Who benefits from the bond greenium?*

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Preliminary - Comments are welcome!

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Abstract

Do green firms fully benefit from lower yields than brown firms? Or instead, do financial intermediaries pocket in part of the greenium? We study these issues focusing on US firms active in the bond market from 2005 to 2022. We show that the greenium is lower on the primary than on the secondary bond market. This main result is robust to a wide variety of robustness checks. Underwriting dealers capture around 80% of the greenium. Based on a theoretical model, we document two channels for this finding related to uncertainty on investors' future climate concerns and to a lack of competition among dealers. Microstructure frictions in the bond primary market appear to decrease the financial incentives for firms to become greener.

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1 Introduction

The corporate sector is the largest source of carbon dioxide (CO2) and other greenhouse gas emissions (CDP, 2017). The Intergovernmental Panel on Climate Change in its latest report, (IPCC, 2021), indicates that net carbon emissions must be reduced to zero by 2050 in order to limit global warming. An international regulation would be needed to align corporate interest to the common good but it is hard to achieve and absent at the time of writing. In this context, financial markets can provide firms with incentives to decrease emissions via investors' divestment or boycotts that can affect asset prices and the cost of capital (for theoretical analyses, see, e.g., Heinkel, Kraus, and Zechner (2001); Pastor, Stambaugh, and Taylor (2021); Gollier and Pouget (2022); Zerbib (2022); Broccardo, Hart, and Zingales (2022); Avramov, Cheng, Lioui, and Tarelli (2022); Edmans, Levit, and Schneemeier (2022).[1]

Do green firms with low carbon emissions benefit from the bond greenium and thus enjoy a lower cost of capital than brown firms? Or instead, do financial intermediaries on the primary market reap part of the greenium in the form of higher returns on their intermediation activities at issuance? We address these issues by comparing the greenium on primary and secondary bond markets. The primary market, in which firms issue financial assets, is the only point at which green firms can directly benefit from investors' willingness to support green over brown projects in the form of a lower cost of capital. However, unlike treasuries, where the primary allocation is determined by an auction that is open to the public, the allocation of corporate bonds is intermediated by the underwriting dealers, similar to the standard practice for equity market initial public offerings (IPOs) (Bessembinder et al., 2020). It is thus not clear that firms fully benefit from investors' green preferences. We focus on the corporate bond market because bonds are an important source of financing for firms. According to the SIFMA (2023), US bond issuance in 2022 mounted to $1,356 billion versus $160 billion for the US equity markets.

[1]For recent review papers on climate finance, see Hong, Karolyi, and Scheinkman (2020) and Giglio, Kelly, and Stroebel (2021), and on sustainable finance, see Edmans and Kacperczyk (2022).

Using a sample of 325 US firms active in the bond market from 2005 to 2022, we establish our main result: the greenium appears lower on the primary market than on the secondary market.[2] Our main specification features a cross-sectional analysis which compares, for a given firm at a given bond issuance date, the greenium on the primary market to the greenium on the secondary market for bond(s) of the same firm that were issued before. Our main result also holds in the time series, comparing bonds' greenium evolution over time from issuance on the primary market to trading in the secondary market.

Our estimates indicate that financial intermediaries pocket in around 80% of the greenium, leaving green firms with only around 20% of the potential decrease in the cost of capital they could get if investors were more directly participating in the primary market. Indeed, in the primary market, we estimate a difference in yield of 6 basis points between green and brown firms, i.e., firms with Scope 1 and 2 carbon emissions one standard deviation below and above average, respectively. On the secondary market, the difference in yield between green and brown firms is around 35 basis points. According to our analyses, the greenium appears stronger and more statistically robust on the secondary than on the primary bond market. Back of the envelop computations suggest that firms that are more than one standard deviation below average in terms of carbon intensity overall missed, in 2022, $295 million in issuance revenues compared to what they could have had if primary and secondary markets were featuring the same greenium.[3]

[2]The presence of a greenium, especially strong on the secondary bond market, echoes findings in the experimental finance literature suggesting that subjects in investment situations are willing to sacrifice expected returns in exchange for a responsible firm's conduct, see, Riedl and Smeets (2017); Bonnefon, Landier, Sastry, and Thesmar (2022); Brodback, Guenster, Pouget, and Wang (2022); Humphrey, Kogan, Sagi, and Starks (2022). These papers link this phenomenon to pro-social tastes or social norms. In the present paper, we are agnostic as to why a greenium arises in the corporate bond market. It may be due to taste, norm or reputation issues, but it may also be due to differences of opinion across investors who may disagree on the level of riskiness of green versus brown firms, see, e.g., Hong and Stein (2003) for a model of financial markets with differences of opinion. We summarize all these different motives for favoring green assets under the umbrella term of green preferences, keeping in mind that these preferences may arise from tastes or from beliefs.

[3]This number, $295 million, comes from the following computation: $1,356 billion, i.e., bond amount issued in 2022, times 0.15, i.e., top 15% of firms in terms of carbon efficiency (corresponding to the percentage of observations one standard deviation above the mean for normal distributions), times 14.5 basis points, i.e., the difference between the yield of a top 15% firm in terms of carbon efficiency on the secondary and on the primary market.

Additional analyses enable us to refine our main results. We illustrate our main findings in a time-series analysis; we show that shocks to climate change concerns (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022) affect bond spreads without affecting our results; our results are strong for both high-yield and investment-grade bonds; they are strong for high carbon intensity industries and, when we split our sample period in two, for both the old and the recent period; our results stay strong when we use absolute CO2 emissions, as opposed to intensity measure. Our results are robust if we use different liquidity measures, and they are stronger the more precise are the CO2 emissions, they hold if we use an additional lag for CO2 emissions (Zhang, 2023) and if we use different winsorizations. Moreover, our results hold if we use two-digit industry fixed effects or firm fixed effects as opposed to one-digit industry fixed effect.

Based on a stylized theoretical model, we study two potential economic forces underlying our main result. The part of the greenium pocketed in by financial intermediaries appears related i) to uncertainty regarding investors' future climate concerns and ii) to a lack of competition among underwriting dealers. These two effects appear equally important in driving our main result. The uncertainty channel echoes the findings of (Avramov, Cheng, Lioui, and Tarelli, 2022) on ESG ratings uncertainty and (Pastor, Stambaugh, and Taylor, 2022) on demand shocks.[4]

The main implications of our investigation are fourfold. First, the impact of investors with green preferences on firms' financial incentives to become green is lower than one may think by looking at secondary market outcomes. Second, uncertainty regarding investors' future climate concerns is detrimental to these incentives. Third, lack of competition among underwriting bond dealers can further harm these incentives. Fourth, green investors should try and participate more directly in primary bond markets in order to increase their impact on firms' financial incentives to become green. Thus, as major holders of corporate bonds, insurance and pension firms can further increase the financial incentives to become green if they directly participate in

[4]See also the model of developed by (Avramov, Lioui, Liu, and Tarelli, 2022).

the primary bond markets.

Our main finding complements the results of Seltzer, Starks, and Zhu (2022) who show that corporate bond credit ratings and spreads react to issuing firms' environmental profile, especially when environmental regulations are strictly enforced. It also bridges a gap with the literature on secondary equity markets: a growing number of papers using implied cost of capital measures identify the presence of a greenium (see, Chava (2014); Pastor, Stambaugh, and Taylor (2022); Hege, Pouget, and Zhang (2023)).[5]

There are two last strands of literature that are related to our work. First, there are a number of empirical papers on the corporate bond market microstructure, see, e.g., Goldstein, Hotchkiss, and Nikolova (2021) on bond dealers' trading; Nikolova and Wang (2022) on flipping; Nagler and Ottonello (2021) on parking; Helwege and Wang (2021) on mega-bond issues; Hendershott, Li, Livdan, and Schürhoff (2019) on secondary market trading networks; Dick-Nielsen, Feldhütter, and Lando (2012); Bao, O'Hara, and Zhou (2018); Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018); Dick-Nielsen and Rossi (2019) on cost of liquidity provision; Cai, Helwege, and Warga (2007) on bond issuance underpricing. Our focus is different and complementary to these papers since we study the greenium and how it is affected by various market microstructure issues.

Second, there is a growing literature on green bonds; see, e.g., Zerbib (2019) on green bonds issued by a variety of supranational, sovereign, municipal and corporate institutions; Tang and Zhang (2020) on the stock price reaction to green bond issuance, Flammer (2021) on corporate green bonds, Baker, Bergstresser, Serafeim, and Wurgler (2018) on municipal green bonds, Pastor, Stambaugh, and Taylor (2022) on sovereign green bonds, Daubanes, Mitali, and Rochet (2022) on the reasons why firms issue green bonds. We study the pricing of bonds issued by firms with various carbon emissions' profiles and study the greenium on primary and secondary

[5] Another stream of literature uses average realized returns as a measure of expected returns, and offers mixed evidence on the existence of a greenium in secondary equity markets, see, e.g.,In, Park, and Monk (2019); Bolton and Kacperczyk (2021, 2023); Zhang (2023); Aswani, Raghunandan, and Rajgopal (2022).

markets to evaluate the direct financial incentives to become greener firms receive from financial markets.

2 Method

2.1 Identification Strategy

Our main coefficient of interest is the sensitivity of bond spreads to CO2 emissions, both on the primary and on the secondary bond markets. Estimation of this coefficient can potentially be affected by three main econometric issues.

The first issue arises from calendar day effects. Bond issuance dates may be different from dates of bond trading in the secondary market. Calendar dates are thus naturally correlated with whether a particular observation belongs to the primary market or the secondary market. Moreover, price sensitivity to the CO2 emission can vary across days. Ardia, Bluteau, Boudt, and Inghelbrecht (2022) construct the Media Climate Change Concerns (MCCC) index and show that its unexpected time-series variations are positively correlated with changes in equity prices at the daily level (see Pastor, Stambaugh, and Taylor (2022) for evidence at the monthly level). Calendar date fixed effects will not address this issue because they would only deal with the impact of particular days on the level of bond spreads.

The second potential issue is related to liquidity effects. The corporate bond market is much less liquid than the equity market. Various papers document the presence of liquidity effects and liquidity risk on bond markets (Lin, Wang, and Wu, 2011; Helwege, Huang, and Wang, 2014; Helwege and Wang, 2021; Dick-Nielsen, Feldhütter, and Lando, 2012; Bao, O'Hara, and Zhou, 2018). Primary market and the secondary market have different market liquidity and the differential market liquidity, one might argue, could have caused the different price sensitivity to the CO2 emission.

Lastly, it is well known that credit risk impacts bond spreads. It is challenging to empirically study this impact because credit risk is not directly observable. Credit ratings are one of the best available proxies for credit risk but their validity is far from perfect. For this reason, a number of papers (Helwege and Turner, 1999; Eom, Helwege, and Huang, 2004; Teixeira, 2007) take structural approaches. Firms could have different credit risk when they issue new bonds and when they do not. Such different credit risk, one might argue, could induce different spread sensitivities to CO2 emissions between the primary market and the secondary market.

In order to address these issues, we devise an identification strategy that mimics as closely as possible the ideal strategy of comparing identical bonds that differ only in one dimension, i.e., the market in which they are trading (primary vs. secondary market). In our main analysis, we thus consider all the dates at which firms have issued bonds. On these dates, we collect data from the bonds newly issued on the primary market and data from the bonds of the same firms issued in the past and trading on the secondary market on the issuance days. For instance, on March 12th, 2022, firm A issues bond A1. Moreover, firm A issued another bond, A2, on Nov 1st, 2020, and A2 was traded on March 12th, 2022, on the secondary market. We estimate A1's offering spread sensitivity to CO2 emissions on the primary market and A2's spread sensitivity to CO2 emissions on the secondary market, on March 12th, 2022, controlling for firm, bond and market characteristics. Our main analysis thus only includes in our primary market sample bonds issued by firms that have already issued bonds in the past.

We therefore mitigate the three potential econometric issues discussed above: calendar day and credit risk issues because we compare primary and secondary markets on the same days for the same firms, controlling for market liquidity. Our main methodology is thus a cross-sectional analysis with samples paired by firms. We offer various robustness tests to show that our results also hold in a time-series analysis. Moreover, in order to avoid potential liquidity spillovers from one market to the other, we also run analyses in which secondary market spreads are not measured on the issuance dates but one day before or after these dates.

2.2 Data Construction

We use four different data sources to construct our main data. We first use S&P Global Trucost to get data on corporate greenhouse gas emissions. We rely on Mergent FISD to obtain data on corporate bond characteristics. We get secondary market prices and trading volume data from TRACE. Lastly, we use COMPUSTAT/CRSP to get data on firm characteristics and stock returns. Our main data sample spans eighteen years, from January 2005 to March 2022. We account for inflation by converting all nominal dollar amounts into 2020 dollars.

