Is Carbon Risk Priced in the Cross-Section of Corporate Bond Returns?*

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Abstract

This paper examines the pricing of a firm's carbon risk in the corporate bond market. Contrary to the "carbon risk premium" hypothesis, bonds of more carbon-intensive firms earn significantly lower returns. This effect cannot be explained by a comprehensive list of bond characteristics and exposure to known risk factors. Investigating sources of the low carbon alpha, we find the underperformance of bonds issued by carbon-intensive firms cannot be fully explained by divestment from institutional investors. Instead, our evidence is most consistent with investor underreaction to the predictability of carbon intensity for firm cash-flow news, creditworthiness, and environmental incidents.

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1 Introduction

Scientists predict a rise in average global temperatures by the end of this century, and many policy makers warn about the potentially dramatic damage that climate change could inflict on the global economy (Hoegh-Guldberg et al., 2018). In the recent decade, consensus has emerged that more stringent governmental regulations and law enforcement are needed to mitigate the potentially catastrophic consequences of climate change. As accumulations of greenhouse gases (GHG) in the earth's atmosphere mostly cause climate change, any regulation should be targeted at significantly curbing firms' carbon emissions (e.g., via a carbon tax or a cap-and-trade program).

Climate change mitigation policies likely produce heterogeneous effects across firms in the economy. Effects are likely most impactful for carbon-intensive firms, as regulations that limit carbon emissions can lead to stranded assets or a large increase in operating costs for carbon-intensive firms. In addition, carbon-intensive firms may experience higher financing costs if banks reduce lending to and institutional investors shun from such firms, due to climate-related capital requirements and general trends towards sustainable investing in financial markets (Delis, De Greiff, and Ongena, 2019; Krueger, Sautner, and Starks, 2020).[1] Furthermore, more stringent emission regulations are likely to be proposed and implemented as the global climate worsens, leading to deteriorating fundamental values of carbon-intensive firms just when climate change matters most to investors' welfare. These conjectures about climate policies naturally lead to the prediction that securities issued by carbon-intensive firms are riskier because they tend to lose value in states of the world where investors dislike and have a higher marginal utility of consumption. As a result, risk-based asset pricing theories predict that investors should demand higher expected returns for holding securities issued by carbon-intensive firms as compensation for higher exposure to climate policy risks (the "carbon risk premium" hypothesis).

In this study, we examine the pricing of carbon risk in the U.S. corporate bond market.

[1] For example, Larry Fink, CEO of BlackRock, said in his recent annual letter to CEOs that the company is considering "exiting investments that present a high sustainability-related risk, such as thermal coal producers" (*Source:* `https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter`). Bank of England Governor Andrew Bailey said the British central bank would look into introducing climate change considerations into its corporate bond buying decisions (*Source:* `https://www.bankofengland.co.uk/news/2020/july/statement-on-banks-commitment-to-combatting-climate-change`).

Despite the proliferation of academic studies on the pricing of climate risk in the equity market (Bansal, Ochoa, and Kiku, 2016; Hong, Li, and Xu, 2019; Bolton and Kacperczyk, 2021; Engle et al., 2020), few studies are devoted to understanding the role of firms' carbon risk in the expected returns of corporate bonds. We focus on corporate bonds for several reasons. First, unlike stocks, corporate bonds have limited upside potential but are significantly exposed to downside risks (Hong and Sraer, 2013; Bai, Bali, and Wen, 2019). Since future climate policies and regulations mainly constitute a downside risk to carbon-intensive firms (Ilhan, Sautner, and Vilkov, 2021; Hoepner et al., 2021), the impacts of uncertain climate policies likely matter more for bond investors than for equity investors. Second, the clientele of corporate bonds in the United States are mainly institutional investors, who are sophisticated and likely take carbon risks into account when investing in carbon-intensive firms.[2] Third, corporate bonds differ along important dimensions, such as credit ratings and maturities. The heterogeneity in various bond characteristics allows us to shed more light on the underlying channels of the pricing of carbon risk.[3] Fourth, debt financing forms a significant portion of firms' capital structures, underscoring the need to study how carbon emissions affect a firm's cost of debt financing.[4] Last, but not the least, the sheer size of and the possibility of fragility in the fast-growing corporate bond market (Goldstein, Jiang, and Ng, 2017) suggest our research question is an important one with profound policy implications.[5,6] Thus, enhancing our understanding of how carbon emissions are related to expected returns in corporate bonds is pivotal.

We rely on firms' carbon emissions data from Trucost and corporate bond pricing data from the enhanced version of the Trade Reporting and Compliance Engine (TRACE). We examine

[2]According to flow of fund data released by the Federal Reserve Board from 1986 to 2019, approximately 78% of corporate bonds were held by institutional investors, including insurance companies, mutual funds, and pension funds. The participation rate of individual investors in the corporate bond market is very low. A recent survey by Krueger, Sautner, and Starks (2020) found that institutional investors indeed consider climate risks to be important for their investment portfolios.

[3]For example, if investors care about carbon risks, the pricing effect should be more pronounced among bonds with higher credit risk or longer maturities, since climate risks should mainly materialize in the long run.

[4]Graham, Leary, and Roberts (2015) report that the average debt-to-assets ratio for public companies was as high as 35% in 2010.

[5]The outstanding amount of corporate bonds issued by non-financial corporations was $5.8 trillion at the end of 2019 (see Table L.213 in the Federal Reserve Board Z.1 flow of funds).

[6]Indeed, regulators and policy makers worldwide have expressed concerns about the extent to which climate risks could affect financial stability. Most notably, Mark Carney, the former head of the Bank of England, recently linked these risks to financial stability (Carney, 2015). A coalition of 39 central banks, representing about half the global economy, including the central banks of England, China, Canada, Japan, and the European Union (but not the United States), has convened a working group to study the effects of climate change on financial markets.

the relation between a firm's carbon emissions intensity (CEI) and the expected return on its corporate bonds. Following existing studies (Ilhan, Sautner, and Vilkov, 2021; In, Park, and Monk, 2019; Pedersen, Fitzgibbons, and Pomorski, 2021) and industry standards (e.g., MSCI Low Carbon Indexes), we construct our measure of CEI as carbon dioxide (CO2) emissions in units of tons scaled by a firm's total revenues (in $millions).[7] Following the portfolio sorts method in Fama and French (1992), we form quintile portfolios of corporate bonds based on firm-level (scope 1) CEI in June of each year t for firms with their fiscal year ending in year $t-1$. Portfolio returns are calculated from July of year t to June of year $t+1$ and rebalanced annually. Since the level of carbon intensity varies intrinsically across industries, we form value-weighted quintile portfolios within each of the 12 Fama-French industries to control for the industry effect and to calculate the average portfolio returns across industries. We find that the bonds of high CEI firms are riskier on average than those of low CEI firms, as indicated by a higher bond market beta, higher downside risk, higher illiquidity, and lower credit ratings. However, the bonds of high CEI firms significantly *underperform* the bonds of low CEI firms over the period from July 2006 to June 2019. This finding directly contradicts the carbon risk premium hypothesis as predicted by risk-based asset pricing models. This low carbon alpha effect is economically significant: corporate bonds in the lowest-CEI quintile generate 1.7% (t-stat. = 2.62) per annum higher returns than bonds in the highest-CEI quintile.

We further confirm that the return predictability of CEI is robust to using various factor models to adjust for firms' risk exposure. We rely on three unique factor models in our main analyses: the five-factor model of Pastor and Stambaugh (2003), the four-factor bond market model of Bai, Bali, and Wen (2019), and the nine-factor model combining the stock and bond market factors. Regardless of the factor model used, we find that the low-CEI portfolio significantly outperforms the high-CEI bond portfolio, with a monthly nine-factor alpha ranging from 0.13% to 0.16%.

[7] According to the Greenhouse Gas Protocol accounting and reporting standard, carbon emissions from a firm's operations and economic activities are typically grouped into three different categories: direct emissions from sources that are owned or controlled by the firm (scope 1); indirect emissions from the generation of electricity, heat or steam purchased by the firm from a utility provider (scope 2); and other indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, etc. (scope 3). In our main analyses, we focus on scope 1 carbon emissions, the disclosure requirements for which are stricter and for which relevant data have been more systematically reported and accurately measured. Scope 3 emissions, on the other hand, are rarely reported by companies, and are at best noisily estimated and inconsistent across different data providers (Busch et al., 2018).

The return predictability of CEI persists in Fama-MacBeth regressions when we include a comprehensive list of bond characteristics and systematic risk measures. The bond characteristics we include are the bond market beta, downside risk as proxied for by 5% value-at-risk (VaR), bond-level illiquidity, credit ratings, time-to-maturity, bond size, and the one-month-lagged bond return. The systematic risk proxies include the term beta, the default beta (Gebhardt, Hvidkjaer, and Swaminathan, 2005), macroeconomic uncertainty beta (Bali, Subrahmanyam, and Wen, 2021b), and climate change news beta (Huynh and Xia, 2021). Similar to the portfolio sorting results, the cross-sectional relation between future bond returns and firms' carbon emissions intensity is negative and highly significant. The multivariate regression results suggest that the CEI measure contains distinct, significant predictive information beyond bond size, maturity, rating, liquidity, market risk, default risk, and climate risk. The results further imply that CEI is a strong and robust predictor of future bond returns.

We conduct a battery of robustness tests to investigate the return predictability of carbon emissions intensity. First, our results remain similar when we construct our CEI measure based on the scope 2 emissions, as well as scope 1 and scope 2 emissions combined. Second, we find that the most carbon-intensive industries do not drive the low carbon alpha. When we exclude the most carbon-intensive industries including the energy, chemicals, and utilities industries, the return spreads between low- and high-CEI bonds remain economically and statistically significant. Third, we perform portfolio analysis at the firm level to control for the impact of multiple bonds issued by the same firm. The results are robust to forming the value-weighted average bond returns across the same firm or to choosing one representative bond of the largest size or most liquid for each firm. Last, the return spread between low- and high-CEI bonds remains significant using alternative factor models, for different subperiods, and is not driven by the period containing the global financial crisis (September 2008 to December 2009).

Our finding of a low carbon alpha, combined with the evidence that bonds of carbon-intensive firms are riskier, suggests that the data does not support the "carbon risk premium" hypothesis. Although risk-based theories predict that carbon intensity should be positively related to expected bond returns, the empirical relation between the two could go in either direction, as predicted by recent theories. Pastor, Stambaugh, and Taylor (2020) show that green assets could perform better than brown assets if investors' environmental, social, and governance (ESG) concerns unexpectedly strengthen. Excess demand from ESG-conscious investors could boost the realized performance of green assets, while hurting that of brown assets. If one computes average returns over a sample period when ESG concerns consistently strengthened more than investors expected, green assets could outperform brown assets.[8] We test this "investor preference" hypothesis by examining whether a firm's carbon emissions intensity is predictive of subsequent changes in institutional ownership of its corporate bonds. We find that institutional investors collectively divest from bonds issued by carbon-intensive firms. However, the predictive power of carbon intensity for future bond returns remains significant after controlling for the contemporaneous changes in bonds' institutional ownership. This suggests that investor divestment from carbon-intensive assets cannot fully explain the outperformance of bonds from low carbon intensity firms.

Pedersen et al. (2021) propose another potential explanation for the outperformance of low carbon assets. Their model predicts that assets with a higher ESG rating could earn higher returns if better ESG performance is an indication of strong firm fundamentals, and the market underreacts to this predictability of fundamentals (the "investor underreaction" hypothesis). We conduct several tests for this hypothesis. First, the investor underreaction hypothesis implies that the return predictability should be larger among bonds with poorer information environments and in periods with low investor attention to climate change issues. Consistent with this hypothesis, we find the low carbon alphas are indeed more pronounced for bonds with higher information asymmetry and in periods when investors did not pay sufficient attention to climate risks.[9]

Second, we directly test whether CEI predicts future firm fundamentals. Our results show that firms with lower carbon intensity are associated with higher future earnings and revenue growth, but investors fail to fully incorporate the information they glean from firms' emission intensity when forming their expectations about future earnings. As a result, CEI also negatively predicts earnings announcement returns. In further support of this channel, we

[8]The idea that changing investor composition over a sustained period of time can affect asset prices is first proposed and tested by Gompers and Metrick (2001), in which they argue the disappearing size premium after 1980s can be explained by the rise of institutional investing.

[9]We assume that bonds with smaller issuance size, non-investment-grade bonds, longer-maturity bonds, and bonds that are more illiquid have higher information asymmetry. Following Choi, Gao, and Jiang (2020), we use Google search volume index on the topics of "climate change" or "global warming" as proxies for investor attention. We also conjecture that investors become more aware of climate policy risks after Paris agreement was adopted in December 2015 (Ilhan, Sautner, and Vilkov, 2021).

find firms with low (high) carbon intensity subsequently experience improved (deteriorating) creditworthiness, as measured by bond credit ratings and the O-score (Ohlson, 1980). Using ESG incidents data from RepRisk, we also show that part of reason why carbon-intensive firms experience lower cash-flow news is that environmental risks are persistent, that is, carbon-intensive firms are more likely to face negative environment incidents than carbon-efficient firms. Collectively, these results are broadly consistent with the "investor underreaction" hypothesis, which posits that risk associated with carbon emissions is underpriced in the corporate bond market.

The rest of this paper proceeds as follows. Section 2 reviews the literature and articulates different hypotheses and associated empirical predictions as motivated by recent theories. Section 3 describes the data and defines the variables used in our empirical analyses. Section 4 presents the main results for the relation between carbon emissions intensity and cross-sectional bond returns. Section 5 investigates the sources of the low carbon alpha in corporate bonds. Section 6 concludes the paper.

2 Literature Review and Hypotheses Development

In subsection 2.1, we provide a brief review of related literature and the contribution of our study to the literature. In subsection 2.2, we develop alternative hypotheses as motivated by recent theories linking firm carbon risk to its expected returns.

2.1 Related literature and contribution

Our study contributes to several strands of the literature. First, our paper adds to a fast-growing climate finance literature that studies whether financial markets can anticipate and efficiently discount risks associated with climate change (Giglio, Kelly, and Stroebel, 2021). Studying this topic is important because of the key role that financial markets play in alleviating this disaster: properly pricing climate risks today not only reduces the possibility of wealth transfers between uninformed and sophisticated agents but also reduces the likelihood of extreme price movements in the future. Evidence to date is still mixed.[10] Closely related to our paper, Ilhan, Sautner, and Vilkov (2021) find that uncertainty about climate policy, as proxied by carbon intensity, is priced in the options market.[11] Bolton and Kacperczyk (2021) document that stocks of firms with higher carbon emissions earn higher returns, although In, Park, and Monk (2019) and Cheema-Fox et al. (2019) find the opposite evidence: carbon-efficient firms are more profitable and earn higher returns. Whether return predictability patterns in equities extend to bonds is an open question, given the markedly different investing clienteles across equities and bonds.

Our study attempts to find some common ground among this mixed evidence by investigating how the corporate bond market prices carbon risk. A recent paper by Seltzer, Starks, and Zhu (2020) examines how state-level environmental regulations affect the credit ratings and yield spreads of corporate bonds. Our paper differs from theirs, however, as we focus on firm-level carbon emissions and investigate the pricing of carbon risk through the lens of expected corporate bond returns. Cao et al. (2021) investigate the trading behavior of mutual funds and insurance companies on firms with different carbon emission levels and show that these investors are more likely to sell corporate bonds in herds if the bonds' issuing firms have higher carbon emissions. Different from their study, we focus on the pricing implications of carbon risks in the corporate bond market and disentangle the alternative hypotheses linking carbon risks to the expected bond returns.

Our paper is also related to the growing literature on the impact of a firm's ESG performance on its cost of capital. Existing studies report mixed evidence. Some studies show that low-ESG assets earn higher expected returns than do high-ESG assets across various contexts, such as the outperformance of "sin" stocks (Hong and Kacperczyk, 2009), higher implied cost capital for firms that derive substantial revenues from the sale of coal or oil (Chava, 2014), and higher expected returns for firms with intense toxic emission (Hsu, Li, and Tsou, 2020). Other studies

[10] Bansal, Ochoa, and Kiku (2016) find that climate change risk, as proxied for by temperature rise, negatively affects stock market valuation, implying that markets do price climate change risk. In contrast, Hong, Li, and Xu (2019) show that global stock markets do not anticipate the effects of worsening droughts on agricultural firms. In the real estate market, Bernstein, Gustafson, and Lewis (2019) show that home buyers take into account the negative effect of sea-level rise on real estate prices in coastal areas, although Murfin and Spiegel (2020) find no evidence of significant valuation effects. Painter (2020) documents that the municipal bond market prices climate change risks, especially for long-term bonds issued by counties more likely to be affected by sea-level rise. Sautner, Van Lent, Vilkov, and Zhang (2021) construct firm-level climate change exposure using earnings call data and find an unconditional climate risk premium close to zero.

[11] Specifically, they document that the cost of option protection against downside tail risks is larger for firms within carbon-intense industries. We differ from their paper by using firm-level carbon intensity measure and performing within-industry analysis.

uncover opposite results, based on different measures of ESG metrics. Firms' stocks perform better if the firms themselves are better-governed (Gompers, Ishii, and Metrick, 2003), have higher employee satisfaction (Edmans, 2011), or higher carbon efficiency (In, Park, and Monk, 2019; Cheema-Fox et al. (2019)). An emerging field examines the pricing of green bonds issued to finance environment-friendly projects.[12] Our study differs from that line of research by examining the impact of carbon emissions on the much larger corporate bond market.

Lastly, this study also contributes to our understanding of the cross-sectional determinants of corporate bond returns. Despite the multitude of stock and firm characteristics to explain the cross section of stock returns, far fewer studies are devoted to explaining the expected returns of corporate bonds.[13] Recent studies examine a few corporate bond characteristics related to default, term, and macroeconomic uncertainty betas (Fama and French, 1993; Gebhardt, Hvidkjaer, and Swaminathan, 2005; Bali, Subrahmanyam, and Wen, 2021b), liquidity risk (Lin, Wang, and Wu, 2011), bond momentum (Jostova et al. (2013)), downside risk and short-term reversal (Bai, Bali, and Wen, 2019), and long-term reversal (Bali, Subrahmanyam, and Wen, 2021a), all of which exhibit significant explanatory power for future bond returns. Our study examines whether firms' carbon emissions intensity (an increasingly important risk factor) is an incrementally important determinant of corporate bond returns.

2.2 Hypotheses development

In this subsection, we develop different hypotheses based on recent theoretical works linking firm environmental performance to asset prices and expected returns (Pastor, Stambaugh, and Taylor, 2020; Pedersen, Fitzgibbons, and Pomorski, 2021).

> ***H1: Carbon risk premium hypothesis****: Carbon risk should be positively priced in the cross section of corporate bond returns if carbon intensive firms are subject to more stringent climate policies in future and such policies are more likely to be proposed and implemented when global climate worsens unexpectedly.*

[12] See, for example, Flammer (2020) and Larcker and Watts (2020) for the evidence on whether green bonds are priced at premium or not.

[13] This gap in the literature is partly explained by the dearth of high-quality corporate bond data and the complex features of corporate bonds, such as optionality, seniority, changing maturity, and risk exposure to a number of financial and macroeconomic factors.

Our first hypothesis, **H1**, is naturally predicted by asset pricing theories when carbon-intensive firms likely lose value in states of the world where investors dislike and have a higher marginal utility of consumption. Alternatively, theories based on investor non-pecuniary preferences for ESG characteristics and limited risk-sharing due to divestment may also predict a positive relation between carbon intensity and expected returns. Pastor et al. (2020) present a model of investing based on ESG criteria and show that green (brown) assets produce negative (positive) alphas.[14] In their model, the lower expected returns from green assets stem from two sources: investors' tastes for green holdings and such stocks' ability to hedge against climate risk. Pedersen et al. (2021) propose a theory in which a positive carbon risk premium arises because of exclusionary screening by institutional investors with an ESG mandate. To the extent that some investors shun companies with high carbon emissions, risk sharing would be limited, and idiosyncratic risk could be priced (Merton, 1987). If the extent of such divestment is high, one would expect to find a return premium for bonds issued by carbon intensive companies.

