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

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Abstract

This article 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.

I. 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. 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.

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As accumulations of greenhouse gases (GHGs) 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 toward 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 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).

Although risk-based theories predict a positive carbon risk premium, the empirical relationship between carbon emission intensity (CEI) and asset returns could go in either direction. One alternative hypothesis based on investor preference shifts predict that green assets could outperform brown assets if investors' preference for green assets unexpectedly strengthen due to increasing awareness of environmental risks (Pástor, Stambaugh, and Taylor (2021)). The rising demand from environmentally 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 environmental concerns consistently strengthened more than investors expected, green assets could outperform brown assets.[2] We call this the "investor preference" hypothesis. Alternatively, being less carbon intensive suggests that the firm is efficient in using the same amount of energy input to generate more sales compared to other firms, which may indicate better management and stronger operating performance.[3] If investors underreact to the predictability of carbon intensity for firm fundamentals, we may observe a negative relation

[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" (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 (https://www.bankofengland.co.uk/news/2020/july/statement-on-banks-commitment-to-combatting-climate-change).

[2]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.

[3]This conjecture is supported by the findings in Bloom, Genakos, Martin, and Sadun (2010) that better managed firms are significantly less energy intensive and more productive.

between carbon intensity and asset returns (Pedersen, Fitzgibbons, and Pomorski (2021)). We call this the "investor underreaction" hypothesis. Thus, whether carbon risk is priced in the financial markets is ultimately an empirical question.

In this study, we examine the pricing of carbon risk in the U.S. corporate bond market. 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), Engle, Giglio, Kelly, Lee, and Stroebel (2020), and Bolton and Kacperczyk (2021)), 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)). Since future climate policies and regulations mainly constitute a downside risk to carbon-intensive firms (Hoepner, Oikonomou, Sautner, Starks, and Zhou (2021), Ilhan, Sautner, and Vilkov (2021)), the impacts of uncertain climate policies likely matter more for investors in the bond market than equity market, especially for high-yield bonds. Second, the clientele of corporate bonds in the United States are predominantly institutional investors, who are sophisticated and likely take carbon risks into account when investing in carbon-intensive assets.[4] Third, corporate bonds differ along important dimensions, such as credit risks and maturities. The heterogeneity in various bond characteristics allows us to shed more light on the underlying channels of the (mis)pricing of carbon risk.[5] 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. 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.

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 the relation between a firm's CEI and the expected return on its corporate bonds. Following existing studies (Ilhan et al. (2021), In, Park, and Monk (2019), and Pedersen et al. (2021)) and industry standards (e.g., MSCI Low Carbon Indexes), we construct our measure of CEI as carbon dioxide (CO_2) emissions in units of tons scaled by a firm's total revenues (in $millions).[6]

[4]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 et al. (2020) found that institutional investors indeed consider climate risks to be important for their investment portfolios.

[5]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.

[6]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

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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 bonds' risk exposure. We rely on three unique factor models in our main analyses: the 5-factor model of Pastor and Stambaugh (2003), the 1-factor bond market model, and the 6-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 6-factor alpha ranging from 0.11% to 0.14%.

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 1-month-lagged bond return. The systematic risk proxies include the term beta, the default beta (Gebhardt, Hvidkjaer, and Swaminathan (2005a)), 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' CEI 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.

We conduct a battery of robustness tests to investigate the return predictability of CEI. Our results remain similar when we use different scopes of carbon emissions, changes in carbon intensity, or industry-level carbon intensity, when we exclude the most carbon-intensive industries, and when we perform portfolio analysis at the firm level. The low carbon alpha is also present in different subperiods, and is not driven by the period containing the global financial crisis. Furthermore, the negative relationship between carbon intensity and bond returns

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, Johnson, and Pioch (2020)).

remains highly significant when we use model-implied bond returns and returns to maturity as two alternative proxies of expected bond returns.

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. Both the "investor preference" and "investor underreaction" hypotheses can potentially explain the negative relation between carbon intensity and bond returns, but with different underlying mechanisms. We first test the "investor preference" hypothesis by examining whether a firm's CEI 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 over our sample period. However, the predictive power of carbon intensity for future bond returns remains significant after controlling for the contemporaneous and lagged changes in bonds' institutional ownership. This suggests that divestment from carbon-intensive assets cannot fully explain the outperformance of bonds from low carbon intensity firms.

We then conduct several tests to examine the plausibility of the "investor underreaction" hypothesis.[7] First, this hypothesis implies that the return predictability should be larger among bonds with higher information asymmetry, exhibiting greater underreaction to news, and in periods with low investor attention to climate change issues. We find evidence consistent with these cross-sectional and time-series predictions. Second, we directly test whether CEI predicts future firm fundamentals. We find 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 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 experience 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 article proceeds as follows: Section II reviews the literature and articulates different hypotheses and associated empirical predictions as motivated by recent theories. Section III describes the data and defines the variables used in our empirical analyses. Section IV presents the main results for the cross-sectional relationship between CEI and bond returns. Section V investigates the sources of the low carbon alpha in corporate bonds. Section VI concludes the article.

[7]The "investor underreaction" hypothesis could be particularly relevant for corporate bonds for two reasons. First, corporate bonds are much less liquid compared to stocks, which may hinder investors' ability to trade quickly and impound the fundamental information into bond prices. Second, previous studies suggest that there is market segmentation between the equity and bond markets (Gebhardt, Hvidkjaer, and Swaminathan (2005b)). Given the higher overall attention investors pay to the equity market, it is possible that fundamental information is first incorporated into stock prices and then gradually diffuse into corporate bond prices.

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II. Literature Review and Hypotheses Development

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

A. Related Literature and Contribution

Our study contributes to several strands of the literature. First, our article 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)). Evidence to date is still mixed.[8] Closely related to our article, Ilhan et al. (2021) find that uncertainty about climate policy, as proxied by carbon intensity, is priced in the options market.[9] Bolton and Kacperczyk (2021) document that stocks of firms with higher carbon emissions earn higher returns, although In et al. (2019) and Pástor, Stambaugh, and Taylor (2022) find the opposite evidence: green 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 article by Seltzer, Starks, and Zhu (2020) examines how state-level environmental regulations affect the credit ratings and yield spreads of corporate bonds. Our article differs from theirs, however, as we examine the relationship between expected bond returns and firm-level carbon risk, while Seltzer et al. (2020) use industry affiliation or broader measure of environmental performance.[10] This difference is important as Ochoa, Paustian, and Wilcox (2022) show that a firm's carbon intensity explains its stock price reaction to carbon tax news much better than its environmental scores from ESG ratings providers.

[8]Bansal et al. (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 et al. (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 (2023) construct firm-level climate change exposure using earnings call data and find an unconditional climate risk premium close to 0.

[9]Specifically, they use industry-level carbon intensity measure to proxy for climate policy uncertainty and show that the cost of option protection against downside tail risks is larger for firms in more carbon-intensive industries. We differ from their article by using firm-level carbon intensity and performing within-industry analysis.

[10]Specifically, their first measure is a dummy variable indicating whether the firm belongs to top polluting industries, which is an industry-level measure of climate regulatory risk. However, this industry measure ignores the significant heterogeneity in carbon intensity across firms in the same industry, as we show in Panel B of Figure A.1 in the Supplementary Material. Their second measure is a firm's environmental scores from Sustainalytics, which can capture many aspects of firm environmental performance (such as toxic pollution or biodiversity) other than carbon emissions and hence a noisier measure of climate regulatory risk.