We closely follow Bolton and Kacperczyk (2021) and Seltzer, Starks, and Zhu (2022) to set up our measures of a firm's environmental profiles regarding climate change. We use firms' Scope 1 and Scope 2 carbon emissions provided by Trucost. Scope 1 refers to carbon emitted by entities that are owned or controlled by the firm. Scope 2 refers to carbon emitted by the firm's energy suppliers. We leave aside Scope 3 emissions because they are much more difficult to measure or estimate. We sum up scope 1 and scope 2 carbon emissions to get total carbon emissions. We thus have three complementary measures of carbon emissions. We use them to compute a firm's carbon intensity as the ratio of carbon emissions on sales' revenue. Our main analysis favors carbon intensity over absolute carbon emissions for three reasons highlighted by Aswani, Raghunandan, and Rajgopal (2022). First, carbon intensity is closely related to energy efficiency, an important element to reduce the social cost of the current energy transition. Second, climate regulations are likely to affect firms independently from their size. For instance, a large firm that pollutes a lot may pay a high carbon tax but, if it has large revenues, it can be spread the tax over a large income. Finally, investors when tilting their portfolios towards climate-friendly firms are also unlikely to let their ranking of firms be affected by size. Nonetheless, we use the log of absolute carbon emissions in robustness analyses.

We use Mergent FISD database to obtain bond-level data on corporate bond characteristics and credit ratings (by Moody's). The bond characteristics include a flag indicating that the bond is redeemable under certain circumstances, maturity in years, and the total amount issued (logged).

As typically done in the literature, we transform the letter ratings to a numerical value so that the lowest rating ("C") is assigned 1 and one notch increase gets a number larger by 1, leading the highest rating ("Aaa") to be assigned 21.

Moreover, using offering terms available from Mergent FISD database, we define offering spread as the difference between a bond's offering yield and the yield of a cash flow-matched synthetic Treasury bond. The discount rates of varying maturities derive from the U.S. Treasury yield curve provided by Gurkaynaka, Sack, and Wrightc (2007).

We use secondary market outcomes from TRACE to construct an illiquidity measure. We follow Amihud (2002); Lin, Wang, and Wu (2011) to construct Amihud's illiquidity measure as follows:

$$ILLIQ_{i,t} = \frac{|r_{i,t}|}{Vol_{i,t}},$$

where $r_{i,t}$ is the daily return between the last day with a transaction and day t, computed on median daily prices, and $Vol_{i,t}$ is the average trading volume across these days in million dollars.[6]

We use trading data from TRACE and bond characteristics data from Mergent FISD to construct bond spreads on the secondary market. We calculate a bond's daily yield as the trading-volume weighted average of the reported yields in a given day. Then, we use a similar approach as above to construct the yield of a cash flow-matched synthetic Treasury bond. We subtract the latter from the former to get corporate bond spreads on the secondary market.

For our main analysis, we impose two data filters. First, as pointed out in Aswani, Raghunandan, and Rajgopal (2022), some of reported CO2 emissions were estimated by the data vendor and these estimated CO2 emissions can potentially bias our empirical estimates. Thus, we closely follow Aswani, Raghunandan, and Rajgopal (2022) to exclude those emissions that are

[6] In studying liquidity risk in corporate bond returns, Lin, Wang, and Wu (2011) used two measures, introduced by Amihud (2002) and by Pastor and Stambaugh (2003), at monthly frequency. Pastor-Stambaugh measure is appropriate to construct an illiquidity measure at monthly frequency while our main analysis is at the daily level. We thus use only the Amihud measure.

estimated. More specifically, we exclude all the data with precision level 1 (See Table A7 for exact definitions of different levels of precision). The second filter relates to the seniority of the bonds. In our sample, there are 6 possible different types of seniorities: senior secured, senior, senior subordinate, subordinate, junior, and junior subordinate. Given that over 96% of the bonds in our sample are senior bonds, we restrict our sample to only senior bonds. Nonetheless, we show that our results are robust to these two data filters in Table A4.

2.3 Summary Statistics

Our data sample covers 4,579 bond issues from 325 unique US firms. In order to limit the impact of outliers, similar to Bolton and Kacperczyk (2021), we winsorize all the variables at top and bottom 1%.[7]

Insert Table 1

The related summary statistics are shown in Table 1. The natural log of carbon emissions indicate that Scope 1 and 2 emissions are of the same magnitude. After taking logs, carbon emissions are not heavily skewed anymore as the median is close to the mean. Carbon intensity measures indicate that a firm, on average, emits 373.9 tons of CO_2 to generate one million of 2020 dollars of sales revenue.

Bond spread is on average 0.71% on the primary market, and 0.71% on the secondary market. A bond issue is underwritten by 2.2 lead underwriters on average. Amihud-illiquidity measure is 0.08 on average yet has high standard deviation of 0.48. The average rating is between “A2” and “A3”, i.e., in the investment grade category. 81% of the bonds are redeemable and the average number of years remaining till maturity is 11.3 years. The amount issued is on average around $974 million. Citi bank lead-underwrite 26% of bonds in our sample.

[7] Table A2 shows the impact of winsorization. Our main results hold even if we do not winsorize our variables.

3 Main empirical analysis

This section develops our main analysis using the methodology introduced in Section 2.1. As indicated above, for this main analysis, we use CO2 intensity measures to proxy for a firm's contribution to climate change.

We select a subset of the whole sample that is needed to construct the above identification strategy: we look at primary market data for firms that have outstanding bonds trading on the secondary market on the various issuance days. We have a total of 1,119 such issuance days.

Then, we use this approach to estimate the following model:

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}. \quad (1)$$

$Spread_{f,i,t}$ is the spread of bond i that is issued at time t by firm f. $CO2_{f,t}$ is firm f's latest carbon intensity measure available at time t. CO2 emissions are reported on an annual basis ad we use the one that is publicly available at the time of bond issuance.[8] For similar reasons, we control for firm characteristics using the latest measures available, reported on a yearly basis. Firm controls include book leverage (COMPUSTAT item: (DLC+DLTT)/AT), pre-tax interest coverage ratio (COMPUSTAT item: XINT/OIBDP), the natural log of total assets (COMPUSTAT item: AT), profitability (COMPUSTAT item: OIBDP/(lagged AT)), the natural log of sales revenue (COMPUSTAT item: SALE), annual average of stock returns, annualized standard deviation of stock returns. We also control for bond characteristics. Bond controls include the Amihud-illiquidity measure on the secondary market, the remaining years to maturity, the natural log of amount outstanding as of time t, dummy variable for whether the bond is redeemable

[8] We account for reporting lag as advised by Zhang (2023): in our main analysis we consider the same reporting lag for CO2 and for financial data. For financial data, we use the year indicated in COMPUSTAT item DATADATE to assess in what year financial data has been made available. We use the previous such year to make sure that data was available to financial market participants. In a robustness analysis, we check that our results hold if we add an additional year of lag for the CO2 variable. We merge Trucost and COMPUSTAT data on a fiscal year basis.

or not, credit ratings issued by Moody's at the issuance, and number of all underwriters. In addition, we include calendar year, month of the year, day of the week, and industry (at the first-digit SIC code level) fixed effects.[9] Lastly, we account for 10 lead underwriter fixed effects. We select 10 lead underwriters based on the dollar amount of bonds underwritten in our sample period. They include the usual suspects such as J.P. Morgan, Citi, and Goldman Sachs.

We first estimate the model for the primary market. We then estimate the model for the secondary market price. We include the same controls in both regressions except for the Amihud illiquidity measure that is only included in the secondary market regression. The results are summarized in Table 2.

Insert Table 2

Table 2, Columns (1) and (2) display our main regression of corporate bond spreads, on the primary and secondary markets, respectively, on carbon intensity based on the sum of scope 1 and 2 emissions. Spreads are positively sensitive to carbon intensity, both on the primary and on the secondary market. Combining these results with the summary statistics offered in Table 2.3 enables us to assess the economic significance of these results. On the primary market, a one standard deviation increase in carbon intensity leads to a 3.1 basis points (bps) increase in spread ($= 0.00352 \cdot 8.742 \cdot 100$). This is in line with the results reported by Seltzer, Starks, and Zhu (2022) on a different sample period and using different environmental profile of firms. This can be compared to the average spread equal to 71 bps on the primary market. On the secondary market, a one standard deviation increase in carbon intensity leads to a 17.7 basis points increase in the secondary market ($= 0.0203 \cdot 8.742 \cdot 100$). To the best of our knowledge, our paper is the first to report a significant greenium on the secondary corporate bond market.

Our main result is obtained by comparing the carbon intensity coefficient displayed in Table 2,

[9]Table A3 shows that our results hold even when we use two-digit SIC codes to account for industry fixed effects.

Columns (1) and (2): the corporate bond spread sensitivity to carbon intensity is around four times larger on the secondary than on the primary market. In other words, the "greenium" is much larger on the secondary than on the primary market. In order to test the statistical significance of this difference in sensitivity, we adopt the following approach. We first stack the primary market data and secondary market data together. We then generate an indicator variable, called $Secondary_{f,i,t}$, and we set it to 1 for a secondary market observation and 0 otherwise. Then, we interact the indicator variable with carbon intensity as well as with all the controls and fixed effects. The coefficient on the interaction term between $Secondary_{f,i,t}$ and $CO2_{f,t}$ shows the difference between bond spread's sensitivity to carbon intensity on the secondary and on the primary market. We thus estimate the following pooled-regression model:

$$
\begin{aligned}
Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\
& + BondControls_{f,i,t} + Secondary_{f,i,t} \times BondControls_{f,i,t} \\
& + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\
& + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t},
\end{aligned} \tag{2}
$$

where $Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. The results of our pooled-regression model are in Table 3, Column (1). The main coefficient of interest, β_2, is related to the interaction and is estimated to be 0.0168 with t-statistics of 6.227. This indicates that the secondary market's spread is significantly more sensitive to carbon intensity than the primary market's spread. This is the main contribution of our paper: the greenium appears five times larger on the secondary than on the primary market. Firms' direct financial incentives to become greener are related to primary market outcomes that affect the cost of capital. Our main result has important implications for the strength of these incentives. Indeed, our main result suggests that the direct incentives financial markets provide firms for becoming greener appear to be lower than one could think by looking at secondary markets only. This is particularly relevant given that studies measuring the greenium on the equity market focus on the secondary market (see, e.g., Bolton and Kacperczyk (2021), Hege, Pouget, and Zhang (2023)).

Insert Table 3

For completeness, we also display the results for Scope 1 and 2 carbon intensity separately. Table 2, Columns (3) and (4) uses scope 1 intensity measure and column (5) and (6) use scope 2 intensity measure. Table 3, Columns (2) and (3) show our estimate of β_2 in Model 2 for Scope 1 and 2, respectively: it is estimated to be 0.00703 with t-statistics of 3.239, for Scope 1, and 0.180 with t-statistics of 6.964, for Scope 2. Thus, our main result applies to different measures of carbon emission: the secondary market's spread is significantly more sensitive to carbon intensity than the primary market's spread.

It is worth discussing how our results relate to the literature that documents underpricing in the corporate bond issuance. Cai, Helwege, and Warga (2007) shows that offering spreads (on the primary market) are larger than the trading spread (on secondary market), in a similar spirit to the equity IPO underpricing. Our main results show that spread sensitivity to carbon intensity is larger on the secondary market than it is on the primary market. Our results might appear as contradicting the underpricing result. However, we focus on the spread's sensitivity to carbon intensity, whereas the underpricing literature focuses on the level of the spread. So we are not studying the same phenomenon.

4 Additional empirical analyses

This section offers additional analyses that refine our main analysis and that test the robustness of our main results.

4.1 Time-series analysis

We start by studying whether we can detect in the time-series our main result that sensitivity to carbon intensity is higher on the secondary than on the primary market. As already indicated, we favor a cross-sectional approach because it better deals with the potential influence of calendar day effects: the greenium could differ across markets due to difference in trading days and in the associated supply and demand characteristics. However, we thought it could be useful to check whether our main result is also found in the time-series so that we can offer a graphical illustration of our main results.

In our time-series analysis, we use the number of months since offering to construct a rolling window. The first rolling window is the offering day and it is denoted as month 0. The second rolling window, named month 1, is between one day and one month since the bond offering; the third rolling window, named month 2, is between one month and two months since the bond offering, etc.

