Carbon Emissions, Mutual Fund Trading, and the Liquidity of Corporate Bonds*

Jie Cao, Yi Li, Xintong Zhan, Weiming Zhang, and Linyu Zhou†

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Abstract

This paper investigates the effect of climate risks on corporate bond mutual funds' trading activities and explores its mechanism. We find that investor flows negatively respond to mutual funds' carbon exposure, leveraging the Paris Agreement as a shock. Such carbon-induced redemptions prompt mutual funds to sell bonds issued by high-carbon companies, especially the bonds held by funds with higher outflow-to-carbon sensitivity. We rule out the alternative hypothesis that a fundamental shift in funds' investment preferences drives the reduction in high-carbon holdings. Moreover, we note a deterioration in the liquidity of high-carbon bonds, particularly those heavily owned by mutual funds.

Keywords: Climate risks, carbon emissions, corporate bonds, mutual funds, redemption risks, liquidity

JEL classification: G11, G20, G23, G41

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†Jie Cao is at School of Accounting and Finance, Hong Kong Polytechnic University, email: jie.cao@polyu.edu.hk. Yi Li is at Board of Governors of the Federal Reserve System, email: yi.li@frb.gov. Xintong Zhan is at School of Management, Fudan University, email: xintongzhan@fudan.edu.cn. Weiming Zhang is at IE Business School, IE University, email: elaine.zhang@ie.edu, and Linyu Zhou is at Chinese Academy of Finance and Development, Central University of Finance and Economics, email: lyzhou@cufe.edu.cn.

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Abstract

This paper investigates the effect of climate risks on corporate bond mutual funds' trading activities and explores its mechanism. We find that investor flows negatively respond to mutual funds' carbon exposure, leveraging the Paris Agreement as a shock. Such carbon-induced redemptions prompt mutual funds to sell bonds issued by high-carbon companies, especially the bonds held by funds with higher outflow-to-carbon sensitivity. We rule out the alternative hypothesis that a fundamental shift in funds' investment preferences drives the reduction in high-carbon holdings. Moreover, we note a deterioration in the liquidity of high-carbon bonds, particularly those heavily owned by mutual funds.

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1 Introduction

Over the past decade, institutional investors have become increasingly aware of climate risks and thus call for more climate risk disclosure from companies (Krueger, Sautner, and Starks (2020) and Ilhan, Krueger, Sautner, and Starks (2023)). Climate-related concerns have become important drivers in equity mutual funds' flows (Hartzmark and Sussman (2019) and Ceccarelli, Ramelli, and Wagner (2024)) and portfolio decisions (Bolton and Kacperczyk (2021), Cao, Titman, Zhan, and Zhang (2023), Starks, Venkat, and Zhu (2024), and Atta-Darkua, Glossner, Krueger, and Matos (2023)). In this paper, we explore the effects of climate-related concerns on investor flows within corporate bond mutual funds and assess how this relationship influences the trading behavior of these funds. Additionally, we investigate the implications of these dynamics for bond liquidity and returns.[1]

Several unique characteristics of the corporate bond market and bond mutual funds highlight their importance in examining the effects of climate risks. First, the over-the-counter nature of the corporate bond market renders it a lot less liquid compared to the equity market (Bao, Pan, and Wang (2011)). Thus, a crucial vulnerability associated with corporate bond mutual funds is that they conduct drastic liquidity transformation, which could trigger large-scale investor redemptions in the face of a negative shock (like concerns about climate risks) and pose fragility to the mutual fund industry and the underlying markets (Goldstein, Jiang, and Ng (2017), Anand, Jotikasthira, and Venkataraman (2021), Falato, Goldstein, and Hortaçsu (2021), Haddad, Moreira, and Muir (2021), Jiang, Li, Sun, and Wang (2022), and Bretscher, Schmid, Sen, and Sharma (2024)). In addition, trading of corporate bond funds can generate substantial distortions in the prices of corporate bonds (Cai, Han, Li, and Li (2019) and Bretscher, Schmid, and Ye (2024)). Therefore, in the face of heightened climate risks, these characteristics can lead to unique investor flow patterns, influence mutual fund trading of corporate bonds, and exert considerable effects on bond

[1] Open-end mutual funds are important investors in the corporate bond market, holding about 20 percent dollar value of outstanding U.S. corporate bonds (Jiang, Li, Sun, and Wang (2022)).

prices and liquidity conditions.

Using a sample spanning from 2007 to 2019, we first show that investor flows of bond mutual funds are negatively related to the carbon exposure of their bond portfolios. We then infer causality by leveraging the Paris Agreement in December 2015 as an exogenous shock. Subsequently, we illustrate how carbon-driven redemptions lead bond mutual funds to divest from bonds issued by high-carbon companies (firms with carbon exposure scores ranking in the top tercile among all firms in each quarter), namely "high-carbon bonds". We rule out the alternative hypothesis suggesting a fundamental shift in mutual funds' investment preferences or ethical considerations towards reducing high-carbon holdings. Finally, aligning with the premise that mutual funds divest from high-carbon bonds due to investor redemption pressures, we observe a deterioration in the liquidity of high-carbon bonds. This effect intensifies for bonds with higher levels of mutual fund ownership and in periods marked by elevated carbon-related concerns.

Our results are summarized as follows. First, using a fund-month sample, we explore the dynamics between investor flows and bond funds' carbon exposure. Our analysis reveals that funds with greater carbon exposure tend to experience increased outflows, after controlling for a variety of fund characteristics and multiple fixed effects. To establish causality, we leverage the Paris Agreement as an exogenous shock that heightens end-investor awareness of climate change and carbon emissions. Our test results show that the negative response of investor flows to the fund's carbon exposure is amplified notably following the Paris Agreement. Our findings indicate that bond fund investors may exhibit a more pronounced negative reaction to funds' carbon exposure compared to equity fund investors (Hartzmark and Sussman (2019)). This heightened sensitivity among bond fund investors may stem from the substantial liquidity transformation performed by bond mutual funds and the associated fragility risks. Specifically, the liquidity mismatch creates a notable first-mover advantage for bond fund investors, intensifying their response to underperformance, especially in times of market distress (Goldstein, Jiang, and Ng (2017), Falato, Goldstein, and Hortaçsu (2021), and Jiang, Li, Sun, and Wang (2022))–a dynamic less evident among equity funds. Consequently, bond fund investors are likely more attuned to adverse shocks, including those related to carbon concerns.

Given the evidence that end investors are concerned with bond funds' carbon exposure, we expect that mutual fund managers might shift their portfolios away from high-carbon bonds to avoid potential large-scale redemptions. To test this hypothesis, we now turn to aggregate mutual fund trading behavior and analyze whether the carbon exposure of a corporate bond has an impact. Specifically, we use the sell herding measure (Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), and Cai, Han, Li, and Li (2019)) to quantify mutual funds' collective selling tendency, which gauges the extent to which a disproportionate number of mutual funds sell a certain security beyond the market-wide selling intensity in a given period. Beginning with a bond-quarter sample spanning from 2007 to 2019 and controlling for a variety of bond/firm characteristics and fixed effects, we find a strong and positive association between the bond's carbon exposure and mutual fund selling. In particular, the mutual fund sell herding measure of a high-carbon bond is 0.9 percentage points (or 6.5% of the standard deviation) higher compared to that of other bonds. Moreover, our results remain strong and robust when we employ an alternative selling measure, outflow-induced selling pressure (Coval and Stafford (2007)), as the dependent variable.

To establish the causal effect of firms' carbon emissions on mutual funds' selling, we again utilize the Paris Agreement as an exogenous shock and employ difference-in-differences analyses on the eight-quarter window around the Paris Agreement. Consistent with the results on fund flows, we find that mutual funds' selling towards bonds with high-carbon issuers is intensified after the Paris Agreement. The results are consistently robust for both mutual fund sell herding measure and outflow-induced selling pressure measure.[2]

[2] A potential concern about utilizing the Paris Agreement as our identification strategy is that there was a simultaneous large decline in oil prices around the Paris Agreement. The decline in oil prices could affect the performance of bonds in the "Energy" industry (which are more likely to be high-carbon bonds) and trigger mutual fund selling of such bonds. To rule out this alternative explanation, we control for bond exposure to oil price shocks and our results hold.

To substantiate that fund managers' selling of high-carbon bonds is motivated by carbon-related redemption risks, we exploit the fact that the sensitivity of investor flows to fund carbon exposure varies significantly across different mutual funds. Thus, corporate bonds with comparable carbon exposure may be subject to varying degrees of carbon-related redemption risks based on the profile of their mutual fund owners. Our analysis reveals that for two high-carbon bonds, the one held by funds with higher flow-to-carbon sensitivity experiences significantly more selling than the bond held by funds with lower flow-to-carbon sensitivity. This indicates that, beyond the bonds' own carbon exposure scores, mutual funds are more inclined to divest from bonds held by funds facing higher redemption risks. Therefore, our findings robustly validate redemption risks as a driving force behind mutual funds' selling of high-carbon bonds.

While our findings strongly suggest that the selling of high-carbon bonds by mutual funds is motivated by concerns over redemption risks associated with such bonds, it is plausible to consider an alternative explanation: mutual funds might be selling high-carbon bonds due to a fundamental shift in their investment preferences or ethics against bonds from high carbon-emitting firms. These shifts could reflect long-term changes in investment attitudes, potentially permanent and irreversible. However, we present two pieces of evidence to counter the idea of such a fundamental shift in investment strategy. Firstly, we utilize the election of President Trump as another shock. Should there be a fundamental shift in trading preferences, investor flows and mutual funds' trading behaviors would remain consistent before and after the election. Contrarily, we observe a significant reversal in both investor outflows and mutual funds' selling of high-carbon bonds following President Trump's election in November 2016, largely offsetting the intensified redemptions and selling effects post the Paris Agreement. Secondly, the price impact of the Paris Agreement on high-carbon bonds, while substantial, appears to be temporary. High-carbon bonds faced significantly larger price drops around the time of the Paris Agreement compared to their low-carbon counterparts, yet these declines swiftly recovered within six months. This pattern aligns better with the dynamics of mutual fund fire sales triggered by escalated carbon-related concerns. Collectively, the countervailing effect of Trump's election on investor flows and mutual fund selling behaviors and the transient nature of the price effects following the Paris Agreement indicate that our findings are unlikely to stem from a fundamental shift towards a preference for low-carbon bonds by mutual funds.

Given our finding that mutual funds tend to divest from high-carbon bonds due to redemption pressures, it naturally follows that the liquidity of these bonds would deteriorate. This is based on the understanding that if mutual funds collectively lower their stakes in high-carbon bonds, dealers might struggle to find interested buyers, resulting in increased trading costs and reduced liquidity. This effect is particularly pronounced considering mutual funds are among the most active traders in the corporate bond market. To examine this hypothesis, we employ three widely-used illiquidity metrics in the corporate bond market—Amihud, Roll, and IRC—to test the relative illiquidity of high-carbon bonds. Our regression analysis shows that the coefficients for the high-carbon dummy are consistently positive and statistically significant, with more pronounced effects observed in bonds with greater mutual fund ownership. Furthermore, our findings highlight a significant decline in the liquidity of high-carbon bonds following the Paris Agreement. Taken together, our findings strongly support the notion that mutual fund sell-offs contribute to increased illiquidity in high-carbon bonds.

Our paper makes several contributions to the literature. First, we identify a new factor that drives corporate bond mutual fund flows, namely, the fund's carbon exposure. Hartzmark and Sussman (2019) find that equity fund flow is higher towards funds being categorized as high sustainability. Ceccarelli, Ramelli, and Wagner (2024) show that equity mutual funds labeled as "low carbon" experience a significant increase in investor demand. We provide the first evidence on the negative flow-to-carbon relationship for mutual funds in the corporate bond market, after controlling for known factors driving fund flows.[3] This finding indicates

[3]For a review on drivers and consequences of equity mutual fund flows, see Christoffersen, Musto, and Wermers (2014). For studies on corporate bond mutual fund flows, see, for example, Chen, Goldstein, and

that end-investors of mutual funds are sophisticated enough to take into account funds' exposure to carbon emissions. Investors' flow sensitivity to fund carbon exposure provides a transmission channel for firms' carbon emissions to affect mutual funds' trading decisions.

Second, we analyze in detail how mutual funds respond to firms' carbon emissions regarding their investments in corporate bonds. The vast majority of papers on institutional investors' responses to firms' carbon emissions have focused on the equity market (see, for example, Bolton and Kacperczyk (2021), Humphrey and Li (2021), Cao, Titman, Zhan, and Zhang (2023), Ceccarelli, Ramelli, and Wagner (2024), and Starks, Venkat, and Zhu (2024)). While Duan, Li, and Wen (2023) and Seltzer, Starks, and Zhu (2024) study aggregate institutional ownership for corporate bonds issued by high-carbon firms, we analyze mutual funds' trading behaviors towards high-carbon bonds and identify funds' concerns about redemption risks as the underlying mechanism.[4]

Third, we are the first to investigate how concerns about firms' environmental performances could affect liquidity in the corporate bond market. The majority of studies on carbon emission effects have focused on the equity market, where liquidity is not a salient issue. However, for corporate bonds, liquidity carries significant implications for both pricing and market stability. Bao, Pan, and Wang (2011) find that market illiquidity overshadows the credit risk component in explaining the prices of high-rated corporate bonds. In addition, multiple papers have shown that the recent COVID-19 crisis essentially reflects itself as a liquidity crisis in the corporate bond market (see, for example, Haddad, Moreira, and Muir (2021), Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga (2021), Giannetti and Jotikasthira (2024), and O'Hara and Zhou (2021)). Our finding of liquidity deterioration for high-carbon bonds not only echoes the results of mutual funds' collective selling of these bonds but also

Jiang (2010), Chen and Qin (2017), and Goldstein, Jiang, and Ng (2017).

