m-1} + \gamma_j + \mu_m + \varepsilon_{i,yr} \quad (4)$$

where i denotes firm, j denotes industry, m denotes year-month. Hence $i \epsilon j$. $RET_{i,m}$ are monthly stock returns for firm i in month m. γ_j are industry fixed effects. μ_m are time fixed effects. Control variables include firm's own GHG emission scores, market beta, market capitalization, book-to-market, momentum, profitability and Amihud illiquidity. Standard errors are clustered by firm and year. Any firm with GHG emission innovations, in the current, prior, or next month, is excluded from our regressions, to alleviate the concern that our results may be driven by information leakage bias. Table V columns 1 to 3 reports regression results on model (3) and columns 4 to 6 report regression results on model (4). Columns 1 and 4 control for firms' own GHG emissions pulse scores at the end of the prior month, columns 2 and 5 control for firms' current month GHG emissions pulse scores, and columns 3 and 6 do not control for firms' own GHG emissions pulse scores. Results are qualitatively similar across columns 1 to 3, and across columns 4 to 6. Thus, in the rest of the paper, we control for firms' own GHG emission pulse scores at the end of the prior month.

<Insert Table V Here >

Columns 1 and 4 support H1, the relative brown hypothesis, but do not document support for H2. Stock monthly returns increase by 10.6 bps with a one-standard-deviation increase in the *II Index*, significant at 1% level. Stock monthly returns increase by 13.9 bps with a one-standard-deviation increase in the $II\ Pos\ Index$, significant at 5% level, and decrease by 21.1 bps with a one-standard-deviation increase in the $II\ Neg\ Index$, significant at 1% level. Both positive and negative industry GHG innovation shocks are priced contemporaneously by the market, consistent with higher expected carbon risk and market efficiency in incorporating the carbon risk premium into prices. The significantly positive coefficients on firms' own GHG emission scores are consistent with literature on higher demanded returns on firms with higher emissions (Bolton and Kacperczyk 2021).

Industry wide carbon emission innovation shocks are unique information and is likely to be orthogonal to the conventional risk factors – market risk premium, size, value, and momentum risk factors (Fama and French, 1993; Carhart 1997). Thus, we argue that the carbon risk associated with industry innovations is embedded in excess returns after adjusted for the conventional risk factors. Consistent with H1, we expect to find higher (lower) alpha associated with *II Index* and $II\ Pos\ Index$ ($II\ Neg\ Index$).

<Insert Table VI Here >

Table VI reports our pooled regressions results. The dependent variables are monthly Fama French 3-factor adjusted alpha and Carhart 4-factor adjusted alpha. The evidence supports H1, the relative brown hypothesis for *II Index* and $II\ Pos\ Index$ but not $II\ Neg\ Index$. Monthly 3-factor and 4-factor adjusted alpha increases by 6.7 bps and 8.1 bps, respectively, with a one-standard-deviation increase in *II Index*, significant at 5% level. Similarly, monthly 3-factor and 4-factor adjusted alpha increase by 11.7 bps and 13.8 bps, respectively, with a one-standard-deviation increase in $II\ Pos\ Index$, significant at 5% level. The economic impact of industry innovation shocks are 44.97 percent (=0.067 / 0.149) to 78.52 percent (=0.117 / 0.149) of firms' own GHG emission impact, suggesting that they are priced as a meaningful carbon risk by equity investors. In contrast, evidence does not support H2, the green transfer hypothesis.

Our findings in Table V and VI are consistent with existing theories on ESG investors' rebalancing between green and brown stock holdings and maximizing their utility as a function of portfolio greenness (Pastor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2020). Results are robust to controlling for firms' own carbon emissions. Thus, relative brownness does not come from firms' own GHG emissions. Instead, it is because ESG investors now have better choices and are incentivized to tilt their holdings toward firms with improved GHG emission scores. Non-ESG investors respond to the lower demand from ESG investors and a new equilibrium between demand and supply of silent firms is reached with higher returns for remaining investors to continue to hold them.

3.2 Weak climate information environment

We next test H1 and H2 in the weak climate information and disclosure environment using the sample from 2007 to 2016 and model specifications (3) and (4) from Section 3.1. Regression results are reported in Table VII.