We restrict our sample to bonds of firms that have not yet updated their emission report. Given that CO2 emissions are annually reported, this restriction mechanically means that months since offering in our restricted sample cannot be greater than 12 months. Realistically, we have sufficient number of observations, i.e., trading prices, when months since offering are equal or less than 10 months. We thus have the following sample: 4,603 primary market prices for month 0, 56,691 for month 1, 57,982 secondary market prices for month 2, 49,135 for month 3, 45,625 for month 4, 40,859 for month 5, 33,958 for month 6, 30,732 for month 7, 26,453 for month 8, 18,834 for month 9, and 13,435 for month 10.

For each rolling window, we estimate the model displayed in Equation (1), with t referring to rolling-window months. We plot β over different rolling windows in Figure 1 using carbon intensity measured as the sum of scope 1 and 2 emissions.

Insert Figure 1

The figure is in line with our main results. The spread is positively sensitive to CO2 emission intensity on the secondary market. This result is statistically significant at 95% confidence level. Moreover, the secondary market spread sensitivity is statistically different from the primary market sensitivity (depicted as month 0 in the figure), starting five months after the offering. This illustrates our main findings. In order to show that the pattern is not specific to a particular definition of CO2 emission, we plot the results for scope 1 and scope 2 carbon intensities in Figure A2 and A3, respectively, in the Appendix.

4.2 Shocks to climate change concerns

In this section, we study how the greenium arising in bond spreads reacts to changes in climate change concerns. For this cross-sectional analysis, we closely follow the methodology applied by Pastor, Stambaugh, and Taylor (2022) to equity prices. More specifically, we measure shocks to climate change concerns as prediction errors from AR(1) models applied to the monthly Media Climate Change Concerns (MCCC) index constructed by Ardia, Bluteau, Boudt, and Inghelbrecht (2022). We measure the shocks based on the past 36 months of data. Then, we estimate how much the greenium is sensitive to the shock to climate change concerns by estimating the following model:

$$\begin{aligned} Spread_{f,i,t} = &\alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot CS_t + \beta_3 \cdot CS_t \times CO2_{f,t} \\ &+ BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}, \end{aligned} \tag{3}$$

where CS_t is the last available monthly climate shock at time t. In order to avoid a look-ahead bias, this last available shock corresponds to the month just before the one at which issuance or trading occurs. The variable of main interest is the interaction term, $\beta_3 \cdot CS_t \times CO2_{f,t}$, and we document the results in Table 4. This analysis yields two findings. First, the corporate bond greenium is positively sensitive to climate concerns shocks, similar in spirit to what is empirically observed in the corporate equity market. Second, our main results hold when we add shocks to climate change concerns in our regressions.

Insert Table 4

4.3 Investment-grade versus high-yield bonds

In order to test whether our main results vary across firms' credit worthiness, we do a subsample analysis based on bonds' credit ratings at issuance. We estimate Equation (2) for investment-grade and high-yield bonds, separately, and report the results in Table 5, Panel A and B, respectively. As shown in Panel B, the sample size is small partly because we try to study high yield bonds among bonds that have senior seniority. Thus, compared to our benchmark data, we apply less data filter. More specifically, for this analysis, we use all types of seniorities: not only senior but also the other five types: senior secured, senior subordinate, subordinate, junior, and junior subordinate. Moreover, we do not exclude CO2 emissions data that are deemed estimated (Aswani et al., 2022). We repeat the analysis on this expanded sample and report the results in Panel C. As expected, the sample size is larger than Panel B.

Insert Table 5

The table has two main takeaways. First, it shows that our main results hold for both subsamples: the greenium is larger on the secondary than on the primary market. Second, it is not clear how the magnitude of our main result varies across credit ratings: the difference in carbon intensity seems higher for high-yield than for investment-grade bonds, for scope 1 and for scope 1 and 2 measures, but lower for scope 2 measure.

4.4 Low versus high carbon intensity industries

This subsection studies whether our main results vary across different types of industries depending on their energy efficiency. We distinguish between high and low carbon intensity industries. High carbon intensity industries, with an above median industry-wide carbon intensity, include 'mining and construction', 'manufacturing', 'transportation, communications, electric, gas and sanitary service' (SIC codes that start with 1,2,3 and 4; manufacturing is associated with two categories, the second and third ones). Low carbon intensity industries, with a below median industry-wide carbon intensity, include ‘wholesale and retail trade’, ‘finance, insurance and real estate’, ‘services’, and ‘public administration’ (SIC codes that start with 5,6,7,8 and 9; services is associated with the seventh and eighth categories). We estimate Equation (2) for high and low carbon intensity industries and report the results in Table 6.

Insert Table 6

For low carbon intensity industries, there seems to be no greenium associated to scope 1 and2 CO2 emissions, neither on the primary nor on the secondary market: sensitivity to carbon intensity appears not significantly different from zero. Consequently, the difference in sensitivity between the two markets is not statistically significant. This might be due to the fact that most CO2 emissions in these industries are in scope 3 that we do not consider here. On the contrary, for high intensity industries, the greenium appears to be significant for both the primary and secondary market and is larger on the secondary than on the primary market.

As a complementary analysis, we distinguish on an annual basis between firms depending on their carbon intensity being below or above the median across our entire sample. Then, we repeat our main analysis. Unreported tables indicate that results are qualitatively similar: the greenium is larger on the secondary than on the primary bond market for the high carbon intensity firms. This shows that results in this subsection are not driven by the way we construct industries.

4.5 Old period vs. new period

This subsection studies how the bond greenium and its differential across the primary and secondary market have evolved over time. As shown in Ardia, Bluteau, Boudt, and Inghelbrecht (2022), climate change concerns have evolved over time and tend to become more prevalent over time. This could have affected the existence and size of the greenium over time. We thus run our main cross-sectional analysis on two subsamples: one ranging from 2005 to 2013, the other ranging from 2014 to 2022. We document the related results in Table 7.

Insert Table 7

Our main variable of interest, $CO2 \times$ Secondary, appears almost equally positive and significant both in the old period and most recent period. This shows that our main result is robust to different periods, despite the plausible belief that it could have changed.

4.6 Absolute CO2 emissions

Our main analysis focuses on carbon intensity as a measure of CO2 emissions by firms, as advocated by Aswani, Raghunandan, and Rajgopal (2022). This subsection however studies whether our results hold when we use absolute CO2 emissions. This is also a relevant emission metrics since, as reminded by Bolton and Kacperczyk (2023), what matters for climate change is the absolute amount of CO2 emitted in the atmosphere. We thus repeat our main analysis and estimate Equation 2 by replacing carbon intensity by the log of absolute emissions. The results are in Table 8.

Insert Table 8

There are two main insights from Table 8, focusing on the sum of scope 1 and 2 emissions. First, we find that spreads on both the primary and the secondary market are sensitive to absolute emissions. Second, the secondary market sensitivity appears larger than the primary market one. A one standard deviation increase in absolute CO2 emission leads to a 3.3 basis points increase in the primary market spread ($= 0.0166 \cdot 1.994 \cdot 100$) and a 8.6 basis points increase in the secondary market ($= 0.0432 \cdot 1.994 \cdot 100$). Similar to our results on carbon intensity, this difference in sensitivity is statistically significant with 2.119 t-statistics. The difference in sensitivity is not statistically significant when one uses scope 1 measure although it is statistically significant when one uses scope 2 measure.

4.7 Robustness analysis

4.7.1 Liquidity Risk

Corporate bonds pricing is sensitive to illiquidity risk (Lin, Wang, and Wu, 2011; Dick-Nielsen, Feldhütter, and Lando, 2012; Bao, O'Hara, and Zhou, 2018). Accordingly, our main cross-sectional specification includes Amihud (2002)'s illiquidity measure as well as the total amount issued as control variables. However, one concern with our methodology could be that bonds of a given firm trading on the secondary market might have different illiquidity on the days in which the firm issues a new bond and on the other days. In other words, an issuance on the primary market could affect liquidity on the secondary market. This would induce a bias in the greenium that we measure on the secondary market. We here focus on the secondary market only and provide two pieces of evidence to alleviate this concerns.

We first show that Amihud (2002)'s illiquidity measure is similar across days with a new bond issuance and days just before or after the issuance. When a given firm issues new bonds, its outstanding bonds' Amihud-illiquidity measure is 0.207 with standard deviation of 1.9. On the days before and after the same firm issues new bonds, the outstanding bonds' Amihud-illiquidity measure is 0.217 with standard deviation of 1.9. The difference between these numbers is statistically insignificant with a t-test of 0.65.

We then show that bond spreads' sensitivity to CO2 intensity on the secondary market does not depend on the days we use to measure spreads, whether it is on the day of the issuance or on the days just before and after the issuance. In order to show this, we estimate Equation 1 for days just before and just after a given firm issues a new bond. Table 9, Columns (2), (4) and (6) include our estimation results. For ease of comparison, Table 9, Columns (1), (3), and (5) reproduce the estimates obtained when secondary market spreads are measured on the day of the issuance, as they appear in Table 2. The price sensitivity to CO2 emissions are not statistically different between the two specifications. The t-statistics is -0.22 between Columns (1) and (2),

-0.24 between (3) and (4), and 0.77 between (5) and (6).[10]

Insert Table 9

4.7.2 More precise measurement of CO2 emissions

As discussed in Section 2, we rule out CO2 measures that are estimated. Our main data source for firms' CO2 emissions is S&P Global Trucost. Some of CO2 emissions were estimated, to different degrees, by the data vendor. In this subsection, we show that our main results are robust to different degrees of estimations.

We first define different degrees of estimation. In some cases, firms disclose their CO2 emission via their 10-K report or via CDP (carbon disclosure project) and the reported number is gathered and made available to the researchers by Trucost. In other cases, due to the lack of reported numbers, the data vendor estimates the firms' CO2 emission based on many different sources such as the firms' production data. As such, there are different degrees of precision levels to the reported CO2 emissions. Trucost documents how the reported CO2 emissions were derived and there are 32 different types in total. We assign each type to different precision level and report our classification in Table A7. For instance, "Exact value from CDP" is assigned to the most precise level, 5. "Estimate derived from production data" is assigned to the most imprecise level, 1. Our classification is more granular but consistent with the one used by Aswani, Raghunandan, and Rajgopal (2022): our level-5 precision corresponds to their type (ii) emissions: directly disclosed total emissions.

Next, we use our classification to construct different subsamples. The precision level for a given firm's scope 1 measure might not be the same as the one for the same firm's scope 2 measure. Thus, we apply the restriction to scope 1 and scope 2 individually. When our carbon intensity measure is based on the sum of Scope 1 and Scope 2 emissions, we require that they both belong

[10]Unreported tables show that our main results also hold when we estimate Equation 1 on the days just before and just after issuance, separately, and when we estimate Equation 1 on the days of issuance but without including Amihud-illiquidity measure as a control or by replacing it by trading volume.

to the appropriate level of precision. This explains why the sample size is different across the three subsamples corresponding to scope 1 and 2, scope 1, and scope 2.

We construct a first subsample by restricting the sample to observations with CO2 emissions' reporting precision level of 3 or above. We run our main specification, displayed in Equation (1). The cross-sectional estimation results are in Table 10, Panel A.

Insert Table 10

Our main results stay robust. When we use the sum of scope 1 and 2 measure, the difference in the sensitivities between the two markets is 0.0163 with a t-statistics of 5.555. The magnitude of this difference is similar to our main results, summarized in Table 2. This suggests that, in our analysis, the precision issue highlighted by Aswani, Raghunandan, and Rajgopal (2022) is not driving our main results.

Similarly, we construct a second and a third subsample by restricting the sample to observations with CO2 emissions' reporting precision level of 4 and 5, respectively, or above. The estimates in all these subsamples appear very similar both in levels and in statistical significance. This shows the robustness of our results and indicates that getting rid of the lower CO2 emissions' reporting precision, level 1, is enough to get an accurate picture of our results.

4.7.3 Other robustness checks

We run a variety of additional robustness tests for our main results. For the sake of brevity, the tables supporting our arguments are not included in the main text but are offered in the Appendix.

Additional lag We start by using a different lag for our main explanatory variable. As mentioned in Section 3, our main regressor, $CO2_{f,t}$, is firm f's latest carbon intensity measure available at time t. In our main analysis, we consider that CO2 data are made available to financial market participants at the same time as accounting data: we lag CO2 emissions by one year as we do with accounting variables, i.e., we use emissions and accounting figures as of the end of the previous fiscal year.

However, as indicated by Zhang (2023), CO2 emissions data might suffer from slightly longer reporting lags than accounting data. In order to test whether this concern affects our results, we lag our CO2 emissions measure (and the associated sales figure that scales it) by one additional year compared to accounting variables. Our main results stay robust to this alternative specification.