[4]In contrast to our primary focus on mutual fund trading dynamics, the focus of Duan, Li, and Wen (2023) and Seltzer, Starks, and Zhu (2024) is on the pricing implications of environmental risks in the corporate bond market. Duan, Li, and Wen (2023) study whether carbon risks are priced in the cross-section of corporate bond returns. Seltzer, Starks, and Zhu (2024) study the relationship between bond yield spreads and the issuers' environmental performance and emphasize the fundamental channel of credit risks in driving bond yield spreads.

deepens the understanding of the pricing implications of carbon emissions. In particular, our finding implies that the effects of carbon exposure on corporate bond prices could also be driven by changes in bonds' liquidity conditions, rather than by credit risks alone.[5]

Finally, our paper emphasizes that constraints faced by institutional investors (like mutual funds' redemption risks) can amplify shocks for underlying markets.[6] We find that a high-carbon bond is more likely to be sold collectively by mutual funds if its holding funds suffer more carbon-induced redemption risks. Our paper complements the literature by showing that redemption risks can reinforce the impact of a new shock, the awareness of carbon emissions, on the underlying market.

The rest of the paper is structured as follows. Section 2 describes our data and sample and explains how we construct some of the key measures in the paper. Section 3 examines the relationship between mutual funds' investor flows and their carbon exposure. Section 4 investigates mutual funds' selling behaviors towards high-carbon bonds. Section 5 assesses whether the divestment from high-carbon bonds by mutual funds is a tactical response to investor redemptions or indicative of a fundamental shift in investment preferences. Section 6 investigates the effects of bonds' carbon exposure on their liquidity. Section 7 concludes.

2 Data, variable construction, and summary statistics

In this section, we first discuss our data sources and sample construction. We then explain how we construct the key measures used in our analysis (including mutual fund flow, fund-level carbon exposure, the sell herding measure, and bond illiquidity measures). Finally, we provide summary statistics for the main variables.

[5] Amiraslani, Lins, Servaes, and Tamayo (2023), Halling, Yu, and Zechner (2021), and Seltzer, Starks, and Zhu (2024) all emphasize the fundamental channel of credit risks in driving bond yield spreads and returns. The existing literature also finds that poorer environmental performance can introduce asset price premia in the bank loan market (Chava (2014)), the municipal bond market (Painter (2020)), the equity market (Bolton and Kacperczyk (2021)), the real estate market (Giglio, Maggiori, Rao, Stroebel, and Weber (2021)), and the option market (Ilhan, Sautner, and Vilkov (2021)).

[6] For papers on how investor flows of fixed-income mutual funds introduce fragility risks to the underlying markets, see Jiang, Li, Sun, and Wang (2022), Li, O'hara, and Zhou (2024), Choi, Hoseinzade, Shin, and Tehranian (2020), Chen, Du, and Sun (2024), and Ma, Xiao, and Zeng (2022).

2.1 Data and sample

Our study combines data from several sources, spanning a sample period from January 2007 to December 2019. To measure corporate carbon emission performances, we obtain the MSCI carbon emission scores from the MSCI ESG rating. Overall, MSCI ESG provides an analysis of a company's exposure to ESG-driven risks and an in-depth comparison against industry peers on how well companies are managing their exposure. Specifically, MSCI follows the ESG Intangible Value Assessment (IVA) three-stage approach to score companies: 1) identify the key ESG drivers (issues) of risks for each industry; 2) evaluate each company's risk exposure and risk management to the key ESG issues based on a granular breakdown of the firm's business; and 3) rank and rate each company against its industry peers.[7]

The key issue of carbon emission in the "E (environments)" part evaluates the extent to which companies face increased costs linked to carbon pricing or regulatory caps. MSCI collects firms' carbon emission data every year from the most recent corporate resources, such as annual reports and corporate social responsibility reports. When direct disclosure is unavailable, MSCI uses GHG (greenhouse gas) data reported by the Carbon Disclosure Project (CDP) or government databases.[8] Companies that proactively invest in low-carbon technologies and increase the carbon efficiency of their facilities or products score higher on this key issue. The MSCI carbon emission score covers all the companies in the MSCI World Index, and corporate bonds issued by these firms take more than 70% of the total corporate bond market cap. The score ranges from 0 to 10 and is generally updated annually, although updates may occur more than once within a year. We invert the original MSCI carbon emission score, recalculating it as 10 minus the original score, to ensure that a higher transformed score reflects a higher level of carbon emissions. We refer to this transformed measure as the carbon exposure score in our paper.

Next, for the corporate bond transaction and price data, we rely on the Enhanced Trade

[7]Please see Appendix B.1 for details of the three steps for MSCI ESG IVA.

[8]Please see Appendix B.2 for details on the key issue of carbon emission.

Reporting and Compliance Engine (TRACE) database. We follow procedures in Dick-Nielsen (2014) to minimize data reporting errors by removing all transactions marked as cancellations, corrections, and reversals, as well as their matched original trades. Agency transactions that may raise concerns of double counting are also deleted. For intraday data, bond transactions that (i) are labeled as when-issued, locked-in, or have special sales conditions; (ii) are with more than 2-day settlement; or (iii) have a trading volume smaller than \$10,000 are eliminated.

We supplement the bond data with Mergent's Fixed Income Securities Database (FISD), which contains both bond issue- and issuer-specific information, such as coupon rate, interest payment frequency, issue date, maturity date, issue size, and bond rating. We focus on fixed rate bonds and exclude bonds that are puttable, convertible, or perpetual. We also exclude mortgage-backed, asset-backed, agency-backed, equity-linked securities, Yankees, Canadians, structured notes, as well as issues denominated in foreign currency. Besides, following the prior literature, we exclude newly issued and about-to-mature bonds (i.e., with age or time-to-maturity of less than six months), as their trading patterns are likely to be driven by mechanical factors. We also supplement our data with firm-level equity information from CRSP and COMPUSTAT.

We obtain data on institutional holdings of fixed-income securities from Thomson Reuters Lipper eMAXX. Thomson Reuters Lipper eMAXX is widely used in academic studies including Manconi, Massa, and Yasuda (2012) and Cai, Han, Li, and Li (2019) among others. This dataset is survivorship-bias free and contains quarter-end bond level holdings of about 20,000 institutional investors, including insurance companies, mutual funds, pension funds, and others.[9] We focus on mutual funds in this paper, and the eMAXX data covers over 90% of the mutual fund universe according to He, Khorrami, and Song (2022). Specifically, the

[9] However, the eMAXX database has limited holding data for pension funds and other institutional investors in the corporate bond market, particularly foreign institutions. Additionally, it does not capture holdings by hedge funds and retail investors. As a result, our ability to thoroughly investigate the trading counterparties of mutual funds, especially concerning bonds with high carbon exposure, is constrained, and therefore, this aspect is not addressed in the paper.

mutual funds in our sample include both bond mutual funds and hybrid mutual funds, with maximum holdings of corporate bonds across all quarters more than $1 million. Following the prior literature, we define the quarterly position change in a mutual fund's holdings of a certain bond as the fund's trading amount on that bond. Such a definition is warranted by the low trading frequency in the corporate bond market.

After compiling data from the aforementioned sources, we construct a dataset at the bond-quarter level. We then restrict this sample to include only those observations where the bond is traded at least once during the quarter and is held by at least one mutual fund in that quarter or the preceding quarter. Our main sample for analysis contains 11,876 unique corporate bonds from 1,082 unique U.S. public firms over the sample period from January 2007 to December 2019.

Our data of mutual fund characteristics and flows come from the Center for Research in Security Prices (CRSP) survivorship-bias-free US mutual fund database. The database contains information about mutual funds' net-of-expense returns, total net assets (TNA), and various fund characteristics such as fund age, expense ratio, and cash holding composition. Following the previous literature, we aggregate share-class level information to fund-level. Different from the sell herding measure calculated on a quarterly basis, analyses of the mutual fund flow employ monthly data of fund returns and TNAs to obtain more robust results (Keswani and Stolin (2008)). We then manually match CRSP mutual fund data with eMAXX fund data based on fund names. To ensure that the funds in our sample maintain a significant position in corporate bonds, we exclude funds if (i) their maximum holdings of corporate bonds across all quarters are less than $1 million; or (ii) their corporate bond holdings never exceed 10% of the fixed-income holdings across all quarters. Furthermore, we remove fund records with an age of less than one year to mitigate data biases associated with young funds. Finally, our mutual fund sample for flow-related analysis contains 1,653 unique mutual funds, with 94,639 fund-month observations.

2.2 Variable construction

2.2.1 Mutual fund flow

Following the previous literature (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)), we compute fund flow as the percentage change in total net assets (TNA) of fund j in month t, adjusted for fund return of that month. Specifically, fund flow is calculated as follows.

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}\left(1 + R_{j,t}\right)}{TNA_{j,t-1}} \tag{1}$$

where $TNA_{j,t}$ is the total net asset value of fund j at the end of month t, and $R_{j,t}$ is the return of fund j of month t.

2.2.2 Fund-level carbon exposure

To measure fund-level carbon exposure of bonds, we follow the methodology in Cao, Titman, Zhan, and Zhang (2023) and take a value-weighted average of the carbon exposure of all bonds in their portfolios at the end of each quarter, using the following equation:

$$Fund\ carbon\ exposure_{j,t} = \sum_i \omega_{i,j,t} Carbon\ exposure_{i,t} \tag{2}$$

where $Carbon\ exposure_{i,t}$ is the carbon exposure score for bond i in the quarter t. $\omega_{i,j,t}$ is the weight of bond i in mutual fund j's total corporate bond holdings with available carbon scores at the end of quarter t, and $Fund\ carbon\ exposure_{j,t}$ is the carbon exposure score for mutual fund j at the end of quarter t. A higher value of $Fund\ carbon\ exposure_{j,t}$ indicates that mutual fund j holds more bonds issued by high-carbon firms.

2.2.3 Sell herding measure (SHM)

To quantify mutual funds' selling activities of corporate bonds, we follow Lakonishok, Shleifer, and Vishny (1992) and Cai, Han, Li, and Li (2019) and estimate the extent of herding by institutional investors in trading corporate bonds. It captures whether a disproportionate number of institutions are buying/selling a certain security beyond the industry-wide buying/selling intensity in a given period. By construction, the herding measure controls for the impact of industry trends, such as the general increase in corporate bond holdings by mutual funds over time. This allows us to focus on the abnormal trading propensity of a specific bond relative to the average trend observed in other bonds. Specifically, we calculate the herding measure of bond i in quarter t for mutual funds, using the following equation:

$$HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]| \tag{3}$$

where $p_{i,t}$ is the proportion of buyers to all active traders of bond fund i in quarter t. The term $E[p_{i,t}]$ is the expected level of buying intensity, estimated using the market-wide intensity of buying $\bar{p}_t$,

$$\bar{p}_t = \frac{\sum_i \# \ of \ Buy_{i,t}}{\sum_i \# \ of \ Buy_{i,t} + \sum_i \# \ of \ Sell_{i,t}} \tag{4}$$

Therefore, the first term in Equation (3) measures how much the trading pattern of bond i varies from the general trading pattern of corporate bonds in quarter t, driven by disproportionally buying or selling by the group of investors under consideration. To account for the fact that the absolute value of $|p_{i,t} - E[p_{i,t}]|$ is always equal or greater than zero, we use the second term in Equation (3) as an adjustment factor, to make the expected value of herding measure under null hypothesis zero.[10]

Next, we follow Wermers (1999) to define the sell herding measure (SHM) for bonds with

[10] We follow Lakonishok, Shleifer, and Vishny (1992) to calculate the adjustment factor in Equation (3). It accounts for the fact that under the null hypothesis of no herding, i.e., when the probability of any institution being a net buyer of any bond is $\bar{p}_t$, the absolute value of $p_{i,t} - E[p_{i,t}]$ is greater than zero. The adjustment factor is, therefore, the expected value of $p_{i,t} - E[p_{i,t}]$ under the null hypothesis of no herding. Since $Buy_{i,t}$ follows a binomial distribution with probability $\bar{p}_t$ of success, the adjustment factor is easily calculated given $\bar{p}_t$ and the number of institutions active on that bond in that quarter.

a lower proportion of buyers than the industry average.[11]

$$SHM_{i,t} = HM_{i,t}|[p_{i,t} < E[p_{i,t}]] \tag{5}$$

In examining the effect of a bond's carbon exposure on its sale by mutual funds, we employ the sell herding measure in our baseline analyses. To ensure robustness, we also construct an alternative metric for mutual fund selling, referred to as the flow-induced selling pressure, following the methodology of Coval and Stafford (2007). This is further defined and explored in Section 4.4.

2.2.4 Illiquidity measures

We construct three widely used corporate bond illiquidity measures at the quarterly frequency: the Amihud measure gauges the price impact of a given trading size; the Roll measure is the implicit bid-ask spread in Roll (1984), estimated as the serial covariance of returns of each bond in each quarter; and the Imputed Round-trip Costs (IRC) measure is calculated following Dick-Nielsen, Feldhütter, and Lando (2012), where we include intraday interdealer transactions. The construction methodologies for the illiquidity measures are detailed in Appendix A. Higher values of these measures indicate that the bonds are more illiquid. All illiquidity measures are winsorized quarterly at 0.5% and 99.5% levels.

2.3 Summary statistics

Table 1 presents summary statistics of mutual fund, bond, and firm characteristics. Panel A shows the summary statistics of mutual funds. On average, the fund flow is 0.96% per month, with large cross-sectional heterogeneity (the average standard deviation is 7.37%). Our fund sample has an average fund carbon exposure of 2.93, indicating the mutual fund

[11] By definition, for a given bond in a given quarter, it has either a buy herding measure or sell herding measure (but not both), depending on its buying intensity relative to the market-wide buying intensity in that quarter.

on average holds bonds with relatively low carbon exposure.[12] Panel B (C) is based on bond-quarter (firm-quarter) observations. Our sample bonds have an average mutual fund sell herding measure of 5.34%. This implies that if 100 funds trade a given bond in a given quarter, there are approximately 5 more mutual funds that herd to sell than expected if each fund trades bonds independently. Average selling pressure is -0.04%, indicating there is a slight buying pressure market-wide by mutual funds that experience extreme flows.[13] The summary statistics for the liquidity measures and other characteristics of the bonds in our sample align with findings from previous literature. Specifically, the average bond illiquidity measure based on Amihud is 0.02% per thousand dollars. The average Roll and IRC illiquidity measures are 1.29% and 0.37%, respectively. On average, bonds in our sample have a credit rating of 7.89 (equivalent to roughly BBB+ for S&P or Baa1 for Moody's), a time-to-maturity of 9.75 years, and a time-since-issuance of 5.57 years.