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Our article 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 (2023)). Other studies 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 have better environmental performance (In et al. (2019), Pástor et al. (2022)). An emerging field examines the pricing of green bonds issued to finance environment-friendly projects.[11] Our study differs from that line of research by examining the impact of carbon emissions on the much larger corporate bond market.[12]

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 et al. (2005a), and Bali et al. (2021b)), liquidity risk (Lin, Wang, and Wu (2011)), bond momentum (Jostova, Nikolova, Philipov, and Stahel (2013)), 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' CEI (an increasingly important risk factor) is an incrementally important determinant of corporate bond returns.

B. Hypotheses Development

In this subsection, we develop different hypotheses based on recent theoretical works linking firm environmental performance to asset prices and expected returns (Pástor et al. (2021), Pedersen et al. (2021)).

Hypothesis 1. Carbon risk premium hypothesis: Corporate bonds issued by firms with higher carbon intensity are riskier and should earn higher average returns than bonds issued by firms with lower carbon intensity.

Our first hypothesis (Hypothesis 1) is naturally predicted by risk-based asset pricing theories. As carbon-intensive firms more likely lose value when climate

[11]See, e.g., Flammer (2021) and Larcker and Watts (2020) for the evidence on whether green bonds are priced at premium or not.

[12]A recent article by Diep, Pomorski, and Richardson (2022) find that ESG measures are not strongly related to future corporate bond excess returns. Their finding differs from ours, probably because they examine more broad ESG metrics over a different sample period.

[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.

policies become more stringent or consumers shift to green products, investors would demand higher expected returns for holding these riskier assets. Alternatively, theories based on limited risk-sharing also predict a positive relation between CEI and expected returns (Merton (1987)). As more investors divest from carbon-intensive assets, corporate bonds issued by carbon-intensive firms will have a more concentrated investor base, leading to limited risk sharing. If the extent of such divestment is high, one would expect to find a return premium for bonds issued by carbon-intensive companies.

Hypothesis 2. Investor preference hypothesis: Corporate bonds issued by firms with lower (higher) carbon emissions intensity perform better (worse) than expected if ESG concerns unexpectedly strengthen.

Our second hypothesis (Hypothesis 2) is motivated by the theoretical work of Pástor et al. (2021) 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 better ESG reputation makes a firm a safer investment, or if investors non-pecuniary value ESG, the equilibrium prediction is that high-ESG firms should obtain lower returns than their peers (this is the prediction of Hypothesis 1). 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.[14] This hypothesis is plausible as evidenced by the sharp rise in the number of institutional investors pledged to divest from fossil fuel companies.[15]

Hypothesis 3. Investor underreaction hypothesis: Corporate bonds issued by firms with lower (higher) carbon emissions intensity have higher (lower) risk-adjusted returns when investors underreact to the predictability of carbon intensity for firm fundamentals.

Our third hypothesis (Hypothesis 3) is motivated by Pedersen et al. (2021), who predict that securities with higher ESG ratings could earn higher abnormal returns when investors do not take into account the predictability of ESG ratings for future firm profitability. The key ingredient in their model is that ESG ratings play two roles by providing useful information about firm fundamentals and 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. However, if investors do not fully take into account the predictability of carbon intensity for firm fundamentals, higher ESG ratings should predict higher abnormal returns subsequently. In our context,

[14]Pástor et al. (2022) provide evidence that the outperformance of green stocks can be attributable to unexpectedly strong increases in environmental concerns in the recent period.

[15]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 (https://gofossilfree.org/divestment/commitments/).

this underreaction hypothesis would predict a negative relation between CEI and future bond returns. This hypothesis is plausible considering that carbon risk is not fully integrated by most bond investors and credit analysts during our sample period.[16]

III. Data and Variable Definitions

Our study utilizes several data sets including i) firm-level carbon emissions data, ii) corporate bond pricing data, and iii) data on institutional holdings of corporate bonds. We provide detailed descriptions on these data sets below.

A. 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 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.[17] Trucost reports carbon emissions in units of tons of CO_2 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. (2020), reported scope 1 and scope 2 emissions data are highly consistent across different data providers.[18] Trucost also reports the CEI for all three scopes, defined as the firm-level GHG emission in CO_2 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/CRSP Merged database. Graph A of Figure 1 shows the mean CEI (scopes 1–3) for the Fama–French 12 industries from 2005 to 2017. The top 3 industries with the highest scope 1 CEI

[16]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).

[17]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.

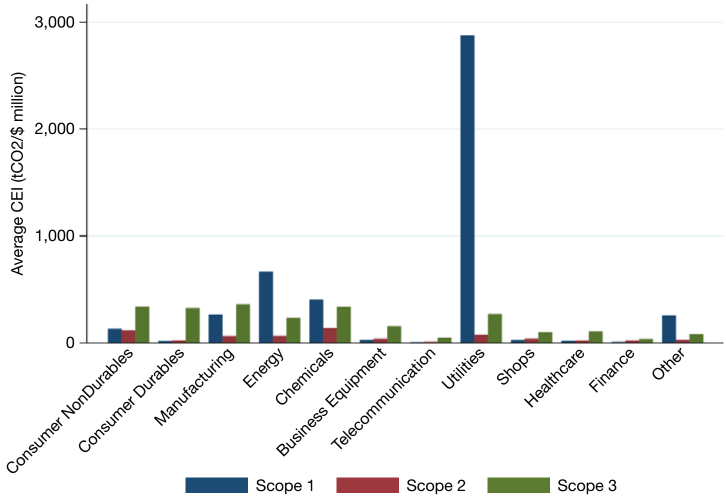
[18]The average correlations for the scope 1 and scope 2 data are 0.99 and 0.98, respectively, across the 5 providers (CDP, Trucost, MSCI, Sustainalytics, and Thomson Reuters). However, only two data providers, Trucost and ISS ESG, estimate scope 3 emissions.

FIGURE 1

Carbon Emissions Intensity

Graph A of Figure 1 depicts the average carbon emissions intensity (CEI) of three scopes by Fama–French 12 industries. Graph B depicts the average CEI of three scopes over time. The sample period is from 2005 to 2017.

Graph A. Average Carbon Emissions Intensity by Fama-French 12 Industries



Graph B. Average Carbon Emissions Intensity over Time

are utilities, energy, and chemicals, respectively.[19] Graph B of Figure 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.

Figure A.1 in the Supplementary Material plots the cross- and within-industry variations in CEI over time. Panel A of Figure A.1 in the Supplementary Material reports significant cross-industry variation, especially for scope 1 emissions. More

[19]In Section IV.C, we examine whether our results remain intact after we exclude the top 3 most carbon-intensive industries. We find similar results showing that the carbon premium applies to a broader category of industries, not just the most carbon-intensive industries.

importantly, our CEI measure exhibits significant cross-sectional variation even within the same industry, as shown in Panel B of Figure A.1 in the Supplementary Material. Overall, Figure A.1 in the Supplementary Material shows that CEI intrinsically varies across industries, and, as a result, we control for the industry effect in our empirical analyses.[20]

B. Corporate Bond Data and Bond Returns

We compile corporate bond pricing data from the enhanced version of the TRACE for the sample period from 2006 to 2019. The TRACE data set 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 by removing bonds that i) are not listed or traded in the U.S. public market or are not issued by U.S. companies; ii) are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked; iii) are convertible; iv) trade under \$5 or above \$1,000; v) have floating coupon rates; and vi) have less than 1 year to maturity. For intraday data, we also eliminate bond transactions that vii) are labeled as when-issued, are locked-in, or have special sales conditions; viii) are canceled, and ix) 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, Kahle, Maxwell, and Xu (2009).[21]

The corporate bond return in month t is computed as

$$r_{i,t} = \frac{P_{i,t} + \mathrm{AI}_{i,t} + \mathrm{COUPON}_{i,t}}{P_{i,t-1} + \mathrm{AI}_{i,t-1}} - 1, \tag{1}$$

where $P_{i,t}$ is the end-of-month transaction price, $\mathrm{AI}_{i,t}$ is accrued interest on the same day of bond prices, and $\mathrm{COUPON}_{i,t}$ 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 1-month Treasury bill rate.