Different Winsorizations As mentioned in Section 2.3, in our main analysis, we winsorize all our variables at 1% level. Even though a 1%-winsorization level is a well-accepted practice in the literature, there is no particular reason to use this rather than another level. We thus study how our main results depend on the level of winsorization by running our main specification without any winsorization and with a 2.5%-winsorization level.

Our main result appears robust to different winsorization levels but there is some sign of outliers affecting our estimates. Indeed, focusing on the sum of scope 1 and 2 emissions, spread sensitivity to carbon intensity appears larger on the secondary than on the primary market for all levels of winsorization but the size and statistical significance of this effect increases with the level of winsorization. A similar pattern arises when scope 1 and scope 2 emissions are used separately used.

Industry controls and firm fixed effects Our main specification controls for industry-level effects at the one-digit SIC code level inducing 9 different broad industries. When we run our main specification by controlling instead for two-digit SIC code industry fixed effects associated in our data with 59 industrial categories, our results are qualitatively and quantitatively similar. This suggests that bond market participants compare firms' carbon intensity across firms not only within broad industries but also within smaller industrial categories.

When we include firm fixed effects, sensitivity to carbon intensity is only significant for the sum of scope 1 and 2 and for scope 1 carbon intensity measures but not for scope 2. The difference in sensitivity across primary and secondary market is significant only for the sum of scope 1 and 2. So our main results remain robust to firm fixed effect but are not as strong as before. This indicates that bond market participants tend to pay more attention to cross-sectional than to time-series differences in carbon intensity.

Data filters In constructing our main data set, as discussed in Section 2, we restricted data to bonds with senior seniority and bonds with precision level 2 or above. We run our analysis without these two filters and find that spread sensitivity to CO2 emission in the secondary market is four times larger than that in the primary market, as opposed to five times in our main analysis. This suggests that, in our analysis, the precision issue highlighted by Aswani, Raghunandan, and Rajgopal (2022) is not driving our main results. On the contrary, our results appear stronger when we correct for the seniority and precision issue.

5 Potential economic channels

Our main result states that corporate bond spreads are less sensitive to carbon intensity on the primary than on the secondary market. In other words, the greenium is lower on the primary than on the secondary market. In this section, we study two potential economic channels: an uncertainty channel, related to the future climate concerns of investors, and a competition channel.

5.1 A conceptual analysis

The appendix offers a very stylized model that can rationalize our main result and that points towards our two channels of interest. The model features a primary market with two types of participants without green preferences: underwriting dealers who liquidate their position on the secondary market and investors who hold their position up to maturity. On the secondary market, investors with green concerns trade with dealers. Despite the absence of green preferences on the primary market, the issuance price reflect green concerns as these concerns matter for the price at which dealers are liquidating their position. However, climate concerns are not fully reflected in the issuance price because some investors without green preferences are also trading on the primary market. This rationalizes our main finding.

When there is more uncertainty regarding the strength of climate concerns on the secondary market, dealers are less aggressive on the primary market due to their risk aversion. This implies that the views of investors with no green preferences weigh larger in the issuance price. This leads to our first channel according to which, when there is more uncertainty on climate concerns, the difference in sensitivity to carbon emissions between the secondary and the primary market spreads is larger.

When there is less competition between underwriting dealers on the primary market, they reduce their aggressiveness to increase their trading profits. As a result, their views, linked to secondary market investors' climate concerns, are less reflected into the issuance price, and the views of investors with no green preferences weigh larger. This leads to our second channel according to which, when there is less competition, the difference in sensitivity to carbon emissions between the secondary and the primary market spreads is larger.

The next subsection tests these two channels by implementing a triple interaction analysis.

5.2 Uncertainty Channel

Our theoretical analysis yields the following testable prediction: the difference between the sensitivity to carbon intensity on the secondary and the primary market increases as future climate change concerns become more uncertain.

In order to test this prediction, we first construct HV_t where HV_t proxies the uncertainty of future climate concerns at time t. For this, we use daily Media Climate Change Concerns index that was constructed and was made available to download by Ardia, Bluteau, Boudt, and Inghelbrecht (2022). To estimate the conditional volatility at day t, we use an ARCH model with 30 lags, from $t-30$ and $t-1$. It is worth mentioning that this uncertainty is different from the shock to the climate concerns that we used in Section 4.2 and were constructed at the monthly level. Then, we set $HV_t = 1$ if the conditional volatility is above the median. Otherwise, we set it to 0.

Then, we slightly update Equation (2) to estimate the following model:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_3 \cdot CO2_{f,t} \times HV_t + \beta_4 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times HV_t \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + HV_t \times Secondary_{f,i,t} \times BondCtrl_{f,i,t} \\ &+ FirmCtrl_{f,t} + Secondary_{f,i,t} \times FirmCtrl_{f,t} + HV_t \times Secondary_{f,i,t} \times FirmCtrl_{f,t} \\ &+ FE + Secondary_{f,i,t} \times FE + HV_t \times Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned} \tag{4}$$

where $Spread_{f,i,t}$ is spread of the bond i that is issued on day t by firm f. Here, HV_t is as defined above. In addition, we interact controls and fixed effects with HV_t to appropriately allow sensitivities to the controls to vary across different types of bonds.

Our main variable of interest is the triple interaction term, $Secondary_{f,i,t} \times CO2_{f,t} \times HV_t$. Testing the prediction is equivalent to testing whether β_4 is positive or not. Table 11 summarizes the relevant results. The coefficient β_4 is estimated to be statistically significantly positive when one uses scope 1 and 2 CO2 emissions or scope 1 CO2 emissions to measure carbon intensity.

Insert Table 11

5.3 Competition among underwriters

Our theoretical analysis yields the following testable prediction: the difference between the sensitivity to carbon intensity on the secondary and the primary market increases as the level of competition between underwriting dealers diminishes.

In order to test this second prediction, we first construct a dummy variable, $LC_{f,i}$, that indicates a low level of competition among underwriters for bond i issued by firm f. Because lead underwriters determine the issuance price, we use the number of lead underwriters to measure competition. Moreover, bonds with larger offered amount mechanically have larger number of lead underwriters. In order to address this, we scale the number of lead underwriters by the amount issued and compute:

$$Ratio = \frac{\text{Number of lead underwriters}}{\text{Amount offered}}.$$

We set $LC_{f,i} = 1$ if the ratio is below the median. Otherwise, we set it to 0.[11][12] We then estimate the following model with triple interaction terms:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_3 \cdot CO2_{f,t} \times LC_{f,i} + \beta_4 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i} \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + LC_{f,i} \times Secondary_{f,i,t} \times BondCtrl_{f,i,t} \\ &+ FirmCtrl_{f,t} + Secondary_{f,i,t} \times FirmCtrl_{f,t} + LC_{f,i} \times Secondary_{f,i,t} \times FirmCtrl_{f,t} \\ &+ FE + Secondary_{f,i,t} \times FE + LC_{f,i} \times Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t}. \end{aligned} \tag{5}$$

$Spread_{f,i,t}$ is the spread of bond i is issued on day t by firm f. Our main variable of interest

[11] The correlation between the two dummy variables, HV_t and $LC_{f,i}$, appears low and equal to 0.055.

[12] For robustness, we use different proxy to construct $LC_{f,i}$. We first take average of underwriters' competitiveness using measures proposed by Manconi, Neretina, and Renneboog (2019). Then, we $LC_{f,i} = 1$ if the average is below the median. Otherwise, we set it to 0. The results are qualitatively similar. We report the related results in the appendix.

is the triple interaction term, $Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i}$. Testing our prediction is equivalent to testing whether β_4 is positive or not. Table 12 summarizes the relevant results. The coefficient β_4 is estimated to be statistically significantly positive for all three measures of CO2 emission.

Insert Table 12

The economic significance of the two channels we document appears similar in magnitude. Because they have the same standard deviation, we can directly compare the estimated coefficients, β_4, corresponding to the triple interactions. These coefficients are 0.0245 and 0.0171 for the uncertainty and the competition channel, respectively, on scope 1 and 2 emission intensity. They are not significantly different from each others (t-statistics is 0.8). We conclude that the uncertainty and competition channels are equally important to explain why the greenium is not as large on the primary than on the secondary market.

6 Conclusion

Do green firms with low carbon emissions benefit from the bond greenium and thus enjoy a lower cost of capital than brown firms? Or instead, do financial intermediaries on the primary market reap part of the greenium in the form of higher returns on their intermediation activities at issuance? We address these issues by comparing the greenium on primary and secondary bond markets. Using a sample of 325 US firms active in the bond market from 2005 to 2022, we establish our main result: the greenium appears lower on the primary market than on the secondary market. Our main specification features a cross-sectional analysis which compares, for a given firm at a given bond issuance date, the greenium on the primary market to the greenium on the secondary market for bond(s) of the same firm that were issued before. Our main result also holds in the time series, comparing bonds' greenium evolution over time from issuance on the primary market to trading in the secondary market, as well as for a variety of robustness checks.

Our evidence suggests that two economic forces underlie our main result. The part of the greenium pocketed in by financial intermediaries appears related i) to uncertainty regarding investors' future climate concerns and ii) to a lack of competition among underwriting dealers. These two effects appear equally important in driving our main result.

The main implications of our investigation are fourfold. First, the impact of investors with green preferences on firms' financial incentives to become green is lower than one may think by looking at secondary market outcomes. Second, uncertainty regarding investor's' future climate concerns is detrimental to these incentives. Third, lack of competition among underwriting bond dealers can further harm these incentives. Fourth, green investors should try and participate more directly in primary bond markets in order to increase their impact on firms' financial incentives to become green. Thus, as major holders of corporate bonds, insurance and pension firms can further increase the financial incentives to become green if they directly participate in the primary bond markets.

In future work, we would like to extend our analysis to equity markets, to find exogenous shocks to better identify the underlying economic channels, and to structurally estimate green preferences.

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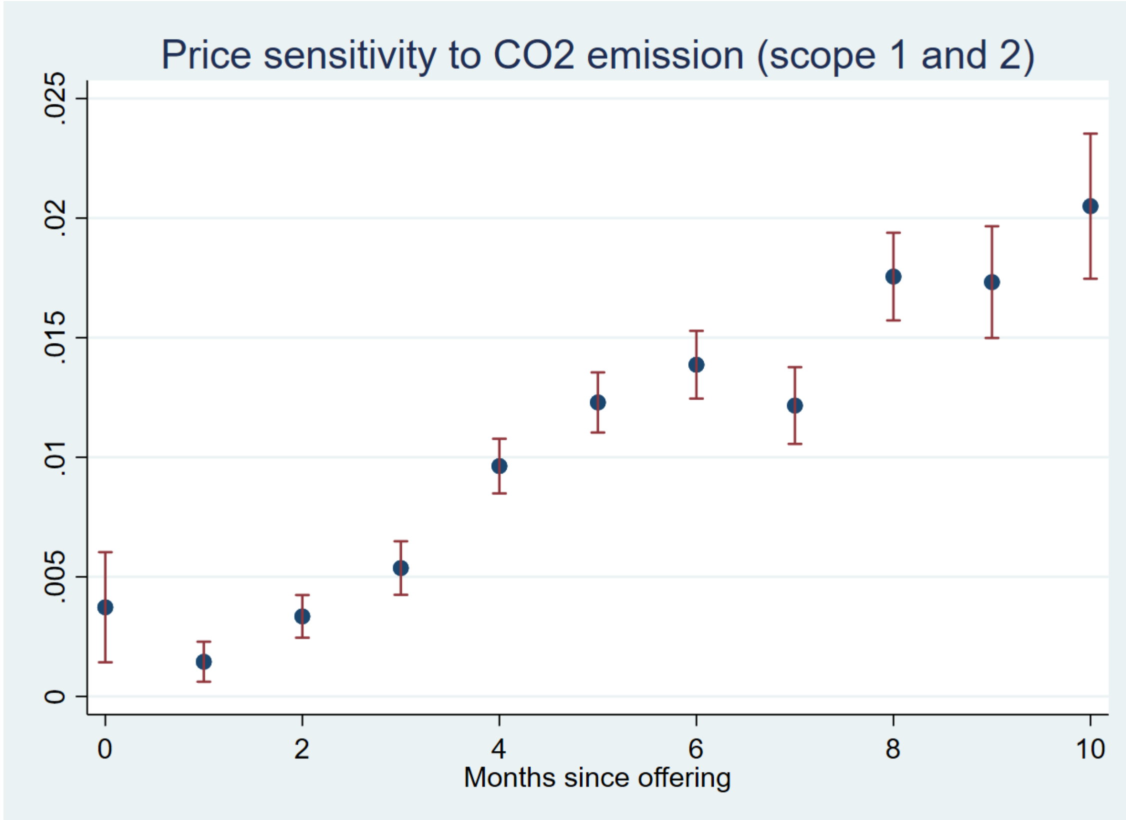


This figure illustrates how price sensitivities to CO2 emission change over months since offering. We use the number of months since offering to construct rolling window. The first rolling window is the offering day and it is denoted as 0 months. The second rolling window is between 1 day and 1 month since the bond offering. The third rolling window is between 1 month and 2 months since the bond offering... For each rolling window, we run the following panel regression:

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}.$$

$Spread_{f,i,t}$ is the spread of bond i that is issued at time t by firm f. $CO2_{f,t}$ is firm f's latest carbon intensity measure available at time t. Then, we plot β over different rolling windows when we use CO2 intensity measure for scope 1+2.