[Insert Table 1 about here]

Bond issuers (i.e., firms) on average have a carbon exposure score of 3.81. At the end of each quarter, we sort all firms into three equal groups according to carbon exposure scores. Bonds issued by firms with carbon exposure scores in the top tercile are assigned with the high-carbon dummy equal to one, and zero otherwise.[14] For other firm-level characteristics, bond issuers are on average large firms with high institutional ownership (an average of 77%) and are followed by 14.15 financial analysts.

[12]To better understand whether fund characteristics are different for funds with different carbon exposure, we sort all the funds into quintiles based on the fund carbon exposure, and report the fund characteristics summary for five groups with different carbon exposure respectively, in Appendix Table A1, Panel A. We do not find a significant difference across groups. In Panel B, we also report the fund characteristics summary for high-yield funds, investment-grade funds, and others.

[13]Small magnitude of selling pressure is consistent with the previous literature (e.g., Jiang, Li, Sun, and Wang (2022)).

[14]The use of the high-carbon dummy rather than the carbon exposure score is intentional for two main reasons. First, it facilitates a clearer interpretation of the regressions' economic significance, especially given the complexity introduced by interaction terms between the high-carbon dummy and other variables. Second, it mitigates concerns about potential systematic changes in MSCI's methodology for calculating carbon emission scores and variations in coverage over time. Specifically, there is a notable increase in the average MSCI carbon emission score in 2012, which coincides with a major revision of the ESG Ratings model and a significant expansion in MSCI's coverage of firms' carbon exposure scores that same year.

In Panel D of Table 1, we provide distribution information on the carbon exposure scores of firms issuing corporate bonds for each of the Fama-French 12 industries. The average carbon exposure scores are comparable across industries, except for the relatively high score of the "Energy" industry, which includes "Oil, Gas, and Coal Extraction and Products" and typically has high carbon emissions.[15] This observation is largely consistent with the manual of MSCI that the measure is adjusted by industry and is thus comparable for two firms from different industries.

To address the concern that MSCI focuses on carbon emissions of certain industries and that the matched sample may not be representative enough for the overall corporate bond market, in Panel E of Table 1 we compare the Fama-French 12 industry distributions of issuers with corporate bonds and those further with MSCI emission scores. The comparison shows that industry compositions for the two groups are similar, indicating that our sample is representative of the general corporate bond market in terms of industry composition.

3 Investor flows and carbon exposure in mutual funds' bond portfolios

We begin our analyses by investigating the relationship between investor flows and the carbon exposure in mutual funds' bond portfolios. Intuitively, if end investors are more likely to withdraw from funds with high-carbon bond portfolios, such investor behavior would serve as a strong incentive for fund managers to sell high-carbon bonds in their portfolios, given that the primary risk for corporate bond mutual funds is their vulnerability to large investor redemptions. This risk is amplified by the substantial liquidity transformation undertaken by these funds, which generates a pronounced first-mover advantage to investors, thereby magnifying their response to any adverse shocks, including carbon-related ones.

[15] To make sure that our results are not driven by this industry alone, we replicate our main tests after excluding bond issuers in the "Energy" industry. Our results are robust to the exclusion of the "Energy" industry.

3.1 Investor flows and bond funds' carbon exposure: A panel regression

Using a fund-month sample, we test how investor flows respond to bond funds' carbon exposure, by regressing the percentage flow of fund j in month t on fund carbon exposure (defined in Section 2.2.2) as of the most recent quarter-end of month $t-1$:[16]

$$Flow_{j,t} = \alpha + \beta \times Fund\ carbon\ exposure_{j,t-1} + \delta \times controls_{j,t-1} + \mu_t + \theta_s + \epsilon_{j,t} \tag{6}$$

where μ_t represents the year-month fixed effects and θ_s is the fund style fixed effects. Here, we use the Lipper Objective Code to identify the style of mutual funds. We control for a set of lagged fund characteristics, including logarithm of TNA, average bond rating in the fund portfolio, monthly return (measured at the end of the previous month), short-term cumulative monthly return over the past 6 months, long-term cumulative monthly return over the past 12 months, percentage of cash holding, expense ratio, turnover ratio, and fund age.

[Insert Table 2 about here]

Results in Table 2 show that funds with higher fund carbon exposure experience larger outflows, robust across different specifications. With time and style fixed effects included in Column (1), a one-standard-deviation (1.75) increase in a fund's carbon exposure is associated with a 0.25-percentage-point increase in fund outflows (around 3.3% of the standard deviation). The effect of fund carbon exposure on investor flows remains prominent after controlling for various fund characteristics and fund fixed effects, as shown in Columns (2)

[16] For a robustness check, we also calculate an alternative metric for assessing fund-level carbon exposure, which we call "fund high-carbon holding." This metric is computed each quarter for every fund as the ratio of the holding value of high-carbon bonds to the total holding value of all corporate bonds for which carbon emission scores are available. Consistent with our paper's criteria for high-carbon bonds, we classify bonds from the top tercile of carbon exposure as high-carbon. This measure captures the proportion of a fund's investments in bonds with substantial carbon exposure. Employing this measure as our principal independent variable yields consistent and significant findings.

to (4).[17,18] In unreported tests, we also explore the possibility of nonlinearity in the flow-to-carbon relationship but find no evidence to support this.[19]

3.2 Causality for the flow-to-carbon relationship: Evidence from the Paris Agreement

Though we have included time fixed effects, fund fixed effects, and various time-varying fund control variables in our panel regressions, we recognize that there might be remaining endogeneity concerns about the documented relationship between investor flows and the funds' carbon exposure. To establish a causal link, we utilize the Paris Agreement as an exogenous shock to end-investor attention to climate change and carbon emissions. On December 12^{th}, 2015, the Paris Agreement was announced at the 21^{st} Conference of the Parties (or COP21) to the United Nations Framework Convention on Climate Change (UNFCCC) in Paris.[20] Under the Paris Agreement, 196 signatories have agreed to take actions to limit global temperature increases. It is broadly considered as a landmark step for global climate change mitigation and adaptation action, and more importantly, it came as a surprise.[21]

[17]We calculate fund flows at the quarterly level and re-run the regression tests from Table 2. The results, presented in Appendix Table A2, confirm that both the statistical significance and economic magnitude are comparable to the monthly regressions in Table 2.

[18]Following Sirri and Tufano (1998), we control for the nonlinearity of the flow-to-performance relationship in the regression. Specifically, we run piecewise linear regressions that allow for variant flow-to-performance sensitivity across different performance quintiles. In unreported tests, the negative effect of lagged fund carbon exposure on fund flows persists, even after controlling for the potential nonlinear dynamics between fund flow and past performance.

[19]The mutual funds in our sample encompass both bonds mutual funds and hybrid mutual funds that maintain nontrivial corporate bond holdings. To address the concern that investor flows into hybrid funds might be driven by the carbon exposure of equity holdings rather than those of bond holdings, we conduct two supplementary tests. Firstly, we refine our sample to include only bond mutual funds (defined by Chen and Qin (2017) and Choi, Hoseinzade, Shin, and Tehranian (2020)) and find that our results remain consistent. Secondly, we incorporate the carbon exposure of equity holdings as an additional control in our regression analyses, and our results are robust to this augmented specification.

[20]For the first time, most UN countries agreed on the need to limit global temperature increase "well below 2°C" above pre-industrial levels (Art 2.1(a)), to strengthen the ability of countries to deal with the impacts of climate change (Art 2.1(b)), and to commit to "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" (Art 2.1(c)). Complete texts of the Paris Agreement can be found at https://unfccc.int/process-and-meetings/the-paris-agreement.

[21]See Savaresi (2016): "On the eve of the conference, few would have expected them to succeed in this task. Yet, to the surprise of many, they did."

For firms with higher carbon exposure, regulatory risks, and litigation risks would increase, as regulations against climate change (like a carbon tax) have a higher probability of being materialized. At the same time, the Paris Agreement would also raise the awareness of global warming for general investors and direct their attention to risks associated with firms' carbon emissions. As a result, after the Paris Agreement was announced, we expect the negative relation between fund flows and fund carbon exposure to be strengthened.

Specifically, we investigate how the flow-carbon relationship changes around the Paris Agreement in the event window of [-6, +6] months (excluding the event month based on the time of fund flow). We run difference-in-differences regressions to test our hypotheses and report the results in Table 3.

[Insert Table 3 about here]

After the Paris Agreement, there are even larger outflows for funds that hold more carbon-intensive bonds. The effect is statistically significant at the 1% level when various fund characteristics and fund fixed effects are controlled for (Column (3)). Our results demonstrate that the sensitivity of investor flows to the funds' carbon exposure is magnified notably after the Paris Agreement, not only supporting the causal effects of fund carbon exposure on investor flows, but also suggesting that mutual fund investors are sophisticated enough to assess funds' carbon-related risks and actively react to changes in such risks.[22]

Our findings reveal that bond mutual fund investors are responsive to the fund's carbon exposure, marking a departure from observations in the equity mutual fund sector. For instance, Hartzmark and Sussman (2019) find that fund flows are affected by Morningstar's sustainable globe ratings, but not the ESG performance of the holdings themselves. The significant sensitivity among bond fund investors to carbon exposure may stem from the substantial liquidity transformation that bond mutual funds engage in, along with the asso-

[22]While we provide strong evidence that funds' carbon exposure leads to investor redemptions, we do not pinpoint the precise type of carbon-related risk investors are concerned about. Instead, we demonstrate that investors indeed respond to carbon-related risks that are present in funds' portfolios. These risks may include policy uncertainty, regulatory risks, and transition risks.

ciated fragility risks. Specifically, this liquidity mismatch creates a pronounced first-mover advantage for investors in corporate bond funds, leading to an amplified withdrawal response to underperformance (Goldstein, Jiang, and Ng (2017)). Furthermore, recent research has shown that redemptions from bond mutual funds are highly sensitive to stress or panic, as evidenced by the significant outflows experience during the COVID-19 crisis (Falato, Goldstein, and Hortaçsu (2021) and Jiang, Li, Sun, and Wang (2022))—a pattern not seen in equity funds. These insights collectively indicate that investors in bond mutual funds are likely to be acutely aware of adverse shocks, including environmental issues like carbon exposure, which are garnering increasing public attention.

4 Carbon emission and mutual fund selling of corporate bonds

In Section 3, we demonstrate that end investors are concerned with the carbon exposure of mutual funds' bond portfolios and make their redemption decisions based on this exposure. Such redemptions pose significant stability risks for bond mutual funds, given the inherent illiquidity and high transaction costs of the corporate bond market, coupled with the provision by mutual funds of daily redemptions to investors. This substantial liquidity transformation by mutual funds can exacerbate withdrawals in response to negative shocks (as discussed in Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017)), potentially leading to fire sales of illiquid bonds. These sales can inflict significant losses on bond funds and trigger further redemptions, creating a downward spiral. Consequently, fund managers would have strong incentives to curtail such redemption risks. In other words, to attract more inflows and avoid potential large-scale redemptions, mutual fund managers might shift their portfolios away from high-carbon bonds.

To explore this possibility, we now turn to aggregate mutual fund trading behavior and analyze whether the carbon emission of a corporate bond issuer has an impact. We use the sell herding measure to capture the magnitude of collective selling among mutual funds, and our results are robust to an alternative measure of mutual fund trading, namely outflow induced selling pressure. The analysis is first conducted with a full sample from January 2007 to December 2019 and the causality is established by exploiting the shock of the Paris Agreement.

4.1 Mutual fund sell herding and bond carbon exposure

To start, we investigate whether mutual funds are more likely to collectively sell bonds issued by firms with high carbon emissions by running bond-quarter panel regressions as follows:

$$SHM_{i,t} = \alpha + \beta \times High\text{-}carbon_{i,t-1} + \delta \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \tag{7}$$

where $SHM_{i,t}$ is the sell herding measure of mutual funds for bond i over quarter t. $High\text{-}carbon_{i,t-1}$ is a dummy variable measured at the previous quarter end, indicating whether the issuer's carbon exposure score falls into the top one-third among all firms.[23]

In the baseline bond-quarter panel regression model, we control for various bond-level characteristics and year-quarter fixed effects, with bond level controls including bond rating, time to maturity, age, coupon rate, and the logarithm of the bond issue size.[24] We further control for stock characteristics of the issuer in later specifications, which include the firm's equity size (the logarithm of the market value of the firm's equity), the logarithm of book-to-market ratio, stock IVOL (the standard deviation of daily residual equity returns), stock institutional ownership, and the number of analysts following that stock.[25] Standard errors are calculated using two-way clustering at the bond and quarter levels. The results are

[23]Utilizing this high-carbon dummy allows easier interpretation of the economic significance of the regression results and alleviates potential concerns for systematic changes to the calculation methodology of raw carbon emission scores. Moreover, approximately 34% of the firms in our sample have experienced at least one change in the high-carbon dummy (shifting from a 0 to a 1, or a 1 to a 0), indicating substantial within-firm variation in the high-carbon dummy. More importantly, the baseline results remain robust if we use the raw emission score or alternative cutoffs to define the dummy such as quintiles.

[24]Note that the inclusion of bond fixed effects renders the coupon size and logarithm of bond issue size redundant in our regression.

[25]Please refer to Appendix A for detailed definitions of all of our variables.

reported in Table 4.

[Insert Table 4 about here]

After controlling for bond characteristics and time fixed effects, the high-carbon dummy is positively associated with mutual funds' collective selling, significant at the 1% level, as reported in Column (1) of Table 4. The coefficient indicates that if a bond is issued by a firm with a high-carbon business model, the mutual funds' collective selling of the bond is one percentage point higher compared to bonds issued by other firms. The estimated coefficient is economically significant and equivalent to 7% of the standard deviation of the mutual fund sell herding measure.