[20]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. The transition matrix shown in Table A.1 in the Supplementary Material indicates that a firm's past CEI is a very informative predictor for its expected carbon intensity in future.

[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.

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%, 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]

C. 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

$$\text{INST}_{it} = \sum_j \left(\frac{\text{HOLDING}_{ijt}}{\text{OUTSTANDING\_AMT}_{it}} \right) = \sum_j h_{jt}, \tag{2}$$

where HOLDING_{ijt} is the par amount holdings of investor j on bond i at time t (from the eMAXX data), $\text{OUTSTANDING\_AMT}_{it}$ 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.

D. Standard Risk Factors

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

1. A *5-factor model with stock market factors*, including the excess return on the market portfolio, proxied for by the value-weighted CRSP index ($\text{MKT}^{\text{STOCK}}$), a size factor (SMB), a BM factor (HML), a momentum factor ($\text{MOM}^{\text{STOCK}}$),

[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.

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TABLE 1

Summary Statistics

Panel A of Table 1 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% 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					
	No. of Obs.	Mean	Median	Std. Dev.	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

and a liquidity risk factor (LIQ^{STOCK}), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003).

2. A *1-factor model with the bond market factor*, including the excess bond market return.[25]
3. A *6-factor model* that combines the five stock market factors described in the first factor model and the bond market factor described in the second factor model.

[25]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 1-month Treasury bill rate. 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.

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IV. Empirical Results

In this section, we first perform asset pricing tests to ascertain the predictive power of firms' CEI on the cross section of corporate bond returns. We start with univariate portfolio-level analyses presenting the average returns and alphas of CEI-sorted portfolios in Section IV.A. We then present the bond-level Fama–MacBeth regression results controlling for bond characteristics and exposures to systematic risk factors in Section IV.B. We conduct a battery of robustness checks in Section IV.C.

A. 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 CEI intrinsically varies 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.[26]

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 1-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 CEI 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$^{\text{STOCK}}$), the size factor (SMB), the BM factor (HML), the momentum factor (MOM), and the liquidity risk factor (LIQ), following Fama and French (1993), Carhart (1997),

[26]The corporate bond sample precludes us from using more granular industry classifications to control for the industry effect.

TABLE 2

Univariate Corporate Bond Portfolios Sorted by Carbon Intensity

In Panel A of Table 2, 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 CO_2 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 1-factor bond alpha, and the 6-factor alpha for each quintile. The last row reports the differences in monthly average returns and alphas for the quintile 5 and quintile 1 portfolios. The 5-factor model with stock market factors includes the excess stock market return (MKT^{STOCK}), the size factor (SMB), the BM factor (HML), the stock momentum factor (MOM), and the liquidity risk factor (LIQ). The 1-factor model includes the excess bond market return. The 6-factor model combines 5 stock market factors and the bond market factor. The average returns and alphas are defined in monthly percentage terms. Panel B reports the average bond 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 portfolio. Newey–West adjusted t-statistics are given in parentheses. *, **, and *** indicate 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	1-Factor Bond Alpha	6-Factor Alpha
Low	36.75	0.37	0.26	0.07	0.06
		(3.66)	(2.42)	(1.40)	(1.37)
2	153.18	0.35	0.24	0.05	0.04
		(3.42)	(2.31)	(1.23)	(0.98)
3	333.77	0.33	0.22	0.05	0.04
		(3.42)	(2.29)	(1.23)	(0.99)
4	518.59	0.31	0.21	0.03	0.02
		(3.28)	(2.14)	(0.69)	(0.40)
High	1127.34	0.23	0.13	−0.04	−0.06
		(2.51)	(1.30)	(−0.26)	(−0.96)
High − low		−0.14***	−0.13***	−0.11***	−0.12***
		(−2.62)	(−3.13)	(−2.19)	(−2.32)

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)

and Pastor and Stambaugh (2003). The third column of Table 2 shows that, similar to the average excess returns, the 5-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). As shown in the fourth and fifth columns, the return difference between the low- and high-CEI bonds remains significant using the bond market factor or the combined six stock and bond market factors.

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. Finally, similar to the findings in Panel B, the results in Table A.2 in the Supplementary Material show that firms with high CEI (i.e., quintile 5) yield a higher stock market beta and BM 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 fundamental performance of firms with different levels of CEI, Panel B of Table A.2 in the Supplementary Material 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 2 years older than firms with low CEI.[27]

B. Bond-Level Fama–MacBeth Regressions

In Section IV.A, 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.[28] 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:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \ln(\mathrm{CEI}_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} \mathrm{CONTROL}_{k,t} + \epsilon_{i,t+1}, \tag{3}$$

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 $\ln(\mathrm{CEI}_{i,t})$, which is the natural logarithm of firm-level CEI in June of each year t for firms with a fiscal year ending in year $t-1$. The term $\mathrm{CONTROL}_{k,t}$ denotes a set of control variables, including i) bond-level characteristics, such as the bond market beta ($\beta_{i,t}^{\mathrm{MKT}}$), downside risk proxied for by the 5% VAR ($\mathrm{VAR}_{i,t}$), bond-level illiquidity (ILLIQ), credit ratings (RATING), time-to-maturity (MATURITY), the bond amount outstanding (SIZE), and the 1-month-lagged bond return (LAG_RETURN); ii) systematic risk proxies, such as the default beta ($\beta_{i,t}^{\mathrm{DEF}}$), the term beta ($\beta_{i,t}^{\mathrm{TERM}}$), and the macroeconomic

[27]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.3 in the Supplementary Material presents significantly negative alpha spreads between the low- and high-CEI portfolios based on the 5-factor model of Fama and French (2015) and Q-factor model of houetal:2015, with a -0.13% per month (t-stat = -2.68) and -0.16% per month (t-stat = -2.81), respectively. The last 2 columns of Table A.3 in the Supplementary Material show that the alpha spreads are very similar when we augment these models with the bond market factors.

[28]We take the natural logarithm of CEI, because CEI has a highly skewed distribution, as shown in Table 1, where the mean of CEI is much higher than the median of CEI.

uncertainty beta ($\beta_{i,t}^{\mathrm{UNC}}$) following Bali, Subrahmanyam, and Wen (2021b); and iii) the climate change news beta ($\beta_{i,t}^{\mathrm{CLIMATE}}$), which measures the covariance between corporate bond returns and unexpected changes in climate change news index following Huynh and Xia (2021).[29] 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 $\ln(\mathrm{CEI})$ and the cross section of future bond returns. In column 1, the average slope $\lambda_{1,t}$ from the monthly regressions of excess returns on $\ln(\mathrm{CEI})$ 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 $\ln(\mathrm{CEI})$ between quintiles 5 and 1 is approximately 3.07, and multiplying this spread by the average slope of -0.046 yields an estimated monthly return spread of 14 basis points (bps).

Column 2 of 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 $\ln(\mathrm{CEI})$ remains negative and highly significant. In other words, controlling for bond characteristics does not affect the predictive power of CEI in the corporate bond market.

In column 3 of Table 3, we test 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. Importantly, the average slope coefficient for $\ln(\mathrm{CEI})$ 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 CEI for future bond returns.