Figure 1: Price sensitivities to scope 1 and 2 carbon emissions in the time-series

Table 1: Summary Statistics

Our data sample covers 4,579 bond issues from 325 unique US firms. The sample spans from 2005 to 2022. We winsorize all the variables at top and bottom 1%. The first panel summarizes CO2 emission measures. We use firms' Scope 1 and Scope 2 carbon emissions. We normalize them by firms' sales to get carbon intensity measures. The second panel shows firm characteristics. The third panel summarizes bond characteristics. We define offering/secondary spread as the difference between a bond's yield and the yield of a cash flow-matched synthetic Treasury bond. We transform the letter ratings to a numerical value so that one notch increase gets a number larger by 1 (e.g. "C" is assigned 1 and "Aaa" is assigned 21). We use Amihud's illiquidity measure.

	N	Mean	SD	Median
CO2 emission measures				
Log(Carbon Emission Scope 1 (tons CO2e))	325	12.87	2.636	12.79
Log(Carbon Emission Scope 2 (tons CO2e))	325	13.00	1.557	12.95
Log(Carbon Emission Scope 1 and 2 (tons CO2e))	325	14.02	1.994	13.94
Carbon intensity scope 1 (tons CO2e/USD m.)/100	325	3.187	8.382	0.144
Carbon intensity scope 2 (tons CO2e/USD m.)/100	325	0.479	0.712	0.220
Carbon intensity scope 1 and 2 (tons CO2e/USD m.)/100	325	3.739	8.742	0.465
Firm characteristics				
Book leverage	325	0.304	0.155	0.289
Interest coverage ratio	325	0.119	0.130	0.0865
Firm size	325	10.52	1.379	10.39
ROA	325	0.148	0.0846	0.141
Firm sale	325	9.928	1.114	9.795
Equity return mean	325	0.126	0.263	0.150
Log(Equity return vol)	325	-1.536	0.455	-1.563
Bond characteristics				
Offering spread (%)	4,198	0.708	0.657	0.529
Secondary spread (%)	9,809	0.709	1.084	0.663
Number of lead underwriters	14,007	2.240	1.366	2
Number of all underwriters	14,007	3.148	2.581	4
Illiquidity	14,007	0.0805	0.530	0.000338
Rating (Moody's)	14,007	15.54	2.785	15
$\mathbb{1}\{$Redeemable$\}$	14,007	0.809	0.393	1
Years to maturity	14,007	11.31	9.768	8.573
Amount outstanding (thousands)	14,007	973,645	883,258	786,414
$\mathbb{1}\{$Lead underwritten by J.P. Morgan$\}$	14,007	0.210	0.407	0
$\mathbb{1}\{$Lead underwritten by Citi$\}$	14,007	0.258	0.438	0
$\mathbb{1}\{$Lead underwritten by Merrill Lynch$\}$	14,007	0.219	0.414	0
$\mathbb{1}\{$Lead underwritten by Barclays$\}$	14,007	0.129	0.335	0
$\mathbb{1}\{$Lead underwritten by Morgan Stanley$\}$	14,007	0.211	0.408	0
$\mathbb{1}\{$Lead underwritten by Goldman Sachs$\}$	14,007	0.160	0.367	0
$\mathbb{1}\{$Lead underwritten by Wells Fargo$\}$	14,007	0.0740	0.262	0
$\mathbb{1}\{$Lead underwritten by Deutsche bank$\}$	14,007	0.125	0.331	0
$\mathbb{1}\{$Lead underwritten by Bank of America$\}$	14,007	0.0592	0.236	0

Table 2: Main Result

(1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market. (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas (3) and (4) ((5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00352***	0.0203***	0.00296***	0.01000***	0.0414***	0.221***
	(2.905)	(9.050)	(2.801)	(5.758)	(3.437)	(10.54)
Years to maturity	0.0373***	0.0560***	0.0374***	0.0562***	0.0373***	0.0558***
	(52.77)	(65.31)	(52.70)	(65.90)	(53.03)	(65.33)
Log(Amount outstanding)	0.0382***	-0.0203***	0.0399***	-0.0204***	0.0388***	-0.0189***
	(7.651)	(-3.721)	(7.923)	(-3.779)	(7.802)	(-3.482)
$\mathbb{1}\{$Redeemable$\}$	0.133***	0.0752***	0.136***	0.0769***	0.125***	0.0746***
	(4.501)	(3.443)	(4.693)	(3.551)	(4.270)	(3.421)
Rating (Moody's)	-0.0613***	-0.0871***	-0.0622***	-0.0871***	-0.0593***	-0.0813***
	(-17.59)	(-17.62)	(-18.21)	(-17.99)	(-16.98)	(-16.35)
Illiquidity		0.0357***		0.0371***		0.0353***
		(3.088)		(3.206)		(3.056)
Number of all underwriters		-0.0128**		-0.0113**		-0.0156***
		(-2.244)		(-2.021)		(-2.751)
Equity return mean	-0.265***	-0.388***	-0.270***	-0.397***	-0.276***	-0.401***
	(-7.449)	(-8.530)	(-7.690)	(-8.998)	(-7.769)	(-8.868)
Log(Equity return vol)	0.271***	0.397***	0.283***	0.393***	0.275***	0.379***
	(12.54)	(13.72)	(13.12)	(13.87)	(12.74)	(13.16)
Book leverage	0.281***	-0.145**	0.279***	-0.135**	0.289***	-0.243***
	(5.109)	(-2.230)	(5.032)	(-2.111)	(5.291)	(-3.739)
ROA	-0.724***	0.155	-0.750***	0.0550	-0.769***	0.0144
	(-6.203)	(0.858)	(-6.399)	(0.311)	(-6.652)	(0.0806)
Interest coverage ratio	0.0388	-0.408***	0.0464	-0.356***	0.0293	-0.342***
	(0.571)	(-6.515)	(0.694)	(-5.759)	(0.434)	(-5.498)
Firm sale	0.0390***	-0.0199	0.0417***	-0.0246	0.0403***	-0.0403**
	(2.924)	(-1.042)	(3.098)	(-1.311)	(3.052)	(-2.151)
Firm size	-0.0396***	0.0478***	-0.0463***	0.0372**	-0.0426***	0.0519***
	(-3.087)	(2.629)	(-3.567)	(2.065)	(-3.329)	(2.868)
Observations	4,198	9,809	4,483	10,039	4,230	9,825
R-squared	0.587	0.599	0.586	0.597	0.587	0.600
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Main Result: Pooled Regression

The table reports our main results by comparing the carbon intensity coefficient displayed in Table 2 between secondary and primary market. In order to test the statistical significance of this difference in sensitivity, we first stack the primary market data and secondary market data together. We then generate an indicator variable, called $Secondary_{f,i,t}$, and we set it to 1 for a secondary market observation and 0 otherwise. Then, we interact the indicator variable with carbon intensity as well as with all the controls and fixed effects. The coefficient on the interaction term between $Secondary_{f,i,t}$ and $CO2_{f,t}$ shows the difference between bond spread's sensitivity to carbon intensity on the secondary and on the primary market. We thus estimate the following pooled-regression model:

$$\begin{aligned}Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ &+ Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ &+ FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t}\end{aligned}$$

The table reports the estimates of β_2. Column (1) reports the results when scope 1 and 2 intensity measure is used. Column (2) reports the results when scope 1 is used. Column (3) reports the results when scope 2 is used.

	(1) Scope 1 and 2 Primary + Secondary	(2) Scope 1 Primary + Secondary	(3) Scope 2 Primary + Secondary
CO2 X Secondary	0.0168***	0.00703***	0.180***
	(6.227)	(3.239)	(6.964)
Observations	14,007	14,522	14,055
R-squared	0.597	0.596	0.598
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Interaction with MCCC shocks

Table studies how the greenium arising in bond spreads reacts to changes in climate change concerns. We measure shocks to climate change concerns as prediction errors from AR(1) models applied to the monthly Media Climate Change Concerns (MCCC) index constructed by Ardia, Bluteau, Boudt, and Inghelbrecht (2022). We measure the shocks based on the past 36 months of data. Then, we estimate how much the greenium is sensitive to the shock to climate change concerns by estimating the following model:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot CS_t + \beta_3 \cdot CS_t \times CO2_{f,t} \\ &+ BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}, \end{aligned} \tag{6}$$

where CS_t is the last available monthly climate shock at time t. The table reports the estimates of β_1 and β_3. The difference in β_1 between the primary market and secondary market is 0.0186*** (5.586) , 0.00552** (2.247) , and 0.238*** (6.429) respectively for scope 1 and 2, scope 1 and scope 2 measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00392***	0.0226***	0.00296**	0.00857***	0.0236	0.263***
	(2.760)	(7.984)	(2.478)	(4.424)	(1.519)	(8.221)
CO2 X CS	0.00845	0.0210*	0.00790*	0.0160**	0.0229	0.299***
	(1.507)	(1.877)	(1.816)	(2.338)	(0.408)	(2.694)
Observations	2,933	7,543	3,160	7,739	2,960	7,559
R-squared	0.631	0.618	0.623	0.615	0.629	0.618
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Investment grade vs high yield bonds

The table shows how our main result depend on the creditworthiness of the bonds. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The estimates of β_2 for investment grade bonds (Panel A) are 0.0176*** (6.149), 0.00727*** (3.269), and 0.209*** (7.813) respectively for scope 1 and 2; scope 1 and scope 2 measures. The estimates of β_2 for high yield bonds (Panel B) are 0.00274 (0.0696), 0.00467 (0.190), and -0.0314 (-0.0748) respectively. The estimates of β_2 for high yield bonds (Panel C) are 0.0436*** (3.478), 0.0462*** (3.554), and 0.0576 (0.457) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: Investment grade						
CO2	0.00209*	0.0197***	0.000954	0.00822***	0.0362***	0.245***
	(1.883)	(8.025)	(1.008)	(4.571)	(3.299)	(11.17)
Observations	4,035	9,714	4,281	9,927	4,067	9,730
R-squared	0.639	0.611	0.631	0.609	0.639	0.613
Panel B: High yield						
CO2	0.00617	0.00891	-0.00563	-0.000957	0.136	0.105
	(0.369)	(0.311)	(-0.519)	(-0.0475)	(1.254)	(0.322)
Observations	134	78	171	95	134	78
R-squared	0.767	0.960	0.702	0.917	0.771	0.960
Panel C: High yield* (with less data filter, no seniority and estimation precision, for larger sample size)						
CO2	0.00106	0.0446***	-0.000140	0.0461***	0.106*	0.164
	(0.190)	(3.694)	(-0.0243)	(3.677)	(1.828)	(1.349)
Observations	416	295	416	295	416	295
R-squared	0.551	0.673	0.551	0.673	0.555	0.656
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: High and low carbon intensity industries

The table shows how our main result depend on the industries: high carbon intensity industries vs. low carbon intensity industries. High carbon intensity industries include ‘Mining and Construction’, ‘Manufacturing’, ‘Transportation and Communications’, ‘Electric, Gas and Sanitary service.’ Low carbon intensity industries ‘Wholesale and Retail Trade’, ‘Finance, Insurance and Real Estate’, ‘Services’ and ‘Public Administration.’ Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The estimates of β_2 for high carbon intensity industries are 0.0187*** (6.457), 0.00804*** (3.348), and 0.269*** (8.673) respectively for scope 1 and 2; scope 1 and scope 2 measures. The estimates of β_2 for low carbon intensity industries are 0.00682 (0.164), 0.0219 (0.151) , and 0.0134 (0.263) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: High carbon intensity industries						
CO2	0.00435***	0.0231***	0.00387***	0.0119***	0.0352**	0.304***
	(3.318)	(9.093)	(3.310)	(5.845)	(2.461)	(11.32)
Observations	2,636	4,351	2,882	4,513	2,651	4,358
R-squared	0.612	0.536	0.605	0.531	0.609	0.541
Panel B: Low carbon intensity industries						
CO2	0.00561	0.0124	0.000969	0.0229	0.00766	0.0210
	(0.285)	(0.417)	(0.0134)	(0.237)	(0.318)	(0.575)
Observations	1,562	5,458	1,601	5,526	1,579	5,467
R-squared	0.612	0.683	0.615	0.684	0.612	0.683
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Old Period vs. New Period