To address the concern that the high-carbon dummy is potentially correlated with other non-observable bond characteristics and firm characteristics, which might confound the relationship between the mutual funds' collective selling and high-carbon dummy, we include the bond fixed effects in Column (2) and further control for stock characteristics in Column (3) of Table 4. The effect of the high-carbon dummy on mutual funds' collective selling remains significant, both statistically and economically. In particular, Column (3) shows that for a given bond, its collective selling by mutual funds increases by 0.9 percentage points when its issuer's carbon exposure changes from normal to high.[26] In unreported tests, we additionally control for bonds' lagged sell herding levels and lagged abnormal returns, and our results are robust.[27]

[26] We also calculate the measure for mutual funds' collective buying behavior, i.e., the buy herding measure defined as $BHM_{i,t} = HM_{i,t}|[p_{i,t} > E[p_{i,t}]]$ and perform similar tests as in Table 4 with the BHM as dependent variable (not reported). We do not find a significant relationship between the buy herding measure and the high-carbon dummy. Thus, while mutual funds tend to sell high-carbon bonds collectively, they do not flock to buy lower-carbon bonds.

[27] In addition to using the high-carbon dummy based on the carbon exposure score, we employ an alternative measure by sourcing firm-level carbon emission intensity data from Trucost. This measure is defined as the logarithm of the sum of Scope 1 (direct emissions from production) and Scope 2 (indirect emissions from the consumption of electricity, heat, or steam) carbon emissions, normalized by firm revenue. The correlation between the high-carbon dummy and carbon emission intensity is 0.27. Our analysis remains robust when replacing the high-carbon dummy with carbon emission intensity as the primary independent variable, as shown in Appendix Table A3. Additionally, in results not presented, we observe consistent findings when employing alternative cutoffs to define the high-carbon dummy.

A potential concern with our findings is that we can find a positive association between a bond's carbon exposure and mutual fund selling even if fund managers do not proactively reduce their holdings in high-carbon bonds. In other words, if managers of high-carbon funds merely scale down their holdings proportionately—a response to experiencing larger redemptions—such flow-induced passive reactions could alone account for our observations. To address this concern, we introduce a flow-adjusted sell herding measure, employing the methodology from Jiang, Li, and Wang (2021) to evaluate the "flow-adjusted trading" activity for each bond within a fund's portfolio. This approach is based on the notion that passive adjustments to portfolio holdings in response to investor flows, like a 1% fund outflow, would typically prompt an equivalent 1% decrease in each bond holding. If the reduction in holdings for a specific bond deviates from this benchmark—either exceeding or falling short of the 1% threshold—the fund is classified as a "flow-adjusted seller" or "flow-adjusted buyer" of that bond. By redefining the terms "buyer" and "seller" in this context, we calculate the flow-adjusted sell herding measure and replace our original sell herding measure with this adjusted version as the dependent variable. The results, presented in Appendix Table A4, show a significantly positive coefficient for the high-carbon dummy, indicating that fund managers are actively divesting from high-carbon bonds rather than simply making uniform reductions across their portfolios in response to investor withdrawals.

4.2 Establishing causality: Evidence from the Paris Agreement

Though we have included bond fixed effects and various control variables in our baseline regressions, we recognize that there might be remaining endogeneity concerns about the documented relationship between a firm's carbon exposure and the trading behavior of mutual funds in the corporate bond market. For example, unobservable firm-level risks might confound this relationship. To establish a causal link from the issuer's carbon exposure to the mutual funds' collective selling of its bonds, we again utilize the Paris Agreement as an exogenous shock and expect the impact of bond carbon exposure on mutual fund sell herding to be intensified after the Paris Agreement.

To test the hypothesis, we employ a difference-in-differences approach. We focus on an event window of [-4, +4] quarters, excluding the event quarter. Specifically, we focus on the sample period from 2014Q4 to 2016Q4, excluding the 4^{th} quarter of 2015 based on the time of dependent variable measurement, and run the following regressions for the Paris Agreement event:

$$SHM_{i,t} = \alpha_1 + \beta_1 \times High\text{-}carbon_{i,t-1} \times PA_t + \gamma_1 \times High\text{-}carbon_{i,t-1} + \delta_1 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \tag{8}$$

where PA_t is a time dummy equal to one for the period after the announcement of the Paris Agreement.[28] Our variable of interest is the interaction term $High\text{-}carbon_{i,t-1} \times PA_t$.[29] If the conjecture is correct, we would find a positive β_1, which captures how the effect of bond carbon exposure on mutual funds' collective selling changes after the Paris Agreement.

[Insert Table 5 about here]

In Table 5, we find mutual funds' collective selling of bonds issued by carbon-intensive firms significantly intensifies after the Paris Agreement, robust across different specifications. Specifically, Column (1) shows that relative to the four quarters before the announcement of the Paris Agreement, a high-carbon bond experiences a 2.6-percentage-point increase (19% of standard deviation) in its mutual funds' collective selling following the Paris Agreement, nearly three times of the corresponding magnitude in the full sample.

To address the concern that our results could be driven by the pre-Paris Agreement (pre-PA) trends on the relation between issuers' carbon exposure and mutual funds' collective selling, we verify the premise of pre-PA parallel trends following the methodology of Borusyak, Jaravel, and Spiess (2024). Specifically, we define the dummies PA(-3) and PA(-2), which equal one for the third to last quarter (2015Q1) and second to last quarter

[28] Note that the effect of the PA dummy is absorbed by the time fixed effects.

[29] During the eight quarters included in our Paris Agreement analysis, 10.3% of firms experienced a change in their high-carbon dummy, either from 0 to 1 or from 1 to 0.

(2015Q2) before the Paris Agreement and zero otherwise, respectively. We interact these two dummies with the high-carbon dummy. The interactions capture whether the sensitivity of mutual funds' collective selling to carbon exposure begins to change before the announcement of the Paris Agreement. In Column (4), the insignificant coefficients on interactions of pre-PA dummies with the high-carbon dummy support the parallel trend assumption before the Paris Agreement.

To further validate the use of the Paris Agreement as an effective exogenous shock for identification, we conduct placebo tests using 2011Q4 and 2012Q4 as the "event" quarters, and re-run the regressions specified in Equation (8). We choose 2011Q4 and 2012Q4 to ensure that the placebo test periods do not overlap with the Paris Agreement test period. The results are presented in Appendix Table A5 and show that the coefficients on the interaction terms are all insignificant in these placebo tests. Therefore, our findings of the Paris Agreement intensifying the effect of carbon emission on mutual funds' collective selling are unlikely to have been driven by seasonality or a random shock.

In summary, these tests show that the effects of carbon exposure on mutual funds' collective selling of corporate bonds get amplified when there are exogenous shocks that lead to higher awareness of climate change. The verification of pre-PA parallel trends further helps establish a causal relationship between a firm's carbon exposure and mutual funds' collective selling of its bonds.

4.3 Flow sensitivity to carbon exposure and mutual fund selling

To provide direct evidence that fund managers' selling of high-carbon bonds is indeed associated with carbon-driven redemption risks, we exploit the fact that the sensitivity of investor flows to fund carbon exposure varies significantly across different mutual funds. Thus, corporate bonds with similar carbon exposure scores may bear different levels of carbon-driven redemption risks due to their mutual fund ownership. Specifically, if a bond is mainly held by funds with higher flow-to-carbon sensitivity, then this bond is more likely to experience intensive selling from mutual funds compared to other bonds with similar carbon exposure.

To quantify this heterogeneity in bonds, we first calculate the fund-level sensitivity of investors' flow to fund carbon exposure, namely, flow-to-carbon sensitivity, each month on a rolling basis.

$$Flow_{j,t} = \alpha + \beta_{j,t} \times Fund\ carbon\ exposure_{j,t-1} + \delta \times controls_{j,t-1} + \epsilon_{j,t} \tag{9}$$

where $\beta_{j,t}$ is estimated based on the past 12-month observations of fund j in month t. $Fund\ carbon\ exposure_{j,t-1}$ is the value-weighted carbon exposure of bonds in the portfolio of fund j as of the most recent quarter-end of month $t-1$. We control for the logarithm of TNA, monthly return, percentage of cash holding, expense ratio, turnover ratio, and fund age in the regression. A more negative $\beta_{j,t}$ indicates that outflows are more responsive to the mutual fund's carbon exposure.[30] Based on a quarterly average of $\beta_{j,t}$, we divide all the mutual funds into two subgroups according to the cross-sectional median, namely high-carbon-sensitivity funds (those with $\beta_{j,t}$ below the median) and low-carbon-sensitivity funds (those with $\beta_{j,t}$ above the median). High-carbon-sensitivity funds are those whose outflows are more sensitive to carbon exposure. Then, for each bond, we measure the portion that is held by high-carbon-sensitivity funds, that is the holding weighted average of high-carbon-sensitivity fund dummies across all of its holding funds. Such a measure quantifies on average how much of a bond is held by mutual funds whose flows are highly sensitive to fund carbon exposure, as demonstrated in Equation (10), and is named as (bond level) flow-sensitivity-to-carbon.

$$(Bond\ level)\ flow\text{-}sensitivity\text{-}to\text{-}carbon_{i,t} = \sum_j \omega_{i,j,t} High\text{-}carbon\text{-}sensitivity\ fund_{j,t} \tag{10}$$

where $\omega_{i,j,t}$ represents the par amount of corporate bond i held by fund j divided by the total amount of the bond held by all mutual funds at the end of quarter t. *High-carbon-sensitivity*

[30] The variation in the flow-to-carbon sensitivity can arise from different information sources, investor types, and more.

$fund_{j,t}$ is a dummy variable equal to one for high-carbon sensitivity funds, and zero otherwise.

If a high-carbon bond is mainly held by funds with high-carbon-sensitivity, we conjecture that its holding mutual funds are more likely to sell it to avoid large redemption of investors, given their flows are more sensitive to their carbon exposure. To test such a conjecture, we categorize all bonds into two groups based on the bond level flow-sensitivity-to-carbon: high- and low-flow-sensitivity-to-carbon. Bonds classified under high-flow-sensitivity-to-carbon are those predominantly owned by mutual funds with flows highly responsive to carbon exposure in the fund. Then in our baseline regression with the sell herding measure as the dependent variable, we additionally include the high-flow-sensitivity-to-carbon dummy and its interaction with the high-carbon dummy, and test whether the interaction has a significant and positive coefficient.

$$
\begin{aligned}
SHM_{i,t} =& \alpha_2 + \beta_2 \times High\text{-}carbon_{i,t-1} \times high\text{-}flow\text{-}sensitivity\text{-}to\text{-}carbon_{i,t} \\
& + \gamma_2 \times High\text{-}carbon_{i,t-1} + \vartheta_2 \times high\text{-}flow\text{-}sensitivity\text{-}to\text{-}carbon_{i,t} \\
& + \delta_2 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t}
\end{aligned} \tag{11}
$$

We show the supporting evidence in Table 6. When a high-carbon bond is held more by mutual funds whose flows are very sensitive to the fund carbon exposure, that bond is more likely to experience collective selling by mutual funds compared to other high-carbon bonds. Specifically, Column (1) shows that for two high-carbon bonds, the one held by more high flow-carbon sensitivity funds experiences significantly higher collective selling among mutual funds than the bond held by more low flow-carbon sensitivity funds. This finding shows that conditional on bonds' own carbon exposure scores, mutual funds have stronger incentives to dump bonds held by funds with higher redemption risks, leading to more intensive selling of such bonds. Thus, our results provide strong support for the redemption risk channel of mutual funds' collective selling of high-carbon bonds.

[Insert Table 6 about here]

Taken together, the evidence presented in Sections 4.1 to 4.3 suggests that, all else being equal, mutual funds tend to sell high-carbon bonds in response to redemption risks posed by end-investors. Such redemption risks fluctuate over time and vary among different mutual funds, depending on investors' attention to climate changes and the sensitivity of flows to funds' carbon exposure.

4.4 Robustness: Using an alternative mutual fund selling measure

So far, we use the sell herding measure to capture mutual funds' collective trading patterns. To show the robustness of our findings, we next employ an alternative mutual fund selling measure (namely, outflow-induced selling pressure) and repeat our tests. The definition of outflow-induced selling pressure follows Coval and Stafford (2007), and it is constructed based on realized fund trades conditional on large fund flows:

$$Selling\,pressure_{i,t} = \frac{\sum_{j=1}^{J}(Sell\text{-}Amt_{j,i,t}|Flow_{j,t} < 20^{th}Pctl - Buy\text{-}Amt_{j,i,t}|Flow_{j,t} > 80^{th}Pctl)}{Bond\ issue\ size_i} \tag{12}$$

where $Sell\text{-}Amt_{j,i,t}$ is the selling amount of mutual fund j on bond i in quarter t, and $Buy\text{-}Amt_{j,i,t}$ is similarly defined. This measure incorporates mutual fund flows into their trading decisions, capturing the difference between sales and purchases of a bond by mutual funds that experience extreme outflows and inflows with large inflows. A large positive value indicates strong outflow-induced selling pressure that is not mitigated by funds' purchases with large inflows. Intuitively, knowing that investors might react to funds' carbon exposure, fund managers have the incentive to prioritize dumping high-carbon bonds to meet redemptions. This leads to potentially higher selling pressure on high-carbon bonds.

[Insert Table 7 about here]

We use the outflow-induced selling pressure as the dependent variable and run our full sample panel regressions, with explanatory variables and controls detailed in Equation (7).