<Insert Table VII Here >

Evidence from Table VII supports H2, the green transfer hypothesis, and does not support H1. When the *II Index* increases by a one-standard-deviation, monthly returns decrease by 14.8 bps, significant at 10% level. When $II\ Pos\ Index$ increases by a one-standard-deviation, monthly returns decrease by 56.3 bps, significant at 1% level. Equity returns, however, do not respond significantly to $II\ Neg\ Index$ change in the pre-Paris Agreement era. Importantly, the green information transfer brings a stronger impact on equity returns when carbon emission disclosure is scarce. The impact of *II Index* on equity returns in the pre-Paris Agreement period is 139.62 percent (= 0.148 / 0.106) of the impact in the post-Paris Agreement period, which reflects the market's strong reaction to industry carbon innovations when novel information gets disclosed.

We next examine how 3-factor and 4-factor adjusted excess returns vary with industry wide GHG emission innovation shocks and report the results to Table VIII. Consistent with Table VII, a one-standard-deviation increase in the *II Index* is associated with 18.5 bps decrease in monthly 3-factor adjusted alpha and 18.5 bps decrease in 4-factor adjusted alpha, both significant at 5% level. A one-standard-deviation increase in the $II\ Pos\ Index$ is associated with 65.7 bps decrease in monthly 3-factor adjusted alpha and 69.3 bps decrease in 4-factor adjusted alphas, both significant at 1% level. Conventional risk factor adjusted returns do not respond significantly to the variations in $II\ Neg\ Index$. The findings further confirm that carbon risk associated with green information transfer from innovative firms in the weak information environment is a novel and priced source of information, orthogonal to conventional risk factors - size, value, and momentum.

<Insert Table VIII Here >

3.3 Disclosure regime hypothesis

The findings in Section 3.1 and Section 3.2 collectively support H3, the disclosure regime hypothesis. We find the relative brown hypothesis dominates in the post-Paris Agreement era, while the green transfer hypothesis dominates in the pre-Paris Agreement era. The conflicts confirm the importance of transparency on firm specific carbon emissions for investors' asset allocations. Investors rely on such information not only to understand firms' own greenness but also to infer how they are going to meet the climate risk and carbon risk challenges of the future. More importantly, industries vary in their capacity to make green productions and make technology breakthroughs. Investors rely on firms' carbon emission information and innovations to understand the frontiers of Greenium in a given industry, without which, they cannot generate reasonable expectations on the silent firms. As the trend we observed from the Pre- to Post-Paris Agreement eras evolved, investors can better tell the "diligent" from the "lazy" in becoming green with a richer GHG emission information set, making allocations that maximize their utilities.

3.4 Product similarity hypothesis

We examine H4, the product similarity hypothesis, in this section to provide more validity and depth to our prior findings. If investors are attempting to discriminate between the silent firms and the innovative firms after industry innovation shocks, we expect the discrimination to be stronger if products in a given industry are more similar for two reasons. First, if products are more similar, they are better substitutes and it is easier for investors and other stakeholders, such as customers and suppliers, to switch to green firms and green products after the shock, if one's utility function includes a carbon emissions component. Second, if production and product similarities are high, technologies that help reduce GHG emissions could be developed and applied to silent firms as they have been developed and applied to innovative firms easier and faster. We expect innovative firms are more likely to be substitutes for silent firms and investor demands to be more elastic when product similarities are higher in the industry.

To capture product differentiation at an industry level, we average total similarity scores obtained from Hoberg and Phillips (2016) across all firms in a SIC2 industry to compute the industry similarity scores. We construct a dummy variable *above_median_similarity* which equals one if its industry similarity score is above median, and zero otherwise. Our main variable of interest is the interaction term between *above_median_similarity* dummy and *II Index*, *II Pos Index* or *II Neg Index*. Model specification (5) below examines hypothesis four and regression results are reported to Table IX. Columns 1 and 2 report on the strong information environment of 2017 – 2021 and Columns 3 and 4 report on the weak information environment of 2007-2016. Control variables are the same as in Table VI.

$$RET_{i,m} = \alpha_0 + \alpha_1 * Above\_Median\_Similarity_{i,j,m}\ X\ II\ Index_{i,j,m} + a_2 * II\ Index_{i,j,m} + \alpha_3 * Above\_Median\_Similarity_{i,j,m} + \sum \alpha_k * control_{i,m-1} + \gamma_j + \mu_m + \varepsilon_{i,yr} \quad (5)$$