The last specification in column 4 of Table 3 controls for all bond return characteristics, systematic risk, and climate change news betas. Similar to our findings in column 1, the cross-sectional relation between future bond returns and CEI is negative and highly significant. The negative average slope of -0.036 for $\ln(\mathrm{CEI})$ 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

[29]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 ($\beta_{i,t}^{\mathrm{CLIMATE}}$). We find that the correlation between $\ln(\mathrm{CEI})$ and β^{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.

TABLE 3

Fama–MacBeth Cross-Sectional Regressions

Table 3 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 CEI 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, and SIZE), downside risk, bond-level illiquidity, and 1-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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Univariate	Controlling for Bond Characteristics	Controlling for Systematic and Climate Change News Betas	Controlling for All Variables
	1	2	3	4
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

information about bond size, maturity, rating, liquidity, market risk, default risk, and climate change news risk. Thus, CEI is a strong and robust predictor of future bond returns.

C. Robustness Checks

1. Realized Versus Expected Bond Returns

Throughout our analyses, we use future bond returns as a proxy for expected bond return. This is motivated by the strand of equity literature in which realized stock returns are often used as a proxy for expected stock return, although we recently experience a revival of approaches using various forward-looking proxies

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of expected returns (e.g., Martin and Wagner (2019), Back, Crotty, and Kazempour (2022), and Chabi-Yo, Dim, and Vilkov (2022)). For the bond market, the standard procedure of using realized returns might distort the true expected return, since high returns now or next period should imply lower expected return until maturity. As a result, in Section A.2 of the Supplementary Material, we conduct two robustness checks for our main results by using i) model-implied bond returns and ii) returns to maturity as proxies for expected bond returns. As shown in Tables A.4 and A.5 in the Supplementary Material, the significantly negative relation between carbon intensity and expected bond returns remains.

2. Additional Robustness Checks

We conduct a battery of additional robustness checks in Section A.2 of the Supplementary Material. As shown in Section A.2 and Tables A.6–A.8 in the Supplementary Material. our results are robust to i) using different categories of carbon emission, ii) excluding the most carbon-intensive industries, iii) using orthogonalized CEI with respect to firm characteristics, iv) conducting the tests at the firm-level and industry-level, and v) conducting tests over different subperiods. Overall, the results indicate that the negative relation between carbon intensity and future bond returns is robust with alternative specifications.

V. Sources of Low Carbon Alpha

The results in Section IV show that bonds from firms with higher CEI *underperform* firms with lower CEI. This result, combined with the fact that bonds from high-CEI firms are riskier than those from low-CEI firms, indicates that the "carbon risk premium" hypothesis (Hypothesis 1) is not supported. In this section, we investigate whether the two alternative hypotheses can explain the low carbon alpha. First, we use the corporate bond institutional holdings data to test the investor preference hypothesis (Hypothesis 2) in Sections V.A.1 and V.A.2. We then test the "investor underreaction" hypothesis (Hypothesis 3) in Sections V.B.1–V.B.4.

A. Testing Investor Preference Hypothesis

1. Carbon Intensity and Corporate Bond Institutional Ownership

The investor preference hypothesis (Hypothesis 2) predicts that corporate bonds for firms with low (high) CEI perform better (worse) than expected if ESG concerns unexpectedly strengthen. Based on a survey about individuals' climate risk perceptions, Krueger et al. (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:

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$$\text{(4)} \quad \Delta\text{INST\_BOND}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \ln(\text{CEI}_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t}\text{CONTROL}_{k,t} + \epsilon_{i,t+1},$$

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 $\ln(\text{CEI}_{i,t})$, which is the natural logarithm of firm-level CEI in June of each year t, for firms with a fiscal year ending in year $t-1$. The term $\text{CONTROL}_{k,t}$ denotes a set of control variables, including bond-level characteristics, such as the bond market beta ($\beta_{i,t}^{\text{MKT}}$), downside risk, bond-level illiquidity, credit ratings, time-to-maturity, the bond amount outstanding (size), and the past 6-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 ($\beta_{i,t}^{\text{DEF}}$), the term beta ($\beta_{i,t}^{\text{TERM}}$), the macroeconomic uncertainty beta ($\beta_{i,t}^{\text{UNC}}$), and the climate change news beta ($\beta_{i,t}^{\text{CLIMATE}}$). To better interpret their economic significance, we standardize all independent variables in the cross section to have a mean of 0 and standard deviation of 1.

Panel A of Table 4 shows the results of changes in bonds' institutional ownership. Column 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 $\ln(\text{CEI})$ alone is -0.471 with a t-statistic of -3.66, implying a 1-standard-deviation increase in $\ln(\text{CEI})$ is associated with a 0.471% decrease in bonds' institutional ownership. This economic magnitude is translated into a 26.5% decrease in ΔINST_BOND relative to the average changes in bond's institutional ownership. Column 2 of Panel A shows that after we control for market risk (β^{BOND}), downside risk, illiquidity, credit ratings, maturity, size, and past 6-month cumulative bond return, the average slope coefficient for CEI remains negative and highly significant.

Column 3 of Panel A of Table 4 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 $\ln(\text{CEI})$ remains negative and highly significant, -0.489 (t-stat $= -4.51$), indicating that exposure to systematic or climate change news risks do not explain the predictive power of CEI for changes in institutional ownership. The last specification in column 4 controls for all bond return characteristics, systematic risk, and climate change news beta. Similar to our findings in column 1, the cross-sectional relation between ΔINST_BOND and CEI is negative and highly significant. The negative average slope of -0.226 on $\ln(\text{CEI})$ in column 4 represents a 12.6% decrease in ΔINST_BOND relative to the average changes in bond's institutional ownership, controlling for everything else.

2. Do Changes in Institutional Ownership Fully Explain the Low Carbon Alpha?

The results in Panel A of Table 4 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 can be fully explained by changes in institutional ownership through the divestment channel. Specifically, we replicate Table 3 in Panel B of Table 4, in which we

TABLE 4

Carbon Emissions Intensity, Institutional Ownership, and Corporate Bond Returns

Panel A of Table 4 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:

$$\text{INST}_{it} = \sum_j \left(\frac{\text{HOLDING}_{ijt}}{\text{OUTSTANDING\_AMT}_{it}} \right) = \sum_j h_{jt},$$

where HOLDING_{ijt} is the par amount holdings of institution j on bond i, $\text{OUTSTANDING\_AMT}_{it}$ 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, and SIZE), downside risk, bond-level illiquidity (ILLIQ), and past 6-month cumulative bond returns ($\text{RETURN}_{t-7:t-2}$). 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 (β^{CLIMATE}). To interpret their economic significance, all the independent variables in Panel A are standardized cross-sectionally to a mean of 0 and standard deviation of 1. Panel B replicates Table 3 by including additional controls of the contemporaneous and 1-year lagged 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Carbon Emission Intensity and Changes in Institutional Ownership