> ***H2: Investor preference hypothesis****: Corporate bonds for firms with a low (high) carbon emissions intensity perform better (worse) than expected if ESG concerns unexpectedly strengthen.*

Our second hypothesis, **H2**, is motivated by the theoretical work of Pastor, Stambaugh, and Taylor (2020), who predict that green assets could outperform brown ones when there is an unexpected shift in customers' tastes for green products and investors' tastes for green holdings. To be clear, their model predicts that if ESG policies make a firm a safer investment, or if investors non-pecuniarly value ESG, a basic general equilibrium argument means that high-ESG firms should obtain lower returns than their peers (this is the prediction of **H1**). However, if investors' non-pecuniary benefit rises or ESG concerns strengthen *unexpectedly* over a given period, green assets can outperform brown assets over that period, despite having lower expected returns in equilibrium (**H2**).[15] This hypothesis is plausible as evidenced by the sharp rise in the number of institutional investors pledged to divest from fossil fuel companies.[16]

[14] This finding is especially true when risk aversion is low and the average ESG preference is strong.

[15] Pastor, Stambaugh, and Taylor (2021) provide evidence that the outperformance of green stocks can be attributable to unexpectedly strong increases in environmental concerns in the recent period.

[16] As of 2021, over 1,300 institutions (e.g., pension funds, investment funds and university endowments) representing approximately US$ 14.5 trillion have publicly pledged to reduce their investments in the fossil fuel industry. *Source:* https://gofossilfree.org/divestment/commitments/

H3: Investor underreaction hypothesis: *Corporate bonds of low carbon intensity firms could earn higher returns if being carbon efficient is an indication of strong firm fundamentals, and the market underreacts to this predictability of fundamentals.*

Our third hypothesis, **H3**, is motivated by Pedersen et al. (2021), who argue that securities with a high-ESG score could earn higher future returns when investors do not take into account the predictability of ESG ratings for future firm profitability. The key ingredients in their model is that the ESG score plays two roles: (1) providing information about firm fundamentals and (2) affecting investor preferences. Companies that manage relevant ESG issues well tend to quickly adapt to changing environmental and social trends, use resources efficiently, have engaged (and, therefore, productive) employees, and can face lower risks of regulatory fines or reputational damage. This positive relation between ESG ratings and firm profitability can lead to a low carbon alpha if the market underreacts to this predictability of fundamentals. The underreaction hypothesis is plausible considering that carbon risk is not fully integrated by most investors and credit analysts during our sample period.[17]

3 Data and Variable Definitions

Our study utilizes several datasets including (1) firm-level carbon emissions data, (2) corporate bond pricing data, and (3) data on institutional holdings of corporate bonds. We provide detailed descriptions on these datasets below.

3.1 Carbon emissions data

We obtain carbon emissions data from S&P Global Trucost. Trucost's firm-level carbon emissions data follow the Greenhouse Gas Protocol, which sets the standards for measuring carbon emissions. The Greenhouse Gas Protocol distinguishes between three different sources of emissions: scope 1 emissions, which cover direct emissions from establishments that are

[17] Only recently, Fitch launched the ESG Relevance Scores to show how ESG factors impact individual credit ratings. https://www.ipe.com/fitch-launches-esg-credit-rating-relevance-scores/10028894.article

owned or controlled by the firm; these include all emissions from fossil fuel used in production. Scope 2 emissions originate from purchased heat, steam, and electricity the company consumes. Scope 3 emissions are generated by the firm's operations and production but originate from sources not owned or controlled by the company.[18] Trucost reports carbon emissions in units of tons of CO2 equivalents (a standard unit for measuring a firm's carbon footprint) emitted in a year across all three scopes. As shown by Busch et al. (2018), reported scope 1 and scope 2 emissions data are highly consistent across different data providers.[19] Trucost also reports the CEI for all three scopes, defined as the firm-level greenhouse gas emission in CO2 equivalents, divided by the total revenue of the firm in millions of U.S. dollars. The sample of carbon emissions data starts from 2005.

To construct our sample, we begin with the universe of all firms in Trucost with a fiscal year ending between calendar years 2005 and 2017. Since the main firm identifier in Trucost is ISIN, we first convert ISIN to GVKEY using S&P Capital IQ and then obtain the primary PERMNO from the Compustat/Center for Research in Security Prices (CRSP) Merged database. Panel A of Fig. 1 shows the mean carbon emissions intensity (scopes 1, 2, and 3) for the Fama-French 12 industries from 2005 to 2017. The top-three industries with the highest scope 1 carbon emissions intensity are Utilities, Energy, and Chemicals, respectively.[20] Panel B of Fig. 1 presents the average CEI over time and reports a declining trend for scope 1 emissions. This result indicates a gradual improvement in carbon efficiency in the average firm's production process.

Fig. 2 plots the cross- and within-industry variations in carbon emissions intensity over time. Panel A of Fig. 2 reports significant cross-industry variation, especially for scope 1 emissions. The standard deviation of cross-industry CEI declines over time but is of large magnitude compared to the average CEI as shown in panel B of Fig. 1. More importantly, our CEI measure exhibits significant cross-sectional variation even within the same industry, as shown

[18]Trucost collects firm-level emissions data from various sources including company reports, environmental reports (CSR/ESG reports, the Carbon Disclosure Project, Environmental Protection Agency filings), and data from company websites. If a firm does not disclose emissions data, Trucost uses an input-output model to estimate the firm's carbon emissions. Following Bolton and Kacperczyk (2021), we use both actual and estimated emissions data in our analyses.

[19]The average correlations for the scope 1 and scope 2 data are 0.99 and 0.98, respectively, across the five providers (CDP, Trucost, MSCI, Sustainalytics, and Thomson Reuters). However, only two data providers, Trucost and ISS ESG, estimate scope 3 emissions.

[20]In Section 4.3, we examine whether our results remain intact after we exclude the top three most carbon-intensive industries. We find similar results showing that the carbon premium applies to a broader category of industries, not just carbon-intensive industries.

in panel B of Fig. 2. Overall, Fig. 2 shows that carbon emissions intensity intrinsically varies across industries, and, as a result, we control for the industry effect in our empirical analyses.

3.1.1 The persistence of carbon emissions intensity

To test whether investors ex-ante require higher expected returns for bonds more exposed to carbon risk, they first need to predict a firm's future carbon emissions reasonably well. Because we use past CEI in asset pricing tests, a natural question is whether historical CEI is a good proxy for the "expected" future carbon intensity. Table A.1 of the Online Appendix investigates this issue by presenting the average year-to-year transition matrix for portfolios sorted on past CEI. Specifically, Panel A of Table A.1 presents the average probability that a firm in decile i (defined by the rows) in one year will be in decile j (defined by the columns) in the subsequent year. If CEI is not persistent at all, then all the probabilities should be approximately 10%, since a high or a low CEI value in one year should say nothing about the CEI values in the following year. Instead, all the top-left to bottom-right diagonal elements of the transition matrix exceed 10%, illustrating that a firm's carbon emissions intensity is highly persistent. Of greater importance, this persistence is especially strong for the extreme portfolios. Panel A of Table A.1 shows that for the one-year-ahead persistence of CEI, firms in decile 1 (decile 10) have a 94.13% (80.30%) chance of appearing in the same decile next year. Similarly, Panel B shows that for the two-year-ahead persistence of CEI, firms in decile 1 (decile 10) have a 89.47% (81.41%) chance of appearing in the same decile the next two years. In Panels C to E, similar results are obtained using a three- to five-year gap between the lagged and lead carbon emissions intensity. Even after a five-year gap is established between the lagged and lead CEI, firms in decile 1 (decile 10) have a 79.52% (81.32%) chance of appearing in the same decile. Overall, Table A.1 indicates that a firm's past CEI is a very informative predictor for its expected carbon intensity in future.

3.2 Corporate bond data and bond returns

We compile corporate bond pricing data from the enhanced version of the Trade Reporting and Compliance Engine (TRACE) for the sample period from 2006 to 2019. The TRACE dataset offers the best-quality corporate bond transactions, with intraday observations on price, trading volume, and buy and sell indicators. We then merge corporate bond pricing data with the Mergent Fixed Income Securities database to obtain bond characteristics, such as offering amount, offering date, maturity date, coupon rate, coupon type, interest payment frequency, bond type, bond rating, bond option features, and issuer information.

For bond pricing data, we adopt the filtering criteria proposed by Bai, Bali, and Wen (2019). Specifically, we remove bonds that (a) are not listed or traded in the U.S. public market or are not issued by U.S. companies; (b) are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked; (c) are convertible; (d) trade under \$5 or above \$1,000; (e) have floating coupon rates; and (f) have less than one year to maturity. For intraday data, we also eliminate bond transactions that (g) are labeled as when-issued, are locked-in, or have special sales conditions; (h) are canceled, and (i) have a trading volume less than \$10,000. From the original intraday transaction records, we first calculate the daily clean price as the trading volume-weighted average of intraday prices to minimize the effect of bid-ask spreads in prices, following Bessembinder et al. (2009).[21]

The corporate bond return in month t is computed as

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + Coupon_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1, \tag{1}$$

where $P_{i,t}$ is the end-of-month transaction price, $AI_{i,t}$ is accrued interest on the same day of bond prices, and $Coupon_{i,t}$ is the coupon payment in month t, if any. The end-of-month price refers to the last daily observation if there are multiple trading records in the last 10 days of a given month.[22] $R_{i,t}$ denotes bond i's excess return, $R_{i,t} = r_{i,t} - r_{f,t}$, where $r_{f,t}$ is the risk-free rate proxied for by the one-month Treasury-bill rate.

After applying the aforementioned data-filtering criteria, we link the Trucost carbon emissions data to the bond pricing data set through the linking table using bond CUSIP as the main identifier. Our sample includes 20,668 bonds issued by 1,178 unique firms, for a total of 1,127,558 bond-month return observations covering the sample period from July 2006 to June 2019. As shown in Table 1, bonds in our sample have an average monthly return of 0.69%,

[21] This approach puts more weights on the trades with low transaction costs and should more accurately reflect the bond prices.

[22] If there is no observation during the last 10 days, we use the last price at which the bond was traded in a given month to calculate monthly return. Our results are similar if we set the bond price to be missing in this case.

an average rating of 8 (i.e., BBB+), an average issue size of US$480 million, and an average time-to-maturity of 9.74 years. The correlation between CEI and other bond characteristics is low, with the absolute values in the range of 0.01 and 0.09. The sample consists of 76% investment-grade bonds and 24% high-yield bonds.[23]

3.3 Corporate bond holdings

To investigate the institutional demand for corporate bonds, we collect the data on institutional holdings of corporate bonds from Thomson Reuters eMaxx data. This data set comprehensively covers quarterly fixed income holdings from U.S. institutional investors, such as insurance companies and mutual funds, for the sample period from 2006 to 2019 (the earliest bond holding data start from 2001).[24] For each bond, we aggregate the shares held by all institutional investors provided in the data. Specifically, for a given bond i at time t, the measure of institutional ownership is defined as

$$INST_{it} = \sum_j \left(\frac{Holding_{ijt}}{OutstandingAmt_{it}} \right) = \sum_j h_{jt}, \quad (2)$$

where $Holding_{ijt}$ is the par amount holdings of investor j on bond i at time t (from the eMAXX data), $OutstandingAmt_{it}$ is bond i's outstanding amount (from the Mergent FISD database), and h_{jt} is the fraction of the outstanding amount held by investor j, expressed as a percentage.

3.4 Standard risk factors

We use three different factor models to adjust the risk exposures of CEI-sorted portfolios:

1. A *five-factor model with stock market factors*, including the excess return on the market portfolio, proxied for by the value-weighted CRSP index (MKT^{Stock}), a size factor (SMB),

[23]We collect bond-level rating information from Mergent FISD historical ratings and assign a number to facilitate the analysis. Specifically, 1 refers to a AAA rating; 2 refers to AA+; ...; and 21 refers to C. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB-). Non-investment-grade bonds have ratings above 10. A larger number indicates higher credit risk or lower credit quality. We determine a bond's rating as the average of ratings provided by S&P and Moody's when both are available or as the rating provided by one of the two rating agencies when only one rating is available.

[24]eMAXX reports the quarterly holdings based on regulatory disclosure to the National Association of Insurance Commissioners (NAIC) and the Securities and Exchange Commission (SEC) for insurance companies and mutual funds, respectively. For major pension funds, it is a voluntary disclosure.

a book-to-market factor (HML), a momentum factor (MOM^{Stock}), and a liquidity risk factor (LIQ^{Stock}), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003).

2. A *four-factor model with bond market factors*, including the aggregate corporate bond market (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF), following Bai, Bali, and Wen (2019). The excess bond market return (MKT^{Bond}) is proxied for by the return of the Merrill Lynch Aggregate Bond Market index in excess of the one-month Treasury-bill rate.[25] DRF is the downside risk factor, defined as the value-weighted average return difference between the highest-VaR portfolio minus the lowest-VaR portfolio within each rating portfolio. CRF is the credit risk factor, defined as the value-weighted average return difference between the highest credit risk portfolio minus the lowest credit risk portfolio within each illiquidity portfolio. LRF is the liquidity risk factor, defined as the value-weighted average return difference between the highest illiquidity portfolio minus the lowest illiquidity portfolio within each rating portfolio.

3. A *nine-factor model* that combines the five stock market factors described in the first factor model and the four bond market factors described in the second factor model.

4 Empirical Results

In this section, we first perform parametric and nonparametric tests to ascertain the predictive power of firms' carbon emissions intensity on the cross-section of corporate bond returns. We start with univariate portfolio-level analyses presenting the average returns, alphas, and average bond and firm characteristics of CEI-sorted portfolios. Second, we present the bond-level Fama-MacBeth cross-sectional regression results controlling for bond characteristics, systematic risk exposures, and climate change news betas. Finally, we perform a battery of robustness checks.

[25] We also consider alternative bond market proxies, such as the Barclays Aggregate Bond index, and the value-weighted average returns of all corporate bonds in our sample. The results from these alternative bond market proxies are similar to those reported in our tables.

4.1 Univariate portfolio analysis

We form quintile portfolios comprising corporate bonds based on the firm-level CEI in June of each year t for firms with a fiscal year ending in year $t-1$. The portfolio returns are calculated for July of year t to June of year $t+1$ and then are rebalanced. The portfolios are value weighted using the amounts outstanding as weights. Since carbon emissions levels intrinsically vary across industries, we form portfolios within each of the 12 Fama-French industries to control for the industry effect and to calculate the average portfolio returns across industries.

Table 2 presents the value-weighted univariate portfolio results. Quintile 1 contains bonds with the lowest CEI, and quintile 5 consists of bonds with the highest CEI. Table 2 shows, for each quintile, the average CEI across the bonds, the next month's value-weighted average excess return, and the one-month-ahead risk-adjusted returns (alphas) produced from the three different factor models. The last row displays the differences in the average returns and the alphas between quintile 5 and quintile 1. The average excess returns and alphas are defined in terms of monthly percentages. Newey-West (1987) adjusted t-statistics are reported in parentheses.

The first column in Table 2 shows significant cross-sectional variation in the average values of carbon emissions intensity when moving from quintile 1 to quintile 5. An increase in the average CEI from 36.75 (the lowest CEI) to $1,227.34$ (the highest CEI) produces a significant dispersion of 1,091. Another notable point in Table 2 is that, the next-month's average excess return decreases from 0.37% to 0.23% per month, a decrease indicating an economically and statistically significant monthly average return difference of -0.14% between quintiles 5 and 1 with a t-statistic of -2.62. This result shows that corporate bonds in the lowest-CEI quintile generate 1.7% per annum higher returns than do bonds in the highest-CEI quintile.

In addition to the average excess returns, Table 2 presents the intercepts (alphas) from the regression of the quintile excess portfolio returns on well-known stock and bond market factors: the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the liquidity risk factor (LIQ), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003). The third column of Table 2 shows that, similar to the average excess returns, the five-factor alpha on the CEI-sorted portfolios also decreases from 0.26% to 0.13% per month as we move from the low-CEI quintile to the high-CEI quintile, indicating a significant alpha difference of -0.13% per month (t-stat.$=$ -3.13). Beyond the well-known stock market factors, we test whether the significant return difference between the low- and high-CEI bonds can be explained by the prominent bond market factors proposed by Bai, Bali, and Wen (2019). The fourth column in Table 2 shows that the four-factor alpha from the bond market factors decreases monotonically from 0.11% to -0.05% per month when moving from the low-CEI to the high-CEI quintile. The corresponding four-factor alpha difference between quintiles 5 and 1 is negative and highly significant at -0.16% per month with a t-statistic of -2.98. The fifth column in Table 2 presents the nine-factor alpha for each quintile from the combined five stock and four bond market factors. Consistent with our earlier results, the nine-factor alpha decreases monotonically from 0.11% to -0.04% per month when moving from the low-CEI quintile to the high-CEI quintile. This decrease gives way to a significant alpha difference of -0.15% per month (t-stat. $= -3.47$).

Next, we investigate the source of the risk-adjusted return difference between low- and high-CEI portfolios: is it due to outperformance by low-CEI bonds, underperformance by high-CEI bonds, or both? For this investigation, we focus on the economic and statistical significance of the risk-adjusted returns of quintile 1 versus quintile 5. As reported in the fifth column of Table 2, the nine-factor alpha of the bonds in quintile 1 (low-CEI bonds) is positive and economically and statistically significant, whereas the corresponding alpha of bonds in quintile 5 (high-CEI bonds) is statistically insignificant. Hence, we conclude that the significantly negative alpha spread between low- and high-CEI bonds is due to outperformance by low-CEI bonds.

We further examine the average bond characteristics of CEI-sorted portfolios. As shown in panel B of Table 2, bonds with high CEI (quintile 5) produce a higher market beta and have higher downside risk, as proxied for by the 5% VaR. In addition, these bonds have lower liquidity, higher credit risk, and are smaller in size. These results suggest that bonds of carbon-intensive firms are riskier than bonds of firms with low carbon intensity. Yet, as shown in panel A of Table 2, these bonds earn lower future returns. Similar to the findings in panel B, the results in panel C show that firms with high CEI (i.e., quintile 5) yield a higher stock market beta and book-to-market ratio, are smaller in size and less liquid, and are more volatile in terms of stock return volatility and idiosyncratic volatility. When we examine the accounting fundamentals for firms with different levels of CEI, panel D shows that high-CEI firms are less profitable on average (i.e., have lower gross profitability, ROA, ROE, and operating profitability). Despite having lower debt-to-equity and debt-to-assets ratios, firms with high CEI have a significantly lower Tobin's Q and cash-to-assets ratio and, on average, are two years older than firms with low CEI.[26]

4.2 Bond-level Fama-MacBeth regressions

In Section 4.1, we tested the significance of CEI as a cross-sectional determinant of future bond returns at the portfolio level. We now examine the cross-sectional relation between CEI and future returns at the bond level using Fama and MacBeth (1973) regressions.[27] We present the time-series averages of the slope coefficients from the regressions of future excess bond returns on CEI and the control variables, including a number of systematic risk measures and bond characteristics:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \quad (3)$$

where $R_{i,t+1}$ is the excess return on bond i from July of year t to June of year $t+1$. The key independent variable is $ln(CEI_{i,t})$, which is the natural log of firm-level carbon emissions intensity in June of each year t for firms with a fiscal year ending in year $t-1$. The term $Controls_{k,t}$ denotes a set of control variables, including (1) bond-level characteristics, such as the bond market beta ($\beta_{i,t}^{MKT}$), downside risk proxied for by the 5% value-at-risk ($VaR_{i,t}$), bond-level illiquidity ($Illiq$), credit ratings ($Rating$), time-to-maturity ($Maturity$), the bond amount outstanding ($Size$), and the one-month-lagged bond return ($Lag\ return$); (2) systematic risk proxies, such as the default beta ($\beta_{i,t}^{DEF}$), the term beta ($\beta_{i,t}^{TERM}$), and the macroeconomic uncertainty beta ($\beta_{i,t}^{UNC}$) following Bali, Subrahmanyam, and Wen (2021b); and (3) the climate change news beta ($\beta_{i,t}^{Climate}$), which measures the covariance between corporate bond returns

[26]Given that low-CEI firms are more profitable than high-CEI firms on average, we also investigate whether the high returns from low-CEI bonds are driven by the profitability premium documented in Fama and French (2015) and Hou, Xue, and Zhang (2015). Table A.2 of the Online Appendix presents significantly negative alpha spreads between the low- and high-CEI portfolios based on the 5-factor model of Fama and French (2015) and 4-factor (Q) model of Hou, Xue, and Zhang (2015), with a −0.13% per month (t-stat. = −2.68) and −0.16% per month (t-stat. = −2.81), respectively. The last two columns of Table A.2 show that the magnitude and statistical significance of the alpha spreads are very similar when we augment these models with the bond market factors of Bai, Bali, and Wen (2019).