<Insert Table IX Here >

The statistically significant coefficients on the interaction terms between *above_median_similarity* and *II Index* (*II Pos Index*) support H4. Columns 1 and 2 provide additional support to H1, the relative brown hypothesis. In a strong information environment, a one-standard-deviation increase in *II Index* is associated with 36.1 bps higher demanded returns for industries with higher similarity and lower product differentiation, significant at 5% level. The impact of *II Index* is 3.41 (= 0.361 / 0.106) times stronger for such similar industries, compared to the average effect in Table V Column 1. Column 2 reports the effect of *II Pos Index* on more similar industries in the strong information environment. The effect of *II Pos Index* is 4.27 (=0.594

/ 0.139) times stronger for such industries, compared to the average effect in Table V Column 4. In contrast, investors' response to industry innovation shocks are not different between similar and more differentiated industries in the weak information environment.

Though this is not causal evidence, it lends confidence to our argument that when products and operations are similar, as described in firms' 10-K annual filings, investors are more likely to treat firms in these industries as substitutes and demands for their stocks are more elastic, resulting in a stronger reaction to industry wide shocks, lower demands for silent firms' equity, higher demanded returns when compared to industries with more product differentiation.[10]

3.5 Silent firm disclosures: Staying quiet

How do silent firms respond to GHG emission innovations by others in the industry? With an increasing amount of discussion in the conventional media and social media, symposia and conferences, ESG investment portfolios and funds, as well as increasing regulation on mandatory and voluntary disclosures regarding carbon risk and climate risk, it is hard to argue that in today's environment firms are unaware of the ESG investors' preferences and utilities. We thus expect silent firms to respond. At the same time, public firms are regulated by the Security Act, Exchange Act and SEC, and we thus do not expect them to actively mislead investors to believe that they have reduced carbon emissions and are on par with innovative firms. The path left for the silent firms (in the short-run) is weaken their links to GHG emission innovations by speaking less in their forthcoming 10-Q filings about climate and carbon issues.

We start with two carbon-related and climate-related wordlists in existing literature to create the wordlists we use to examine firms' response to industry peer shocks. The first is developed by Li, Shan, Tang and Yao (2024) and can be found in their Table 2. The second is developed by Matsumura, Prakash and Vera-Munoz (2022). To create our wordlist (i.e., Wordlist 1) we utilize the transition climate risk list from Li et al. (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 Wordlist 1 by adding the wordlist used in Matsumura et al. (2022), to catch possible omissions from the first list. This is more full and complete wordlist, Wordlist 2.

[10] We also examined GHG emission distance between innovative firms and silent firms within industry, and how response to industry wide innovation shocks varies with the distance. Model specification is: $RET_{i,m} = \alpha_0 + \alpha_1 * Distance_{\ i,m}\ X\ II\ Index_{i,j,m} + \alpha_2 * II\ Index_{i,j,m} + \sum \alpha_k * control_{i,m-1} + \gamma_i + \mu_{yr} + \varepsilon_{i,m}$. Results are reported to Appendix Table AIV. Results are consistent with intuition that when GHG emission distance between innovative firms and silent firms increases, the impact of industry wide innovation decreases.

Using these wordlists, we parse firms' 10-Q filings and count the number of times the words in each wordlist are used in a given filing. We refer to the number of times a word is used in the filing as *wordcount*.

$$WordCount_{i,m} = \beta_0 + \beta_1 * II\ Index_{i,j,m} + \sum \beta_k * control_{i,m} + \gamma_j + \mu_m + \varepsilon_{i,yr} \qquad (6)$$

We test H5 on firm disclosure as a response to industry GHG emission innovations using pooled regressions on model specification (6). The dependent variable is *wordcount* in the forthcoming 10-Q filing and is standardized across the sample. The same control variables are used as in Table VI, including industry and time fixed effects with standard deviations clustered by firm and year. Regression results are reported to Table X. Panel A reports on the stronger climate information environment while Panel B reports on the weaker climate information environment. In both panels, columns 1 and 2 report on Wordlist 1, the transition climate risk list by Li et al. (2021) and columns 3 and 4 report on Wordlist 2, the expanded wordlist.