Dependent Variable = ΔINST_BOND	Univariate 1	Controlling for Bond Characteristics 2	Controlling for Systematic and Climate Change News Betas 3	Controlling for All Variables 4
ln(CEI)	−0.471*** (−3.66)	−0.211** (−2.65)	−0.489*** (−4.51)	−0.226** (−2.42)
β^{BOND}		0.312*** (5.18)		0.276*** (3.49)
DOWNSIDE_RISK (5% VAR)		−0.018 (−0.19)		−0.013 (−0.14)
ILLIQ		0.402** (2.29)		0.355** (2.29)
RATING		−0.725*** (−4.60)		−0.693*** (−4.75)
MATURITY		0.379*** (3.95)		0.343*** (3.76)
SIZE		−0.146 (−1.91)		−0.119 (−1.70)
$\text{RETURN}_{t-7:t-2}$		4.744*** (10.97)		4.738*** (10.97)
β^{DEF}			−0.144 (−0.72)	−0.089 (−0.55)
β^{TERM}			0.396 (1.63)	0.125 (0.65)
β^{UNC}			−0.328** (−2.34)	−0.189 (−1.61)
β^{CLIMATE}			−0.126 (−1.37)	−0.095 (−1.50)
INTERCEPT	−2.224*** (−4.12)	−2.098*** (−3.70)	−2.583*** (−4.41)	−2.112*** (−3.80)
Industry fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.016	0.277	0.033	0.280

(continued on next page)

TABLE 4 (continued)

Carbon Emissions Intensity, Institutional Ownership, and Corporate Bond Returns

Panel B. Carbon Emissions Intensity, Changes in Institutional Ownership, and Bond Returns

Dependent Variable = $\text{RETURN}_{t+1:t+12}$	Univariate 1	Controlling for Bond Characteristics 2	Controlling for Systematic and Climate Change News Betas 3	Controlling for All Variables 4
ln(CEI)	−0.035** (−2.35)	−0.026** (−2.29)	−0.029** (−2.31)	−0.031** (−2.36)
ΔINST_BOND	0.494 (1.15)	0.467 (1.62)	0.414 (1.31)	0.396 (1.38)
1-year lagged ΔINST_BOND	0.104 (0.46)	−0.111 (−0.32)	0.074 (0.29)	−0.059 (−0.18)
β^{BOND}		0.052 (0.55)		0.242 (1.44)
DOWNSIDE_RISK (5% VAR)		0.031** (2.24)		0.030 (1.23)
ILLIQ		0.018** (2.08)		0.017** (2.00)
RATING		0.025 (0.52)		0.023 (0.52)
MATURITY		0.002 (0.29)		0.001 (0.05)
SIZE		0.055 (1.29)		0.038 (1.11)
LAG_RETURN		−0.255*** (−7.53)		−0.265*** (−5.46)
β^{DEF}			0.017 (0.11)	−0.060 (−0.80)
β^{TERM}			−0.168 (−0.80)	−0.010 (−0.07)
β^{UNC}			−0.229 (−1.73)	0.280 (1.62)
β^{CLIMATE}			0.1937 (0.88)	1.173 (0.63)
INTERCEPT	0.503 (1.59)	0.004 (0.01)	0.275 (1.20)	0.004 (0.01)
Industry fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.065	0.273	0.132	0.292

include both the contemporaneous and lagged changes in bonds' institutional ownership (ΔINST_BOND) as additional controls,

$$(5)\quad R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \ln(\text{CEI}_{i,t}) + \lambda_{2,t} \cdot \Delta\text{INST\_BOND}_{i,t+1} + \lambda_{3,t} \cdot \Delta\text{INST\_BOND}_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \text{CONTROL}_{k,t} + \epsilon_{i,t+1},$$

where $R_{i,t+1}$ is the bond excess return from July of year t to June of year $t+1$. $\Delta\text{INST\_BOND}_{i,t+1}$ denotes contemporaneous changes in bonds' institutional ownership measured over the same time horizon as the dependent variable bond returns. To account for the possibility that bond prices may be stale and do not necessarily react to contemporaneous changes in ownership, we also include the 1-year lagged changes in institutional ownership, $\Delta\text{INST\_BOND}_{i,t}$, in the regression. We include the same set of control variables, $\text{CONTROL}_{k,t}$, 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 the contemporaneous and lagged changes in bonds' institutional ownership.

Panel B of Table 4 shows that the coefficients for ln(CEI) remain significantly negative for all specifications. After controlling for contemporaneous and lagged changes in institutional ownership, bond characteristics and systematic/climate change news betas, column 4 shows a coefficient of −0.031 (*t*-stat = −2.36) for ln(CEI), indicating that divestment from bond investors cannot fully explain the outperformance of low-CEI bonds shown in Table 3. The coefficient of −0.031 for ln(CEI) in Panel B of Table 4 is smaller than that of Table 3, −0.036 in column 4, representing a 14% reduction in the return spread once changes in institutional ownership is controlled for. However, the predictive power of CEI for future bond returns remains economically and statistically significant. In addition, Panel B of Table 4 shows that although the coefficients for contemporaneous ΔINST_BOND are positive, none of them is significant, and the adjusted R^2s are similar to those in Table 3, indicating that shifts in institutional demand do not have significant pricing impacts on corporate bonds.[30]

B. Testing Investor Underreaction Hypothesis

1. Subsample Analyses

The investor underreaction hypothesis (Hypothesis 3) implies that the return predictability should be more pronounced among bonds with higher information asymmetry. To test this hypothesis, Table 5 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, and bond-level illiquidity.[31]

Panel A of Table 5 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 6-factor alpha −0.16% (*t*-stat = −2.22) per month, compared to −0.09% (*t*-stat = −1.88) for large bonds. Similarly, Panels B–D show

[30]We conduct another robustness test in the Supplementary Material to examine whether ownership change by certain types of institutions can explain the negative return predictability of carbon intensity. We construct changes in ownership by three different types of institutional investors including i) mutual funds, ii) insurance companies, and iii) pension funds. As shown in Table A.9 in the Supplementary Material, the coefficients of ln(CEI) remain significantly negative across all specifications, indicating that divestment from bond investors cannot fully explains the negative relationship between carbon intensity and future bond returns.

[31]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. 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. 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 away bond misvaluations (Ivashchenko (2019)).

TABLE 5

Subsample Analyses: Univariate Corporate Bond Portfolios Sorted by Carbon Intensity

Table 5 replicates Table 2 for i) large and small bonds based on the median issuance size in Panel A, ii) investment-grade and non-investment-grade bonds in Panel B, iii) short- and long-maturity bonds based on the median time-to-maturity in Panel C, and iv) liquid and illiquid bonds based on the median bond-level illiquidity in Panel D, respectively.

Panel A. Large Bonds Versus Small Bonds

	SIZE > SIZE^{MEDIAN}		SIZE ≤ SIZE^{MEDIAN}	
	Average Return	6-Factor Alpha	Average Return	6-Factor Alpha
Low	0.32	0.03	0.39	0.06
	(3.35)	(0.90)	(3.62)	(1.38)
2	0.38	0.09	0.33	0.01
	(3.91)	(1.59)	(3.12)	(0.31)
3	0.29	0.00	0.36	0.05
	(3.07)	(0.07)	(3.54)	(1.34)
4	0.37	0.09	0.29	−0.02
	(4.03)	(2.13)	(2.74)	(−0.40)
High	0.22	−0.06	0.25	−0.11
	(2.24)	(−1.12)	(1.94)	(−1.60)
High − low	−0.10**	−0.09*	−0.15***	−0.16**
	(−2.21)	(−1.88)	(−2.81)	(−2.22)

Panel B. Investment-Grade Versus Non-Investment-Grade Bonds

	INVESTMENT_GRADE		NON_INVESTMENT_GRADE	
	Average Return	6-Factor Alpha	Average Return	6-Factor Alpha
Low	0.37	0.06	0.41	0.04
	(3.63)	(1.71)	(2.58)	(0.28)
2	0.36	0.08	0.44	0.09
	(3.86)	(2.26)	(2.89)	(0.93)
3	0.35	0.08	0.30	−0.10
	(3.87)	(2.47)	(1.73)	(−0.79)
4	0.35	0.09	0.34	−0.05
	(3.91)	(2.22)	(2.29)	(−0.53)
High	0.25	−0.02	0.14	−0.20
	(1.98)	(−1.20)	(0.82)	(−2.10)
High − low	−0.12**	−0.08	−0.27***	−0.24***
	(−2.17)	(−1.57)	(−3.54)	(−2.79)