The table shows how our main result depend on whether it is old period (2005-2013) or new period (2014-2022). Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The estimates of β_2 for old period are 0.0154*** (2.842), 0.00300 (0.738), and 0.313*** (5.579) respectively for scope 1 and 2; scope 1 and scope 2 measures. The estimates of β_2 for new period are 0.00946*** (3.519), 0.00600*** (2.579) , and 0.110*** (4.336) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: Old period						
CO2	0.00511**	0.0205***	0.00489**	0.00789**	0.0243	0.337***
	(2.113)	(4.583)	(2.467)	(2.443)	(0.972)	(7.226)
Observations	1,571	4,037	1,739	4,197	1,598	4,053
R-squared	0.581	0.622	0.575	0.620	0.580	0.624
Panel B: New period						
CO2	0.00151	0.0110***	0.000475	0.00648***	0.0465***	0.156***
	(1.162)	(4.929)	(0.402)	(3.453)	(3.677)	(7.627)
Observations	2,626	5,772	2,743	5,842	2,631	5,772
R-squared	0.613	0.615	0.609	0.613	0.615	0.617
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Absolute CO2 emissions

The table shows that our main result is robust to different definition of CO2 emission: total CO2 emission. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The estimates of β_2 are 0.0266** (2.119) , 0.00892 (1.039), and 0.0295** (2.019) respectively for scope 1 and 2; scope 1 and scope 2 measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.0166***	0.0432***	0.00502	0.0139**	0.0159**	0.0453***
	(2.747)	(4.375)	(1.168)	(2.087)	(2.230)	(3.994)
Observations	4,198	9,809	4,483	10,039	4,226	9,822
R-squared	0.587	0.596	0.585	0.596	0.586	0.596
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Robustness: Liquidity risk

Table shows that bond spreads' sensitivity to CO2 intensity on the secondary market does not depend on the days we use to measure spreads, whether it is on the day of the issuance or on the days just before and after the issuance. In order to show this, we estimate Equation 1 for days just before and just after a given firm issues a new bond. Columns (2), (4) and (6) include our estimation results. Columns (1), (3), and (5) reproduce the estimates obtained when secondary market spreads are measured on the day of the issuance, as they appear in Table 2. The t-statistics is -0.22 between Columns (1) and (2), -0.24 between (3) and (4), and 0.77 between (5) and (6).

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
CO2	0.0203***	0.0209***	0.01000***	0.0105***	0.221***	0.202***
	(9.050)	(14.47)	(5.758)	(9.507)	(10.54)	(15.27)
Years to maturity	0.0560***	0.0548***	0.0562***	0.0548***	0.0558***	0.0545***
	(65.31)	(94.32)	(65.90)	(94.75)	(65.33)	(94.15)
Log(Amount outstanding)	-0.0203***	-0.0247***	-0.0204***	-0.0252***	-0.0189***	-0.0232***
	(-3.721)	(-6.576)	(-3.779)	(-6.777)	(-3.482)	(-6.197)
$\mathbb{1}\{$Redeemable$\}$	0.0752***	0.0711***	0.0769***	0.0767***	0.0746***	0.0713***
	(3.443)	(4.815)	(3.551)	(5.244)	(3.421)	(4.837)
Rating (Moody's)	-0.0871***	-0.0707***	-0.0871***	-0.0722***	-0.0813***	-0.0652***
	(-17.62)	(-21.72)	(-17.99)	(-22.73)	(-16.35)	(-19.92)
Equity return mean	-0.388***	-0.372***	-0.397***	-0.387***	-0.401***	-0.390***
	(-8.530)	(-12.54)	(-8.998)	(-13.40)	(-8.868)	(-13.21)
Log(Equity return vol)	0.397***	0.374***	0.393***	0.369***	0.379***	0.358***
	(13.72)	(19.55)	(13.87)	(19.72)	(13.16)	(18.81)
Book leverage	-0.145**	-0.110***	-0.135**	-0.0837**	-0.243***	-0.202***
	(-2.230)	(-2.588)	(-2.111)	(-1.998)	(-3.739)	(-4.757)
ROA	0.155	0.0479	0.0550	-0.0596	0.0144	-0.0929
	(0.858)	(0.405)	(0.311)	(-0.512)	(0.0806)	(-0.793)
Interest coverage ratio	-0.408***	-0.286***	-0.356***	-0.263***	-0.342***	-0.222***
	(-6.515)	(-7.082)	(-5.759)	(-6.604)	(-5.498)	(-5.525)
Firm sale	-0.0199	-0.0234*	-0.0246	-0.0298**	-0.0403**	-0.0408***
	(-1.042)	(-1.889)	(-1.311)	(-2.436)	(-2.151)	(-3.352)
Firm size	0.0478***	0.0458***	0.0372**	0.0393***	0.0519***	0.0476***
	(2.629)	(3.899)	(2.065)	(3.372)	(2.868)	(4.064)
Illiquidity	0.0357***	0.0551***	0.0371***	0.0559***	0.0353***	0.0551***
	(3.088)	(6.958)	(3.206)	(7.052)	(3.056)	(6.966)
Number of all underwriters	-0.0128**	-0.0118***	-0.0113**	-0.0104***	-0.0156***	-0.0144***
	(-2.244)	(-3.080)	(-2.021)	(-2.771)	(-2.751)	(-3.759)
Observations	9,809	23,784	10,039	24,429	9,825	23,837
R-squared	0.599	0.562	0.597	0.560	0.600	0.562
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Robustness: More precise definition of CO2 emission

The table shows that our main result is robust to different precision levels of CO2 emission definitions. Precision level classifications are in Table A7. The description of results are similar to what is described in Table 8. When we focus on the sample with precision level 3 or above (Panel A), the estimates of β_2 are 0.0163*** (5.555), 0.00719*** (2.898), and 0.168*** (5.988) respectively for scope 1 and 2; scope 1 and scope 2 measures. When we focus on the sample with precision level 4 or above (Panel B), the estimates of β_2 are 0.0163*** (5.547), 0.00700*** (2.814), and 0.168*** (5.942) respectively. When we focus on the sample with precision level 5 (Panel C), the estimates of β_2 are 0.0163*** (5.590) , 0.00828*** (3.339), and 0.167*** (5.904) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: Precision level 3 or above						
CO2	0.00348***	0.0197***	0.00561***	0.0128***	0.0178	0.186***
	(2.686)	(7.998)	(4.754)	(6.363)	(1.408)	(7.907)
Observations	2,987	7,137	3,268	7,403	3,927	9,328
R-squared	0.607	0.633	0.601	0.621	0.589	0.597
Panel B: Precision level 4 or above						
CO2	0.00312**	0.0194***	0.00540***	0.0124***	0.0161	0.184***
	(2.429)	(7.849)	(4.572)	(6.158)	(1.264)	(7.812)
Observations	2,928	7,118	3,212	7,386	3,866	9,309
R-squared	0.610	0.633	0.600	0.622	0.591	0.597
Panel C: Precision level 5						
CO2	0.00299**	0.0193***	0.00479***	0.0131***	0.0153	0.182***
	(2.299)	(7.859)	(4.087)	(6.494)	(1.200)	(7.728)
Observations	2,871	6,824	3,142	7,086	3,822	9,096
R-squared	0.611	0.646	0.612	0.635	0.593	0.601
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Channel: Uncertainty

Table tests uncertainty channel. We first construct HV_t where HV_t proxies the uncertainty of future climate concerns at time t. For this, we use daily Media Climate Change Concerns index that was constructed and was made available to download by Ardia, Bluteau, Boudt, and Inghelbrecht (2022). We use ARCH model to estimate the conditional volatility at day t conditioned on all the daily data between $t-1$ and $t-30$. Then, we set $HV_t = 1$ if the measure is above the median. Otherwise, we set it to 0. Then, we slightly update Model (2) to estimate the following model:

$$\begin{aligned}
Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\
&+ \beta_3 \cdot CO2_{f,t} \times HV_t + \beta_4 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times HV_t \\
&+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + HV_t \times Secondary_{f,i,t} \times BondCtrl_{f,i,t} \\
&+ FirmCtrl_{f,t} + Secondary_{f,i,t} \times FirmCtrl_{f,t} + HV_t \times Secondary_{f,i,t} \times FirmCtrl_{f,t} \\
&+ FE + Secondary_{f,i,t} \times FE + HV_t \times Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t}
\end{aligned}$$

where $Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. In addition, we interact controls and fixed effects with HV_t to appropriately allow sensitivities to the controls to vary across different types of bonds. Table reports the estimates of β_4.

	(1) Scope 1 and 2	(2) Scope 1	(3) Scope 2
CO2 X Secondary X HV	0.0245***	0.0107**	-0.0201
	(3.623)	(2.156)	(-0.277)
Observations	10,600	11,042	10,645
R-squared	0.631	0.627	0.629
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Bond controls X Secondary X HV	YES	YES	YES
Firm controls X Secondary X HV	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES
Industry X Secondary X HV FE	YES	YES	YES
Year X Secondary X HV FE	YES	YES	YES
Month X Secondary X HV FE	YES	YES	YES
DOW X Secondary X HV FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary X HV FE	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Channel: Competition among underwriters

Table tests competition channel. We first construct $LC_{f,i}$ where it proxies the degree of competition among the lead underwriters for the bond i that is issued by firm f. We define

$$Ratio = \frac{\text{Number of lead underwriters}}{\text{Amount offered}}$$

And we set $LC_{f,i} = 1$ if the ratio is below the median. Otherwise, we set it to 0. Then, we estimate the following:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_3 \cdot CO2_{f,t} \times LC_{f,i} + \beta_4 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i} \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + LC_{f,i} \times Secondary_{f,i,t} \times BondCtrl_{f,i,t} \\ &+ FirmCtrl_{f,t} + Secondary_{f,i,t} \times FirmCtrl_{f,t} + LC_{f,i} \times Secondary_{f,i,t} \times FirmCtrl_{f,t} \\ &+ FE + Secondary_{f,i,t} \times FE + LC_{f,i} \times Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned} \tag{7}$$

$Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. In addition, we interact controls and fixed effects with $LC_{f,t}$. Table reports the estimates for β_4.

	(1) Scope 1 and 2	(2) Scope 1	(3) Scope 2
CO2 X Secondary X LC	0.0171***	0.0130***	0.0962*
	(3.013)	(2.755)	(1.709)
Observations	13,989	14,503	14,037
R-squared	0.616	0.614	0.616
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Bond controls X Secondary X LC	YES	YES	YES
Firm controls X Secondary X LC	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES
Industry X Secondary X LC FE	YES	YES	YES
Year X Secondary X LC FE	YES	YES	YES
Month X Secondary X LC FE	YES	YES	YES
DOW X Secondary X LC FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary X LC FE	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix for “Who benefits from the bond greenium?”
by Daniel Kim and Sébastien Pouget

A A simple model

To elucidate the potential drivers of our main results, we set up a model, in spirit of Gollier and Pouget (2022). Our model is very stylized but it can rationalize the fact that the greenium is lower on the primary than on the secondary market and it points to the two potential channels that we study, namely the uncertainty and competition channels.