The results are shown in Table 7. The positive and significant coefficient on the high-carbon dummy confirms our conjecture that bonds issued by firms with carbon-intensive businesses are subject to more substantial outflow-induced selling pressure from mutual funds. In Column (1), where bond characteristics and time fixed effects are controlled for, high-carbon bonds experience outflow-induced selling pressure that is 0.039 percentage points (7.4% of the standard deviation) higher relative to other bonds, indicating a nontrivial economic magnitude.[31] Turning to causality, we again focus on the Paris Agreement and expect an intensified effect following the announcement. Specifically, we use outflow-induced selling pressure as the dependent variable and run similar difference-in-differences regressions as in Equation (8). The results presented in Table 8 show strongly positive coefficients on the interaction term between the high-carbon dummy and the post-Paris Agreement dummy, providing evidence for the causal effect of carbon emission on outflow-induced selling from mutual funds.

[Insert Table 8 about here]

In sum, using two different measures of mutual funds' selling behaviors, we show that mutual funds are more likely to collectively sell high-carbon bonds, and such bonds are more likely to experience larger redemption-induced selling from mutual funds. Both effects are intensified following the Paris Agreement.

4.5 An alternative explanation for evidence around the Paris Agreement: Negative oil price shocks

In this subsection, we address a potential concern for the adoption of the Paris Agreement as our identification strategy: What if mutual funds' intensified selling of high-carbon bonds

[31] Additionally, using the change in mutual fund ownership as an alternative dependent variable, we find that corporate bonds with higher carbon exposure experience more aggregate selling by mutual funds in the following quarter. The results are presented in Appendix Table A6. For high-carbon bonds, mutual fund ownership decreases by 11 basis points (7% of the standard deviation) more than for other bonds over the subsequent quarter.

following the Paris Agreement is driven by negative oil price shocks? This concern is legitimate for the following two reasons: First, oil prices had a notable decline over the period from 2014Q4 to 2016Q1, which overlaps with the event window of the Paris Agreement;[32] second, about 10% of bonds in our sample belong to the "Energy" industry which is more likely to be in the high-carbon category and exposed to oil price shocks. Issuers with high exposure to negative oil shocks would suffer from the sharp oil price decline, and the underlying bonds would experience collective selling from mutual funds.[33]

[Insert Figure 1 about here]

To investigate the possibility that the increase in the collective selling by mutual funds after the Paris Agreement may be caused by negative oil price shocks rather than concerns for carbon emissions, we next disentangle the effects of carbon emissions from those of oil price changes and show that our Paris Agreement results are unaffected after controlling for bonds' individual exposure to oil price shocks.

Following Demirer, Jategaonkar, and Khalifa (2015), we calculate a firm-level exposure to oil price shocks by running the following regression within each quarter, and assign the firm level oil exposure to all the bonds issued by that firm:

$$R_{f,t,w} = \alpha_{f,t} + \mu_{f,t} \times R_{m,t,w} + \beta_{f,t} \times R_{oil,t,w} + \epsilon_{f,t,w} \tag{13}$$

where $R_{f,t,w}$ and $R_{m,t,w}$ are the excess return for firm f and stock market of week w in quarter t, respectively. $R_{oil,t,w}$ is the return of Brent crude oil price of week w in quarter t.[34]

[32] In Figure 1, we plot daily West Texas Intermediate (WTI) and Brent crude oil spot prices from 2002 to 2019. The oil price declined much from 2014Q4 to 2016Q1 and reversed afterwards.

[33] Admittedly, issuers with low exposure to negative oil shocks could benefit from the oil price decline, which should lead to buying instead of selling of the underlying bonds and hence does not weaken our findings.

[34] Brent crude oil price is used to calculate oil returns as this type of oil accounts for a large percentage of global oil consumption (Degiannakis, Filis, and Kizys (2014)) and most of the Gulf Cooperation Council countries use the price of Brent as a benchmark in pricing their oil types. Of the total world oil consumption of 70-80 million barrels a day, Brent oil serves as a benchmark for between 40 and 50 million barrels a day, and West Texas Intermediate crude oil for 12-15 million barrels a day (Levin, Bean, Berkovitz, and Stuber (2003)).

$\beta_{f,t}$ is the loading on the oil factor, i.e., oil exposure, for firm f in quarter t.[35] $\beta_{f,t}$ measures the sensitivity of a firm's stock price to the movement of oil price in a given quarter, thus serving as a time-varying proxy of exposure to oil price shocks for all the bonds issued by that firm.

We then augment the specification of Equation (8) (i.e., the difference-in-differences test) by including $\beta_{f,t}$ (i.e., bond issuer's exposure to oil price shocks) and its interaction with the Paris Agreement dummy. By doing so, we control for the firm-level effects (and additional firm-level effects following the Paris Agreement) of oil price shocks on mutual fund selling. Results are shown in Table 9.

[Insert Table 9 about here]

After controlling for the effects of oil price shocks, the impact of the high-carbon dummy on mutual funds' collective selling after the Paris Agreement remains strong across different specifications. The magnitudes and significances of the coefficients on the interaction of high-carbon and PA dummies are similar to their corresponding values in Table 5. Bond issuers' oil exposure does not have much impact on mutual funds' collective selling. In addition, results in Table 9 are robust if we use alternative measures of firm's oil exposure, including 1) WTI oil prices, 2) daily or monthly returns as specified in Ilhan, Sautner, and Vilkov (2021), 3) the absolute value of oil exposure $\beta_{f,t}$, and 4) the sum of factor loadings on oil returns of the past three weeks.

In a nutshell, we disentangle the roles of bonds' carbon and oil exposures on mutual fund selling and verify that the intensified selling of bonds following the Paris Agreement is driven by bonds' carbon exposure rather than their oil exposure.

[35]The average correlation between the oil exposure and high-carbon dummy at the firm level is 0.07.

5 Mutual funds' selling of high-carbon bonds: Strategic response to investor redemptions or fundamental shift in investment preferences?

In this section, we explore an alternative theory that could also account for mutual funds' selling of high-carbon bonds. While we show strong evidence that mutual funds' selling of high-carbon bonds is driven by funds' concerns about redemption risks associated with such bonds, it is possible that such effect could also be driven by mutual funds' fundamental shifts in their investment preferences or ethics against bonds issued by firms with high carbon exposure. Such shifts represent funds' long-term investment attitudes and are likely to be long-lasting and irreversible.[36] Nevertheless, in the following discussion, we present two major pieces of evidence that challenge the notion of a fundamental shift in investment preference.

5.1 Reversal of mutual fund selling following President Trump's election

We first examine whether the election of President Trump, which is supposed to have opposite effects to the Paris Agreement on carbon-related risks, has any impact on our documented results. If there is a permanent shift in mutual fund investment preferences, we would expect the selling trend for high-carbon bonds to be largely unaffected after Trump's election, that is, a continued higher mutual funds' collective selling of bonds issued by high-carbon firms.

The unexpected election of President Trump in November 2016 is generally considered to offset the effects of the Paris Agreement in terms of environment-related risks. Specifically, the two presidential candidates' positions on environmental issues are very different. Presi-

[36] For example, Wells Fargo Asset Management launched a climate transition credit strategy in June 2021 with the intention to decarbonize their fixed-income portfolios. State Street also recently announced the launch of the State Street Sustainable Climate Bond Funds, which aim to significantly reduce investors' exposure to carbon emissions.

dent Trump, who repeatedly denied that climate change is caused by humans, was inclined to less stringent climate policies and complained about the Paris Agreement: "This agreement gives foreign bureaucrats control over how much energy we use on our land, in our country. No way." He tweeted that "the badly flawed Paris Climate Agreement protects the polluters, hurts Americans, and costs a fortune. NOT ON MY WATCH!". Hillary Clinton, in contrast, called climate change an "urgent threat", and listed "climate change" and "protecting animals and wildlife" as two major topics on her campaign website. As a result, the concerns of more stringent climate regulations and heightened carbon-related risks are expected to decline after President Trump's unexpected election, especially for the high-carbon firms.

We carry out a difference-in-differences test with the event of Trump's election, as in the following regression.

$$SHM_{i,t} = \alpha_3 + \beta_3 \times High\text{-}carbon_{i,t-1} \times TE_t + \gamma_3 \times High\text{-}carbon_{i,t-1} + \delta_3 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \quad (14)$$

where TE_t is a time dummy equals one for the period after Trump was elected as the U.S. President. The sample period is from 2015Q4 to 2017Q4 (with the exclusion of the event quarter, 2016Q4).

[Insert Table 10 about here]

Panel A of Table 10 reports the results of the sell herding measure. We find that the coefficients on $High\text{-}carbon_{i,t-1} \times TE_t$ are significantly negative, offsetting the positive effects found in the Paris Agreement tests. Specifically, Column (1) shows that a high-carbon bond experiences an additional 3.49-percentage-point decline in its mutual funds' collective selling following the election of President Trump, comparable in magnitude to the amplifying effect following the Paris Agreement. Thus, the effects of carbon exposure on mutual funds' collective selling of corporate bonds get notably attenuated when there is a potential reversal on climate-related policies, suggesting that the effect of the Paris Agreement is largely driven by mutual funds' concerns about increased carbon-related risks rather than by a permanent shift in funds' preferences for low-carbon bonds. In Panel B of Table 10, we find a similar reverse pattern for the alternative mutual fund selling measure, flow-induced selling pressure, which again indicates our results are not driven by a permanent shift in funds' investment preferences.

We next examine changes in the flow-to-carbon relationship around Trump's election and report the results in Table 11. We find that the negative flow-to-carbon relationship significantly weakens after Trump's election. This suggests that end investors of mutual funds reduce redemptions from funds with high carbon exposures following Trump's election, reversing their reactions following the Paris Agreement. This shift in investor behaviors may reflect perceived changes in regulation risks associated with these events. Consequently, mutual funds adjust their portfolio allocations based on end investors' evolving views on carbon emissions.

[Insert Table 11 about here]

In sum, our Trump election tests serve two purposes. First, they provide strong support for our argument that investor redemption patterns drive mutual fund trading behavior related to carbon exposures. Second, they help rule out the alternative channel of a permanent shift in mutual fund investment preferences.

5.2 Price impacts following the Paris Agreement

We next analyze bond price movements around the Paris Agreement. Intuitively, if mutual funds' collective selling of high-carbon bonds following the Paris Agreement is driven by funds' shift in investment preferences, the price impact on these high-carbon bonds should persist over time. In contrast, if mutual funds' collective selling of high-carbon bonds is driven by their widespread concerns about carbon-related redemption risks (i.e., panic sales), the high-carbon bonds should experience temporary price depressions and subsequent reversals.[37]

[37] As noted in Bali, Subrahmanyam, and Wen (2021), liquidity effects are most often connected with short-term return reversals, which do appear to prevail in corporate bonds.

To investigate bond return patterns around the Paris Agreement, we focus on monthly corporate bond returns. We first calculate raw monthly bond returns, following Gebhardt, Hvidkjaer, and Swaminathan (2005):

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 \tag{15}$$

where $P_{i,t}$ is the month-end price of month t for the individual corporate bond i, $AI_{i,t}$ is the accrued interest, and $C_{i,t}$ is the coupon payment, if any, from the end of month $t-1$ to the end of month t for corporate bond i. Following the prior literature, the abnormal monthly bond return is then computed as the raw return subtracted by the size-weighted average return of the pool of bonds that share similar credit ratings and time-to-maturity in that month.

In Table 12, we examine monthly abnormal returns around the Paris Agreement for high- and low-carbon bonds, as well as their differences. The sample period is from June 2015 to June 2016, and month "0" is the event month, i.e., December 2015. High-carbon bonds are those whose issuers' carbon exposure scores fall into the top tercile among all firms in November 2015, and low-carbon bonds are the rest. In Panel A, we focus on bonds that are heavily held by mutual funds. Specifically, at the end of 2015Q3, bonds are sorted into quartiles based on their ownership by mutual funds (calculated as the total par value of mutual fund holdings scaled by bond issue size), and those in the top quartile are considered heavily held by mutual funds.[38] The first two rows of Panel A report median levels of monthly abnormal returns for high- and low-carbon bonds, respectively, and the last row reports their difference.

[Insert Table 12 about here]

Among bonds heavily held by mutual funds, high-carbon bonds experience significantly lower abnormal returns relative to other bonds around the Paris Agreement, with the largest

[38]Results are essentially unchanged if we rebalance the portfolios based on bonds' carbon exposure score and mutual fund ownership at the end of each month.

return differences observed in the month of the Paris Agreement announcement (-0.99%). However, the differences in abnormal returns between high- and low-carbon bonds reverse in the following few months, and the initial price depression for the high-carbon bonds largely recovers within half a year. The drastic price depression around the Paris Agreement and subsequent return reversals for high-carbon bonds heavily held by mutual funds indicate that mutual funds' selling of high-carbon bonds is unlikely driven by permanent shifts in funds' investment preferences or ethics.

To provide further support that the price patterns documented above are dominantly driven by mutual fund trading, Panel B of Table 12 repeats the analysis for bonds lightly held by mutual funds (i.e., bonds with mutual fund ownership in the bottom quartile at the end of 2015Q3). Panel B shows that the return differences between high- and low-carbon bonds lightly held by mutual funds are insignificant in the month of the Paris Agreement announcement, and the return difference is also much smaller (-0.47%) compared with that for bonds heavily held by mutual funds. There are generally no significant return differences in other months as well, suggesting that carbon exposure has a limited price impact on bonds with low mutual fund ownership, thus lending strong support that the drastic carbon-related price movements around the Paris Agreement are largely driven by mutual fund trading.

To illustrate the role of mutual fund ownership on the return differences between high and low-carbon bonds around the Paris Agreement, we also plot the differences between the cumulative monthly abnormal returns on high- and low-carbon bonds (from June 2015 to June 2016) in Figure 2, for those with mutual fund ownership in the top and bottom quartiles. Portfolios are constructed based on bond carbon exposure score in November 2015 and mutual fund ownership at the end of 2015Q3.

[Insert Figure 2 about here]

Figure 2 shows that the cumulative abnormal return for the (High – Low) carbon portfolio constructed with bonds heavily held by mutual funds reaches its lowest point in January

2016, with a magnitude of -2.93%. The return spread then begins to narrow gradually and recovers within half a year after the Paris Agreement. The (High – Low) carbon portfolio constructed with bonds lightly held by mutual funds, in comparison, experiences notably smaller price declines and reversals around the Paris Agreement.