<Insert Table X Here >

The significantly negative coefficients on *II Index* and *II Pos Index* support H5 in the strong information environment. In response to industry GHG emission innovations, firms talk less and decrease their disclosure on carbon issues in the forthcoming 10-Q filings. From Panel A, a one-standard-deviation increase in the *II Index* is associated with 0.2% (0.2%) of one-standard-deviation decrease in using climate words from wordlist 1 (wordlist 2), significant at 5% (5%) level. Similarly, a one-standard-deviation increase in the *II Pos Index* is associated with 0.5% (0.3%) of one-standard-deviation decrease in using climate words from wordlist 1 (wordlist 2), significant at 5% level. Indeed, firms appear to respond in the short run by limiting their carbon and climate related disclosures to distance themselves from innovative firms.

Consistent with intuition, results from Panel B in the weak climate information environment are insignificant with respect to the indices. Firms enjoy green transfer from innovative firms and the ensuing lower demanded equity returns when ESG investors assume similar green initiatives and reduced carbon emissions may be applied to silent firms in the near future. Thus, the silent firms do not seek to distance themselves from innovative firms, and do not change carbon risk disclosure behavior in the forthcoming quarter.

In all, firms asymmetrically utilize climate words and carbon risk disclosure in their forthcoming 10-Q filings as a rational response to vastly different investor expectations in the stronger versus weaker information environments. Silent firms speak less to distance themselves from equity market' penalties in the stronger information environment, while those in the weaker information environment don't alter their disclosures so as to enjoy the benefits of green transfer. This asymmetric behavior is mostly enabled by the flexibility of qualitative disclosures.

3.6 Robustness test 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). We use both TNIC_2 and TNIC_3 as alternative industry classifications in this test. 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. 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 deemed related."

Since TNIC_2 and TNIC_3 industry classifications cater more specifically to each firm and its products to provide unique industry classification and industry peers, the *II index* and its variations constructed in this way are also unique to each firm. For a given firm, we start with its TNIC_2 industry peers, excluding itself, and compute the TNIC_2 *II Index* as the sum product of GHG emission pulse score innovations and the number of unique articles on the same day across all firms as its TNIC_2 industry peers. Similarly, we compute TNIC_2 *Pos (Neg) Index* as the sum product of positive (negative) GHG emission innovations and the number of unique articles on the same day across all firms as its TNIC_2 industry peers. TNIC_3 *II Index* and TNIC_3 *Pos* (*Neg*) *II Index* are constructed in a similar manner, with industry peers defined following TNIC_3 classification. Results are reported to Appendix Table AV and our main findings are robust to the use of alternative proxies for industry classifications.

IV. Conclusion

Motivated by the debate on whether to require mandatory climate risk disclosures for publicly traded firms, and how such a ruling could change the landscape of climate information processing and equity pricing, this study examines two research questions. First, how do firms' carbon risk and demanded equity returns vary with greenhouse gas emission innovations by their industry peers, holding firms' own carbon emissions constant? Second, does the climate information environment play a role in the way GHG emission information is interpretated and priced?

We construct a monthly industry *II Index* and its two alternatives with respect to positive and negative innovations to capture shocks on silent firms coming from the aggregate GHG emission innovations made by their industry peers. We propose several hypotheses, the first being the relative brown hypothesis which suggests that there is a positive relationship between *II Index* (and its variations) and silent firms' carbon risk premium and demanded equity returns. Second, the green transfer hypothesis, posits a negative relationship between the two. Third, we hypothesize that climate disclosure and the information environment play a decisive role in how investors process new GHG emission innovations. In the stronger information environment, the relative brown hypothesis dominates and investors rebalance their portfolio between the new brown and green stocks. However, we find that in the weaker disclosure environment the green transfer hypothesis dominates, and investors extrapolate green innovations from innovative firms to silent firms. That is, we observe green spillover in the weaker information environment.

Carbon risk is an increasingly influential physical, environmental, and social risk. A deeper and timely understanding of firms' carbon risk and climate risk is essential for institutional investors, various stakeholders, policy makers, regulators, and the firms themselves. It is also essential for silent firms to understand that their silence is not free in the equity market. With the SEC's recent focus on standardizing 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 2007 –2021. We report over the whole sample period, the strong information environment from 2007 to 2016, and the weak information environment from 2017 to 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 2007 –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.