[27]We take the natural log of CEI, because carbon intensity has a highly skewed distribution.

and unexpected changes in climate change news index following Huynh and Xia (2021).[28] To account for systematic differences in carbon emissions across industries, we also control for the Fama-French 12 industry fixed effects in all specifications. This step is consistent with that taken in our univariate portfolio analysis.

Table 3 reports the time-series average of the intercepts, the slope coefficients (λs), and the adjusted R^2 values over the 156 months from July 2006 to June 2019. Newey-West-adjusted t-statistics are reported in parentheses. The univariate regression results reveal a negative and significant relation between CEI and the cross-section of future bond returns. In regression (1), the average slope $\lambda_{1,t}$ from the monthly regressions of excess returns on $ln(CEI)$ alone is -0.046 with a t-statistic of -2.76. The economic magnitude of the associated effect is similar to that shown in Table 2 for the univariate quintile portfolios of CEI. The spread in the average $ln(CEI)$ between quintiles 5 and 1 is approximately 3.42, and multiplying this spread by the average slope of -0.046 yields an estimated monthly return spread of 16 basis points (bps).[29]

Regression specification (2) in Table 3 shows that after we control for market risk (β^{Bond}), downside risk, illiquidity, credit ratings, maturity, size, and the previous month's bond return, the average slope coefficient for $ln(CEI)$ remains negative and highly significant. In other words, controlling for bond characteristics does not affect the predictive power of carbon emissions intensity in the corporate bond market.

Regression (3) tests the cross-sectional predictive power of CEI, while controlling for other systematic risk measures, namely, the default beta, the term beta, and the macroeconomic uncertainty beta. In addition, we control for the climate change news beta in Huynh and Xia (2021), who show that shocks to the climate change news index is priced in corporate bonds. In particular, they show that corporate bonds with a higher climate change news beta earns lower future returns, consistent with the asset pricing implications of excess demand for bonds with the potential to hedge against climate risk. Consistent with Bali, Subrahmanyam,

[28]Following their study, we estimate the exposure of individual bonds to the climate change news index based on monthly rolling regressions using a 36-month fixed window estimation. We require at least 24 months of return observations to construct the climate change news beta ($\beta_{i,t}^{Climate}$). We find that the correlation between $ln(CEI)$ and $\beta^{Climate}$ is quite low at -0.04, indicating a significant difference between a firm's carbon emissions intensity and the climate change news beta which measures the bonds' ability to hedge against climate change news risk.

[29]Note that the ordinary least squares (OLS) methodology used in the Fama-MacBeth regressions equally weights each cross-sectional observation so that the regression results are more aligned with the equal-weighted portfolios. Thus, the CEI obtained from the Fama-MacBeth regressions, 0.16% per month, is somewhat higher than the 0.14% per month obtained from the value-weighted portfolios (see Table 2).

and Wen (2021b), Regression (3) shows a significantly negative relation between the bond macroeconomic uncertainty beta (β^{UNC}) and future bond returns. The average slope on β^{UNC} is economically and statistically significant at -0.134 (t-statistic $= -2.98$). Importantly, the average slope coefficient for $ln(CEI)$ remains negative and highly significant, -0.038 (t-stat. $= -2.56$), indicating that exposures to systematic risk or climate change news index do not explain the predictive power of carbon emissions intensity for future bond returns.

The last specification, Regression (4), controls for all bond return characteristics, systematic risk, and climate change news betas. Similar to our findings in Regression (1), the cross-sectional relation between future bond returns and CEI is negative and highly significant. The negative average slope of -0.036 for $ln(CEI)$ in Regression (5) represents an economically significant effect of 0.12% per month between the top and bottom quintiles, controlling for everything else. These results show that our carbon intensity measure carries distinct, significant information beyond information about bond size, maturity, rating, liquidity, market risk, default risk, and climate change news risk. Thus, carbon emissions intensity is a strong and robust predictor of future bond returns.

4.3 Robustness checks

4.3.1 Different categories of carbon emission

Our results so far use a firm's scope 1 carbon emissions scaled by total revenue as the main measure of carbon emissions intensity. As is shown by Bolton and Kacperczyk (2021), the data on scope 1 and scope 2 emissions are widely reported. Scope 3 emissions, on the other hand, are estimated using an input-output matrix and have only been widely reported by companies as of recently. As a result, in this section, we examine whether our main results hold using a different category of carbon emissions based on scope 2 emissions scaled by total revenue as the main measure of carbon emissions intensity. In addition, we combine scope 1 and scope 2 emissions to generate a broader category measure of carbon emissions intensity, $Total\ Scope$, defined as below:

$$Total\ Scope = \frac{Scope\ 1(tCO2e) + Scope\ 2(tCO2e)}{revenue(\$mil)}. \tag{4}$$

Panel A of Table 4 shows that our main findings remain similar when we use different categories of carbon emissions. The average return and nine-factor alpha spreads between low- and high-CEI bonds are −0.12% (t-stat. = −1.90) and −0.15% (t-stat. = −3.04), respectively, when we use a firm's scope 2 carbon emissions as the main measure of carbon emissions intensity. Moreover, panel A shows economically and statistically significant returns and alpha spreads when we combine both scope 1 and scope 2 carbon emissions ($Total\ Scope$), indicating a significant relation between the broader measure of carbon emissions intensity and future bond returns.

4.3.2 Excluding the most carbon-intensive industries

Carbon emissions intrinsically vary across industries, and we control for industry effects when forming portfolios in Section 4.1 and in the cross-sectional regression analyses in Section 4.2. In this section, we further investigate whether our results remain intact when we exclude the most carbon-intensive industries that could drive the main results. For instance, firms in the energy, chemical, or utility industry are highly likely to be carbon-intensive compared to firms in other industries. To investigate whether the low carbon alpha exists across a broader category of industries, not just the most carbon-intensive industries, we exclude the most carbon-intensive industries one by one and then all together.[30]

Panel B of Table 4 shows that the most carbon-intensive industries do not drive our main results, rather the effect exists among a broader category of industries. Specifically, the nine-factor alpha spreads between low- and high-CEI bonds remain economically and statistically significant and are −0.09% (t-stat. = −2.78), −0.14% (t-stat. = −3.57), and −0.14% (t-stat. = −3.59), respectively, when we exclude the energy, chemical, or utilities industry one by one. Moreover, when we exclude all three carbon-intensive industries, the average return and nine-factor alpha spreads between low- and high-CEI bonds are −0.11% (t-stat. = −2.39) and −0.12% (t-stat. = −3.04), respectively, indicating the presence of a pervasive low carbon alpha

[30]We also perform an additional test to ascertain the predictive power of carbon emissions intensity of corporate bond returns at the industry level in Table A.3 of the Online Appendix. We form quintile portfolios of corporate bonds based on the average industry-level CEI using the Fama-French 30 industry classifications. Consistent with the earlier findings in Table 2, Table A.3 of the Online Appendix shows the average return and nine-factor alpha spreads of corporate bonds between low- and high-CEI industry are −0.15% (t-stat. = −2.62) and −0.12% (t-stat. = −2.38), respectively, indicating the presence of a pervasive low carbon alpha at the industry-level.

in other industries.

4.3.3 Firm-level evidence

Our empirical analyses thus far have been based on bond-level data since we test whether the carbon emissions intensity of a firm predicts the firm's future bond returns. One concern is that firms with large numbers of distinct bond issues can have a material impact on the cross-sectional relations that we are testing. In this section, we use three different approaches to control for the effect of multiple bonds issued by the same firm by (1) forming value-weighted average bond returns across the same firm and (2) picking the largest bond or the most-liquid bond as representative of the firm to replicate our portfolio-level analysis using this firm-level data set. Panel C of Table 4 presents the value-weighted quintile portfolios, which indicate significant differences in the cross-section of firm-level bond returns. Specifically, the value-weighted average return and nine-factor alpha spreads between low-CEI and high-CEI firms are −0.10% (t-stat. = −2.78) and −0.12% (t-statistic = −2.93), respectively. In panel C when the largest or the most-liquid bond is chosen as the representative of the firm, the return effect remains highly significant.

4.3.4 Subperiod analyses

We examine whether our finding is robust across different subperiods. First, we estimate the carbon premium after excluding the period of the financial crisis, which we define as September 2008 to December 2009. Lins, Servaes, and Tamayo (2017) find that high-corporate-social-responsibility (CSR) firms reported significantly better stock and operating performance than do low-CSR firms during the 2008–2009 financial crisis. Carbon emissions is an important component of firms' ESG rating, so the outperformance of low-CEI bonds could be concentrated in the crisis period. Panel D of Table 4 shows that the average return and alpha spreads between the low- and high-CEI portfolios are, respectively, −0.14% per month (t-stat. = −2.21) and −0.12% per month (t-stat. = −3.17), indicating that excluding the crisis period does not affect our results.

Second, we investigate the carbon premium for the two subperiods based on a six-year interval: (a) the first precrisis subperiod from July 2006 to June 2013 and (b) the most recent subperiod from July 2013 to June 2019. Panel D of Table 4 shows the effect is stronger for the first subperiod; the average return and alpha spreads between the low- and high-CEI portfolios are, respectively, −0.18% per month (t-stat. = −2.06) and −0.16% per month (t-stat. = −2.46). The carbon premium has a weaker economic significance for the second subperiod but remains statistically significant; the average return and alpha spreads between the low- and high-CEI portfolios are, respectively, −0.11% per month (t-stat. = −1.96) and −0.10% per month (t-stat. = −2.48).

5 Sources of Low Carbon Alpha

The return predictability results in Section 4 show that bonds from firms with higher CEI *underperform* firms with lower CEI. This result, combined with the evidence that bonds from high-CEI firms are riskier than those from low-CEI firms, indicates that **H1** (the "carbon risk premium" hypothesis) is not supported.[31]

On the other hand, **H2** (the "investor preference" hypothesis) predicts that green firms could outperform brown firms if investors' preferences for ESG unexpectedly strengthens over the sample period. We rely on the corporate bond institutional holdings data to test the asset pricing implications of the investor preference hypothesis in Sections 5.1.1 and 5.1.2.

Finally, carbon intensity can be predictive of firms' expected profitability and fundamental performance, which can affect the expected return of corporate bonds if investors underreact to this predictability of fundamentals (Pedersen, Fitzgibbons, and Pomorski, 2021). To test this "investor underreaction" hypothesis (**H3**), we first conduct subsample analysis conditional on bonds with different information asymmetry, and over subperiods with time-varying public attention to climate change in Section 5.2.1. We then test whether investors are negatively surprised by the poorer future performance of high-CEI firms in Sections 5.2.2 and 5.2.3. Moreover, we explore one specific channel through which high CEI translates into poor fundamental performance, by investigating the relation between CEI and a firm's future environmental incidents in Section 5.2.4. We further investigate the implication of carbon

[31] The prediction in **H1** is that bonds issued by carbon-intensive firms are riskier because such bonds are more likely to lose value when climate policies become more stringent and consumers shift to green firms, affecting the profitability and solvency of brown firms.

emissions intensity for a firm's left tail risk in Section 5.2.5, as a major driver of integrating ESG scores into the investment process is to reduce downside risk exposures (BlackRock, 2015). Finally, we show the return prediction of the investor underreaction hypothesis also hold true for stock market in Section 5.2.6.

5.1 Testing investor preference hypothesis

5.1.1 Carbon emissions intensity and corporate bond institutional ownership

The investor preference hypothesis (**H2**) predicts that corporate bonds for firms with low (high) carbon emissions intensity perform better (worse) than expected if ESG concerns unexpectedly strengthen (Pastor, Stambaugh, and Taylor, 2020). Based on a survey about individuals' climate risk perceptions, Krueger, Sautner, and Starks (2020) show that institutional investors believe climate risks have financial consequences for their portfolio firms and that climate risks, particularly regulatory risks, already have begun to materialize. To test this hypothesis, we rely on Refinitiv eMAXX corporate bond holdings data.

We first examine the cross-sectional relation between CEI and future changes in institutional ownership using Fama-MacBeth regressions. We present the time-series averages of the slope coefficients from the regressions of changes in institutional ownership on CEI and the control variables, including a number of systematic risk measures and bond characteristics:

$$\Delta INST\_Bond_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \tag{5}$$

where the dependent variable is the change in bonds' institutional ownership (ΔINST_Bond), defined as the institutional ownership in June of year $t+1$ minus the institutional ownership in June of year t. The key independent variable is $ln(CEI_{i,t})$, which is the natural log of firm-level carbon emissions intensity in June of each year t, for firms with a fiscal year ending in year $t-1$. The term $Controls_{k,t}$ denotes a set of control variables, including bond-level characteristics, such as the bond market beta ($\beta_{i,t}^{MKT}$), downside risk, bond-level illiquidity, credit ratings, time-to-maturity, the bond amount outstanding (size), and the past six-month cumulative bond returns ($R_{t-7:t-2}$). We also include additional controls related to systematic and climate risk proxies, such as the default beta ($\beta_{i,t}^{DEF}$), the term beta ($\beta_{i,t}^{TERM}$), the macroeconomic uncertainty beta ($\beta_{i,t}^{UNC}$), and the climate change news beta ($\beta_{i,t}^{Climate}$). To better interpret their economic significance, we standardize all independent variables in the cross section to have a mean of zero and standard deviation of one.

Panel A of Table 5 shows the results of changes in bonds' institutional ownership. Regression (1) of panel A shows a negative and significant relation between CEI and changes in bonds' institutional ownership. The average slope $\lambda_{1,t}$ for $ln(CEI)$ alone is -0.471 with a t-statistic of -3.66, implying a one-standard-deviation increase in $ln(CEI)$ is associated with a 0.471% decrease in bonds' institutional ownership. This economic magnitude is translated into a 26.5% decrease in ΔINST_Bond given the average ΔINST_Bond in our bond sample is 1.77%. Regression specification (2) in panel A shows that after we control for market risk (β^{Bond}), downside risk, illiquidity, credit ratings, maturity, size, and past six-month cumulative bond return, the average slope coefficient for CEI remains negative and highly significant.

Regression (3) in panel A of Table 5 tests the cross-sectional predictive power of CEI, while controlling for exposures to other systematic/climate change news risks. Importantly, the average slope coefficient for $ln(CEI)$ remains negative and highly significant, -0.489 (t-stat. $= -4.51$), indicating that systematic risk or climate change news betas do not explain the predictive power of carbon emissions intensity for changes in institutional ownership. The last specification, Regression (4), controls for all bond return characteristics, systematic risk, and climate change news beta. Similar to our findings in Regression (1), the cross-sectional relation between ΔINST_Bond and CEI is negative and highly significant. The negative average slope of -0.226 on $ln(CEI)$ in Regression (4) represents a 12.6% decrease in ΔINST_Bond relative to the average changes in bond's institutional ownership, controlling for everything else.

5.1.2 Do changes in institutional ownership fully explain the low carbon alpha?

The results in panel A of Table 5 suggest that institutional investors divest from bonds issued by firms with high carbon intensity. However, whether divestment by institutions can generate sufficient impacts on bond returns is unclear. To further investigate how ownership changes affect future bond returns, we examine whether the underperformance associated with high-CEI bonds (i.e., the findings in Table 3) can be fully explained by changes in institutional ownership through the divestment channel. Specifically, we replicate Table 3 in panel B of Table 5, where we include as one additional control the contemporaneous changes in bonds' institutional ownership (ΔINST_Bond),

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \lambda_{2,t} \cdot \Delta INST\_Bond_{i,t+1} + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \quad (6)$$

where $R_{i,t+1}$ is the bond excess return from July of year t to June of year $t+1$. Δ INST_Bond$_{i,t+1}$ denotes contemporaneous changes in bonds' institutional ownership measured over the same time horizon as the dependent variable bond returns. We include the same set of control variables, $Controls_{k,t}$, used in Table 3. If changes in bonds' institutional ownership fully explain the high (low) returns associated with low- (high-)CEI bonds, then we should expect that $ln(CEI)$ loses its predictive power for future bond returns once we control for ΔINST_Bond.

Panel B of Table 5 shows that the coefficients for $ln(CEI)$ remain significantly negative for all specifications. After controlling for contemporaneous changes in institutional ownership, bond characteristics and systematic/climate change news betas, regression (4) shows a coefficient of −0.027 (t-stat. = −2.15) for carbon emissions intensity, indicating that ΔINST_Bond cannot fully explain the outperformance of low-CEI bonds shown in Table 3. The coefficient of −0.027 for $ln(CEI)$ in panel B of Table 5 is smaller than that of Table 3, −0.036 in regression (4), representing a 25% reduction in the return spread once ΔINST_Bond is controlled for. However, the predictive power of carbon emissions intensity for future bond returns remains economically and statistically significant. In addition, panel B of Table 5 shows that although the coefficients for ΔINST_Bond are positive, none of them is significant, and the adjusted R-squared's are similar to those in Table 3, indicating that shifts in institutional demand do not have significant pricing impacts on corporate bonds.[32]

[32]We conduct two additional robustness tests on the relation between changes in institutional ownership and future bond returns. First, to control for the persistent effect of ΔINST_Bond, Table A.4 of the Online Appendix replicates the results in Panel B of Table 5 by including additional lagged controls of the changes in bonds' institutional ownership (ΔINST_Bond), including the 1-year and 2-year lagged change of ΔINST_Bond. Second, to address potential non-linearity between ΔINST_Bond and future bond returns, Table A.5 of the Online Appendix replicates the results in Panel B of Table 5 by including dummy variables of the change in bonds' institutional ownership. As shown by both tables, the coefficients for $ln(CEI)$ remain significantly negative for all specifications, indicating that none of the contemporaneous or lagged changes in institutional ownership fully explains the negative relation between carbon emission and future bond returns.

5.2 Testing investor underreaction hypothesis

5.2.1 Subsample analyses

Investor underreaction hypothesis (**H3**) implies that the return predictability should be more pronounced among bonds with higher information asymmetry. To test this hypothesis, Table 6 presents results for the univariate portfolios sorted by CEI for the subsample of bonds based on commonly used information asymmetry proxies, including issuance size, credit rating, time-to-maturity, as well as bond-level illiquidity.[33] These proxies for information asymmetry in the bond market are motivated by a number of studies. For example, Glosten and Milgrom (1985) show that the realized bid-ask spread widens with the asymmetry of information and is related to the extent of informed trading. Moreover, Han and Zhou (2014) argue that information motives are present in the pricing of bonds of various credit quality by pointing to the positive relationship between microstructure-based information asymmetry measures and bond yield spreads. Hendershott, Kozhan, and Raman (2020) show that information-driven trading is present in high-yield bonds but not in the investment-grade universe.

Panel A of Table 6 shows that the return and alpha spreads are economically and statistically significant for both large and small bonds, but this effect is stronger among small bonds with a nine-factor alpha -0.22% (t-stat. $= -3.94$) per month, compared to -0.15% (t-stat. $= -2.00$) for large bonds. Similarly, panels B to D show that the average return and alpha spreads between the low- and high-CEI portfolios are more pronounced for bonds with lower credit rating, longer time-to-maturity, and are more illiquid. For example, the nine-factor alpha spreads between the low- and high-CEI portfolios are -0.23% (t-stat. $= -3.06$) for longer-maturity bonds and -0.13% (t-stat. $= -3.02$) for shorter-maturity bonds. Overall, the subsample results indicate a more pronounced low carbon alpha for bonds with higher information asymmetry, consistent with the idea that underreaction to fundamentals is more likely to occur when information is less available (Hong, Lim, and Stein, 2000).

Another implication of investor underreaction hypothesis is that the return predictability of CEI should be weaker during periods when investor attention to climate risks is high. To test this prediction empirically, we follow Choi, Gao, and Jiang (2020) and use the Abnormal Google

[33]Bond issuance sizes are typical proxies for trade informativeness in the literature, as they are related to broader investor base and, again, more in-depth analyst coverage, which supposedly leads to a higher number of investors who are ready to arbitrage out bond misvaluations (Ivashchenko, 2019).