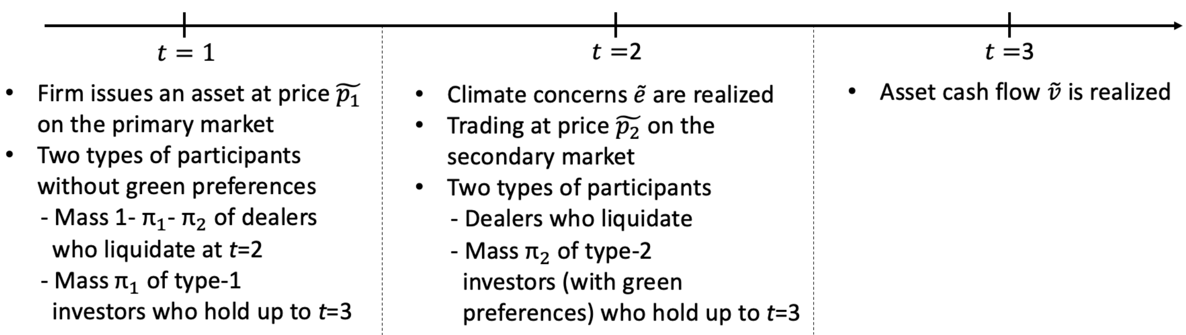


Figure A1: Timeline for the model

Our model includes three dates as illustrated in Figure A1. At date 1, the firm issues assets on the primary market, at price $\tilde{p}_1$, for an amount normalized to 1. Underwriting dealers trade on the primary market at date 1 and liquidate their position on the secondary market at date 2, at price $\tilde{p}_2$. They form a continuum of mass $1-\pi$ with $0 < \pi \leq 1$. Investors buy and hold the assets up to date 3. There are two types of investors. Type-1 investors form a continuum of mass π_1 and buy at date 1. Type-2 investors form a continuum of mass π_2, with $\pi_1 + \pi_2 = \pi$, and buy at date 2. At date 3, assets mature and deliver a financial cash flow denoted by $\tilde{v}$, normally distributed with mean μ_v and variance σ_v^2. At date 3, the firm also generates carbon emissions inducing a climate change externality.

We assume that all agents in our model have a constant relative risk aversion utility function with parameter A. They have the following mean-variance objective: $\max_{q_i} \mathbb{E}(\tilde{w}_i(q_i)) - \frac{A}{2} \cdot \mathbb{V}(\tilde{w}_i(q_i))$, in which q_i represents the quantity traded by agent i, positive for a purchase and negative for a sale, and $\tilde{w}_i(q_i)$ is agent i's final wealth. We can write an agent's objective as a mean-variance optimization program because, as will become clear later, $\tilde{w}_i(q_i)$ is normally distributed.

Agents have no endowment in assets nor in cash and can borrow or lend at the risk-free rate that is normalized to 0. For a dealer, we have $\tilde{w}_d = q_d(\tilde{p}_2 - \tilde{p}_1)$; for a type-1 investor, we have $\tilde{w}_1 = q_1(\tilde{v} - \tilde{p}_1)$. Type-2 investors care about the climate externality and we assume that $\tilde{w}_2 = q_2(\tilde{v} + \tilde{e} - \tilde{p}_2)$.[13] The variable $\tilde{e}$, normally distributed with mean μ_e and variance σ_e^2, represents how much type-2 investors care about the climate externality. When they trade, agents submit limit orders and thus can condition on the current price. The random variable $\tilde{e}$ is realized just before trading at date 2.[14] A a result, in our model, the correlation between $\tilde{v}$ and $\tilde{e}$ is irrelevant.

We are agnostic regarding the reason(s) why type-2 investors care about the externality. They might enjoy a warm-glow or a reputational benefit for holding assets of a firm with a good climate performance, either in relative terms (i.e., a firm with a low carbon intensity), or in absolute terms (i.e., a firm with low carbon emissions). In this case, $\tilde{e}$ enters the utility function because investors internalize the good environmental impact of the firm relative to more polluting firms (see also, e.g., Pastor, Stambaugh, and Taylor (2021)). Alternatively, type-2 investors might believe that a firm with a good climate performance enjoys an additional return materialized by $\tilde{e}$.

Given these ingredients, we solve the model backward. At date 2, on the secondary market, each type-2 investor demands a quantity $q_2 = \frac{\mu_v + e - p_2}{A\sigma_v^2}$.[15] The supply at this date derives from dealers who liquidate their position: this amounts to $(1-\pi)q_d$. Market clearing at date 2 is ensured if $\pi_2 q_2 = (1-\pi)q_d$ which yields the implicit secondary market price: $p_2 = \mu_v + e -$

[13] We could consider that type-1 investors also care about the climate externality, potentially with a different intensity than type-2 investors. In this case, our results would hold as long as type-1 investors' climate concerns are less intense than type-2 investors' ones.

[14] We thus assume that type-2 investors are able to perceive whether the firm's operations are more or less polluting before learning about the profitability of these operations.

[15] We write random variables with a tilde and their realisation without a tilde.

$\frac{1-\pi}{\pi_2} q_d A \sigma_v^2$.

At date 1, on the primary market, type-1 investors demand a quantity $q_1 = \frac{\mu_v - p_1}{A\sigma_v^2}$ since they hold the asset up to maturity. A dealer's maximization problem depends on the aggregate quantity that will be traded by dealers at date 2 denoted by $(1-\pi)q'_d$. A dealer's optimal trade at date 1 is thus: $q_d = \frac{\mu_v + \mu_e - \frac{1-\pi}{\pi_2} q'_d A\sigma_v^2 - p_1}{A\sigma_e^2}$. Rational expectations entail that $q_d = q'_d$. So we have: $q_d = \frac{\mu_v + \mu_e - p_1}{A(\sigma_e^2 + \frac{1-\pi}{\pi_2}\sigma_v^2)}$. The market-clearing equation at date 1 is $(1-\pi)q_d + \pi_1 q_1 = 1$ which yields the explicit primary price: $p_1 = \mu_v + \frac{X}{X+Y}\mu_e - \frac{1}{X+Y}$, with $X = \frac{1-\pi}{A(\sigma_e^2 + \frac{1-\pi}{\pi_2}\sigma_v^2)}$ and $Y = \frac{\pi_1}{A\sigma_v^2}$.

Given this price p_1, we obtain $q_d = \frac{X + XY\mu_e}{(1-\pi)(X+Y)}$ and plug it into the secondary market price equation to obtain the explicit formula: $p_2 = \mu_v + e - \frac{\pi_1}{\pi_2}\frac{X+XY\mu_e}{XY+Y^2}$. From an econometric point of view, we are interested in the average secondary market price: $\mathbb{E}(p_2) = \mu_v + \mu_e - \frac{\pi_1}{\pi_2}\frac{X+XY\mu_e}{XY+Y^2}$.

We can now derive our main result regarding the sensitivity of prices to investors' climate change concerns measured by μ_e. Our analysis shows that $\frac{\partial p_1}{\partial \mu_e} = \frac{X}{X+Y}$ and $\frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} = 1 - \frac{\pi_1}{\pi_2}\frac{XY}{XY+Y^2}$. Both of these partial derivatives are greater than 0 and smaller than 1, and we have $\frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} - \frac{\partial p_1}{\partial \mu_e} = \frac{\pi_1\pi_2\sigma_e^2}{\pi_1\pi_2\sigma_e^2 + \pi(1-\pi)\sigma_v^2}$. When $\pi_1\pi_2\sigma_e^2 > 0$, the sensitivity of prices to climate change concerns is thus larger on the secondary than on the primary market. This rationalizes our main empirical result.

The intuition for this main result is as follows. Type-2 investors care about climate change but they do not participate in the primary market. Their concerns are incorporated in the primary market price only thanks to dealers' participation. Because they liquidate their position on the secondary market, dealers try to predict the price at which they will trade which depends on type-2 investors' climate concerns. However, the primary market price does not only reflect dealers' trades, it also incorporates type-1 investors' views. As long as these investors care less about climate change than type-2 investors, the primary price will be less sensitive to climate change concerns than the secondary market price.

To point towards our first potential uncertainty channel, we note that $\frac{\partial \frac{\partial \mathbb{E}(p_2)}{\partial \mu_e} - \frac{\partial p_1}{\partial \mu_e}}{\partial \sigma_e} > 0$. Thus, when uncertainty regarding climate change concerns is higher, there is a higher difference between sensitivities on the secondary and on the primary market than when uncertainty is low.

The intuition for this result is that, when there is more uncertainty about type-2 investors climate concerns, dealers are trading less aggressively on the primary market and thus their views, which depend on their expectation of type-2 investors climate concerns, have less influence on the price. As a result, the more uncertainty on climate concerns there is, the less aggressive dealers trade and the less climate change concerns are incorporated into the primary market price.

To point towards our second potential competition channel, we slightly modify our set up and assume that there is only one dealer with weight $1-\pi$ on the market. The dealer who knows that liquidation at date 2 will affect prices maximizes $q_d(\mu_v+\mu_e-\frac{1-\pi}{\pi_2}q_dA\sigma_v^2-p_1)-\frac{A}{2}q_d^2\sigma_e^2$. Dealer's demand is thus $q_d=\frac{\mu_v+\mu_e-p_1}{A(\sigma_e^2+2\frac{1-\pi}{\pi_2}\sigma_v^2)}$. All results we obtained previously hold by replacing X by $X'=\frac{1-\pi}{A(\sigma_e^2+2\frac{1-\pi}{\pi_2}\sigma_v^2)}<X$. We thus have that the difference in sensitivities is now equal to: $\frac{\partial\mathbb{E}(p_2)}{\partial\mu_e}-\frac{\partial p_1}{\partial\mu_e}=\frac{\pi_1\pi_2\sigma_e^2+\pi_1(1-\pi)\sigma_v^2}{\pi_1\pi_2\sigma_e^2+\pi(1-\pi)\sigma_v^2+\pi_1(1-\pi)\sigma_v^2}$. This is greater than the difference in sensitivity when there is perfect competition. Thus there is a higher difference between secondary and primary market sensitivity when there is low competition among dealers.

The intuition of this result is that, when there is less competition on the primary market, dealers are trading less aggressively. As before, this implies that their views, which depend on their expectation of type-2 investors climate concerns, have less influence on the primary price.

B More Robustness Check

B.1 Additional lag

Table A1: Robustness: Additional lags

The table shows how our main result is robust to lagging CO2 emission measure by one extra year. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = &\alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ &+ Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ &+ FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The estimates of β_2 are 0.0136*** (5.282) , 0.00591*** (2.823), and 0.159*** (5.934) respectively for scope 1 and 2; scope 1 and scope 2 measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00271**	0.0164***	0.00214**	0.00805***	0.0363***	0.196***
	(2.342)	(7.576)	(2.112)	(4.775)	(2.940)	(8.873)
Observations	4,192	9,809	4,475	10,039	4,222	9,825
R-squared	0.587	0.598	0.586	0.597	0.587	0.599
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.2 Different Winsorizations

Table A2: Robustness: Winsorization

The table shows how our main result is robust to different levels of winsorization: no winsorization or 2.5% winsorization on both ends. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

When we do not winsorize (Panel A), the estimates of β_2 are 0.0109*** (5.084), 0.00375** (2.331), and 0.143*** (8.813) respectively for scope 1 and 2; scope 1 and scope 2 measures. When we winsorize at 2.5% on both ends, the estimates of β_2 are 0.0265*** (7.382), 0.0158*** (4.760), and 0.194*** (6.275) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: No winsorization						
CO2	0.00252***	0.0134***	0.00210***	0.00584***	0.00797	0.151***
	(2.685)	(7.392)	(2.762)	(4.428)	(1.176)	(10.56)
Observations	4,198	9,809	4,483	10,039	4,230	9,825
R-squared	0.589	0.601	0.588	0.600	0.588	0.603
Panel B: 2.5% winsorization on both ends						
CO2	0.00436***	0.0308***	0.00364**	0.0194***	0.0479***	0.242***
	(2.647)	(10.49)	(2.253)	(7.343)	(3.310)	(9.709)
Observations	4,198	9,809	4,483	10,039	4,230	9,825
R-squared	0.587	0.599	0.586	0.597	0.587	0.598
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnder1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 More granular fixed effects

Table A3: Robustness: Different industry fixed effects

The table shows how our main results vary over different industry fixed effects in place of one-digit SIC industry fixed effects. Columns (1), (3), and (5) report the results when the model is estimated on the primary market whereas columns (2), (4), and (6) report the results estimated on the secondary market. Columns (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas columns (3) and (4) (columns (5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

When we apply 2-digit SIC code industry fixed effects (Panel A), the estimates of β_2 are 0.0172*** (4.476) , 0.00424 (1.338), and 0.277*** (7.974) respectively for scope 1 and 2; scope 1 and scope 2 measures. When we apply firm fixed effects (Panel B), the estimates of β_2 are 0.0521*** (3.068) , 0.00659 (0.440), and 0.0391 (0.367) respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
Panel A: Two digit SIC industry FE						
CO2	0.00416***	0.0214***	0.00244*	0.00669**	0.0347**	0.312***
	(2.631)	(6.339)	(1.750)	(2.470)	(2.300)	(10.59)
Observations	4,192	9,807	4,479	10,037	4,224	9,823
R-squared	0.618	0.607	0.615	0.605	0.617	0.610
Panel B: Firm FE						
CO2	0.0179***	0.0700***	0.0238***	0.0304**	0.0276	0.0667
	(2.925)	(4.514)	(3.848)	(2.345)	(0.667)	(0.712)
Observations	4,153	9,774	4,433	10,000	4,184	9,790
R-squared	0.707	0.649	0.700	0.647	0.707	0.648
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Group FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.4 Data filters