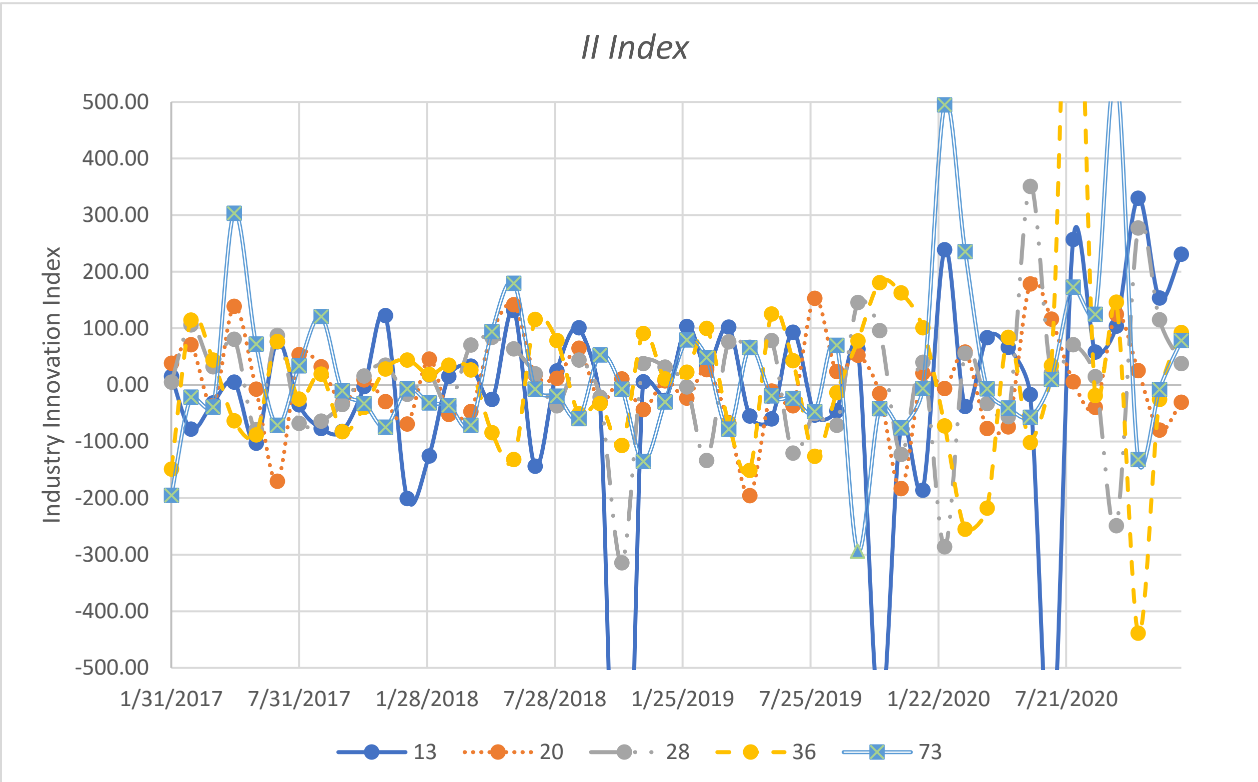
Panel A. Strong Information Environment	Wordlist 1		Wordlist 2	
	1	2	3	4
II Index	-0.002**		-0.002**	
	(0.034)		(0.050)	
II Pos Index		-0.005**		-0.003**
		(0.017)		(0.012)
II Neg Index		-0.003		0.000
		(0.253)		(0.717)
GHG Emission Pulse Score L1	0.036*	0.036*	0.028	0.028
	(0.050)	(0.050)	(0.103)	(0.103)
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