Search Volume Index (ASVI) on the topics of "climate change" or "global warming" as proxies for investor attention to climate change.[34] Panel A of Table A.6 of the Online Appendix shows that the low carbon alpha is indeed much weaker in periods when investor attention to climate change increases. Specifically, the monthly return difference between the low- and high-CEI quintile are both economically and statistically insignificant at 0.05% (t-stat. = 0.84) and 0.07% (t-stat. = 1.25) per month, respectively, when ASVI on the topics of climate change and global warming increases. In sharp contrast, the low carbon alpha is much larger at 0.26% (t-stat. = 4.30) and 0.23% (t-stat. = 3.81) per month when investor attention to climate change decreases. Second, prior studies show that investors become more aware of climate policy risks after the Paris Agreement adopted in December 2015 (Monasterolo and De Angelis, 2020). We thus conjecture that the low carbon alpha should be weaker in the post-Paris agreement period. In Panel B of Table A.6, we report the low-minus-high CEI portfolio returns over two subperiods: July 2006 to December 2015 (Pre-Paris agreement) and January 2016 to June 2019 (Post-Paris agreement). We find a much attenuated low carbon alpha that is statistically insignificant in the post-Paris agreement period but a monthly return spread of 0.19% per month (t-stat. = 3.65) prior to the agreement. Finally, to further investigate whether there is a regime shift after the Paris agreement, we conduct a structural break test on the low-minus-high return with unknown break date in Panel C of Table A.6. The test identifies March 2016 as the structural break date, which aligns well with the time when Paris agreement was adopted.

5.2.2 Carbon emissions intensity and cash flow surprises

We further examine whether the low carbon alpha in the bond market could be explained by investors underreacting to the predictability of CEI for firm fundamentals (**H3**). If this is the underlying channel, we expect that a firm's carbon emissions intensity negatively predicts its future fundamental performance, and investors are systematically surprised when the fundamental information is disclosed to the market. We use earnings and revenue surprise as measures of firm fundamental news to test this hypothesis.

Our first proxy for cash flow surprises is standardized unexpected earnings (SUE). SUE is defined as the change of quarterly earnings-per-share (EPS) from four quarters ago divided

[34] ASVI is calculated as the natural log of the ratio of SVI to the average SVI over the previous three months. A positive (negative) value of ASVI is associated with an increase (decrease) in investor attention.

by the standard deviation of this change in quarterly earnings over the prior eight quarters. In our setting, we examine the predictability of carbon emissions intensity for future earnings surprises using SUE as the dependent variable and CEI as the primary explanatory variable. Specifically, we use the following regression specification:

$$SUE_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \tag{7}$$

where $SUE_{i,t+1}$ is the standardized unexpected earnings of firm i over the period of July of year t to June of year $t+1$. The key independent variable is $ln(CEI_{i,t})$, the natural log of firm-level carbon emissions intensity in June of each year t, for firms with a fiscal year ending in year $t-1$. $Control_{k,t}$ denotes a set of control variables, including a one-quarter-lagged dependent variable, a four-quarter-lagged dependent variable, firm size, the book-to-market ratio, return-on-equity (ROE), R&D intensity (R&D), investment, operating cash flows (OCF), institutional ownership, and momentum. We also include industry and/or quarter fixed effects in the regression. Standard errors are clustered at the firm level. Columns 1 and 2 of Table 7 report the regression results. The coefficient for $ln(CEI)$ is significantly negative for both specifications. With industry and quarter fixed effects in column 2, the coefficient for $ln(CEI)$ is -0.0128 (t-stat. $= -2.19$), indicating that a one-standard-deviation increase in $ln(CEI)$ leads to a 0.0312 (=0.0128 $\times$ 2.4389) lower SUE, which is economically meaningful compared to the mean SUE of 0.2016.

We use the standardized unexpected revenue growth estimator ($SURGE$) as an alternative measure of firm fundamental news (Jegadeesh and Livnat, 2006). $SURGE$ is defined as the change in revenue per share from its value four quarters ago divided by the standard deviation of this change in quarterly revenue per share over the prior eight quarters. We use the same specification as in Equation 7, except we replace SUE with $SURGE$, and use the same set of control variables. Columns 3 and 4 of Table 7 report the regression results. The coefficients for $ln(CEI)$ are significantly negative, suggesting that more carbon-intensive firms subsequently have lower revenue growth.

To test whether investors underreact to the predictability of CEI for future cash flow surprises, we examine market reactions around earnings announcements. We extract quarterly earnings announcement dates from Compustat and calculate the cumulative abnormal return

CAR(−2, +1) in a four-day window around the earnings announcements, with abnormal returns defined as raw stock returns adjusted by the CRSP value-weighted index return. We use the same specification used in Equation 7, except we replace SUE with CAR(−2, +1), and use the same set of control variables. Columns 5 and 6 of Table 7 report the regression results. The coefficients for $ln(CEI)$ are significantly negative for both specifications. With industry and quarter fixed effects in column 6, the economic magnitude suggests that a one-standard-deviation increase in $ln(CEI)$ leads to a 5-bps lower market reaction around earnings announcements.

Overall, our finding that firms with higher carbon emissions intensity have lower earnings (revenue) surprise and a more negative earnings announement return suggests that investors fail to unravel the information contained in firms' carbon intensity when forming expectations about future earnings. As a result, investors are systematically surprised when fundamental news is subsequently disclosed to the market via earnings announcements. Since bonds represent contigent claims on firms' cash flows and underlying assets, investors underreaction to the predictive power of CEI for firm fundamentals may well explain the underperformance of high-CEI bonds.

5.2.3 Carbon emissions intensity and firms' creditworthiness

In Section 5.2.2, we show that firms with a high- (low-)CEI are associated with subsequent poorer (better) fundamental performance. Poorer firm fundamentals should naturally lead to deteriorated creditworthiness for the firm, and lower creditworthiness should then drive the underperformance of bonds from high-CEI firms. We test this prediction by examining the relation between CEI and subsequent changes in bond credit ratings. Specifically, our dependent variable of interest is the change in bond credit rating ($\Delta Rating$), and our key explanatory variable is firm-level CEI. Our regression specification is

$$\Delta Rating_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \tag{8}$$

where $\Delta Rating_{i,t+1}$ is the credit rating of bond i in June of year $t+1$ minus its credit rating in June of year t. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. A higher numerical score implies higher default risk or lower creditworthiness. The key independent variable is $ln(CEI_{i,t})$, the natural log of firm-level carbon emissions intensity in June of each year t, for firms with a fiscal year ending in year $t-1$. $Control_{k,t}$ denotes control variables, including firm size, the book-to-market ratio, return-on-equity (ROE), R&D intensity (R&D), investment, operating cash flows (OCF), and institutional ownership. We also include bond and year fixed effects, and we cluster standard errors at the firm level. Column 1 of Table 8 shows that the coefficients for $ln(CEI)$ are significantly positive, indicating that high carbon intensity firm experiences deteriorated credit rating on its bonds over the next year.

In addition to bond credit ratings, we construct Ohlson (1980)'s O-score as an alternative proxy of firm creditworthiness. A higher O-score represents a higher probability of financial distress and lower firm creditworthiness. We use the same specification used in Equation 8, except that we replace $\Delta Rating_{i,t+1}$ with the change in firm-level O-score, and use the same set of control variables. Specifically, the dependent variable $\Delta \text{O\_Score}_{i,t+1}$ is the O-score of firm i in June of year $t+1$ minus its most recent quarter O-score before June of year t. Column 2 of Table 8 reports the results. Consistent with the results on credit rating changes, we find that firms with high carbon intensity experience an increase in the probability of financial distress in the future. Overall, these results lend support to the conjecture that the source of the low carbon alpha arises from the predictability of CEI for a change in firm creditworthiness.[35]

5.2.4 Carbon emissions intensity and environmental incidents

Our results so far suggest that firms with higher carbon emissions intensity have more negative cash flow news and deteriorating creditworthiness in the future. In this section, we explore one specific channel through which higher CEI translates into lower future firm fundamentals. Our conjecture is that a firm's environmental risk is persistent and carbon-intensive firms are more likely to face negative environment incidents in the future than carbon efficient firms. If investors are not aware of or fully react to these firms' persistently high environmental risks, carbon-intensive firms could experience negative cash flow shocks and lower realized

[35] In addition to changes in a firm's creditworthiness, we also investigate the relation between CEI and subsequent changes in bond yield-to-maturity (YTM). Table A.7 of the Online Appendix shows that firms with low (high) carbon emissions intensity experience a reduction (increase) in yield-to-maturity in the future, consistent with the conjecture that bonds for high-CEI firms are perceived to be more risky because of the deteriorating firm fundamentals, lower creditworthiness, and higher probability of financial distress.

bond returns.

To analyze the persistency in a firm's environment risks, we obtain the data on ESG incidents from RepRisk, a Zurich-based provider of ESG data. RepRisk uses a rigorous process to identify and rate *negative* ESG incidents, using information from over 80,000 sources on firm incidents that are related to one of the 28 predefined ESG incidents.[36] The incident is quantified by the RepRisk Index, a proprietary algorithm, which measures the ESG-related risk exposure of a firm. The RepRisk index ranges from 0 to 100, with a higher number indicating a higher ESG risk exposure. The RepRisk index of a firm increases whenever the firm is associated with an ESG incident, and the relative increase depends on the severity, the reach, and the novelty of the incident and on the intensity of the news about the incident. One important advantage of the RepRisk index is that it is constructed using realized ESG incidents that are identified by systematically searching through the news, and hence is less subjective and less prone to manipulation by firms (Gloßner, 2018).

We test our prediction by examining whether carbon-intensive firms have more environmental incidents than peer firms. As every positive change in the RepRisk index indicates an ESG incident, we measure the overall amount of ESG incidents in a year using the annual sum of the positive changes in the RepRisk Index. To ensure that we capture a firm's environmental incidents rather than the "Social" and "Governance" aspects of the RepRisk Index, we require the percentage of environmental issues used to compute the RepRisk Index is greater than 50%.[37] Our regression specification is

$$Ln(1 + Incidents_{i,t+1}) = \lambda_{0,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \tag{9}$$

where $Incidents_{i,t+1}$ is the sum of all positive changes in the RepRisk Index of firm i from July of year t to June of year $t+1$. We take the natural log of the variable $Incidents_{i,t+1}$ because it

[36] These sources include print and online media (including local, national, and international media), NGOs, government agencies, think tanks, social media, along with many others. To screen these sources, RepRisk uses a variety of artificial intelligence tools, such as advanced search algorithms, semantic web-tools, or web-crawls. Second, every identified incident is checked by a 1st-level RepRisk analyst who ensures that the incident is ESG-related, meets a severity threshold, and is not a duplicate of an older incident. Third, the incident is analyzed by a 2nd-level RepRisk analyst who considers the severity of the incident, the reach of the information source, and the novelty of the incident. Fourth, every incident undergoes a quality review by a RepRisk senior analyst who ensures that the second and third steps are processed according to RepRisk's rules.

[37] Our results are similar if we use alternative threshold of 60% and 80% as cutoff.

is highly skewed to the right. Note that the variable $Ln(1 + Incidents_{i,t+1})$ has a value of zero when firm i has no ESG incidents over a period. The key independent variable is $ln(CEI_{i,t})$, the natural log of firm-level carbon emissions intensity in June of each year t, for firms with a fiscal year ending in year $t-1$. $Control_{k,t}$ denotes the same set of control variables as in Equation 8. We also include industry and/or year fixed effects and cluster standard errors at the firm level.

Table 9 shows the regression results. Column (1) shows that the coefficient on $ln(CEI)$ is 0.16 with a highly significant t-statistic of 15.90, indicating that high-CEI firms experience more environmental incidents in the next year than low-CEI firms do. Multiplying the coefficient on $ln(CEI)$ with the spread in the average $ln(CEI)$ between quintiles 5 and 1 in Table 2 yields an estimated difference of 0.547 ($=0.16 \times 3.42$). As a result, the economic significance shows that high-CEI firms (quintile 5) experiences 54.7% more environmental incidents than low-CEI firms (quintile 1) over the following year. In column 2, we control for industry fixed effects and find similar results. Overall, the results support our conjecture that carbon-intensive firms have persistently high environment risk exposures, which are subsequently manifested in more environmental incidents, poorer fundamentals, and deteriorating creditworthiness.[38]

5.2.5 Carbon emissions intensity and downside risk

Finally, we investigate the implication of carbon emissions intensity for a firm's left tail risk, as bond values are particularly sensitive to downside risk (Hong and Sraer, 2013). This test is partly motivated by practitioners' argument that a major driver of integrating ESG scores into the investment process is to reduce downside risk exposures, as negative ESG exposures could imply substantial legal, reputational, operational, and financial risks (BlackRock, 2015). Following the literature (Chen, Hong, and Stein, 2001; Kim, Li, and Zhang, 2011), we use stock price crash risk proxies to measure the downside risk of a firm. To calculate firm-specific

[38]The results in Sections 5.2.2 and 5.2.3 show that firms with high carbon emissions intensity have poorer future fundamentals as well as deteriorating credit ratings. We further examine whether the CEI/return relation is most pronounced among firms with high leverage, compared to those with low leverage, given that firms with higher leverage ratio more likely fall into financial distress when facing negative environmental incidents. Consistent with this prediction, Table A.8 of the Online Appendix shows significantly negative return and alpha spreads between the low- and high-CEI portfolios for high-levered firms, in the range of -0.38% per month (t-stat. $= -2.16$) and -0.60% per month (t-stat. $= -3.24$). In contrast, the low carbon alpha is insignificant among firms with below-the-median leverage.

crash risk measures, we first estimate firm-specific weekly returns for each firm and year.[39] Specifically, the firm-specific weekly return, denoted by W, is defined as the natural log of one plus the residual return from the expanded market model regression,

$$r_{i,t} = \beta_{0,t} + \beta_{1,t} r_{m,t-2} + \beta_{2,t} r_{m,t-1} + \beta_{3,t} r_{m,t} + \beta_{4,t} r_{m,t+1} + \beta_{5,t} r_{m,t+2} + \epsilon_{i,t}, \tag{10}$$

where $r_{i,t}$ is the return on stock i in week t and $r_{m,t}$ is the return on the CRSP value-weighted market index in week t. We include the pre- and post-two weeks for the market index return to allow for nonsynchronous trading. The firm-specific return for firm i in week t, $W_{i,t}$, is measured by the natural log of one plus the residual return from Equation 10, $W_{i,t} = ln(1 + \epsilon_{i,t})$.

Following Chen, Hong, and Stein (2001), our first measure of crash risk is the negative conditional return skewness (NCSKEW). NCSKEW for a firm-year is calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power, as shown in Equation 11,

$$NCSKEW_{i,t} = \frac{n\,(n-1)^3 \sum W_{i,t}^3}{(n-1)\,(n-2)\left(\sum W_{i,t}^2\right)^{3/2}} \tag{11}$$

Our second measure of crash risk is the "down-to-up volatility" (DUVOL), which captures asymmetric volatilities between negative and positive firm-specific weekly returns. DUVOL for a firm-year is calculated by first separating all weeks with returns below the sample mean ("down" weeks), from those with returns above the sample mean ("up" weeks), and then taking the standard deviation for each of these subsamples separately. We then take the natural log of the ratio of the standard deviation on the down weeks to the standard deviation on the up weeks, as shown in Equation 12,

$$DUVOL_{i,t} = log\left\{\frac{(n_u-1)\sum_{Down} W_{i,t}^2}{(n_d-1)\sum_{Up} W_{i,t}^2}\right\} \tag{12}$$

[39] The crash risk measures are constructed using weekly stock return data from July 2006 to June 2019. Specifically, we first calculate the weekly return by compounding daily returns from Monday to Friday, and then assign weekly returns to the 12-month period over July of year t to June of year $t+1$ for each firm-year. We require at least 26 weeks of data available in a firm-year.

In our setting, we examine the predictability of carbon emissions intensity for the future stock price crash risk using the specification below,

$$NCSKEW(DUVOL)_{i,t+1} = \lambda_{o,t} + \lambda_{1,t} \cdot ln(CEI_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1}, \quad (13)$$

where $NCSKEW_{i,t+1}$ is the negative conditional return skewness of firm i over the period from July of year t to June of year $t+1$. $DUVOL_{i,t+1}$ is the "down-to-up volatility" of firm i over the period from July of year t to June of year $t+1$. The key independent variable is $ln(CEI_{i,t})$, the natural log of firm-level carbon emissions intensity in June of each year t, for firms with a fiscal year ending in year $t-1$. $Control_{k,t}$ denotes control variables, including the one-year-lagged dependent variable, DTURN, SIGMA, RET, firm size, the book-to-market ratio, return-on-assets, and leverage, specified in the Appendix. We also include industry and year fixed effects in the regression and cluster standard errors at the firm level. Table 10 reports the regression results and shows that the coefficients of $ln(CEI_{i,t})$ are significantly positive, 0.0170 (t-stat. = 2.25) and 0.0096 (t-stat. = 2.08), respectively, for NCSKEW and DUVOL, indicating that firms with high carbon emissions intensity experience elevated future stock price crash risk. Our result is consistent with Kim et al. (2014) who document that socially responsible firms experience lower future stock price crash risk.

5.2.6 Stock-level evidence

As both bonds and equities are claims to the same firm's underlying assets and cash flows, the investor underreaction hypothesis would naturally predict a low carbon alpha in the stock market as well. We thus conduct portfolio analysis for stocks in Table A.9 of the Online Appendix. As our corporate bond sample is only a subset of the stock sample, we separately examine the return predictability of CEI among all stocks and stocks with bonds.

Panel A reports the excess returns and alphas for quintile portfolios sorted on firm-level CEI over the period from July 2006 to June 2019. The asset pricing models we use include FFCPS model,[40] Fama and French (2015) 5-factor model, and the Hou, Xue, and Zhang (2015) Q-

[40] The Fama and French (1993) plus the Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor.

factor models. Consistent with our bond-level results, we find the low-CEI stocks significantly outperform high-CEI stocks, with a monthly alpha for the long-short portfolio ranging from 0.25% to 0.53%. The outperformance of low-CEI stocks is especially pronounced among stocks with corporate bonds, which is consistent with our evidence of a stronger low carbon alpha for high-leverage firms. In Panel B, we conduct portfolio analysis over the subperiod of January 2010 to June 2019. Consistent with In, Park, and Monk (2019), we find the low carbon alpha is larger and more significant over this period compared with the full sample results. Overall, we find consistent evidence across stocks and bonds that investors underreact to the predictability of carbon intensity for firm fundamentals.[41]

6 Conclusion

Despite the immense literature on the effects of climate risk on the expected returns of equities, far fewer studies are devoted to understanding the role of climate risk in the expected returns of corporate bonds. Our paper is one of the first in the literature to explore whether a firm's carbon risk, as measured by its carbon emissions intensity, is priced in the cross-section of corporate bond returns. Contrary to the "carbon risk premium" hypothesis, we find that bonds issued by firms with higher carbon intensity earn significantly lower future returns. The effect cannot be explained by a comprehensive list of bond and firm characteristics or by exposure to known stock or bond risk factors.

Examining the sources of "low carbon alpha", we find the underperformance of bonds issued by carbon-intensive firms cannot be fully explained by divestment from institutional investors. Instead, our evidence is most consistent with investors underreacting to carbon risk in the corporate bond market, as carbon intensity is predictive of lower future cash flow surprises,

[41] Our stock-level results in Table A.9 differ from Bolton and Kacperczyk (2021) who document that firms with higher carbon emission levels earn higher stock returns, but are consistent with the findings in In, Park, and Monk, 2019 and Cheema-Fox et al. (2019). The differences in the findings between Bolton and Kacperczyk (2021) and ours are two-fold. First, the asset pricing implications are different. Bolton and Kacperczyk (2021) examine the *contemporaneous* relation between raw carbon emissions and stock returns, while we investigate the predictive power of carbon intensity for *future* expected stock returns. Second, the main measures are different. While they use the level of carbon emissions as the main measure, we focus on the carbon emission intensity (CEI), a more commonly used measure based on industry standards (e.g., MSCI Low Carbon Indexes) and a better metric to capture firms' exposure to climate policy risk (see Ilhan, Sautner, and Vilkov, 2021; In, Park, and Monk, 2019). We are able to replicate the main findings in Bolton and Kacperczyk (2021) when exactly following their approach using similar measures and methodology.

deteriorating firm creditworthiness, more environment incidents, and elevated crash risk. Given the growing bond issuance by corporations and increasing flows to bond funds by households, the inefficient pricing of carbon risk in the corporate bond market has important consequences for climate mitigation policies and financial stability.