Panel C. Short-Maturity Versus Long-Maturity Bonds

	1_YEAR < MATURITY ≤ 6_YEAR		MATURITY > 6_YEAR	
	Average Return	6-Factor Alpha	Average Return	6-Factor Alpha
Low	0.26	0.07	0.47	0.01
	(3.97)	(1.76)	(3.13)	(0.01)
2	0.25	0.08	0.47	0.02
	(3.75)	(1.88)	(3.16)	(0.25)
3	0.21	0.04	0.44	−0.02
	(3.31)	(1.19)	(2.99)	(−0.28)
4	0.20	(0.05)	0.40	−0.06
	(3.63)	(1.54)	(2.63)	(−0.70)
High	0.17	−0.02	0.31	−0.14
	(2.14)	(−0.51)	(2.08)	(−1.87)
High − low	−0.10**	−0.09**	−0.15**	−0.14**
	(−2.34)	(−1.98)	(−2.56)	(−2.27)

Panel D. Liquid Bonds Versus Illiquid Bonds

	ILLIQ ≤ ILLIQ^{MEDIAN}		ILLIQ > ILLIQ^{MEDIAN}	
	Average Return	6-Factor Alpha	Average Return	6-Factor Alpha
Low	0.37	0.08	0.43	0.02
	(4.07)	(1.72)	(3.27)	(0.42)
2	0.29	0.02	0.48	0.10
	(3.14)	(0.50)	(3.89)	(2.01)
3	0.32	0.06	0.34	−0.04
	(3.60)	(1.70)	(2.75)	(−0.61)
4	0.33	0.09	0.34	−0.07
	(4.34)	(1.81)	(2.45)	(−0.88)
High	0.28	0.03	0.21	−0.16
	(3.42)	(0.94)	(1.65)	(−2.50)
High − low	−0.09**	−0.05	−0.22***	−0.19***
	(−2.06)	(−1.40)	(−3.28)	(−3.15)

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 higher illiquidity.

Next, we focus on the subsample of bonds that exhibit greater underreaction to news. To that end, we conduct subsample tests based on the stock–bond momentum spillover effect, for which previous studies attribute to bond prices underreacting to firm fundamental information (Gebhardt et al. (2005b), Haesen, Houweling, and Zundert (2017)). We first run cross-sectional regressions of future bond returns on stock return momentum (e.g., cumulative stock returns from month $t-7$ to $t-2$) at the firm-level to obtain the cross-sectional coefficients γ, which captures the stock momentum spillover effect for corporate bonds. We then divide the sample into 2 groups using the median value of γ. Table A.10 in the Supplementary Material reports the portfolio returns and alphas of corporate bonds sorted by CEI within each of the 2 groups. Consistent with the prediction of the underreaction hypothesis, we find a much larger low carbon alpha for bonds with a greater stock–bond momentum spillover effect. For example, the monthly 6-factor alpha for the high-minus-low CEI portfolio is −0.31% (−0.11%) with a t-statistic of −2.62 (−1.96) for bonds with above (below) average stock–bond momentum spillover effect.

Another implication of the underreaction hypothesis is that we should observe a larger low carbon alpha using change in CEI as compared to the level of CEI, since the change in CEI is less likely to be anticipated by investors. Table A.11 in the Supplementary Material reports the alphas of quintile portfolios sorted by change in CEI, defined as the difference in a firm's CEI reported in year t and year $t-1$. Consistent with this conjecture, the alphas of the high-minus-low portfolios are more pronounced when we use change in CEI as compared to the level of CEI. For example, the 6-factor alpha is −0.16% (t-stat = −2.98) for the high-minus-low portfolio sorted by change in CEI, while the corresponding alpha is −0.12% (t-stat = −2.32) for the high-minus-low portfolio sorted on the level of CEI.

Finally, the underreaction hypothesis predicts that the return predictability of CEI should be weaker during periods when investors pay higher attention to climate change issues. To test this prediction empirically, we follow Choi, Gao, and Jiang (2020) and use the Abnormal Google Search Volume Index (ASVI) on the topics of "climate change" or "global warming" as proxies for investor attention to climate change.[32] Panel A of Table A.12 in the Supplementary Material 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 is signed in Dec. 2015 (Monasterolo and De Angelis (2020)). We thus conjecture that the low carbon alpha should be weaker in the post-Paris agreement period. Panel B of Table A.12 in the Supplementary Material reports the low-minus-high CEI portfolio returns over 2 subperiods: July 2006 to Dec. 2015 (Pre-Paris agreement) and Jan. 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 CEI portfolio return with unknown break date in Panel C of Table A.12 in the Supplementary Material. The test identifies Mar. 2016 as the structural break date, which aligns well with the time when Paris agreement was signed.

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 (Hypothesis 3). If this is the underlying channel, we expect that a firm's

[32] ASVI is calculated as the natural logarithm of the ratio of SVI to the average SVI over the previous 3 months. A positive (negative) value of ASVI is associated with an increase (decrease) in investor attention.

CEI 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 4 quarters ago divided by the standard deviation of this change in quarterly earnings over the prior 8 quarters. In our setting, we examine the predictability of CEI for future earnings surprises using SUE as the dependent variable and CEI as the primary explanatory variable. Specifically, we use the following regression specification:

$$\text{(6)} \qquad \text{SUE}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \ln(\text{CEI}_{i,t}) + \sum_{k=1}^{K} \lambda_{k,t} \text{CONTROL}_{k,t} + \epsilon_{i,t+1},$$

where $\text{SUE}_{i,t+1}$ 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 $\ln(\text{CEI}_{i,t})$, the natural logarithm of firm-level CEI in June of each year t, for firms with a fiscal year ending in year $t-1$. $\text{CONTROL}_{k,t}$ denotes a set of control variables, including a 1-quarter-lagged dependent variable, a 4-quarter-lagged dependent variable, firm size, the BM 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 6 report the regression results. The coefficient for $\ln(\text{CEI})$ is significantly negative for both specifications. With industry and quarter fixed effects in column 2, the coefficient for $\ln(\text{CEI})$ is -0.0128 (t-stat $= -2.19$), indicating that a 1-standard-deviation increase in $\ln(\text{CEI})$ 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 4 quarters ago divided by the standard deviation of this change in quarterly revenue per share over the prior 8 quarters. We use the same specification as in equation (6), except we replace SUE with SURGE, and use the same set of control variables. Columns 3 and 4 of Table 6 report the regression results. The coefficients for $\ln(\text{CEI})$ 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 4-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 (6)), except we replace SUE with CAR(-2, +1), and use the same set of control variables. Columns 5 and 6 of Table 6 report the regression results. The coefficients for $\ln(\text{CEI})$ are significantly negative for both specifications. With industry and

TABLE 6

Carbon Emissions Intensity and Cash Flow Surprises

Table 6 reports the panel regression of earnings/revenue surprises on firms' carbon emissions intensity. The dependent variable are earnings surprises (SUE), revenue surprises (SURGE), and earnings announcement return (CAR(−2, +1)). SUE is defined as the change in split-adjusted quarterly earnings per share from its value 4 quarters ago divided by the standard deviation of this change over the prior 8 quarters (4 quarters minimum). SURGE is defined as the change in revenue per share from its value 4 quarters ago divided by the standard deviation of this change over the prior 8 quarters (4 quarters minimum). CAR(−2, +1) is defined as cumulative abnormal return from 2 days before to 1 day after the earning announcement date (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), defined as the logarithm of carbon emissions intensity (scope 1) in the fiscal year ending in calendar year $t-1$. FIRM_SIZE is defined as the 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 for this table 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.