Together, findings in Table 12 and Figure 2 suggest that the price depression of high-carbon bonds around the Paris Agreement is temporary and largely driven by intensive and non-fundamental-based selling from mutual funds, likely triggered by elevated concerns about carbon-related redemption risks.

6 Carbon emission and corporate bond liquidity

Our results so far show that mutual funds tend to collectively sell high-carbon bonds when there are heightened concerns about carbon-related redemption risks. Such trading behaviors could affect bond liquidity, which has significant implications for bond pricing and market stability. In particular, if most mutual funds shy away from high-carbon bonds at the same time, dealers will find it difficult to find potential buyers for such bonds, trading costs will increase, and liquidity will suffer. In this section, we test the relation between corporate bond liquidity and the issuer's carbon exposure score and also explore the role played by mutual funds in this relation.

To examine whether the issuer's carbon exposure affects subsequent bond illiquidity, we first run panel regressions for our full sample, using three bond illiquidity measures defined in Section 2.2.4, namely Amihud, Roll, and IRC as dependent variables. Our key independent variable is the lagged high-carbon dummy, and other control variables are defined as in Equation (7).

$$Bond\ illiquidity_{i,t} = \alpha + \beta \times High\text{-}carbon_{i,t-1} + \delta \times controls_{i,t-1} + \mu_t + \sigma_i + \epsilon_{i,t} \quad (16)$$

Panel A of Table 13 reports the regression results for the full sample. The coefficients of the high-carbon dummy are significantly positive for all three illiquidity measures after controlling for bond characteristics, supporting the robust impact of the high-carbon dummy on future bond illiquidity. The economic significance is also sizable. For instance, the Roll illiquidity measure for a high-carbon bond is 0.13-percentage-point (8.7% of the standard deviation) higher, compared with other bonds.[39]

[Insert Table 13 about here]

To provide supporting evidence that the effects of bonds' carbon exposure on liquidity are largely driven by mutual fund trading, in Panels B and C we perform regressions for bonds with high (top quartile) and low (bottom quartile) mutual fund ownership, respectively.[40] We find the positive coefficients of the high-carbon dummy on future illiquidity measures are only significant for bonds heavily held by mutual funds, consistent with our hypothesis that the collective selling by mutual funds deteriorates the liquidity of high-carbon bonds.

Next, we test the impacts of carbon exposure on bond illiquidity around two carbon-related shocks. Specifically, in the sub-sample of bonds with high (top quartile) mutual fund ownership, we investigate whether the positive relationship between carbon exposure and bond illiquidity intensifies after the announcement of the Paris Agreement and whether such a pattern is mitigated after the election of President Trump. We conduct difference-in-differences analyses similar to Equation (8), using bond illiquidity measures as the dependent variables, and present the empirical findings in Table 14.

[Insert Table 14 about here]

Consistent with our documented results that the announcement of the Paris Agreement amplifies the effects of carbon emission on mutual fund selling, we find that the Paris Agreement also increases the adverse effects of carbon exposure on corporate bond liquidity. Panel

[39] Results essentially hold after additionally including the stock controls. The effects of control variables are consistent with the existing literature, so we do not show them for brevity.

[40] Results are largely consistent if we assign high and low mutual fund ownership based on quintiles at each quarter.

A shows that the coefficients on the interaction term are significantly positive for all three illiquidity measures. In Panel B, we find that the positive effect of carbon exposure on bond illiquidity is substantially alleviated following the election of President Trump. The interaction term has significantly negative coefficients, robust across illiquidity measures. These findings support the causal effects of carbon exposure on bond liquidity.[41]

Taken together, this section shows that issuing firms' carbon exposure has significant negative impacts on corporate bond liquidity, especially for bonds held more by mutual funds and when concerns about carbon-related risks heighten. Liquidity carries significant implications for corporate bond pricing. For instance, Bao, Pan, and Wang (2011) find that market-level illiquidity overshadows the credit risk component in explaining the prices of higher-rated corporate bonds. Thus, our finding of liquidity deterioration for high-carbon bonds not only echoes our results on mutual funds' collective selling of these bonds, but also deepens our understanding of the pricing implications of carbon exposure. Importantly, our finding implies that the effects of carbon exposure on corporate bond pricing could also be driven by changes in bonds' liquidity conditions, rather than by credit risks alone.[42]

7 Conclusion

Concerns and debates surrounding global warming and carbon emissions have prominently featured in the headlines in recent years, notably with 196 signatories endorsing the Paris Agreement in 2015, and the U.S.'s subsequent withdrawal under the Trump administration. Within the sphere of corporate bond mutual funds, this paper investigates the reaction of investor flows to the carbon exposure of fund bond portfolios. The illiquid nature of the

[41] We also examine alternative liquidity measures, including the total number of trading days and average turnover per quarter. We observe no significant impact of the high-carbon dummy on these alternative metrics. This outcome likely reflects our focus on bonds held and traded by mutual funds, which tend to be more liquid due to mutual funds' liquidity preferences and their trading activities. Measures like the number of trading days and turnover are more relevant for bonds that trade less frequently in the market, where liquidity metrics based on price impact are challenging to compute.

[42] Existing literature all emphasizes the role of credit risks in driving bond yield spreads and returns when studying pricing effects of environment-related risks. See, e.g., Amiraslani, Lins, Servaes, and Tamayo (2023), Halling, Yu, and Zechner (2021), and Seltzer, Starks, and Zhu (2024).

corporate bond market and the significant liquidity mismatch faced by bond mutual funds notably influence this flow-to-carbon relationship. Furthermore, this relationship could significantly impact fund managers' trading decisions regarding corporate bonds, subsequently affecting bond liquidity and returns.

In this paper, we analyze how investor flows respond to carbon exposure within a fund's bond portfolio and examine the impact of a bond's carbon exposure on mutual funds' trading behaviors and the bond's liquidity condition. We conduct our analyses with a comprehensive dataset from January 2007 to December 2019 and also exploit the shock of the Paris Agreement in December 2015 to establish causality. Our findings reveal a marked outflow from funds with high carbon exposure, a trend that intensifies following the Paris Agreement. Motivated by concerns over carbon-related redemption risks, mutual funds are more inclined to collectively divest from corporate bonds issued by firms with higher carbon exposure, with these tendencies significantly amplified post-Paris Agreement.

Consistent with the notion that mutual funds collectively sell high-carbon bonds under the pressure from investor redemptions, we also find that the liquidity condition of high-carbon bonds deteriorates, and the effect is stronger among bonds with higher mutual fund ownership and during times of heightened carbon-related concerns. Our finding indicates that pricing implications of carbon exposure for corporate bonds could also be driven by the bonds' liquidity conditions, not solely by credit risks.

Results in our paper shed new light on the ongoing discussion about why mutual funds consider carbon exposure in their investment decisions. Our findings suggest that the emphasis on climate change by governments and policymakers can introduce carbon-related redemption risks to illiquid assets with high carbon exposure, prompting mutual funds to collectively reduce their exposure to these risks. We find no evidence supporting a fundamental shift in mutual funds' investment preferences or ethics. In particular, the impacts of carbon exposure on investor flows and mutual fund selling activity are notably offset following the election of President Trump, highlighting the fluid nature of mutual funds' attitudes towards carbon exposure. Moreover, the price depression effect on high-carbon bonds around the Paris Agreement is drastic yet transient, aligning more with the price pattern of non-fundamental-driven fire sales by mutual funds, rather than a shift in their overarching investment strategy.

References

Amiraslani, Hami, Karl V. Lins, Henri Servaes, and Ane Tamayo. 2023. Trust, social capital, and the bond market benefits of ESG performance. *Review of Accounting Studies* 28: 421–462.

Anand, Amber, Chotibhak Jotikasthira, and Kumar Venkataraman. 2021. Mutual fund trading style and bond market fragility. *Review of Financial Studies* 34: 2993—3044.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61: 259–299.

Atta-Darkua, Vaska, Simon Glossner, Philipp Krueger, and Pedro Matos. 2023. Decarbonizing institutional investor portfolios: Helping to green the planet or just greening your portfolio? *Working Paper.*

Bali, Turan G., Avanidhar Subrahmanyam, and Quan Wen. 2021. Long-term reversals in the corporate bond market. *Journal of Financial Economics* 139: 656–677.

Bao, Jack, Jun Pan, and Jiang Wang. 2011. The illiquidity of corporate bonds. *Journal of Finance* 66: 911-946.

Bolton, Patrick, and Marcin Kacperczyk. 2021. Do investors care about carbon risk? *Journal of Financial Economics* 142: 517–549.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2024. Revisiting event study designs: Robust and efficient estimation. *Review of Economic Studies* 00: 1–33.

Bretscher, Lorenzo, Lukas Schmid, Ishita Sen, and Varun Sharma. 2024. Institutional corporate bond pricing. *Swiss Finance Institute Research Paper* 21–07.

Bretscher, Lorenzo, Lukas Schmid, and Tiange Ye. 2024. Passive demand and active supply: Evidence from maturity-mandated corporate bond funds. *Working Paper.*

Cai, Fang, Song Han, Dan Li, and Yi Li. 2019. Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics* 131: 139–167.

Cao, Jie, Sheridan Titman, Xintong Zhan, and Weiming Zhang. 2023. ESG preference, institutional trading, and stock return patterns. *Journal of Financial and Quantitative Analysis* 58: 1843–1877.

Ceccarelli, Marco, Stefano Ramelli, and Alexander F. Wagner. 2024. Low carbon mutual funds. *Review of Finance* 28: 45-74.

Chava, Sudheer. 2014. Environmental externalities and cost of capital. *Management Science* 60: 2223–2247.

Chen, Yong, Mengqiao Du, and Zheng Sun. 2024. Large funds and corporate bond market fragility. *Working Paper*.

Chen, Qi, Itay Goldstein, and Wei Jiang. 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics* 97: 239–262.

Chen, Yong, and Nan Qin. 2017. The behavior of investor flows in corporate bond mutual funds. *Management Science* 63: 1365–1381.

Chevalier, Judith, and Glenn Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105: 1167–1200.

Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian. 2020. Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics* 138: 432–457.

Christoffersen, Susan EK, David K. Musto, and Russ Wermers. 2014. Investor flows to asset managers: Causes and consequences. *Annual Review of Financial Economics* 6: 289–310.

Coval, Joshua, and Erik Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86: 479–512.

Degiannakis, Stavros, George Filis, and Renatas Kizys. 2014. The effects of oil price shocks on stock market volatility: Evidence from European data. *Energy Journal* 35: 35–56.

Demirer, Riza, Shrikant P. Jategaonkar, and Ahmed AA Khalifa. 2015. Oil price risk exposure and the cross-section of stock returns: The case of net exporting countries. *Energy Economics* 49: 132–140.

Dick-Nielsen, Jens. 2014. How to clean enhanced TRACE data. *Working Paper*.

Dick-Nielsen, Jens, Peter Feldhütter, and David Lando. 2012. Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics* 103: 471–492.

Duan, Tinghua, Frank Weikai Li, and Quan Wen. 2023. Is carbon risk priced in the cross section of corporate bond returns? *Journal of Financial and Quantitative Analysis*: 1–35.

Falato, Antonio, Itay Goldstein, and Ali Hortaçsu. 2021. Financial fragility in the COVID-19 crisis: The case of investment funds in corporate bond markets. *Journal of Monetary Economics* 123: 35–52.

Fama, Eugene F., and Kenneth R. French. 1992. The cross-section of expected stock returns. *Journal of Finance* 47: 427–465.

Fama, Eugene F., and Kenneth R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3–56.

Gebhardt, William R., Soeren Hvidkjaer, and Bhaskaran Swaminathan. 2005. The cross-section of expected corporate bond returns: Betas or characteristics? *Journal of Financial Economics* 75: 85–114.

Giannetti, Mariassunta, and Chotibhak Jotikasthira. 2024. Bond price fragility and the structure of the mutual fund industry. *Review of Financial Studies* 37: 2063–2109.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber. 2021. Climate change and long-run discount rates: Evidence from real estate. *Review of Financial Studies* 34: 3527–3571.

Goldstein, Itay, Hao Jiang, and David T. Ng. 2017. Investor flows and fragility in corporate bond funds. *Journal of Financial Economics* 126: 592–613.

Haddad, Valentin, Alan Moreira, and Tyler Muir. 2021. When selling becomes viral: Disruptions in debt markets in the Covid-19 crisis and the Fed's response. *Review of Financial Studies* 34: 5309–5351.

Halling, Michael, Jin Yu, and Josef Zechner. 2021. Primary corporate bond markets and social responsibility. *Working Paper*.

Hartzmark, Samuel M., and Abigail B. Sussman. 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. *Journal of Finance* 74: 2789–2837.

He, Zhiguo, Paymon Khorrami, and Zhaogang Song. 2022. Commonality in credit spread changes: Dealer inventory and intermediary distress. *Review of Financial Studies* 35: 4630–4673.

Humphrey, Jacquelyn E., and Yong Li. 2021. Who goes green: Reducing mutual fund emissions and its consequences. *Journal of Banking and Finance* 126: 106098.

Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T. Starks. 2023. Climate risk disclosure and institutional investors. *Review of Financial Studies* 36: 2617-2650.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov. 2021. Carbon tail risk. *Review of Financial Studies* 34: 1540–1571.

Jiang, Hao, Yi Li, Zheng Sun, and Ashley Wang. 2022. Does mutual fund illiquidity introduce fragility into asset prices? Evidence from the corporate bond market. *Journal of Financial Economics* 143: 277–302.

Jiang, Hao, Dan Li, and Ashley Wang. 2021. Dynamic Liquidity Management by Corporate Bond Mutual Funds. *Journal of Financial and Quantitative Analysis* 56: 1622–1652.

Kargar, Mahyar, Benjamin Lester, David Lindsay, Shuo Liu, Pierre-Olivier Weill, and Diego Zúñiga. 2021. Corporate bond liquidity during the COVID-19 crisis. *Review of Financial Studies* 34: 5352–5401.