Appendix: Variable Definitions

Variables	Description
Carbon Emission Variables	
Carbon emissions intensity (scope 1)	Scope 1 emissions divided by the firm's revenue (unit: tCO2e/$million). Scope 1 emissions are greenhouse gas emissions generated from burning fossil fuels and production processes which are owned or controlled by the company (unit: tCO2e).
Carbon emissions intensity (scope 2)	Scope 2 emissions divided by the firm's revenue (unit: tCO2e/$million). Scope 2 emissions are greenhouse gas emissions from consumption of purchased electricity, heat or steam by the company (unit: tCO2e).
Carbon emissions intensity (scope 3)	Scope 3 emissions dvided by the firm's revenue (unit: tCO2e/$million). Scope 3 emissions are other indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, etc. (unit: tCO2e).
ln(CEI)	The natural logarithm of carbon emissions intensity (scope 1).
Corporate Bond Variables	
β^{Bond}	The bond market beta is estimated for each bond from the time-series regressions of individual bond excess returns on the bond market excess returns (MKT^{Bond}) using a 36-month rolling window. MKT^{Bond} is the aggregate bond market portfolio, proxied by the Merrill Lynch U.S. Aggregate Bond Index.
Downside risk	Downside risk is the 5% Value-at-Risk (VaR) of corporate bond return, defined as the second lowest monthly return observation over the past 36 months. The original VaR measure is multiplied by -1 so that a higher VaR indicates higher downside risk.
Illiq	Bond illiquidity is computed as the autocovariance of the daily bond price changes within each month, multiplied by -1 as defined in Bao, Pan, and Wang (2011).
Rating	Raings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. Numerical ratings of 10 or below (BBB- or better) are considered investment grade, and ratings of 11 or higher (BB + or worse) are labeled high yield.
ΔRating	The bond credit rating in June of year $t+1$ minus the bond credit rating in June of year t.
Maturity	The time to maturity of the bond in years.
Size	The total amount outstanding for the bond (Size, $ billion).
Lag return	The holding period bond return in the previous month $t-1$.
$\text{Return}_{(t-7:t-2)}$	The cumulative holding period bond returns from month $t-7$ to month $t-2$.
β^{DEF}	The default risk beta is estimated for each bond from the time-series regressions of individual bond excess returns on the default factor (DEF) using a 36-month rolling window, after controlling for the bond market excess return (MKT^{Bond}) and the term factor (TERM).
β^{TERM}	The term risk beta is estimated for each bond from the time-series regressions of individual bond excess returns on the term factor (TERM) using a 36-month rolling window, after controlling for the bond market excess return (MKT^{Bond}) and the default factor (DEF).

Variables	Description
β^{UNC}	The macroeconomic uncertainty risk beta is estimated for each bond from the time-series regressions of individual bond excess returns on the macroeconomic uncertainty factor (UNC) using a 36-month rolling window, after controlling for the bond market excess return (MKT^{Bond}).
$\beta^{Climate}$	The climate change news beta is estimated for each bond from the time-series regressions of individual bond excess returns on the climate change news index (Climate) using a 36-month rolling window, after controlling for the bond market excess return (MKT^{Bond}).
ΔINST_Bond	The bond institutional ownership in June of year $t+1$ minus the bond institutional ownership in June of year t. The bond institutional ownership is the fraction of the outstanding amount held by institutions in percentage.
Firm Variables	
β^{Stock}	The bond market beta is estimated for each stock from the time-series regressions of individual stock excess returns on the CRSP value-weighted market index excess returns using a 36-month rolling window.
Firm size	The natural logarithm of market capitalization at the end of June.
BM	The book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity at the end of December of year $t-1$. The book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit if available, minus the book value of preferred stock.
MOM	The cumulative holding period stock returns from month $t-12$ to $t-2$ preceding the quarterly earnings announcement month.
Amihud	Amihud Illiquidity measure, calculated as the absolute price change scaled by the volume.
VOL	The stock return volatility based on the past 60 monthly returns.
IVOL	The idiosyncratic volatility based on the Fama-French 3 factor model using the past 60 monthly returns.
INST_Stock	The number of shares held by institutions from 13F filings divided by the total number of outstanding shares at the end of December.
Gross profit/Assets	Gorss profit divided by total assets.
ROA	Operating income before depreciation as a fraction of average total assets based on most recent two periods.
ROE	Income before extraordinary items divided by average book value of equity.
Operating profit/Assets	Operating profit divided by total assets.
Debt/Equity ratio	Total debt divided by the book value of equity.
Tobin's Q	The ratio of the market value of assets (market cap of equity plus book value of debt) divided by the book value of assets.
Cash/Assets	Cash holdings divided by total assets.
Age	The number of years since the IPO year.
SUE	The change in split-adjusted quarterly earnings per share from its value four quarters ago divided by the standard deviation of this change over the prior eight quarters (four quarters minimum).
SURGE	The change in revenue per share from its value four quarters ago divided by the standard deviation of this change over the prior eight quarters (four quarters minimum).

Variables	Description
CAR(−2,+1)	Four-day cumulative abnormal return from two days before to one day after the earning announcement day (day 0), where daily abnormal return is the difference between daily stock return and the CRSP value-weighted market index return.
R&D	R&D expenditures divided by sales.
Investment	The annual growth in total assets.
OCF	The operating cash flows divided by lagged total assets.
ΔO_Score	The one-year ahead change of O-Score relative to the most recent quarter before June of year t.
Incidents	The sum of all positive changes in the RepRisk Index for a firm from June of year t to June of year $t+1$. A higher index number indicates a higher ESG risk exposure and each positive change represents an ESG incident. To ensure we capture a firm's environmental incidents rather than the S and G aspects of the RepRisk Index, we require the percentage of environmental issues used to compute the RepRisk Index is greater than 50%.
NCSKEW	The negative of the third moment of firm-specific weekly returns for each firm sample year and divided by the standard deviation of firm-specific weekly returns raised to the third power.
DTURN	The average monthly share turnover form July of year $t-1$ to June of year t minus the average monthly share turnover from July of year $t2$ to June of year $t1$, where the monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.
SIGMA	The standard deviation of firm-specific weekly returns from July of year $t1$ to June of year t.
RET	The average firm-specific weekly returns from July of year $t1$ to June of year t.

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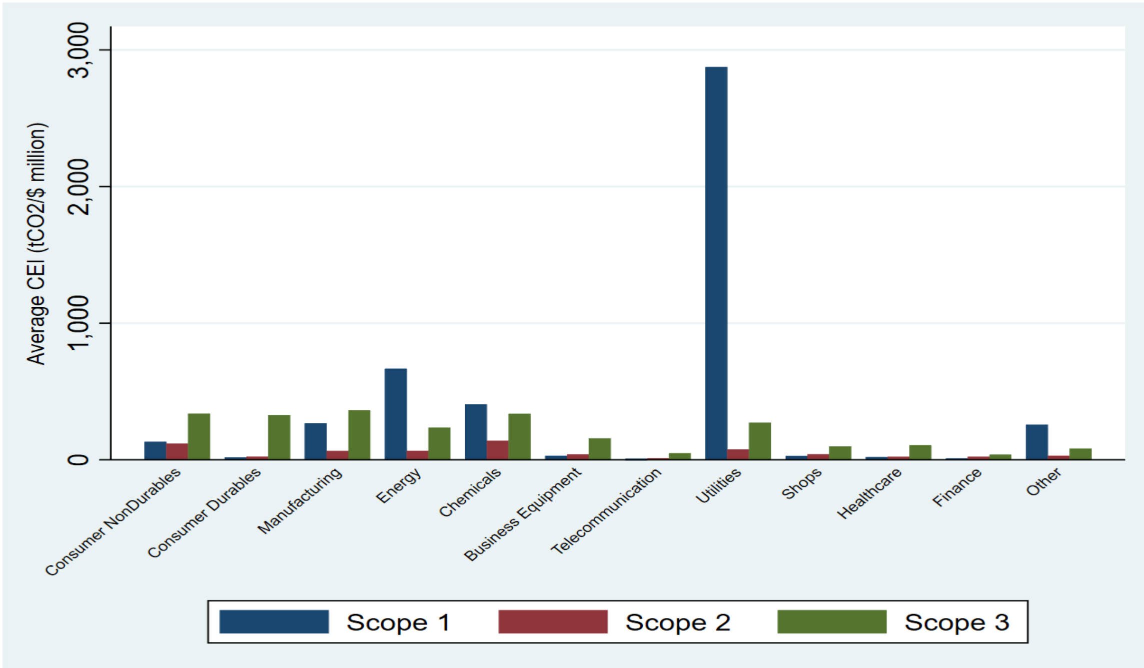
Figure 1. Carbon Emissions Intensity

Panel A: Average carbon emissions intensity by Fama-French 12 industries

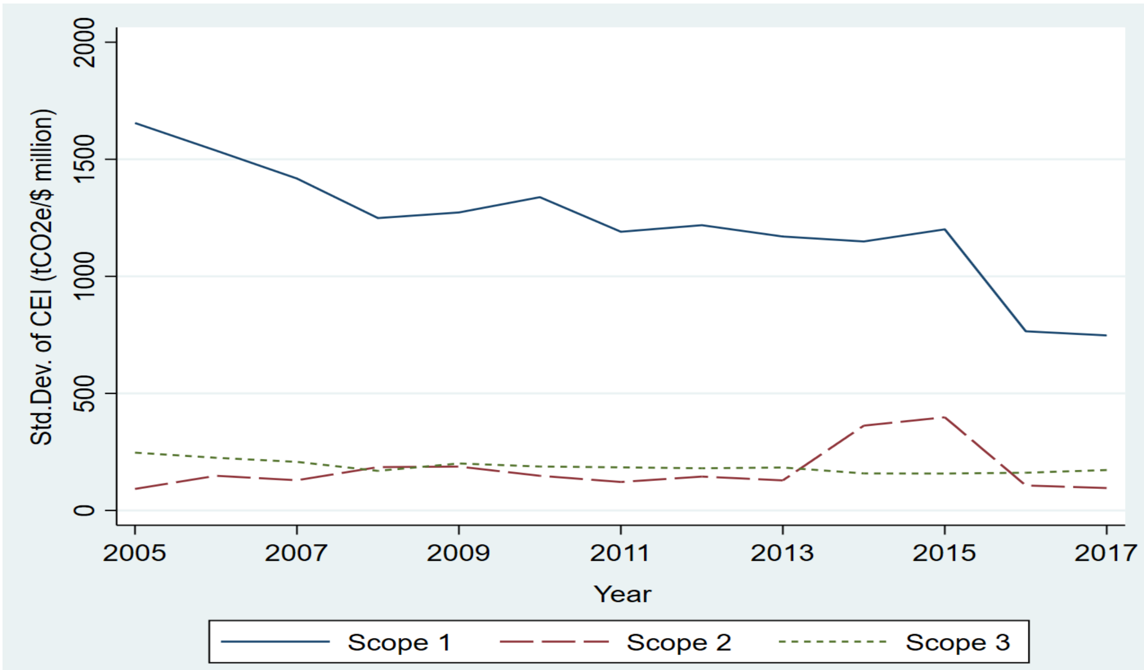


Panel B: Average carbon emissions intensity over time

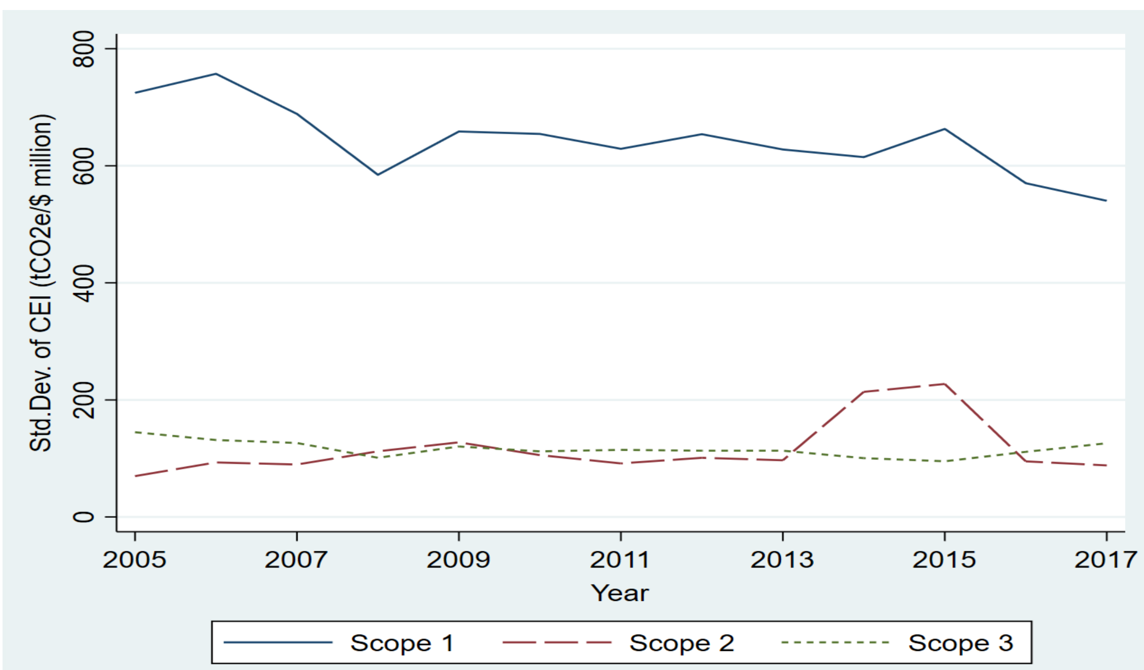
The top panel of the figure depicts the average carbon emissions intensity (CEI) by Fama-French 12 industries based on the Trucost dataset. The bottom panel depicts the average CEI over time. The sample period is from 2005 to 2017.

Figure 2. Cross and Within-Industry Variation in Carbon Emissions Intensity

Panel A: Cross-industry standard deviation in carbon emissions intensity



Panel B: Average within-industry standard deviation in carbon emissions intensity



The figure depicts the cross-industry (within-industry) standard deviations in carbon emissions intensity over time based on the Trucost dataset. The sample period is from 2005 to 2017.

Table 1 Summary Statistics

Panel A reports the number of bond-month observations, the cross-sectional mean, median, standard deviation and percentiles for corporate bond monthly returns and bond characteristics including credit rating, time-to-maturity (Maturity, year), amount outstanding (Size, $ billion), bond market beta (β^{Bond}), downside risk (5% Value-at-Risk, VaR), and illiquidity (Illiq). Carbon emissions intensity (CEI) is defined as the firm-level scope 1 greenhouse gas emissions in CO_2 equivalents generated from burning fossil fuels and production processes which are owned or controlled by the company, divided by the total revenue of the firm in millions of dollars. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. Numerical ratings of 10 or below (BBB- or better) are considered investment grade. β^{Bond} is the individual bond exposure to the aggregate bond market portfolio (MKT^{Bond}), proxied by the Merrill Lynch U.S. Aggregate Bond Index. Downside risk is the 5% Value-at-Risk (VaR) of corporate bond return, defined as the second lowest monthly return observation over the past 36 months. The original VaR measure is multiplied by -1 so that a higher VaR indicates higher downside risk. Bond illiquidity is computed as the autocovariance of the daily price changes within each month, multiplied by -1. Panel B reports the time-series average of the cross-sectional correlations. The sample period is from July 2006 to June 2019.

Panel A: Cross-sectional statistics over the sample period of July 2006 – June 2019

					Percentiles					
	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Bond return (%)	1,127,558	0.69	0.48	3.93	-8.41	-4.05	-0.72	1.85	6.15	11.95
Carbon emissions intensity (CEI)	736,904	444.91	10.89	1205.74	0.31	0.42	1.17	89.16	3813.54	5320.97
Credit rating (Rating)	1,113,082	8.46	7.82	3.79	1.77	2.84	5.77	10.43	15.90	18.58
Time-to-maturity (Maturity, year)	1,181,362	9.74	6.43	9.36	1.11	1.51	3.55	12.79	27.46	32.34
Amount out (Size, $billion)	1,181,362	0.48	0.34	0.56	0.00	0.01	0.12	0.62	1.58	2.76
Bond market beta (β^{Bond})	667,060	1.06	0.86	0.90	-0.39	0.10	0.50	1.40	2.77	4.05
Downside risk (5% VaR)	660,335	6.28	4.91	5.04	0.84	1.42	3.01	7.98	15.72	24.89
Illiq	769,028	1.36	0.28	3.82	-0.78	-0.16	0.05	1.15	6.59	15.59

Panel B: Average cross-sectional correlations

	CEI	Rating	Maturity	Size	β^{Bond}	VaR	Illiq
CEI	1	0.009	0.091	-0.078	-0.001	-0.026	0.009
Rating		1	-0.135	-0.055	0.112	0.436	0.096
Maturity			1	-0.009	0.365	0.219	0.094
Size				1	0.063	-0.108	-0.144
β^{Bond}					1	0.414	0.092
VaR						1	0.251
Illiq							1

Table 2 Univariate Portfolios of Corporate Bonds Sorted by the Firm-Level Carbon Emissions Intensity (CEI)

In Panel A, we form quintile portfolios of corporate bonds based on the firm-level carbon emissions intensity (CEI) in June of each year t for firms with fiscal year ending in year $t-1$. The portfolio returns are calculated for July of year t to June of year $t+1$ and then rebalanced. CEI is defined as the firm-level greenhouse gas emission in CO2 equivalents divided by the total revenue of the firm in millions of dollars. Panel A reports results for the scope 1 carbon emission, defined as greenhouse gas emissions generated from burning fossil fuels and production processes which are owned or controlled by the company. The portfolios are value-weighted using amounts outstanding as weights. Since carbon emission levels intrinsically vary across industries, we form portfolios within each of the 12 Fama-French industries to control for the industry effect and the calculate the average portfolio returns across industries. Quintile 1 is the portfolio with the lowest CEI and Quintile 5 is the portfolio with the highest CEI. The table reports the average CEI, the next-month average excess return, the 5-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 9-factor alpha for each quintile. The last row shows the differences monthly average returns and the differences in alphas with respect to the factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the stock momentum factor (MOM), and the liquidity risk factor (LIQ). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). The 9-factor model combines 5 stock market factors and 4 bond market factors. The average returns and alphas are defined in monthly percentage terms. Panel B reports the average bond portfolio characteristics including the bond market beta (β^{Bond}), downside risk (5% Value-at-Risk, VaR), illiquidity (Illiq), credit rating (Rating), time-to-maturity (Maturity, years), and amount outstanding (Size, in $billion) for each quintile. Panel C reports the average firm-level characteristics including stock market beta (β^{Stock}), Firm size (natural log of market equity), BM (book-to-market), MOM ($\text{Return}_{t-12:t-2}$), Amihud measure of illiquidity, VOL (stock return volatility based on the past 60 monthly returns), IVOL (idiosyncratic volatility based on the Fama-French 3 factor model using the past 60 monthly returns), and institutional ownership (INST_Stock, %). Panel D reports the average firm-level fundamental characteristics including Gross profit/Assets, ROA (return-on-assets), ROE (return-on-equity), Operating profit/Assets, Debt/Equity ratio, Debt/Assets ratio, Tobin's Q, Cash/Assets ratio, and firm age. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

Panel A: Quintile portfolios of corporate bonds sorted by firm-level CEI

Quintiles	Average CEI	Average return	5-factor stock alpha	4-factor bond alpha	9-factor alpha
Low	36.75	0.37	0.26	0.11	0.11
		(3.66)	(2.42)	(2.38)	(2.62)
2	153.18	0.35	0.24	0.03	0.04
		(3.42)	(2.31)	(0.77)	(1.00)
3	333.77	0.33	0.22	0.05	0.06
		(3.42)	(2.29)	(1.08)	(1.55)
4	518.59	0.31	0.21	0.03	0.03
		(3.28)	(2.14)	(0.65)	(0.68)
High	1127.34	0.23	0.13	-0.05	-0.04
		(2.51)	(1.30)	(-0.69)	(-0.84)
High − Low		-0.14***	-0.13***	-0.16***	-0.15***
		(-2.62)	(-3.13)	(-2.98)	(-3.47)

Table 2 (Continued)

Panel B: Average bond portfolio characteristics

	β^{Bond}	Downside Risk (5% VaR)	Illiq	Rating	Maturity	Size
Low	0.98	4.77	0.90	7.61	9.25	0.65
2	1.06	5.03	0.89	8.27	8.99	0.60
3	1.01	4.48	0.91	8.02	8.66	0.58
4	0.86	4.38	0.91	7.69	9.24	0.59
High	1.14	5.20	1.17	9.01	8.64	0.51
High − Low	0.15**	0.42***	0.27***	1.41***	-0.61***	-0.13***
	(2.14)	(3.56)	(4.14)	(13.15)	(-8.67)	(-10.24)