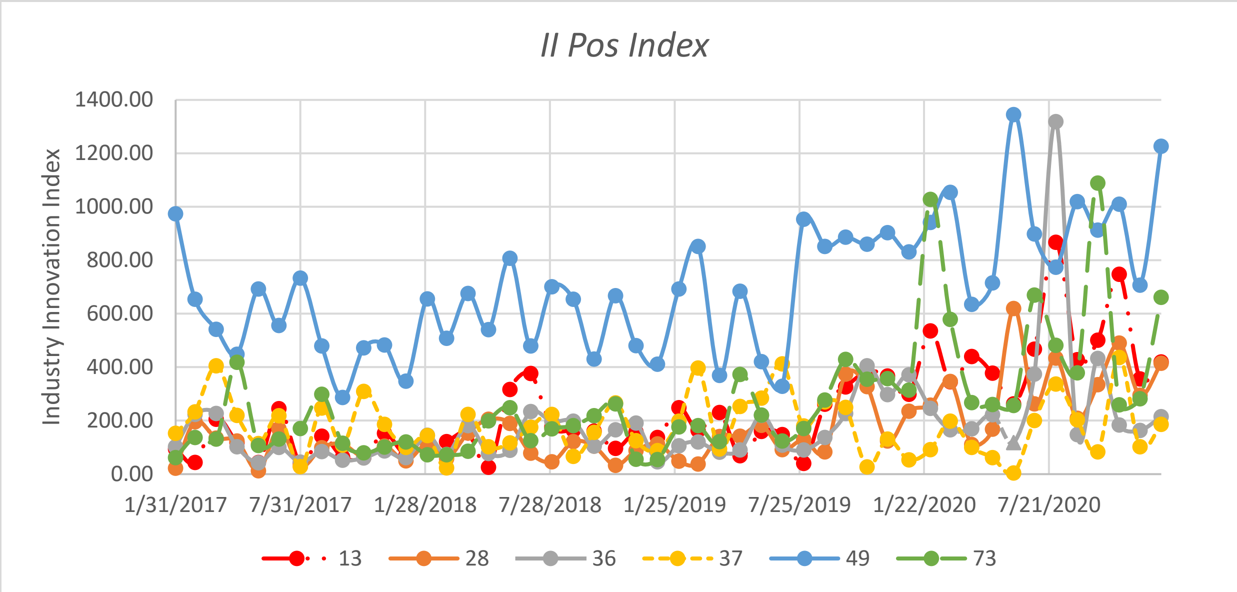
Figure plots time series variations in *II Index*, *II Pos Index* and *II Neg Index* of the most volatile industries in 2017-2021. Panel A graphs *II Index* and Panel B graphs *II Pos Index* and *II Neg Index*. Industries are defined by the first 2 digits of their SIC code. Industries with the most volatile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

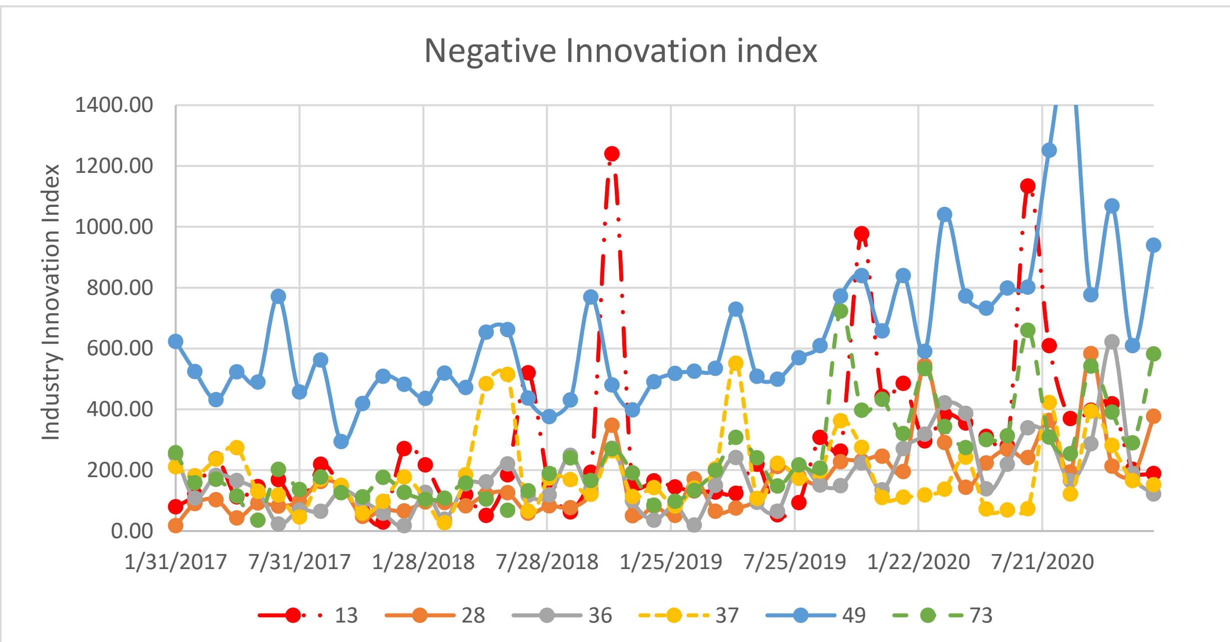
Panel A. The time-series variations of *II Index* for the most volatile industries



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 2007 –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