Keswani, Aneel, and David Stolin. 2008. Which money is smart? Mutual fund buys and sells of individual and institutional investors. *Journal of Finance* 63: 85–118.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks. 2020. The importance of climate risks for institutional investors. *Review of Financial Studies* 33: 1067–1111.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny. 1992. The impact of institutional trading on stock prices. *Journal of Financial Economics* 32: 23–43.

Levin, Carl, Elise J. Bean, Dan M. Berkovitz, and Laura Stuber. 2003. US Strategic petroleum reserve: Recent policy has increased costs to consumers but not overall US Energy Security. *Report Prepared by the Minority Staff of the Permanent Subcommittee on Investigations (United States Senate)* 266.

Li, Yi, Maureen O'Hara, and Xing Alex Zhou. 2024. Mutual fund fragility, dealer liquidity provisions, and the pricing of municipal bonds. *Management Science* 70: 4802–4823.

Ma, Yiming, Kairong Xiao, and Yao Zeng. 2022. Mutual fund liquidity transformation and reverse flight to liquidity. *Review of Financial Studies* 35: 4674–4711.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda. 2012. The role of institutional investors in propagating the crisis of 2007-2008. *Journal of Financial Economics* 104: 491–518.

O'Hara, Maureen, and Xing Alex Zhou. 2021. Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. *Journal of Financial Economics* 142: 46–68.

Painter, Marcus. 2020. An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics* 135: 468–482.

Roll, Richard. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39: 1127–1139.

Savaresi, Annalisa. 2016. The Paris Agreement: A new beginning? *Journal of Energy and Natural Resources Law* 34: 16–26.

Seltzer, Lee H., Laura Starks, and Qifei Zhu. 2024. Climate regulatory risks and corporate bonds. *Working Paper.*

Sirri, Erik R., and Peter Tufano. 1998. Costly search and mutual fund flows. *Journal of Finance* 53: 1589–1622.

Starks, Laura T., Parth Venkat, and Qifei Zhu. 2024. Corporate ESG profiles and investor horizons. *Journal of Finance* (forthcoming).

Wermers, Russ. 1999. Mutual fund herding and the impact on stock prices. *Journal of Finance* 54: 581–622.

Figure 1. Daily crude oil price

This figure plots daily West Texas Intermediate (WTI) and Brent crude oil spot prices in dollars per Barrel from 2002 to 2019.

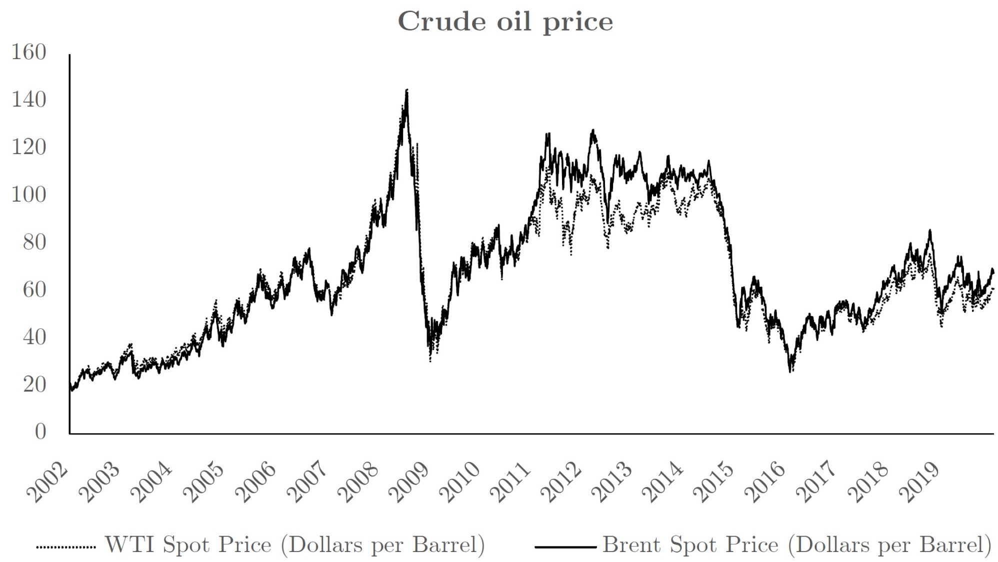


Figure 2. Cumulative monthly abnormal returns around the Paris Agreement

This figure shows the differences between the cumulative monthly abnormal returns on high- and low-carbon bonds for those with mutual fund ownership in the top and bottom quartiles from June 2015 to June 2016, respectively. Portfolios are constructed based on the rank of bond carbon exposure score in November 2015 and mutual fund ownership at the end of 2015Q3.

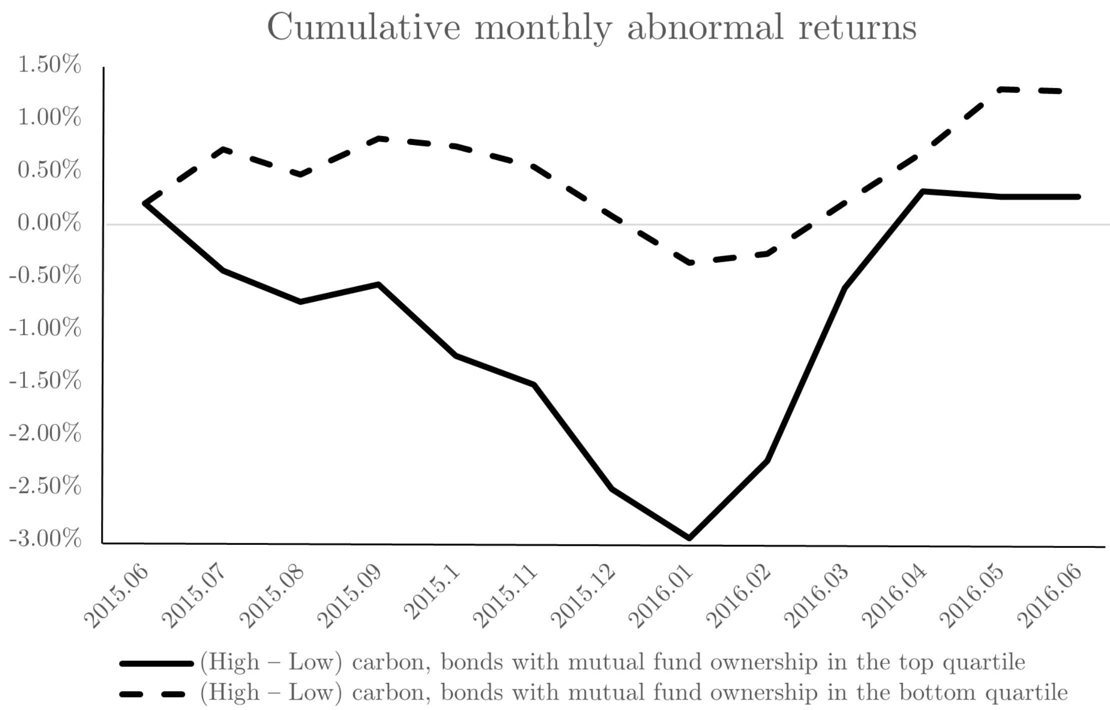


Table 1. Summary statistics

This table provides descriptive statistics of the data used in our empirical analysis, over the sample period from 2007Q1 to 2019Q4. Panel A reports the number of fund-month observations (N), the mean, standard deviation (Std), lower quartile (Q1), median, and upper quartile (Q3) for fund flow, total net assets (TNA, in millions of dollars), fund age (time-since-issuance in months), fund turnover (minimum of aggregated sales or aggregated purchases of securities, divided by the average of total net assets of the fund over past 12 months, in percentage), expense ratio in percentage, fund return of last month in percentage, and fund carbon exposure. Panel B reports the number of bond-quarter observations (N), the mean, standard deviation (Std), lower quartile (Q1), median, and upper quartile (Q3) for quarterly sell herding measure (SHM) of mutual funds, outflow-induced selling pressure, illiquidity measures including the Amihud, Roll, and IRC measures, and other bond characteristics including bond rating, time-to-maturity in years (Maturity), time-since-issuance in years (Age), coupon rate, and logarithm of bond issue size (Ln(Size)). Panel C reports summary statistics for firm-quarter variables including the carbon exposure score, high-carbon dummy, logarithm of firm size (Ln(ME)), the logarithm of book-to-market ratio (Ln(BM)), Stock IVOL, stock institutional ownership and number of analysts (Analyst). The variables' definitions are provided in Appendix A. Panel D reports the mean, median, and standard deviation (Std) of carbon exposure scores for firms across the Fama-French 12 industries. Panel E reports the industry distributions (in percentage) for all the issuers, and the issuers with non-missing carbon exposure scores, respectively. We focus on fixed-rate bonds and exclude bonds that are puttable, convertible, and perpetual. We also exclude mortgage-backed, asset-backed, agency-backed and equity-linked securities, Yankees, Canadians, structured notes, as well as issues denominated in foreign currency. We only consider observations with Age or Maturity longer than 6 months. All variables are winsorized each quarter at the 0.5% level.

	N	Mean	Std	P25	P50	P75
			Panel A: Fund-month variables			
Flow (%)	94,639	0.96	7.37	-1.02	0.07	1.75
TNA	94,639	2606.23	8978.35	90.00	378.40	1382.10
Fund age (in months)	93,385	106.27	89.45	40.00	80.00	154.00
Turnover ratio (%)	87,077	105.25	130.02	36.00	61.00	114.00
Expense ratio (%)	86,770	0.91	0.48	0.60	0.91	1.18
Lagged return (%)	93,035	0.38	1.72	-0.23	0.31	1.07
Fund carbon exposure	92,773	2.93	1.75	1.54	2.61	4.29

	N	Mean	Std	P25	P50	P75
Panel B: Bond-quarter variables						
SHM (%)	41,796	5.34	13.95	-6.77	2.25	12.38
Selling pressure (%)	88,337	-0.04	0.53	-0.10	-0.02	0.00
Amihud (% per thousand $)	170,929	0.02	0.03	0.00	0.01	0.03
Roll (%)	164,221	1.29	1.50	0.47	0.88	1.59
IRC (%)	156,991	0.37	0.32	0.15	0.27	0.49
Rating	146,847	7.89	2.83	6.00	8.00	9.00
Maturity (in years)	173,739	9.75	8.98	3.25	6.25	14.75
Age (in years)	173,739	5.57	4.62	2.25	4.25	7.25
Coupon (%)	173,739	5.15	1.77	3.88	5.25	6.38
Ln(Size)	173,739	13.10	0.86	12.61	13.12	13.59
Panel C: Firm-quarter variables						
Carbon exposure score	23,716	3.81	2.88	1.30	3.70	5.70
High-carbon	23,716	0.29	0.46	0.00	0.00	1.00
Ln(ME)	22,053	9.35	1.31	8.48	9.31	10.17
Ln(BM)	22,048	-0.70	0.96	-1.23	-0.71	-0.21
Stock IVOL	23,715	0.06	0.04	0.04	0.05	0.07
Institutional ownership	23,472	0.77	0.16	0.68	0.79	0.88
Analyst	23,716	14.15	8.80	7.33	14.33	20.00

Panel D: Time-series averages of cross-sectional distribution of carbon exposure score

Industry	Mean	P50	Std
1 Consumer Nondurables	2.78	2.00	2.78
2 Consumer Durables	2.37	1.67	2.48
3 Manufacturing	4.15	3.93	3.00
4 Enrgy	7.07	7.60	2.29
5 Chemicals and Allied Products	4.11	4.00	2.89
6 Business Equipment	2.46	2.00	2.43
7 Telephone and Television Transmission	3.38	3.70	2.43
8 Utilities	4.34	4.37	2.86
9 Shops	3.11	3.30	2.43
10 Healthcare	2.40	2.00	2.30
11 Finance	3.31	3.30	2.54
12 Other	4.55	4.34	2.53

Panel E: Comparison of bond issuers' industry distribution

Industry	Industry share (for all issuers, %)	Industry share (for issuers with MSCI scores, %)
1 Consumer Nondurables	5.34	4.87
2 Consumer Durables	2.42	2.55
3 Manufacturing	10.02	11.21
4 Enrgy	8.81	8.81
5 Chemicals and Allied Products	3.27	3.86
6 Business Equipment	7.45	8.11
7 Telephone and Television Transmission	3.88	3.17
8 Utilities	6.95	7.81
9 Shops	8.71	9.35
10 Healthcare	5.69	5.87
11 Finance	21.80	20.17
12 Other	15.66	14.22

Table 2. Fund carbon exposure and mutual fund flow

This table reports fund-month panel regression results, over the sample period from January 2007 to December 2019. The dependent variable is mutual fund flow in month t. The fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon exposure score within that fund as of the most recent quarter-end before month t, with details provided in Appendix A. Control variables include fund average bond rating, logarithm of TNA, lagged return as of month $t-1$, short-term (ST) cumulative monthly return from month $t-6$ to $t-1$, long-term (LT) cumulative monthly return from month $t-12$ to $t-1$, percentage of cash holding, expense ratio, turnover ratio, and fund age, as of the most recent quarter-end before month t. We include month and style fixed effects in Column (1), and further include fund fixed effects from Columns (2) to (4). All variables are winsorized at the 0.5% level each month. Standard errors are clustered at the fund and month levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund flow				
	(1)	(2)	(3)	(4)
Fund carbon exposure	**-0.141*** **	**-0.166*** **	**-0.203*** **	**-0.142** **
	(-3.03)	**(-3.13)**	**(-3.79)**	**(-2.50)**
Fund average (bond) rating			0.043	0.008
			(0.81)	(0.17)
Ln(TNA)			-2.176***	-1.554***
			(-11.76)	(-9.50)
Lagged return			16.369***	2.351
			(3.99)	(0.63)
Cash holding			0.015***	0.012**
			(2.81)	(2.20)
Expense ratio			-1.651***	-0.660
			(-2.65)	(-1.31)
Turnover ratio			0.009	0.020
			(0.09)	(0.20)
Fund age			-0.010***	-0.009***
			(-4.59)	(-4.35)
ST cumulative return				5.886***
				(3.15)
LT cumulative return				9.321***
				(7.00)
Time FE	Y	Y	Y	Y
Style FE	Y	Y	Y	Y
Fund FE	N	Y	Y	Y
Adj-R^2	0.027	0.136	0.164	0.142
# of obs	87599	87598	84753	76235