Panel C: Average firm characteristics

	β^{Stock}	Firm size	BM	MOM	Amihud	VOL (%)	IVOL (%)	INST_Stock (%)
Low	1.11	23.95	0.54	0.10	0.16	8.22	6.35	70.42%
2	1.10	23.77	0.57	0.11	0.16	8.58	6.76	70.72%
3	1.09	23.94	0.53	0.11	0.15	8.09	6.19	70.54%
4	1.09	23.99	0.58	0.11	0.16	8.18	6.28	70.47%
High	1.19	23.38	0.62	0.11	0.21	9.09	7.07	74.78%
High − Low	0.09***	-0.56***	0.08***	0.01	0.05***	0.88***	0.72***	4.36***
	(3.29)	(-9.34)	(4.93)	(0.60)	(3.48)	(5.95)	(5.83)	(7.55)

Panel D: Average firm characteristics (accounting fundamentals)

	Gross profit/Assets	ROA	ROE	Operating profit/Assets	Debt/Equity ratio	Debt/Assets	Tobin's Q	Cash/Assets	Age (yr)
Low	0.30	0.14	0.18	0.13	3.04	0.68	1.90	0.14	37.68
2	0.25	0.13	0.14	0.11	3.09	0.69	1.62	0.12	40.31
3	0.26	0.13	0.16	0.12	3.40	0.71	1.67	0.09	45.16
4	0.23	0.13	0.15	0.12	3.16	0.67	1.64	0.09	45.06
High	0.22	0.13	0.12	0.11	2.39	0.66	1.64	0.09	39.48
High − Low	-0.07***	-0.02***	-0.06***	-0.02***	-0.65***	-0.02***	-0.26***	-0.05***	1.80***
	(-16.70)	(-3.84)	(-7.76)	(-4.66)	(-4.06)	(-3.45)	(-8.65)	(-8.99)	(3.66)

Table 3 Fama-MacBeth Cross-Sectional Regressions

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of future corporate bond excess returns on the logarithm of carbon emissions intensity (CEI), with and without controls. The dependent variable is the corporate bond excess return from July of year t to June of year $t+1$ and key independent variable independent variable ln(CEI) is based on the firm-level carbon emissions intensity in June of each year t for firms with fiscal year ending in year $t-1$. Control variables include bond market beta (β^{Bond}), bond characteristics (ratings, maturity, size), downside risk, bond-level illiquidity, and one-month lagged returns. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. A higher numerical score implies higher credit risk. Time-to-maturity is defined in terms of years and Size is defined in terms of $billion. Illiq is the bond-level illiquidity computed as the autocovariance of the daily price changes within each month. We also control for systematic risk betas such as the default beta (β^{DEF}), term beta (β^{TERM}), macroeconomic uncertainty beta (β^{UNC}), and climate change news beta ($\beta^{Climate}$). Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last row reports the average adjusted R^2 values and we control for the Fama-French 12 industry fixed effects in all specifications. Numbers in bold denote statistical significance at the 5% level or below.

	(1) Univariate	(2) Controlling for bond characteristics	(3) Controlling for systematic and climate change news betas	(4) Controlling for all variables
ln(CEI)	**-0.046**	**-0.042**	**-0.038**	**-0.036**
	(-2.76)	(-2.59)	(-2.51)	(-2.30)
β^{Bond}		**0.225**		**0.244**
		(3.17)		(3.77)
Downside risk (5% VaR)		**0.105**		**0.091**
		(3.18)		(3.54)
Illiq		0.002		0.003
		(0.20)		(0.34)
Rating		0.004		0.011
		(0.27)		(0.99)
Maturity		**0.011**		**0.008**
		(2.50)		(2.07)
Size		0.006		0.007
		(0.22)		(0.27)
Lag return		**-0.117**		**-0.129**
		(-5.00)		(-5.57)
β^{DEF}			-0.259	-0.064
			(-1.80)	(-0.87)
β^{TERM}			**0.407**	0.151
			(2.29)	(1.41)
β^{UNC}			**-0.151**	**-0.159**
			(-2.37)	(-2.63)
$\beta^{Climate}$			-0.873	0.090
			(-0.89)	(0.11)
Intercept	0.251	0.276	0.260	0.208
	(1.86)	(1.94)	(2.13)	(2.09)
Industry Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.045	0.248	0.122	0.270

Table 4 Robustness Checks

This table conducts a battery of robustness checks. Panel A reports results using different categories of a firm's carbon emissions based on the scope 2 emissions scaled by total revenue, as well as scope 1 and scope 2 emissions combined, as the main measure of CEI. Panel B investigates whether the main results remain intact when excluding the most carbon-intensive industries such as the energy, chemicals, and utilities industries. Panel C conducts firm-level analyses and uses three different approaches to control for the effect of multiple bonds issued by the same firm by (1) forming the value-weighted average of the bond returns across the same firm, (2) picking one bond of the largest size, and (3) picking the most liquid bond as representative of the firm and replicate the portfolio-level analysis using this firm-level data set. Panel D conducts subperiod analyses for the two subperiods based on a six-year interval.

Panel A: Quintile portfolios of corporate bonds sorted by firm-level scope 2 carbon emissions and scope 1 and 2 combined

	Scope 2 carbon emissions only			
	Average return	5-factor stock alpha	4-factor bond alpha	9-factor alpha
Low	0.36	0.26	0.09	0.08
	(3.77)	(2.49)	(2.41)	(2.56)
2	0.37	0.26	0.08	0.08
	(3.81)	(2.58)	(2.65)	(3.09)
3	0.34	0.24	0.07	0.07
	(3.68)	(2.59)	(1.75)	(1.94)
4	0.34	0.23	0.00	0.01
	(3.30)	(2.29)	(0.05)	(0.32)
High	0.23	0.08	-0.07	-0.06
	(1.94)	(0.67)	(-0.94)	(-0.97)
High − Low	-0.12*	-0.18***	-0.15***	-0.15***
	(-1.90)	(-2.87)	(-2.93)	(-3.04)

	Scope 1 and 2 carbon emissions combined (Total Scope)			
	Average return	5-factor stock alpha	4-factor bond alpha	9-factor alpha
Low	0.36	0.26	0.09	0.08
	(3.77)	(2.51)	(2.41)	(2.53)
2	0.36	0.26	0.06	0.07
	(3.65)	(2.51)	(1.61)	(2.24)
3	0.31	0.19	0.03	0.04
	(3.09)	(1.88)	(0.71)	(1.06)
4	0.36	0.26	0.07	0.06
	(3.96)	(2.96)	(1.95)	(1.92)
High	0.25	0.11	-0.07	-0.07
	(2.23)	(0.98)	(-1.12)	(-1.23)
High − Low	-0.11**	-0.15***	-0.15***	-0.16***
	(-2.17)	(-3.15)	(-3.08)	(-3.23)

Panel B: Excluding the most carbon-intensive industries

	Excluding energy industry only		Excluding chemicals industry only		Excluding utilities industry only		Excluding all three industries	
	Average return	9-factor alpha	Average return	9-factor alpha	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.37	0.09	0.37	0.08	0.37	0.09	0.36	0.08
	(3.63)	(2.72)	(3.56)	(2.33)	(3.63)	(2.63)	(3.44)	(2.34)
2	0.37	0.09	0.34	0.03	0.34	0.03	0.36	0.08
	(3.86)	(2.89)	(3.27)	(0.73)	(3.36)	(0.88)	(3.65)	(2.49)
3	0.35	0.09	0.32	0.04	0.32	0.05	0.32	0.06
	(3.59)	(2.39)	(3.24)	(1.16)	(3.35)	(1.29)	(3.29)	(1.61)
4	0.31	0.03	0.30	0.03	0.31	0.02	0.29	0.03
	(3.29)	(0.87)	(3.21)	(0.72)	(3.22)	(0.52)	(3.14)	(0.77)
High	0.28	-0.00	0.25	-0.06	0.25	-0.06	0.25	-0.04
	(2.79)	(-0.11)	(2.33)	(-1.21)	(2.32)	(-1.16)	(2.38)	(-0.85)
High − Low	-0.09**	-0.09***	-0.12***	-0.14***	-0.12**	-0.14***	-0.11**	-0.12***
	(-2.17)	(-2.78)	(-2.87)	(-3.57)	(-2.58)	(-3.59)	(-2.39)	(-3.04)

Table 4 (Continued)

Panel C: Firm-level analysis

	Firm-level bond returns		Largest bond		Most liquid bond	
	Average return	9-factor alpha	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.39	0.13	0.38	0.10	0.38	0.11
	(4.03)	(2.89)	(3.80)	(3.02)	(4.05)	(3.00)
2	0.37	0.08	0.33	-0.00	0.33	0.03
	(3.77)	(1.82)	(2.92)	(-0.06)	(3.05)	(0.53)
3	0.28	0.02	0.35	0.06	0.25	-0.04
	(2.90)	(0.42)	(3.55)	(1.30)	(2.39)	(-0.71)
4	0.33	0.06	0.31	0.00	0.32	0.03
	(3.46)	(1.64)	(3.05)	(0.01)	(3.32)	(0.61)
High	0.29	0.01	0.24	-0.05	0.25	-0.01
	(2.92)	(0.11)	(2.20)	(-1.01)	(2.32)	(-0.24)
High − Low	-0.10***	-0.12***	-0.15**	-0.15***	-0.13**	-0.12**
	(-2.78)	(-2.93)	(-2.44)	(-3.43)	(-2.50)	(-2.42)

Panel D: Subperiod analysis

	Excluding crisis period (2008 – 2009)		1st Subperiod: July 2006 to June 2013		2nd subperiod: July 2013 to June 2019	
	Average return	9-factor alpha	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.35	0.06	0.40	0.17	0.34	0.10
	(4.48)	(2.21)	(2.42)	(2.11)	(3.09)	(1.87)
2	0.31	0.01	0.42	0.13	0.26	-0.08
	(3.97)	(0.24)	(2.65)	(2.33)	(2.20)	(-1.92)
3	0.32	0.03	0.40	0.15	0.26	-0.05
	(4.23)	(1.00)	(2.50)	(2.47)	(2.52)	(-1.67)
4	0.33	0.05	0.32	0.03	0.31	-0.00
	(4.36)	(1.62)	(2.02)	(0.61)	(2.98)	(-0.08)
High	0.21	-0.06	0.22	0.01	0.23	-0.01
	(3.24)	(-1.53)	(1.59)	(0.07)	(2.22)	(-1.87)
High − Low	-0.14**	-0.12***	-0.18**	-0.16**	-0.11*	-0.10**
	(-2.21)	(-3.17)	(-2.06)	(-2.46)	(-1.96)	(-2.48)

Table 5 Carbon Emissions Intensity, Institutional Ownership, and Corporate Bond Returns

Panel A of this table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of changes in corporate bonds' institutional ownership on firms' carbon emissions intensity. The dependent variable is the change in bonds' institutional ownership (ΔINST_Bond), defined as the institutional ownership in June of year $t+1$ minus the institutional ownership in June of year t. For a given bond i in month t, the measure of institutional ownership is defined as:

$$INST_{it} = \sum_j \left(\frac{Holding_{ijt}}{OutstandingAmt_{it}} \right) = \sum_j h_{jt},$$

where $Holding_{ijt}$ is the par amount holdings of institution j on bond i, $OutstandingAmt_{it}$ is bond i's outstanding amount, and h_{jt} is the fraction of the outstanding amount held by institution j, in percentage. The key independent variable is the logarithm of firm-level carbon emissions intensity in June of each year t for firms with fiscal year ending in year $t-1$. Control variables include bond market beta (β^{Bond}), bond characteristics (ratings, maturity, size), downside risk, bond-level illiquidity (Illiq), and past six-month cumulative bond returns ($Return_{t-7:t-2}$). We also control for systematic risk betas such as the default beta (β^{DEF}), term beta (β^{TERM}), macroeconomic uncertainty beta (β^{UNC}), and climate change news beta ($\beta^{Climate}$). To interpret their economic significance, all the independent variables in Panel A are standardized cross-sectionally to a mean of zero and standard deviation of one. Panel B replicates Table 3 by including additional controls of the contemporaneous changes in bonds' institutional ownership (ΔINST_Bond). The dependent variable in Panel B is the corporate bond excess return from July of year t to June of year $t+1$. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last row reports the average adjusted R^2 values and we control for the Fama-French 12 industry fixed effects in all specifications. Numbers in bold denote statistical significance at the 5% level or below.

Panel A: Carbon emission intensity and changes in institutional ownership

Dep.var = ΔINST_Bond	(1) Univariate	(2) Controlling for bond characteristics	(3) Controlling for systematic and climate change news betas	(4) Controlling for all variables
ln(CEI)	**-0.471**	**-0.211**	**-0.489**	**-0.226**
	(-3.66)	(-2.65)	(-4.51)	(-2.42)
β^{Bond}		**0.312**		**0.276**
		(5.18)		(3.49)
Downside risk (5% VaR)		-0.018		-0.013
		(-0.19)		(-0.14)
Illiq		**0.402**		**0.355**
		(2.29)		(2.29)
Rating		**-0.725**		**-0.693**
		(-4.60)		(-4.75)
Maturity		**0.379**		**0.343**
		(3.95)		(3.76)
Size		-0.146		-0.119
		(-1.91)		(-1.70)
$\text{Return}_{(t-7:t-2)}$		**4.744**		**4.738**
		(10.97)		(10.97)
β^{DEF}			-0.144	-0.089
			(-0.72)	(-0.55)
β^{TERM}			0.396	0.125
			(1.63)	(0.65)
β^{UNC}			**-0.328**	-0.189
			(-2.34)	(-1.61)
$\beta^{Climate}$			-0.126	-0.095
			(-1.37)	(-1.50)
Intercept	-2.224	-2.098	-2.583	-2.112
	(-4.12)	(-3.70)	(-4.41)	(-3.80)
Industry Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.016	0.277	0.033	0.280

Table 5 (Continued)

Panel B: Carbon emissions intensity, changes in institutional ownership, and bond returns

Dep.var = $\text{Return}_{t+1:t+12}$	(1) Univariate	(2) Controlling for bond characteristics	(3) Controlling for systematic and eclimate risk beta	(4) Controlling for all variables
ln(CEI)	**-0.039**	**-0.036**	**-0.031**	**-0.027**
	(-2.59)	(-2.03)	(-2.35)	(-2.15)
ΔINST_Bond	0.125	0.134	0.042	0.122
	(0.60)	(0.79)	(0.21)	(0.73)
β^{Bond}		0.066		**0.148**
		(1.12)		(2.32)
Downside risk (5% VaR)		**0.046**		**0.040**
		(2.41)		(2.09)
Illiq		-0.001		-0.001
		(-0.13)		(-0.10)
Rating		0.005		0.004
		(0.23)		(0.24)
Maturity		0.003		0.002
		(0.72)		(0.51)
Size		0.032		0.026
		(0.79)		(0.64)
Lag return		**-0.197**		**-0.206**
		(-6.34)		(-6.86)
β^{DEF}			-0.168	-0.012
			(-1.07)	(-0.23)
β^{TERM}			0.103	-0.017
			(0.66)	(-0.18)
β^{UNC}			**-0.258**	-0.217
			(-2.43)	(-1.45)
$\beta^{Climate}$			-0.035	0.537
			(-0.03)	(0.56)
Intercept	0.153	0.311	0.260	0.208
	(0.72)	(1.60)	(2.13)	(2.09)
Industry Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.046	0.256	0.122	0.270

Table 6 Subsample Analyses: Univariate Portfolios of Corporate Bonds Sorted by the Firm-Level Carbon Emissions Intensity (CEI)

This table replicates Table 2 for (1) large and small bonds based on the median issuance size, (2) investment-grade and non-investment-grade bonds, (3) short- and long-maturity bonds based on the median time-to-maturity, and (4) liquid and illiquid bonds based on the median bond-level illiquidity, respectively.

Panel A: Large bonds versus small bonds

	Size > Size^{Median}		Size ≤ Size^{Median}	
	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.32	0.06	0.39	0.14
	(3.35)	(1.62)	(3.62)	(2.05)
2	0.38	0.04	0.33	0.09
	(3.91)	(0.81)	(3.12)	(1.90)
3	0.29	0.08	0.36	0.02
	(3.07)	(1.52)	(3.54)	(0.42)
4	0.37	0.02	0.29	0.10
	(4.03)	(0.38)	(2.74)	(2.75)
High	0.22	-0.09	0.25	-0.08
	(2.24)	(-0.86)	(1.94)	(-1.37)
High − Low	-0.10**	-0.15**	-0.15***	-0.22***
	(-2.21)	(-2.00)	(-2.81)	(-3.94)

Panel B: Investment-grade versus non-investment-grade bonds

	Investment-grade		Non-investment-grade	
	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.37	0.08	0.41	0.25
	(3.63)	(1.99)	(2.58)	(2.19)
2	0.36	0.06	0.44	0.13
	(3.86)	(1.62)	(2.89)	(1.27)
3	0.35	0.09	0.30	-0.05
	(3.87)	(2.76)	(1.73)	(-0.44)
4	0.35	0.06	0.34	0.06
	(3.91)	(1.65)	(2.29)	(0.78)
High	0.25	-0.02	0.14	-0.11
	(1.98)	(-0.64)	(0.82)	(-1.04)
High − Low	-0.12**	-0.10**	-0.27***	-0.36***
	(-2.17)	(-2.01)	(-3.54)	(-4.08)

Panel C: Short maturity versus long maturity bonds

	1 yr < Maturity ≤ 6 yr		Maturity > 6 yr	
	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.26	0.12	0.47	0.13
	(3.97)	(3.79)	(3.13)	(2.44)
2	0.25	0.09	0.47	0.02
	(3.75)	(2.23)	(3.16)	(0.32)
3	0.21	0.08	0.44	-0.00
	(3.31)	(2.25)	(2.99)	(-0.05)
4	0.20	0.08	0.40	-0.03
	(3.63)	(2.95)	(2.63)	(-0.46)
High	0.17	-0.01	0.31	-0.10
	(2.14)	(-0.28)	(2.08)	(-1.62)
High − Low	-0.10**	-0.13***	-0.15**	-0.23***
	(-2.34)	(-3.02)	(-2.56)	(-3.06)

Panel D: Liquid bonds versus Illiquid bonds

	Illiq ≤ Illiq^{Median}		Illiq > Illiq^{Median}	
	Average return	9-factor alpha	Average return	9-factor alpha
Low	0.37	0.11	0.43	0.04
	(4.07)	(4.22)	(3.27)	(0.79)
2	0.29	0.03	0.48	0.09
	(3.14)	(0.65)	(3.89)	(1.89)
3	0.32	0.09	0.34	-0.04
	(3.60)	(2.58)	(2.75)	(-0.61)
4	0.33	0.09	0.34	-0.03
	(4.34)	(2.79)	(2.45)	(-0.56)
High	0.28	0.03	0.21	-0.15
	(3.42)	(0.83)	(1.65)	(-2.40)
High − Low	-0.09**	-0.08**	-0.22***	-0.20***
	(-2.06)	(-2.21)	(-3.28)	(-3.54)