	SUE		SURGE		CAR (−2, +1)	
Variables	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)
LAGGED_DEPENDENT_VARIABLE	0.3259***	0.3237***	0.7441***	0.7394***	−0.0089	−0.0092
	(29.91)	(30.14)	(102.15)	(100.99)	(−1.14)	(−1.19)
LAGGED_DEPENDENT_VARIABLE	−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
No. of obs.	28,691	28,691	28,654	28,654	28,666	28,666

quarter fixed effects in column 6, the economic magnitude suggests that the spread in ln(CEI) between the quintiles 5 and 1 leads to a 15 bps lower market reaction around earnings announcements.

Overall, our finding that firms with higher CEI have lower earnings (revenue) surprise and a more negative earnings announcement 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

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when fundamental news is subsequently disclosed to the market via earnings announcements. Since bonds represent contingent claims on firms' cash flows and underlying assets, investors underreaction to the predictive power of CEI for firm fundamentals help explain the underperformance of high-CEI bonds.[33]

3. Carbon Emissions Intensity and Firm Creditworthiness

In Section V.B.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 (ΔRATING), and our key explanatory variable is firm-level CEI. Our regression specification is

$$(7)\qquad \Delta\text{RATING}_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\cdot\ln(\text{CEI}_{i,t}) + \sum_{k=1}^{K}\lambda_{k,t}\text{CONTROL}_{k,t} + \epsilon_{i,t+1},$$

where $\Delta\text{RATING}_{i,t+1}$ 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 indicates higher default risk or lower creditworthiness. $\text{CONTROL}_{k,t}$ denotes control variables, including lagged bond rating, firm size, the BM ratio, ROE, R&D, investment, 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 7 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's (1980) 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 (7)), except that we replace $\Delta\text{RATING}_{i,t+1}$ with $\Delta\text{O\_SCORE}_{i,t+1}$, defined as the 1-year ahead change in O-score relative to the most recent quarter before June of year t. We also replace lagged bond rating with lagged O-score in the list of controls. Column 2 of Table 7 show that firms with high carbon intensity experience an increase in the probability of financial distress subsequently.

[33]To examine whether the low carbon alpha, we document is fully explained by the underreaction of bond prices to earnings news documented in Nozawa, Qiu, and Xiong (2022), we conduct the back-of-envelope calculation as follows: First, Table 4 of Nozawa et al. (2022) reports that the coefficient of CAR $(-1,+1)$ is 0.069 when predicting corporate bond return over the following month. Combined with the coefficient estimates of ln(CEI) in Table 6, it suggests that the spread in ln(CEI) between quintiles 5 and 1 would predict a monthly bond return spread of 1.04 bps if the only reason why CEI predicts future bond returns is due to its predictability for future earnings news. Compared to the monthly bond return spread of 11 bps between the quintiles 5 and 1, the low carbon alpha implied by bond prices underreaction to earnings news is smaller. This suggests that the predictability of CEI for future bond returns does not only come from its predictability for future earnings news. In Table 7, we provide evidence that CEI also conveys information about the changes in default risk of the underlying firm, which is particularly important for determining bond returns.

TABLE 7

Carbon Emissions Intensity and Changes in Firm Creditworthiness

Table 7 reports the panel regression of changes in firm creditworthiness on firm-level carbon emissions intensity. In column 1, the dependent variable is ΔRATING, 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, with 1 referring to an AAA rating and 21 referring to a C rating. A higher numerical score implies lower creditworthiness. In column 2, the dependent variable is the firm's ΔO_SCORE, defined as the 1-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 logarithm of carbon emissions intensity (scope 1) in the fiscal year ending in calendar year $t-1$. RATING_t and O_SCORE_t represent the most recent bond credit rating and firm O-score before June of year t, respectively. 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 ΔRATING 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 at bond level in column 1 and firm level in column 2. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	ΔRATING	ΔO_SCORE
Variables	1	2
ln(CEI)	0.0371***	0.0087*
	(4.19)	(1.78)
RATING_t	−0.2667***	
	(−37.12)	
O_SCORE_t		−0.2125***
		(−15.91)
FIRM_SIZE	−0.0681***	−0.0726***
	(−5.34)	(−8.77)
BM	0.3969***	0.0453
	(22.44)	(1.54)
ROE	−0.2649***	−0.1584**
	(−6.42)	(−2.50)
R&D	−0.0726***	−1.0587***
	(−3.04)	(−4.61)
INVESTMENT	−2.3565***	0.0825
	(−2.78)	(1.53)
OCF	0.3205***	0.0004
	(2.67)	(0.00)
INST_STOCK	−0.1328***	−0.0710*
	(−3.94)	(−1.66)
CONSTANT	3.5292***	1.3432***
	(10.82)	(6.95)
Bond FEs	Yes	–
Industry FEs	–	Yes
Year FEs	Yes	Yes
Adj. R^2	0.312	0.182
No. of obs.	43,485	4,500

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.[34]

[34]The results in Sections V.B.2 and V.B.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 higher leverage ratio, compared to those with low leverage ratio, given that firms with higher leverage ratio more likely fall into financial distress when experiencing deteriorating fundamentals. Consistent with this prediction, Table A.13 in the Supplementary Material shows significantly negative return and alpha spreads between the low- and high-CEI portfolios for highly levered firms, in the range of −0.31% per month (t-stat = −2.57) and −0.60% per

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4. 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. As our corporate bond sample is only a subset of the stock sample, we separately examine the stock return predictability of CEI for all publicly traded firms and firms with corporate bonds.

Panel A of Table 8 reports the average returns and alphas for quintile portfolios sorted on firm-level CEI over the period from July 2006 to June 2019. The asset

TABLE 8

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 CO_2 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 of Table 8 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 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 significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2006 to June 2019.