Table A4: Robustness: Less data filter

The table shows how our main result is robust to different data filters implied. In particular, compared to our benchmark case (Table 2), we do not impose two data filters: bonds with senior seniority and bonds with precision level 2 or above, and we include seniority FE. (1), (3), and (5) report the results when the model is estimated on the primary market whereas (2), (4), and (6) report the results estimated on the secondary market. (1) and (2) report the results when scope 1 and 2 intensity measure is used whereas (3) and (4) ((5) and (6)) report the results when scope 1 (scope 2) is used.

$$Spread_{f,i,t} = \alpha + \beta \cdot CO2_{f,t} + BondControls_{f,i,t} + FirmControls_{f,t} + FE + \varepsilon_{f,i,t}$$

Then, we compare the carbon intensity coefficient between secondary and primary market by estimating the following pooled-regression model:

$$\begin{aligned} Spread_{f,i,t} = & \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} + BondControls_{f,i,t} \\ & + Secondary_{f,i,t} \times BondControls_{f,i,t} + FirmControls_{f,t} + Secondary_{f,i,t} \times FirmControls_{f,t} \\ & + FE + Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned}$$

The estimates of β_2 are 0.00687*** (3.369) , 0.00516** (2.454) , and 0.178*** (7.334) respectively for scope 1 and 2; scope 1 and scope 2 measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Scope 1 and 2		Scope 1		Scope 2	
	Primary	Secondary	Primary	Secondary	Primary	Secondary
CO2	0.00234**	0.00921***	0.00239**	0.00755***	0.0425***	0.221***
	(2.223)	(5.549)	(2.182)	(4.445)	(3.406)	(11.08)
Observations	6,291	12,020	6,291	12,020	6,291	12,020
R-squared	0.529	0.560	0.529	0.559	0.530	0.563
Bond controls	YES	YES	YES	YES	YES	YES
Firm controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.5 Robustness: Competition among underwriters

Table A5: Robustness: Channel - Competition among underwriters

Table tests competition channel. We first construct $LC_{f,i}$ where it proxies the degree of competition among the lead underwriters for the bond i that is issued by firm f. We take average of underwriters' competitiveness using measures proposed by Manconi, Neretina, and Renneboog (2019). Then, we set $LC_{f,i} = 1$ if the average is below the median. Otherwise, we set it to 0. Then, we estimate the following:

$$\begin{aligned} Spread_{f,i,t} =& \alpha + \beta_1 \cdot CO2_{f,t} + \beta_2 \cdot Secondary_{f,i,t} \times CO2_{f,t} \\ &+ \beta_3 \cdot CO2_{f,t} \times LC_{f,i} + \beta_4 \cdot Secondary_{f,i,t} \times CO2_{f,t} \times LC_{f,i} \\ &+ BondCtrl_{f,i,t} + Secondary_{f,i,t} \times BondCtrl_{f,i,t} + LC_{f,i} \times Secondary_{f,i,t} \times BondCtrl_{f,i,t} \\ &+ FirmCtrl_{f,t} + Secondary_{f,i,t} \times FirmCtrl_{f,t} + LC_{f,i} \times Secondary_{f,i,t} \times FirmCtrl_{f,t} \\ &+ FE + Secondary_{f,i,t} \times FE + LC_{f,i} \times Secondary_{f,i,t} \times FE + \varepsilon_{f,i,t} \end{aligned} \tag{8}$$

$Spread_{f,i,t}$ is spread of the bond i that is issued at time t by firm f. In addition, we interact controls and fixed effects with $LC_{f,t}$. Table reports the estimates for β_4.

	(1) Scope 1 and 2	(2) Scope 1	(3) Scope 2
CO2 X Secondary X LC	0.0347***	0.0130**	0.201***
	(4.324)	(2.016)	(2.619)
Observations	9,871	10,200	9,907
R-squared	0.659	0.654	0.658
Bond controls	YES	YES	YES
Firm controls	YES	YES	YES
Bond controls X Secondary	YES	YES	YES
Firm controls X Secondary	YES	YES	YES
Bond controls X Secondary X LC	YES	YES	YES
Firm controls X Secondary X LC	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
DOW FE	YES	YES	YES
LeadUnderwriter1-10 FE	YES	YES	YES
Industry X Secondary FE	YES	YES	YES
Year X Secondary FE	YES	YES	YES
Month X Secondary FE	YES	YES	YES
DOW X Secondary FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary FE	YES	YES	YES
Industry X Secondary X LC FE	YES	YES	YES
Year X Secondary X LC FE	YES	YES	YES
Month X Secondary X LC FE	YES	YES	YES
DOW X Secondary X LC FE	YES	YES	YES
LeadUnderwriter1-10 X Secondary X LC FE	YES	YES	YES

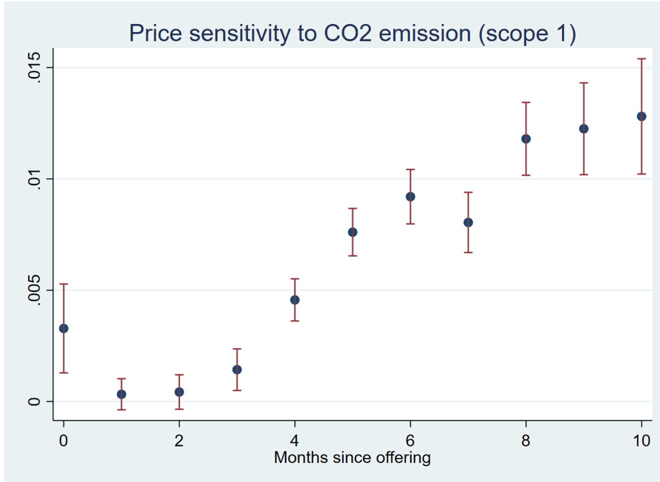
Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.6 More time-series analysis

Table A6: Summary statistics for time series analysis

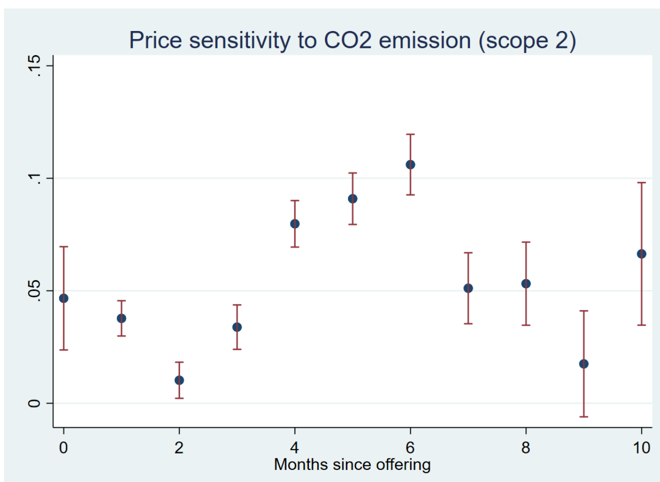
Table show summary statistics for the sample that are used in our time series analysis (see Section 4.1). Our data sample covers 4,603 bond issues from 347 unique US firms. The sample spans from 2005 to 2022. We winsorize all the variables at top and bottom 1%. Variable definitions are similar to what is described in Table 1.

	N	Mean	SD	Median
CO2 emission measures				
Log(Carbon Emission Scope 1 (tons CO2e))	347	12.65	2.667	12.59
Log(Carbon Emission Scope 2 (tons CO2e))	347	12.94	1.555	12.89
Log(Carbon Emission Scope 1 and 2 (tons CO2e))	347	13.90	1.999	13.81
Carbon intensity scope 1 (tons CO2e/USD m.)/100	347	2.959	8.124	0.126
Carbon intensity scope 2 (tons CO2e/USD m.)/100	347	0.452	0.694	0.200
Carbon intensity scope 1 and 2 (tons CO2e/USD m.)/100	347	3.478	8.482	0.411
Firm characteristics				
Book leverage	347	0.293	0.155	0.273
Interest coverage ratio	347	0.110	0.128	0.0810
Firm size	347	10.70	1.543	10.47
ROA	347	0.140	0.0880	0.136
Firm sale	347	9.935	1.129	9.816
Equity return mean	347	0.123	0.266	0.149
Log(Equity return vol)	347	-1.529	0.451	-1.550
Bond characteristics				
Offering spread (%)	4,603	0.685	0.641	0.511
Secondary spread (%)	373,705	0.519	1.004	0.399
Number of lead underwriters	377,070	2.784	1.243	3
Number of all underwriters	377,088	5.305	1.312	6
Illiquidity	378,308	0.0169	0.228	0.000748
Rating (Moody's)	378,308	15.12	2.763	15
$\mathbb{1}$\{Redeemable\}	378,308	0.906	0.292	1
Years to maturity	378,308	11.66	9.721	9.512
Amount outstanding (thousands)	378,308	1.086e+06	734,907	954,132
$\mathbb{1}$\{Lead underwritten by J.P. Morgan\}	378,308	0.396	0.489	0
$\mathbb{1}$\{Lead underwritten by Citi\}	378,308	0.360	0.480	0
$\mathbb{1}$\{Lead underwritten by Merrill Lynch\}	378,308	0.235	0.424	0
$\mathbb{1}$\{Lead underwritten by Barclays\}	378,308	0.205	0.404	0
$\mathbb{1}$\{Lead underwritten by Morgan Stanley\}	378,308	0.175	0.380	0
$\mathbb{1}$\{Lead underwritten by Goldman Sachs\}	378,308	0.146	0.353	0
$\mathbb{1}$\{Lead underwritten by Wells Fargo\}	378,308	0.103	0.304	0
$\mathbb{1}$\{Lead underwritten by Deutsche bank\}	378,308	0.151	0.358	0
$\mathbb{1}$\{Lead underwritten by Bank of America\}	378,308	0.170	0.375	0



This figure reproduces Figure 1 using scope 1 carbon intensity measure. This figure illustrates how price sensitivities to CO2 emission change over months since offering.

Figure A2: Price sensitivities to CO2 emission when we use scope 1 measures



This figure reproduces Figure 1 using scope 2 carbon intensity measure. This figure illustrates how price sensitivities to CO2 emission change over months since offering.

Figure A3: Price sensitivities to CO2 emission when we use scope 2 measures

C Additional Tables

Table A7: Trucost's carbon disclosure

Table summarizes the precision levels of CO2 emission definition. Trucost documents how the reported CO2 emissions were derived and there are 32 different types in total. We assign each type to different precision level and the following table reports our classification. Precision level 1 corresponds to the most imprecise one whereas precision level 5 corresponds to the most precise one. Our classification is more granular but consistent with the one used by Aswani, Raghunandan, and Rajgopal (2022): our level-5 precision corresponds to their type ii): directly disclosed total emissions.

Trucost's carbon disclosure	Precision
Derived from previous year	1
Estimate based on partial data disclosure in Annual Report/10-K/Financial Accounts	1
Estimate based on partial data disclosure in CDP	1
Estimate based on partial data disclosure in Environmental/CSR	1
Estimate based on partial data disclosure in personal communication	1
Estimate derived from production data	1
Estimate scaled according to company-specific data	1
Estimate used instead of disclosure - data does not cover global operations	1
Estimate used instead of disclosure - data is normalised and no aggregating factor is available	1
Estimated data	1
Value derived from data provided in Annual Report/Financial Accounts Disclosure	2
Value derived from data provided in CDP	2
Value derived from data provided in Environmental/CSR	2
Value derived from data provided in personal communication	2
Value derived from fuel use provided in Annual Report/Financial Accounts Disclosure	2
Value derived from fuel use provided in CDP	2
Value derived from fuel use provided in Environmental/CSR	2
Value derived from fuel use provided in personal communication	2
Value split from data provided in Annual Report/Financial Accounts Disclosure	3
Value split from data provided in CDP	3
Value split from data provided in Environmental/CSR	3
Value split from data provided in personal communication	3
Value summed up from data provided in Annual Report/Financial Accounts Disclosure	4
Value summed up from data provided in CDP	4
Value summed up from data provided in Environmental/CSR	4
Value summed up from data provided in personal communication	4
Data approximated from chart/graph in Annual Report/10-K/Financial Accounts	5
Data approximated from chart/graph in Environmental Report/CSR Report/Website	5
Exact Value from Annual Report/10K/Financial Accounts Disclosure	5
Exact Value from CDP	5
Exact Value from Environmental/CSR	5
Exact Value from personal communication	5