Table 7 Carbon Emissions Intensity and Cash Flow Surprises

This table reports the panel regression of earnings/revenue surprise on firms' carbon emission intensity. The dependent variable are earnings surprise (SUE), revenue surprise ($SURGE$), and earnings announcement return CAR(-2, $+1$). SUE is defined as the change in split-adjusted quarterly earnings per share from its value four quarters ago divided by the standard deviation of this change over the prior eight quarters (four quarters minimum). $SURGE$ is defined as the change in revenue per share from its value four quarters ago divided by the standard deviation of this change over the prior eight quarters (four quarters minimum). CAR(-2, $+1$) is defined as four-day cumulative abnormal return from two days before to one day after the earning announcement day (day 0), where daily abnormal return is the difference between daily stock return and the CRSP value-weighted market index return. The independent variable is $ln(CEI)$, which is defined as the nature logarithm of carbon emission intensity (scope 1) in the fiscal year ending in calendar year $t-1$. Firm size is defined as the natural logarithm of market capitalization at the end of June in each year. BM is the book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity at the end of December of year $t-1$. Book value of equity equals the value of stockholders' equity, plus deferred taxes and investment tax credits, and minus the book value of preferred stock. ROE is defined as income before extraordinary items in the fiscal year ending in calendar year $t-1$ divided by average book value of equity in the fiscal year ending in calendar year $t-1$. R&D is defined as R&D expenditures in the fiscal year ending in calendar year $t-1$ divided by sales in calendar year $t-1$. Investment is defined as the annual growth in total assets in fiscal year ending in calendar year $t-1$. OCF is defined as operating cash flows in the fiscal year ending in calendar year $t-1$ divided by lagged total assets. INST_Stock is defined as the sum of shares held by institutions from 13F filings at the end of December of year $t-1$. Momentum (MOM) is defined as the cumulative holding period returns from month $t-12$ to $t-2$ preceding the quarterly earnings announcement month. Industry is based on Fama-French 12 industry categories. The unit of analysis is at firm-quarter level. All variables are winsorized at 2.5% level, except for Firm size and MOM. Numbers in parentheses are t-statistics based on standard errors clustered by firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	SUE		SURGE		CAR (-2, $+1$)	
	(1)	(2)	(3)	(4)	(5)	(6)
ln (CEI)	-0.0177***	-0.0128**	-0.0446***	-0.0262***	-0.0004***	-0.0005**
	(-5.48)	(-2.19)	(-12.29)	(-4.20)	(-2.60)	(-1.99)
Dependent variable$_{t-1}$	0.3259***	0.3237***	0.7441***	0.7394***	-0.0089	-0.0092
	(29.91)	(30.14)	(102.15)	(100.99)	(-1.14)	(-1.19)
Dependent variable$_{t-4}$	-0.1881***	-0.1893***	-0.0398***	-0.0444***	-0.0043	-0.0046
	(-22.05)	(-22.43)	(-8.28)	(-9.13)	(-0.61)	(-0.65)
Firm size	0.0402***	0.0410***	0.0411***	0.0382***	-0.0005	-0.0004
	(4.85)	(4.96)	(5.43)	(5.08)	(-1.61)	(-1.28)
BM	-0.2813***	-0.2655***	-0.1855***	-0.1815***	-0.0013	-0.0009
	(-12.70)	(-11.38)	(-7.17)	(-6.62)	(-0.91)	(-0.62)
ROE	-0.3164***	-0.3568***	0.2154***	0.2580***	0.0027	0.0012
	(-5.39)	(-5.96)	(3.25)	(3.85)	(0.81)	(0.35)
R&D	-1.1300***	-0.9871***	-0.7490***	-0.7030*	0.0169	0.0289*
	(-4.49)	(-2.97)	(-2.74)	(-1.91)	(1.44)	(1.75)
Investment	-0.0065	0.0001	-0.1788***	-0.1644***	-0.0053**	-0.0053**
	(-0.14)	(0.00)	(-3.74)	(-3.35)	(-2.18)	(-2.15)
OCF	0.5771***	0.7639***	0.7893***	0.7867***	-0.0003	0.0040
	(3.08)	(3.90)	(4.32)	(3.95)	(-0.05)	(0.50)
INST_Stock	0.1320***	0.1333***	0.2007***	0.1745***	0.0050**	0.0053**
	(3.08)	(3.09)	(5.02)	(4.35)	(2.34)	(2.43)
MOM	0.4454***	0.4397***	0.2733***	0.2757***	-0.0025*	-0.0026**
	(7.40)	(7.37)	(7.09)	(6.95)	(-1.94)	(-2.01)
Constant	-0.6590***	-0.7187***	-0.6860***	-0.6589***	0.0103	0.0077
	(-3.30)	(-3.55)	(-3.83)	(-3.63)	(1.29)	(0.94)
Industry FEs	NO	YES	NO	YES	NO	YES
Quarter FEs	YES	YES	YES	YES	YES	YES
Adj. R^2	0.1970	0.1990	0.6270	0.6290	0.0074	0.0075
Observations	28,691	28,691	28,654	28,654	28,666	28,666

Table 8 Carbon Emissions Intensity and Change in Firm Creditworthiness

This table reports the panel regression of change in firm creditworthiness on firms' carbon emission intensity. In columns (1), the dependent variable is $\Delta Rating$, which is defined as the bond credit rating in June of year $t+1$ minus the bond credit rating in June of year t. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. A higher numerical score implies higher credit risk. In column (2), the dependent variable is ΔO_Score, defined as the one-year ahead change of O-Score relative to the most recent quarter before June of year t. The independent variable is ln(CEI), defined as the nature logarithm of carbon emission intensity (scope 1) in the fiscal year ending in calendar year $t-1$. Firm size is defined as the natural logarithm of market capitalization at the end of June in each year. BM is the book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity at the end of December of year $t-1$. Book value of equity equals the value of stockholders' equity, plus deferred taxes and investment tax credits, and minus the book value of preferred stock. ROE is defined as income before extraordinary items in the fiscal year ending in calendar year $t-1$ divided by average book value of equity in the fiscal year ending in calendar year $t-1$. R&D is defined as R&D expenditures in the fiscal year ending in calendar year $t-1$ divided by sales in calendar year $t-1$. Investment is defined as the annual growth in total assets in fiscal year ending in calendar year $t-1$. OCF is defined as operating cash flows in the fiscal year ending in calendar year $t-1$ divided by lagged total assets. INST_Stock is defined as the sum of shares held by institutions from 13F filings at the end of December of year $t-1$. Industry is based on Fama-French 12 industry categories. The unit of analysis for $\Delta Rating$ is at bond-year level, and for ΔO_Score is at firm-year level. All variables are winsorized at 2.5% level, except for Firm size. Numbers in parentheses are t-statistics based on standard errors clustered by bond level in column (1) and firm level in column (2). ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	$\Delta Rating$	ΔO_Score
	(1)	(2)
ln(CEI)	0.0252***	0.0076**
	(3.02)	(2.01)
Firm size	0.1515***	0.0069
	(12.96)	(1.24)
BM	0.2827***	-0.0674**
	(14.62)	(-2.41)
ROE	-0.1396***	-0.1401**
	(-3.59)	(-2.30)
R&D	-2.1716**	0.6535***
	(-2.56)	(4.86)
Investment	-0.0528**	-0.0107
	(-2.07)	(-0.19)
OCF	0.6572***	-0.4574***
	(5.27)	(-2.87)
INST_Stock	-0.1526***	0.0080
	(-4.78)	(0.22)
Constant	-3.6909***	-0.1722
	(-12.76)	(-1.23)
Bond FEs	YES	-
Industry FEs	-	YES
Year FEs	YES	YES
Adj. R^2	0.2130	0.1120
Observations	43,485	4,500

Table 9 Carbon Emissions Intensity and Environmental Incidents

This table reports the panel regression of the frequency of environmental incidents on firms' carbon emissions intensity. The dependent variable is $ln(1 + Incidents)$, defined as the nature logarithm of one plus the sum of all positive changes in the RepRisk Index from July of year t to June of year $t + 1$. To ensure we capture a firm's environmental incidents rather than the S and G aspects of the RepRisk Index, we require the percentage of environmental issues used to compute the RepRisk Index is greater than 50%. $Ln(1 + Incidents)$ has a value of zero when there is no ESG incidents in the year. The key independent variable is ln(CEI), defined as the natural logarithm of carbon emissions intensity (scope 1) in the fiscal year ending in calendar year $t - 1$. Firm size is defined as the natural logarithm of market capitalization at the end of June in each year. BM is the book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity at the end of December of year $t-1$. Book value of equity equals the value of stockholders' equity, plus deferred taxes and investment tax credits, and minus the book value of preferred stock. ROE is defined as income before extraordinary items in the fiscal year ending in calendar year $t - 1$ divided by average book value of equity in the fiscal year ending in calendar year $t - 1$. R&D is defined as R&D expenditures in the fiscal year ending in calendar year $t - 1$ divided by sales in calendar year $t - 1$. Investment is defined as the annual growth in total assets in fiscal year ending in calendar year $t - 1$. OCF is defined as operating cash flows in the fiscal year ending in calendar year $t - 1$ divided by lagged total assets. INST_Stock is defined as the sum of shares held by institutions from 13F filings at the end of December of year $t - 1$. The unit of analysis is at firm-year level. All variables are winsorized at 2.5% level, except for Firm size. Numbers in parentheses are t-statistics based on standard errors clustered by firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The sample period is from July 2007 to June 2019.

Variables	ln(1+Incidents)	
	(1)	(2)
ln(CEI)	0.1596***	0.1255***
	(15.90)	(9.79)
Firm size	0.0961***	0.0830***
	(6.06)	(5.96)
BM	0.2456***	0.1224**
	(5.13)	(2.58)
ROE	-0.0114	0.0580
	(-0.11)	(0.61)
R&D	-1.4576***	-0.9789***
	(-4.37)	(-2.60)
Investment	0.0504	0.0138
	(0.62)	(0.17)
OCF	0.2686	-0.0999
	(0.79)	(-0.33)
INST_Stock	-0.0959	-0.0457
	(-1.37)	(-0.69)
Constant	-2.3840***	-1.9198***
	(-6.23)	(-5.73)
Industry FEs	NO	YES
Year FEs	YES	YES
Adj. R^2	0.1790	0.2110
Observations	6,674	6,674

Table 10 Carbon Emissions Intensity and Stock Price Crash Risk

This table reports the panel regression of stock price crash risk on firms' carbon emissions intensity. The dependent variables are $NCSKEW$ and $DUVOL$ from July of year t to June of year $t+1$. The key independent variable is ln(CEI), defined as the natural logarithm of carbon emissions intensity (scope 1) in the fiscal year ending in calendar year $t-1$. DTURN is the average monthly share turnover form July of year $t-1$ to June of year t minus the average monthly share turnover from July of year $t-2$ to June of year $t-1$, where the monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month. SIGMA is the standard deviation of firm-specific weekly returns from July of year $t-1$ to June of year t. RET is the average firm-specific weekly returns from July of year $t-1$ to June of year t. Firm size is defined as the natural logarithm of market capitalization at the end of June in each year. BM is the book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity at the end of December of year $t-1$. Book value of equity equals to the value of stockholders' equity, plus deferred taxes, and investment tax credits, and minus the book value of preferred stock. ROA is defined as operating income before depreciation in the fiscal year ending in calendar year $t-1$ as a fraction of average total assets based between the fiscal year ending in calendar year $t-1$ and the fiscal year ending in calendar year $t-2$. Leverage is the total debt as fraction of total assets in the fiscal year ending in calendar year $t-1$. Numbers in parentheses are t-statistics based on standard errors clustered by firm level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Variables	NCSKEW (1)	DUVOL (2)
ln(CEI)	0.0170**	0.0096**
	(2.25)	(2.08)
Dependent variable$_{t-1}$	0.0542***	0.0740***
	(3.54)	(5.36)
DTURN	0.7836	1.7411
	(0.12)	(0.44)
SIGMA	-0.1628	-0.0132
	(-0.32)	(-0.04)
RET	4.1660**	4.4990***
	(2.17)	(3.87)
Firm size	0.0076	0.0030
	(0.96)	(0.60)
BM	-0.0370	-0.0253
	(-1.17)	(-1.27)
ROA	0.4108**	0.2857***
	(2.32)	(2.60)
Leverage	0.0447	0.0855**
	(0.63)	(2.03)
Constant	-0.1971	-0.1002
	(-0.99)	(-0.79)
Industry FEs	YES	YES
Year FEs	YES	YES
Adj. R^2	0.0143	0.0247
Observations	7,803	7,803

Is Carbon Risk Priced in the Cross-Section of Corporate Bond Returns?

Online Appendix

To save space in the paper, we present additional analyses in the Online Appendix. Specifically, Table A.1 reports the year-to-year transition matrix for portfolios of firms sorted on the carbon emissions intensity (CEI) from one- to five-year ahead and shows that CEI is highly persistent over time.

Table A.2 replicates the results in Table 2 for quintile portfolios of corporate bonds based on the firm-level carbon emissions intensity (CEI) based on alternative factor models including the profitability and investment factors from Fama and French (2015) and Hou, Xue, and Zhang (2015).

Table A.3 replicates the results in Table 2 based on the industry-level carbon emissions intensity (CEI) using the Fama-French 30 industry classifications.

Table A.4 replicates Panel B of Table 5 by including additional lagged controls of the changes in bonds' institutional ownership (ΔINST_Bond), including the 1-year lagged change of ΔINST_Bond from July of year $t-1$ to June of year t, as well as the 2-year lagged change of ΔINST_Bond from July of year $t-2$ to June of year $t-1$.

Table A.5 replicates Panel B of Table 5 by including dummy variables of the change in bonds' institutional ownership (ΔINST_Bond), including the 1-year lagged change of ΔINST_Bond from July of year $t-1$ to June of year t, to address potential non-linearity between ΔINST_Bond and future bond returns.

Table A.6 reports the monthly return difference (Low − High) between the low-CEI portfolio (Quintile 1) and the high-CEI portfolio (Quintile 5), conditioning on measures of investor attention to climate change.

Table A.7 investigates the relation between CEI and subsequent changes in bond yield-to-maturity (YTM) and shows that firms with low (high) carbon emissions intensity experience a reduction (increase) in yield-to-maturity in the future.

Table A.8 replicates Table 2 for firms with high and low leverage, respectively, based on the the median value of firms' leverage in the sample.

Table A.9 reports the univariate portfolio results of individual stocks sorted by the carbon emissions intensity (CEI).

Table A.1 Persistence and Transition Matrix of Carbon Emissions Intensity

This table reports the year-to-year transition matrix for portfolios of firms sorted on the carbon emissions intensity from one- to five-year-ahead. Each year from 2005 to 2017, we form decile portfolios of firms based on their scope 1 carbon emissions intensity (CEI), defined as the firm-level greenhouse gas emission in CO2 equivalents divided by the total revenue of the firm in millions of dollars. The table presents the average probability that a firm in decile i (defined by the rows) in one year will be in decile j (defined by the columns) in the subsequent year. If carbon emissions intensity were completely random, then all the probabilities should be approximately 10%, since a high or low CEI in one year should say nothing about the carbon emissions intensity in the following year. Instead, all the diagonal elements of the transition matrix exceed 10%, illustrating that CEI is highly persistent.

Panel A: One-year-ahead

Decile	Low CEI	2	3	4	5	6	7	8	9	High CEI
Low CEI	**94.13%**	3.47%	0.68%	0.85%	0.21%	0.38%	0.08%	0.17%	0.00%	0.04%
2	9.43%	**58.03%**	3.21%	1.44%	0.46%	0.38%	0.17%	0.13%	0.04%	0.00%
3	0.38%	6.68%	**73.42%**	3.30%	1.10%	0.46%	0.25%	0.34%	0.00%	0.04%
4	0.30%	0.51%	6.93%	**72.61%**	4.31%	2.07%	0.51%	0.42%	0.08%	0.00%
5	0.08%	0.21%	0.51%	8.79%	**74.26%**	4.31%	0.59%	0.21%	0.04%	0.00%
6	0.04%	0.04%	0.38%	0.80%	7.48%	**68.09%**	5.92%	0.97%	0.17%	0.00%
7	0.00%	0.04%	0.21%	0.34%	1.06%	7.44%	**68.98%**	6.47%	0.30%	0.17%
8	0.00%	0.13%	0.17%	0.21%	0.93%	0.97%	7.95%	**69.86%**	4.95%	0.34%
9	0.04%	0.00%	0.08%	0.00%	0.04%	0.13%	0.17%	5.62%	**74.85%**	5.16%
High CEI	0.00%	0.00%	0.00%	0.00%	0.04%	0.00%	0.04%	0.38%	5.28%	**80.30%**

Panel B: Two-year-ahead

Decile	Low CEI	2	3	4	5	6	7	8	9	High CEI
Low CEI	**89.47%**	5.48%	1.04%	2.03%	0.44%	0.93%	0.16%	0.38%	0.00%	0.05%
2	12.34%	**59.70%**	4.99%	2.96%	1.04%	0.88%	0.38%	0.22%	0.11%	0.05%
3	1.15%	11.84%	**68.20%**	4.88%	2.36%	1.37%	0.55%	0.49%	0.00%	0.05%
4	0.55%	1.81%	13.27%	**65.02%**	6.25%	3.40%	1.15%	1.04%	0.11%	0.00%
5	0.22%	0.38%	1.15%	14.97%	**67.43%**	6.74%	1.37%	0.33%	0.22%	0.00%
6	0.05%	0.05%	0.88%	1.86%	11.84%	**64.80%**	7.89%	1.97%	0.27%	0.00%
7	0.05%	0.11%	0.22%	0.71%	2.19%	11.73%	**66.23%**	7.46%	0.38%	0.33%
8	0.00%	0.27%	0.44%	0.49%	1.04%	1.32%	9.92%	**69.08%**	7.51%	0.82%
9	0.05%	0.00%	0.22%	0.00%	0.05%	0.27%	0.49%	8.22%	**73.68%**	8.06%
High CEI	0.00%	0.00%	0.00%	0.00%	0.05%	0.00%	0.11%	0.66%	8.55%	**81.41%**

Panel C: Three-year-ahead

Decile	Low CEI	2	3	4	5	6	7	8	9	High CEI
Low CEI	**84.05%**	7.83%	1.73%	3.16%	0.60%	1.43%	0.60%	0.60%	0.00%	0.00%
2	12.49%	**70.13%**	6.47%	4.89%	1.81%	1.66%	0.75%	0.15%	0.23%	0.08%
3	1.50%	18.13%	**65.46%**	6.02%	3.46%	2.41%	1.13%	0.68%	0.08%	0.08%
4	1.05%	2.78%	19.71%	**60.12%**	8.20%	4.89%	1.66%	1.73%	0.15%	0.00%
5	0.45%	0.68%	1.88%	23.02%	**62.45%**	9.48%	2.48%	0.60%	0.08%	0.00%
6	0.00%	0.23%	1.13%	3.01%	14.75%	**66.29%**	10.31%	2.71%	0.45%	0.00%
7	0.08%	0.15%	0.38%	1.05%	3.46%	16.10%	**64.79%**	9.26%	0.15%	0.53%
8	0.00%	0.38%	0.68%	0.83%	0.90%	1.81%	12.94%	**69.22%**	11.21%	1.35%
9	0.08%	0.00%	0.23%	0.00%	0.00%	0.45%	0.98%	11.51%	**73.89%**	11.66%
High CEI	0.00%	0.00%	0.00%	0.08%	0.00%	0.00%	0.15%	1.05%	12.42%	**84.95%**

Table A.1: **(Continued)**

Panel D: Four-year-ahead

Decile	Low CEI	2	3	4	5	6	7	8	9	High CEI
Low CEI	**81.39%**	8.31%	2.16%	3.90%	0.78%	1.65%	1.13%	0.69%	0.00%	0.00%
2	13.94%	**67.53%**	6.15%	5.89%	2.51%	1.73%	0.87%	0.17%	0.35%	0.00%
3	2.42%	19.65%	**60.52%**	7.53%	3.98%	3.38%	1.39%	0.87%	0.17%	0.09%
4	1.47%	3.98%	23.81%	**49.70%**	8.48%	6.75%	2.42%	2.42%	0.17%	0.00%
5	0.52%	0.69%	2.42%	29.18%	**57.14%**	11.43%	2.60%	0.87%	0.09%	0.00%
6	0.09%	0.26%	1.56%	3.72%	17.32%	**57.14%**	10.74%	3.72%	0.43%	0.00%
7	0.00%	0.17%	0.35%	1.39%	4.94%	18.53%	**62.86%**	9.18%	0.26%	0.61%
8	0.00%	0.35%	1.04%	1.04%	0.78%	2.16%	14.37%	**66.15%**	11.95%	1.90%
9	0.09%	0.00%	0.35%	0.00%	0.00%	0.69%	1.13%	12.64%	**70.82%**	13.33%
High CEI	0.00%	0.00%	0.00%	0.00%	0.09%	0.00%	0.17%	1.30%	14.37%	**83.03%**