	All Stocks						Stocks with Bonds				
	Average CEI	Average Return	FFCPS Alpha	FF 5-Factor Alpha	*Q*-Factor Alpha		Average CEI	Average Return	FFCPS Alpha	FF 5-Factor Alpha	*Q*-Factor Alpha
Panel A. Full Sample: July 2006–June 2019											
Low	20.69	0.93	0.11	0.05	0.17	Low	17.44	1.03	0.27	0.24	0.30
		(2.22)	(1.46)	(0.49)	(1.34)			(2.77)	(3.00)	(2.20)	(2.81)
2	57.52	0.83	0.08	0.03	0.11	2	64.27	0.96	0.22	0.16	0.30
		(2.11)	(1.13)	(0.35)	(1.35)			(2.06)	(1.44)	(0.87)	(1.70)
3	186.24	0.79	0.00	−0.03	0.03	3	168.94	0.95	0.26	0.25	0.28
		(1.92)	(0.02)	(−0.31)	(0.36)			(2.49)	(2.08)	(1.85)	(2.08)
4	417.12	0.84	0.07	0.02	0.12	4	453.75	0.90	0.13	0.10	0.25
		(2.05)	(0.95)	(0.26)	(1.18)			(1.93)	(0.81)	(0.59)	(1.27)
High	1,149.57	0.71	−0.14	−0.16	−0.07	High	1,218.84	0.69	−0.14	−0.28	−0.15
		(1.56)	(−0.85)	(−0.88)	(−0.41)			(1.67)	(−0.90)	(−1.69)	(−0.84)
High − low		−0.22*	−0.25*	−0.20	−0.24*	High − low		−0.33**	−0.41***	−0.53***	−0.46***
		(−1.74)	(−1.83)	(−1.39)	(−1.72)			(−2.38)	(−2.79)	(−3.20)	(−2.81)
Panel B. Subsample: Jan. 2010–June 2019											
Low	17.99	1.13	0.02	−0.03	−0.02	Low	14.89	1.21	0.16	0.10	0.13
		(4.31)	(0.33)	(−0.38)	(−0.23)			(4.14)	(1.57)	(1.04)	(1.46)
2	50.91	1.05	0.02	−0.03	−0.00	2	51.77	1.10	0.21	0.06	0.12
		(3.82)	(0.27)	(−0.46)	(−0.06)			(3.97)	(1.33)	(0.44)	(0.79)
3	166.20	1.04	−0.01	−0.08	−0.06	3	149.26	1.19	0.23	0.21	0.22
		(3.28)	(−0.07)	(−0.76)	(−0.55)			(3.81)	(1.41)	(1.28)	(1.41)
4	397.91	1.06	0.06	−0.04	−0.01	4	418.06	1.14	0.18	0.08	0.07
		(4.28)	(0.91)	(−0.58)	(−0.09)			(4.17)	(1.45)	(0.73)	(0.64)
High	1,088.19	0.80	−0.27	−0.38	−0.33	High	1,146.58	0.80	−0.27	−0.52	−0.48
		(2.46)	(−2.25)	(−2.70)	(−2.34)			(2.39)	(−1.66)	(−2.93)	(−2.35)
High − low		−0.34**	−0.29**	−0.35**	−0.31**	High − low		−0.41***	−0.43***	−0.63***	−0.62***
		(−2.53)	(−2.61)	(−2.31)	(−2.21)			(−2.74)	(−2.86)	(−3.58)	(−3.11)

pricing models we use include FFCPS model,[35] Fama and French (2015) 5-factor model, and the Hou et al. (2015) *Q*-factor models. Consistent with our bond-level results, 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 firms with higher leverage ratio. In Panel B, we conduct portfolio analysis over the subperiod of Jan. 2010 to June 2019. Consistent with In et al. (2019), the low carbon alpha is larger 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.

Our stock-level results in Table 8 differ from Bolton and Kacperczyk (2021) who document that firms with higher levels of carbon emissions earn higher stock returns, but are consistent with the findings in In et al. (2019) and Pástor et al. (2022). There are two main differences in empirical specifications between our article and Bolton and Kacperczyk (2021). First, Bolton and Kacperczyk (2021) examine the *contemporaneous* relation between the level of carbon emissions and stock returns, while we investigate the predictability of carbon intensity for *future* stock returns. Second, the main measures of carbon emissions are different. While they use the level of carbon emissions as the main measure of carbon risk, we focus on CEI, a more commonly used metric of carbon risk by both practitioners (e.g., MSCI Low Carbon Indexes) and academic studies.[36]

To better understand and reconcile our main findings with those of Bolton and Kacperczyk (2021), we follow the exact specifications of Bolton and Kacperczyk (2021) and conduct panel regressions of stock returns on different measures of carbon emissions, including i) the logarithm of carbon emissions level ($\ln(CO_2)$), ii) the changes in the logarithm of carbon emissions level ($\Delta\ln(CO_2)$), iii) CEI (scaled by 100), and iv) the logarithm of CEI (ln(CEI)). Table A.14 in the Supplementary Material reports results using contemporaneous stock return as the dependent variable, whereas Table A.15 in the Supplementary Material uses future stock returns. As shown in Table A.14 in the Supplementary Material, we are able to replicate the main findings in Bolton and Kacperczyk (2021) when exactly following their approach using similar measures and methodology. Specifically, in column 1, we find a significant and positive coefficient of $\ln(CO_2)$, which is consistent with the positive carbon risk premium documented in Panel A of Table 8 of Bolton and Kacperczyk (2021). In column 2, we use $\Delta\ln(CO_2)$ and also find a significant and positive coefficient, consistent with Panel B of Table 8 of Bolton and Kacperczyk (2021) that documents a positive relation between growth in carbon emission and contemporaneous stock returns. In column 3, we use CEI and find its coefficient to be insignificant. This result is consistent with Panel C of Table 8 of

month (t-stat = −3.24). In contrast, the low carbon alpha is insignificant among firms with below-the-median leverage.

[35]The FFCPS model is the Fama and French (1993) three factors plus the Carhart (1997) momentum factor and the Pastor and Stambaugh (2003) liquidity factor.

[36]Several published studies use intensity-based measures of emissions, including Ilhan et al. (2021), Ehlers, Packer, and de Greiff (2022), Hsu et al. (2023), etc.

Bolton and Kacperczyk (2021) that documents an insignificant relation between carbon intensity and contemporaneous stock return. However, the insignificant coefficient of CEI is due to the highly skewed distribution of CEI, as shown in Table 1 and Figure A.2 in the Supplementary Material.[37] Column 4 of Table A.14 in the Supplementary Material shows that once we take the logarithm of CEI, the relation between carbon intensity and contemporaneous stock returns becomes significantly negative.

Table A.15 in the Supplementary Material presents a different picture when we change the dependent variable to future stock returns, while keeping all independent variables the same. The results show an insignificant relation between the level of carbon emissions (ln(CO_2)) and future stock returns, but a significantly negative relation between carbon intensity (ln(CEI)) and future stock returns, which is consistent with our portfolio analysis in Table 8.[38]

Finally, we conduct similar analyses using bond returns. In Table A.16 in the Supplementary Material, we run Fama–MacBeth regressions of contemporaneous bond returns on different measures of carbon emissions. The results show a significantly negative relation between the logarithm of carbon intensity (ln(CEI)) and contemporaneous bond return, but this relation is insignificant for the level and growth rate of carbon emissions. Table A.17 in the Supplementary Material reports Fama–MacBeth regression results with future bond returns as the dependent variable. We find a strong negative relation between ln(CEI) and future bond return, consistent with our main findings.

Overall, the above comparison suggests that the difference between our article and Bolton and Kacperczyk (2021) is mainly driven by whether one uses the level of carbon emission or carbon intensity as the measure of carbon risk. The relationship between carbon intensity and stock/bond return is always negative and significant, regardless of whether we examine the contemporaneous or predictive relation. These findings support the notion that both bond and stock investors underreact to the predictability of carbon intensity for firm fundamentals.

VI. 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 article is one of the first in the literature to explore whether a firm's carbon risk, as measured by its CEI, is priced in the cross section of corporate bond returns. Contrary to the "carbon risk premium"

[37]Figure A.2 in the Supplementary Material plots the kernel density estimates of CEI (Panel A) and ln(CEI) (Panel B). This is why we take the logarithm of CEI when we use it as the independent variable of interest in a regression setting, since ln(CEI) is closer to a normal distribution, as shown in Panel B of Figure A.2 in the Supplementary Material.

[38]Note that the portfolio sorting result would be the same whether we use carbon emission intensity (CEI) or its log transformation as the sorting variable. However, it will make a difference using regression approach. It suggests the importance of taking into account of the skewed distribution of the CEI variable in a regression setting. Although Bolton and Kacperczyk (2021) report an insignificant relationship between CEI and stock returns using panel regressions, their article never report the corresponding portfolio sorting results using CEI.

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 news, 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 regulatory policies and financial stability.

Supplementary Material

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