Panel E: Five-year-ahead

Decile	Low	2	3	4	5	6	7	8	9	High
Low CEI	**79.52%**	8.39%	3.00%	3.80%	0.80%	2.10%	1.30%	1.10%	0.00%	0.00%
2	14.49%	**64.84%**	6.09%	7.19%	2.70%	1.90%	1.10%	0.20%	0.20%	0.00%
3	3.10%	21.28%	**55.84%**	8.29%	4.70%	3.90%	1.90%	0.80%	0.30%	0.10%
4	1.80%	4.60%	26.37%	**42.46%**	8.09%	8.39%	3.20%	3.10%	0.20%	0.00%
5	0.60%	0.70%	2.50%	33.37%	**50.65%**	13.29%	2.30%	1.40%	0.10%	0.00%
6	0.20%	0.20%	2.00%	4.50%	22.48%	**48.95%**	11.09%	4.00%	0.50%	0.00%
7	0.00%	0.20%	0.70%	1.50%	4.90%	21.78%	**59.54%**	8.79%	0.60%	0.60%
8	0.00%	0.30%	1.30%	1.00%	1.00%	2.50%	15.68%	**62.44%**	12.59%	2.60%
9	0.10%	0.00%	0.50%	0.00%	0.00%	0.80%	1.10%	13.59%	**68.63%**	14.19%
High CEI	0.00%	0.00%	0.00%	0.10%	0.00%	0.00%	0.20%	1.50%	15.68%	**81.32%**

Table A.2 Alternative Factor Models for the Univariate Portfolios of Corporate Bonds Sorted by the Firm-Level Carbon Emissions Intensity (CEI)

This table replicates the results in Table 2 for quintile portfolios of corporate bonds based on the firm-level carbon emissions intensity (CEI) based on alternative factor models including the profitability and investment factors from Fama and French (2015) and Hou, Xue, and Zhang (2015). The table reports the average CEI, the next-month average excess return, 5-factor alpha from Fama and French (2015), the Q4-factor alpha from Hou, Xue, and Zhang (2015), the 9-factor and 8-factor alpha from combining these models with the bond market factors from Bai, Bali, and Wen (2019) for each quintile. The bond market factors from Bai, Bali, and Wen (2019) include the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

Quintiles	Average CEI	Average return	FF 5-factor alpha	Q4-factor alpha	(FF5 + BBW) 9-factor alpha	(Q4 + BBW) 8-factor alpha
Low	36.75	0.37	0.24	0.34	0.08	0.11
		(3.66)	(2.16)	(3.22)	(2.28)	(2.54)
2	153.18	0.35	0.22	0.33	0.03	0.08
		(3.42)	(2.03)	(3.33)	(0.59)	(1.66)
3	333.77	0.33	0.22	0.31	0.06	0.10
		(3.42)	(2.21)	(3.23)	(1.53)	(2.15)
4	518.59	0.31	0.19	0.28	0.03	0.04
		(3.28)	(1.88)	(2.80)	(0.99)	(0.98)
High	1127.34	0.23	0.11	0.18	-0.06	-0.02
		(2.51)	(1.29)	(2.26)	(-0.61)	(-0.41)
High − Low		-0.14***	-0.13***	-0.16***	-0.14***	-0.13**
		(-2.62)	(-2.68)	(-2.81)	(-2.69)	(-2.40)

Table A.3 Univariate Portfolios of Corporate Bonds Sorted by the Industry-Level Carbon Emissions Intensity (CEI)

This table replicates the results in Table 2 based on the industry-level carbon emissions intensity (CEI) using the Fama-French 30 industry classifications. We form quintile portfolios of corporate bonds based on the average carbon emissions intensity (CEI) at the industry level in June of each year t for firms with fiscal year ending in year $t-1$. The portfolio returns are calculated for July of year t to June of year $t+1$ and then rebalanced. CEI is defined as the firm-level greenhouse gas emission in CO2 equivalents divided by the total revenue of the firm in millions of dollars. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

Quintiles	Average industry-level CEI	Average return	5-factor stock alpha	4-factor bond alpha	9-factor alpha
Low	6.38	0.41	0.27	0.03	0.02
		(3.38)	(2.29)	(0.68)	(0.35)
2	10.21	0.34	0.23	0.05	0.05
		(2.63)	(1.92)	(0.88)	(0.86)
3	11.21	0.32	0.22	0.12	0.07
		(2.84)	(1.71)	(3.71)	(2.47)
4	15.47	0.33	0.26	0.04	0.04
		(3.43)	(2.56)	(1.38)	(1.27)
High	948.16	0.25	0.11	-0.10	-0.10
		(2.67)	(1.66)	(-2.08)	(-1.75)
High − Low		-0.15**	-0.16**	-0.13**	-0.12**
		(-2.62)	(-2.45)	(-2.14)	(-2.38)

Table A.4 Robustness Check (1): Carbon Emissions Intensity, Institutional Ownership, and Corporate Bond Returns

This table replicates Panel B of Table 5 by including additional lagged controls of the changes in bonds' institutional ownership (ΔINST_Bond), including the 1-year lagged change of ΔINST_Bond from July of year $t-1$ to June of year t, as well as the 2-year lagged change of ΔINST_Bond from July of year $t-2$ to June of year $t-1$. The dependent variable is the corporate bond excess return from July of year t to June of year $t+1$. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last row reports the average adjusted R^2 values and we control for the Fama-French 12 industry fixed effects in all specifications. Numbers in bold denote statistical significance at the 5% level or below.

Dep.var = $\text{Return}_{t+1:t+12}$	(1) Univariate	(2) Controlling for bond characteristics	(3) Controlling for systematic and eclimate risk beta	(4) Controlling for all variables
ln(CEI)	**-0.037**	**-0.029**	**-0.021**	**-0.022**
	(-2.48)	(-2.25)	(-2.08)	(-2.06)
ΔINST_Bond	1.163	0.518	0.659	0.414
	(1.69)	(1.04)	(1.37)	(0.80)
1-year lagged ΔINST_Bond	-0.513	-0.451	-0.399	-0.393
	(-1.45)	(-1.11)	(-1.22)	(-1.00)
2-year lagged ΔINST_Bond	0.313	0.336	0.332	0.349
	(1.26)	(1.44)	(1.53)	(1.48)
β^{Bond}		0.050		0.164
		(0.46)		(1.46)
Downside risk (5% VaR)		0.026		0.027
		(0.98)		(1.03)
Illiq		**0.022**		**0.020**
		(2.35)		(2.28)
Rating		0.013		0.008
		(0.24)		(0.16)
Maturity		0.005		0.003
		(0.74)		(0.37)
Size		0.081		0.063
		(1.21)		(1.12)
Lag return		**-0.272**		**-0.282**
		(-5.27)		(-6.09)
β^{DEF}			0.023	-0.029
			(0.13)	(-0.38)
β^{TERM}			-0.110	-0.027
			(-0.49)	(-0.16)
β^{UNC}			-0.295	0.159
			(-1.78)	(0.92)
$\beta^{Climate}$			1.447	1.198
			(0.68)	(0.60)
Intercept	0.624	0.128	0.327	0.176
	(1.67)	(0.33)	(1.19)	(0.49)
Industry Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.074	0.287	0.140	0.304

Table A.5 Robustness Check (2): Carbon Emissions Intensity, Institutional Ownership, and Corporate Bond Returns

This table replicates Panel B of Table 5 by including dummy variables of the change in bonds' institutional ownership (ΔINST_Bond), based on the 1-year lagged change of ΔINST_Bond from July of year $t-1$ to June of year t. ΔINST_Quintile_5 is a dummy variable that equals to 1 if ΔINST belongs to the highest quintile of decreases in institutional ownership. Similarly, ΔINST_Quintile_4, ΔINST_Quintile_3, and ΔINST_Quintile_2 are dummy variables that equal to 1 if the value falls belong to the 4th, 3rd, and 2rd quintile of decreases in institutional ownership. The dependent variable is the corporate bond excess return from July of year t to June of year $t+1$. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last row reports the average adjusted R^2 values and we control for the Fama-French 12 industry fixed effects in all specifications. Numbers in bold denote statistical significance at the 5% level or below.

Dep.var = $\text{Return}_{t+1:t+12}$	(1) Univariate	(2) Controlling for bond characteristics	(3) Controlling for systematic and eclimate risk beta	(4) Controlling for all variables
ln(CEI)	**-0.025**	**-0.022**	**-0.028**	**-0.019**
	(-2.51)	(-2.11)	(-2.74)	(-2.02)
ΔINST_Quintile_5	**-0.127**	-0.078	**-0.177**	-0.060
	(-2.49)	(-1.11)	(-2.73)	(-0.80)
ΔINST_Quintile_4	-0.110	-0.024	-0.129	-0.013
	(-1.54)	(-0.50)	(-1.53)	(-0.26)
ΔINST_Quintile_3	-0.073	-0.055	-0.079	-0.034
	(-1.96)	(-1.43)	(-1.66)	(-0.84)
ΔINST_Quintile_2	-0.048	-0.027	-0.053	-0.021
	(-1.22)	(-0.72)	(-1.13)	(-0.55)
β^{Bond}		0.120		0.159
		(1.63)		(1.79)
Downside risk (5% VaR)		-0.023		-0.027
		(-0.73)		(-1.03)
ILLIQ		0.018		0.018
		(1.38)		(1.46)
Rating		0.020		0.022
		(0.75)		(0.97)
Maturity		0.007		0.005
		(1.26)		(0.79)
Size		0.022		0.023
		(1.31)		(1.35)
Lag return		**-0.149**		**-0.157**
		(-6.28)		(-6.75)
β^{DEF}			0.103	-0.055
			(0.80)	(-0.67)
β^{TERM}			-0.220	0.081
			(-1.23)	(0.72)
β^{UNC}			**-0.105**	-0.131
			(-1.06)	(-1.09)
$\beta^{Climate}$			-0.023	0.210
			(-0.10)	(0.23)
Intercept	0.486	-0.011	0.489	-0.055
	(2.37)	(-0.07)	(2.47)	(-0.39)
Industry Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.056	0.271	0.113	0.287

Table A.6 Investor Attention and Returns of the Carbon Emissions Intensity Sorted Portfolios of Corporate Bonds

This table reports the monthly return difference (Low − High) between the low-CEI portfolio (Quintile 1) and the high-CEI portfolio (Quintile 5), conditioning on measures of investor attention to climate change. In Panel A, we follow Choi et al. (2020) and measure investor attention to climate change using the Abnormal Google Search Volume Index (ASVI), calculated as the natural log of the ratio of SVI to the average SVI over the previous three month. ASVI_Climate Change is the ASVI corresponding to searches related to the topic "Climate Change", whereas ASVI_Global Warming is the ASVI corresponding to searches related to the topic "Global Warming". Positive (negative) ASVI is associated with an increase (decrease) in investor attention. In Panel B, we conduct subperiod analysis for the pre- and post-Paris agreement period. In Panel C, we conduct structural break test on the low-minus-high return with unknown break date. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

Panel A: Investor attention and the low carbon alpha

Variables	Low − High	*t*-stat	Variables	Low − High	*t*-stat
ASVI increases			ASVI decreases		
ASVI_Climate Change ≥ 0	0.05	0.84	ASVI_Climate Change < 0	0.26***	4.30
ASVI_Global Warming ≥ 0	0.07	1.25	ASVI_Global Warming < 0	0.23***	3.81

Panel B: Pre- and Post-Paris agreement and the low carbon alpha

Pre-Paris Agreement	0.19***	3.65	Post-Paris Agreement	0.02	0.45
			Difference in Mean (Post − Pre)	-0.16**	-2.38

Panel C: Tests for structural break for the low carbon alpha

Test for Unknown Structural Break Date	2016m3
p-value	0.022

Table A.7 Carbon Emissions Intensity (CEI) and Yield-to-Maturity (YTM): Fama-MacBeth Cross-Sectional Regressions

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of future changes in yield-to-maturity (YTM) on the logarithm of carbon emissions intensity (CEI), with and without controls. The dependent variable is the change in YTM from July of year t to June of year $t+1$, relative to the YTM in June of year t, and key independent variable ln(CEI) is based on the firm-level carbon emissions intensity in June of each year t for firms with fiscal year ending in year $t-1$. Control variables include bond market beta (β^{Bond}), bond characteristics (maturity, size), downside risk, and bond-level illiquidity. Time-to-maturity is defined in terms of years and Size is defined in terms of $billion. Illiq is the bond-level illiquidity computed as the autocovariance of the daily price changes within each month. We also control for systematic risk betas such as the default beta (β^{DEF}), term beta (β^{TERM}), macroeconomic uncertainty beta (β^{UNC}), and climate change news beta ($\beta^{Climate}$). Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last row reports the average adjusted R^2 values and we control for the Fama-French 12 industry fixed effects in all specifications. Numbers in bold denote statistical significance at the 5% level or below.

	(1) Univariate	(2) Controlling for bond characteristics	(3) Controlling for systematic and climate change news betas	(4) Controlling for all variables
ln(CEI)	**0.051**	**0.056**	**0.048**	**0.050**
	(6.18)	(4.17)	(3.84)	(4.03)
β^{Bond}		**-0.499**		**-0.703**
		(-2.70)		(-6.04)
Downside risk (5% VaR)		**0.669**		**0.505**
		(8.08)		(7.72)
Illiq		**0.091**		**0.086**
		(4.05)		(4.39)
Maturity		**0.030**		**0.054**
		(2.53)		(4.91)
Size		**-0.143**		**-0.176**
		(-4.58)		(-5.02)
β^{DEF}			**1.734**	**0.854**
			(6.65)	(4.30)
β^{TERM}			**-2.369**	**-1.584**
			(-6.07)	(-5.88)
β^{UNC}			**-1.469**	**-0.652**
			(-4.23)	(-2.52)
$\beta^{Climate}$			-6.625	2.216
			(-1.87)	(0.91)
Industry Fixed Effects	YES	YES	YES	YES
Adj. R^2	0.064	0.468	0.279	0.514

Table A.8 Univariate Portfolios of Corporate Bonds Sorted by the Firm-Level Carbon Emissions Intensity (CEI) Conditioning on Firm Leverage

This table replicates Table 2 for firms with high and low leverage, respectively, based on the the median value of firms' leverage in the sample. Leverage is defined as total debt (i.e., the sum of long term debt (DLTT) and debt in current liabilities (DLC)) as percentage of total assets. We form quintile portfolios of corporate bonds based on the firm-level carbon emissions intensity (CEI) in June of each year t for firms with fiscal year ending in year $t-1$. The portfolio returns are calculated for July of year t to June of year $t+1$ and then rebalanced. CEI is defined as the firm-level greenhouse gas emission in CO2 equivalents divided by the total revenue of the firm in millions of dollars. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

	Leverage $\leq$ Median				Leverage $>$ Median			
	Average return	5-factor Stock alpha	4-factor bond alpha	9-factor alpha	Average return	5-factor Stock alpha	4-factor bond alpha	9-factor alpha
Low	0.37	0.26	0.07	0.06	0.33	0.11	0.04	0.02
	(3.55)	(2.31)	(2.02)	(1.78)	(2.05)	(0.81)	(0.42)	(0.20)
2	0.35	0.24	0.04	0.05	0.12	-0.02	-0.20	-0.14
	(3.31)	(2.15)	(0.72)	(1.11)	(0.70)	(-0.15)	(-1.58)	(-1.21)
3	0.32	0.22	0.07	0.07	0.25	0.08	-0.01	0.03
	(3.43)	(2.18)	(1.45)	(1.70)	(1.78)	(0.56)	(-0.13)	(0.32)
4	0.33	0.24	0.05	0.04	0.45	0.29	0.11	0.10
	(3.67)	(2.60)	(1.41)	(1.14)	(3.02)	(1.98)	(0.82)	(0.68)
High	0.33	0.22	0.03	0.04	-0.25	-0.50	-0.34	-0.41
	(3.41)	(2.31)	(0.58)	(1.01)	(-1.12)	(-2.28)	(-2.29)	(-2.66)
High − Low	-0.03	-0.04	-0.04	-0.02	-0.58***	-0.60***	-0.38**	-0.43***
	(-0.95)	(-0.98)	(-1.11)	(-0.59)	(-3.15)	(-3.24)	(-2.16)	(-2.66)

Table A.9 Univariate Portfolios of Individual Stocks Sorted by the Firm-Level Carbon Emission Intensity (CEI)

Quintile portfolios of individual stocks are formed based on the firm-level carbon emission intensity (CEI) in June of each year t for firms with fiscal year ending in year $t-1$. The portfolio returns are calculated for July of year t to June of year $t+1$ and then rebalanced. Carbon emission intensity is defined as the firm-level greenhouse gas emission in CO2 equivalents, a standard unit for measuring a firm's carbon footprint, divided by the total revenue of the firm in millions of dollars. Panel A reports results for the Scope 1 carbon emission, defined as greenhouse gas emissions generated from burning fossil fuels and production processes which are owned or controlled by the company. The portfolios are value-weighted using market capitalization as weights. Since carbon emission levels intrinsically vary across industries, we form portfolios within each of the 12 Fama-French industries to control for the industry effect and the calculate the average portfolio returns across industries. Quintile 1 is the portfolio with the lowest CEI and Quintile 5 is the portfolio with the highest CEI. The table reports the average CEI, the next-month average excess return, the 5-factor FFCPS alpha from stock market factors, the Fama-French (2015) 5-factor alpha, and the Q-factor alpha for each quintile. The last row shows the differences monthly average returns and the differences in alphas with respect to the factor models. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

Panel A: Full sample: July 2006 – June 2019

	Average CEI	Average return	FFCPS alpha	FF 5-factor alpha	Q-factor alpha
	All stocks				
Low	20.69	0.93	0.11	0.05	0.17
		(2.22)	(1.46)	(0.49)	(1.34)
2	57.52	0.83	0.08	0.03	0.11
		(2.11)	(1.13)	(0.35)	(1.35)
3	186.24	0.79	0.00	-0.03	0.03
		(1.92)	(0.02)	(-0.31)	(0.36)
4	417.12	0.84	0.07	0.02	0.12
		(2.05)	(0.95)	(0.26)	(1.18)
High	1149.57	0.71	-0.14	-0.16	-0.07
		(1.56)	(-0.85)	(-0.88)	(-0.41)
High − Low		-0.22*	-0.25*	-0.20	-0.24*
		(-1.74)	(-1.83)	(-1.39)	(-1.72)

	Average CEI	Average return	FFCPS alpha	FF 5-factor alpha	Q-factor alpha
	Stocks with bonds				
Low	17.44	1.03	0.27	0.24	0.30
		(2.77)	(3.00)	(2.20)	(2.81)
2	64.27	0.96	0.22	0.16	0.30
		(2.06)	(1.44)	(0.87)	(1.70)
3	168.94	0.95	0.26	0.25	0.28
		(2.49)	(2.08)	(1.85)	(2.08)
4	453.75	0.90	0.13	0.10	0.25
		(1.93)	(0.81)	(0.59)	(1.27)
High	1218.84	0.69	-0.14	-0.28	-0.15
		(1.67)	(-0.90)	(-1.69)	(-0.84)
High − Low		-0.33**	-0.41***	-0.53***	-0.46***
		(-2.38)	(-2.79)	(-3.20)	(-2.81)

Panel B: Subsample: Jan 2010 – June 2019

	Average CEI	Average return	FFCPS alpha	FF 5-factor alpha	Q-factor alpha
	All stocks				
Low	17.99	1.13	0.02	-0.03	-0.02
		(4.31)	(0.33)	(-0.38)	(-0.23)
2	50.91	1.05	0.02	-0.03	-0.00
		(3.82)	(0.27)	(-0.46)	(-0.06)
3	166.20	1.04	-0.01	-0.08	-0.06
		(3.28)	(-0.07)	(-0.76)	(-0.55)
4	397.91	1.06	0.06	-0.04	-0.01
		(4.28)	(0.91)	(-0.58)	(-0.09)
High	1088.19	0.80	-0.27	-0.38	-0.33
		(2.46)	(-2.25)	(-2.70)	(-2.34)
High − Low		-0.34**	-0.29**	-0.35**	-0.31**
		(-2.53)	(-2.61)	(-2.31)	(-2.21)

	Average CEI	Average return	FFCPS alpha	FF 5-factor alpha	Q-factor alpha
	Stocks with bonds				
Low	14.89	1.21	0.16	0.10	0.13
		(4.14)	(1.57)	(1.04)	(1.46)
2	51.77	1.10	0.21	0.06	0.12
		(3.97)	(1.33)	(0.44)	(0.79)
3	149.26	1.19	0.23	0.21	0.22
		(3.81)	(1.41)	(1.28)	(1.41)
4	418.06	1.14	0.18	0.08	0.07
		(4.17)	(1.45)	(0.73)	(0.64)
High	1146.58	0.80	-0.27	-0.52	-0.48
		(2.39)	(-1.66)	(-2.93)	(-2.35)
High − Low		-0.41***	-0.43***	-0.63***	-0.62***
		(-2.74)	(-2.86)	(-3.58)	(-3.11)