Table 3. Fund carbon exposure and mutual fund flow around the Paris Agreement

This table reports fund-month panel regression results, over the sample period from June 2015 to June 2016 (December 2015 is deleted). The dependent variable is mutual fund flow in month t, and the deleted month is based on the time of dependent variable measurement. The fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon emission exposure within that fund as of the most recent quarter-end before month t, with details provided in Appendix A. Control variables include fund average bond rating, logarithm of TNA, lagged return as of month $t-1$, short-term (ST) cumulative monthly return from month $t-6$ to $t-1$, long-term (LT) cumulative monthly return from month $t-12$ to $t-1$, percentage of cash holding, expense ratio, turnover ratio, and fund age, as of the most recent quarter-end before month t. We include month and style fixed effects in Columns (1), and further include fund fixed effects in Columns (2) and (3). All variables are winsorized at the 0.5% level each month. Standard errors are clustered at the fund and month levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund flow			
	(1)	(2)	(3)
Fund carbon exposure × PA	**-0.231***	**-0.253****	**-0.325*****
	(-1.90)	**(-2.07)**	**(-2.91)**
Fund carbon exposure	-0.232**	-0.134	-0.169
	(-2.50)	(-1.08)	(-1.39)
Fund Controls	N	N	Y
Time FE	Y	Y	Y
Style FE	Y	Y	Y
Fund FE	N	Y	Y
Adj-R^2	0.035	0.230	0.247
# of obs	10684	10671	9802

Table 4. Carbon emission and mutual fund selling

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is the sell herding measure (SHM) of mutual funds measured in quarter t. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. Column (1) includes time fixed effects and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Column (3) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund SHM			
	(1)	(2)	(3)
High-carbon	**1.022*** **	**1.052** **	**0.909** **
	(3.53)	**(2.65)**	**(2.20)**
Rating	0.240***	-0.073	0.060
	(3.23)	(-0.52)	(0.41)
Maturity	-0.096***	0.875***	0.892***
	(-4.52)	(6.20)	(6.01)
Age	0.239***	23.177***	22.962***
	(3.96)	(18.78)	(16.11)
Coupon	0.292***		
	(2.95)		
Ln(Size)	-1.106***		
	(-3.62)		
Ln(ME)			0.607
			(1.33)
Ln(BM)			-0.052
			(-0.15)
Stock IVOL			5.574
			(1.23)
Institutional ownership			-0.385
			(-0.19)
Analyst			-0.000
			(-0.01)
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.060	0.163	0.163
# of obs	41796	40104	36501

Table 5. Carbon emission and mutual fund selling around the Paris Agreement

This table reports bond-quarter panel regression results, over the sample period from 2014Q4 to 2016Q4 (2015Q4 is deleted). The dependent variable is the sell herding measure (SHM) of mutual funds measured in quarter t, and the deleted quarter is based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. PA is a dummy equal to one for the time period after the Paris Agreement (after 2015Q4), and zero otherwise. PA(-3) and PA(-2) equal one for the third to last quarter (2015Q1) and second to last quarter (2015Q2) before the Paris Agreement and zero otherwise, respectively. Column (1) includes time fixed effects, and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Columns (3) and (4) additionally control for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund SHM				
	(1)	(2)	(3)	(4)
High-carbon × PA	**2.595*****	**2.279****	**2.180****	**2.385***
	(3.69)	**(3.00)**	**(2.20)**	**(1.82)**
High-carbon × PA(-3)				0.328
				(0.29)
High-carbon × PA(-2)				0.528
				(0.29)
High-carbon	0.039	-0.989	-0.498	-0.690
	(0.10)	(-0.98)	(-0.31)	(-0.49)
Bond Controls	Y	Y	Y	Y
Stock Controls	N	N	Y	Y
Time FE	Y	Y	Y	Y
Bond FE	N	Y	Y	Y
Adj-R^2	0.033	0.195	0.195	0.194
# of obs	9028	7662	7041	7041

Table 6. Mutual funds' selling response to carbon emission: Amplified by -sensitivity-to-carbon

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is the sell herding measure (SHM) of mutual funds measured in quarter t. Bond flow-sensitivity-to-carbon measures the aggregate bond level sensitivity to carbon, induced from investors' reaction to fund carbon exposure. Each quarter, we categorize all bonds into two groups based on the median of bond flow-sensitivity-to-carbon: high- and low-flow-sensitivity-to-carbon. (Bond level) high-flow-sensitivity-to-carbon is a dummy equal to one for bonds with high-flow-sensitivity-to-carbon. The definition is provided in Appendix A. Column (1) includes time fixed effects and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Column (3) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund SHM			
	(1)	(2)	(3)
High-carbon × (bond level) high-flow-sensitivity-to-carbon	**1.236***** **(2.93)**	**1.158**** **(2.62)**	**0.972*** **(1.92)**
High-carbon	0.654 (1.64)	0.618 (1.22)	0.664 (1.29)
(Bond level) high-flow-sensitivity-to-carbon	-1.261*** (-3.31)	-1.245*** (-3.84)	-1.201*** (-3.65)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.046	0.159	0.159
# of obs	35622	34000	31144

Table 7. Carbon emission and mutual fund selling: Alternative selling measure

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is the flow-induced mutual fund selling pressure measured in quarter t. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. Column (1) includes time fixed effects, and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Column (3) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund selling pressure			
	(1)	(2)	(3)
High-carbon	**0.039*** **	**0.031***	**0.042*** **
	(2.94)	**(1.89)**	**(3.35)**
Rating	0.009***	0.006	0.009
	(2.71)	(0.93)	(1.11)
Maturity	0.003***	0.007	0.010**
	(3.83)	(1.61)	(2.13)
Age	-0.005***	-0.022	-0.016
	(-3.30)	(-0.48)	(-0.34)
Coupon	0.019***		
	(4.63)		
Ln(Size)	0.038***		
	(4.62)		
Ln(ME)			0.010
			(0.69)
Ln(BM)			-0.013
			(-1.11)
Stock IVOL			-0.242
			(-0.45)
Institutional ownership			0.068
			(1.60)
Analyst			-0.001**
			(-2.34)
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.037	0.105	0.102
# of obs	88336	87487	81124

Table 8. Carbon emission and mutual fund selling around the Paris Agreement: Alternative selling measure

This table reports bond-quarter panel regression results, over the sample period from 2014Q4 to 2016Q4 (2015Q4 is deleted). The dependent variable is the flow-induced mutual fund selling pressure measured in quarter t, and the deleted quarter is based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. PA is a dummy equal to one for the time period after the Paris Agreement (after 2015Q4), and zero otherwise. Column (1) includes time fixed effects, and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Column (3) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund selling pressure			
	(1)	(2)	(3)
High-carbon × PA	**0.170****	**0.210*****	**0.197*****
	(2.29)	**(3.70)**	**(3.81)**
High-carbon	-0.009	-0.046	-0.067**
	(-0.20)	(-1.21)	(-2.00)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.054	0.154	0.152
# of obs	20744	19927	18602

Table 9. Carbon emission, oil exposure, and mutual fund selling around the Paris Agreement

This table reports quarterly panel regression results controlling for effects of oil exposure, over the sample period from 2014Q4 to 2016Q4 (2015Q4 is deleted). The dependent variable is the sell herding measure (SHM) of mutual funds measured in quarter t, and the deleted quarters are based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. PA is a dummy indicating the time period after the Paris Agreement (after 2015Q4). Column (1) includes time fixed effects and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Columns (3) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund SHM			
	(1)	(2)	(3)
High-carbon × PA	**2.492*** **	**1.749** **	**1.660***
	(3.49)	**(2.00)**	**(1.76)**
Oil exposure × PA	0.205	2.592	4.032**
	(0.16)	(1.55)	(2.09)
High-carbon	0.100	-0.724	-0.229
	(0.28)	(-0.72)	(-0.18)
Oil exposure	0.098	-0.875	-1.077
	(0.11)	(-0.77)	(-0.82)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.033	0.195	0.196
# of obs	9028	7662	7041

Table 10. Carbon emission and mutual fund selling around Trump's election

This table reports bond-quarter panel regression results, over the sample period from 2015Q4 to 2017Q4 (2016Q4 is deleted). The dependent variables are the sell herding measure (SHM) of mutual funds in Panel A and outflow-induced selling pressure in Panel B. The dependent variables are measured in quarter t, and the deleted quarter is based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. TE is a dummy equal to one for the time period after Trump's election (after 2016Q4), and zero otherwise. Column (1) includes time fixed effects and controls for bond rating, maturity, age, bond coupon, and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Column (3) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mutual fund SHM around Trump's election			
	(1)	(2)	(3)
High-carbon × TE	**-3.493*** **	**-4.277*** **	**-3.931*** **
	(-5.81)	**(-5.18)**	**(-3.98)**
High-carbon	3.474***	2.134*	2.075*
	(6.98)	(1.82)	(1.79)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.043	0.246	0.247
# of obs	9325	7803	7222

Panel B: Mutual fund selling pressure			
	(1)	(2)	(3)
High-carbon × TE	**-0.157** **	**-0.150*** **	**-0.130*** **
	(-2.41)	**(-2.65)**	**(-2.67)**
High-carbon	0.185***	0.161***	0.151***
	(3.69)	(2.98)	(2.69)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.049	0.128	0.129
# of obs	22828	22007	20542

Table 11. Fund carbon exposure and mutual fund flow around Trump's election

This table reports fund-month panel regression results over the sample period from May 2016 to May 2017 (November 2016 is deleted). The dependent variable is mutual fund flow in month t, and the deleted month is based on the time of dependent variable measurement. The fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon exposure within that fund as of the most recent quarter-end before month t, with details provided in Appendix A. Control variables include fund average bond rating, logarithm of TNA, lagged return as of month $t-1$, short-term cumulative monthly return from month $t-6$ to $t-1$, long-term cumulative monthly return from month $t-12$ to $t-1$, percentage of cash holding, expense ratio, turnover ratio, and fund age, as of the most recent quarter-end before month t. We include month and style fixed effects in Column (1), and further include fund fixed effects in Columns (2) and (3). All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund flow			
	(1)	(2)	(3)
Fund carbon exposure × TE	**0.184***	**0.196***	**0.211****
	(1.93)	**(1.97)**	**(2.02)**
Fund carbon exposure	-0.145*	-0.172**	-0.128
	(-1.77)	(-2.12)	(-1.54)
Fund Controls	N	N	Y
Time FE	Y	Y	Y
Style FE	Y	Y	Y
Fund FE	N	Y	Y
Adj-R^2	0.033	0.229	0.233
# of obs	9979	9975	9526

Table 12. Monthly abnormal bond returns around the Paris Agreement

This table reports medians of monthly abnormal returns of corporate bonds in percentage on the window of [-6, +6] months around the Paris Agreement. Month "0" is December 2015, i.e., the month of the announcement of the Paris Agreement. Bonds are sorted into quartiles based on the mutual fund ownership at the end of 2015Q3, i.e., the total par value of mutual fund holdings scaled by bond issue size. High- (Low-) carbon bonds are those whose issuers' carbon exposure scores fall into the top tercile (otherwise) among all firms in November 2015. Panel A and B show monthly abnormal returns for bonds with mutual fund ownership in the top and bottom quartiles, respectively. (High – Low) carbon shows the differences between the medians of monthly abnormal returns of the High- and Low-carbon groups. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Month	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
Panel A: Bonds with mutual fund ownership in the top quartile													
Low-carbon	0.17%	0.29%	0.26%	0.46%	-0.11%	0.26%	0.57%	0.80%	0.03%	-1.01%	-0.41%	-0.02%	-0.41%
High-carbon	0.37%	-0.35%	-0.04%	0.62%	-0.79%	-0.01%	-0.42%	0.33%	0.77%	0.64%	0.51%	-0.07%	-0.41%
(High – Low) carbon	**0.20%****	**-0.64%*****	**-0.30%****	**0.16%**	**-0.68%*****	**-0.27%**	**-0.99%*****	**-0.47%**	**0.74%*****	**1.64%*****	**0.92%*****	**-0.05%**	**0.00%**
Panel B: Bonds with mutual fund ownership in the bottom quartile													
Low-carbon	0.13%	0.06%	0.12%	0.18%	-0.17%	0.04%	0.29%	0.62%	0.04%	-0.97%	-0.37%	0.27%	-0.30%
High-carbon	0.33%	0.57%	-0.12%	0.52%	-0.25%	-0.15%	-0.18%	0.18%	0.12%	-0.48%	0.12%	0.87%	-0.33%
(High – Low) carbon	**0.20%**	**0.51%**	**-0.24%**	**0.34%**	**-0.08%**	**-0.19%**	**-0.47%**	**-0.44%**	**0.08%**	**0.48%**	**0.48%**	**0.60%****	**-0.02%**

Table 13. Carbon emission and bond illiquidity

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variables are three illiquidity measures including the Amihud, Roll, and IRC measures in quarter t. The independent variables are measured of quarter $t-1$ and defined in Appendix A. Panel A reports regression coefficients for all bonds in the sample. In Panels B and C, we show regression coefficients for bonds with mutual fund ownership in the cross-sectional top and bottom quartiles, separately. We include time and bond fixed effects through all the columns. Bond controls include bond rating, maturity, and age. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Amihud	Roll	IRC
Panel A: All bonds			
	(1)	(2)	(3)
High-carbon	**0.002***** **(3.55)**	**0.127***** **(3.00)**	**0.013***** **(2.62)**
Time FE	Y	Y	Y
Bond FE	Y	Y	Y
Bond Controls	Y	Y	Y
Adj-R^2	0.451	0.545	0.524
# of obs	163530	146107	170307
Panel B: Bonds with mutual fund ownership in the top or bottom quartiles			
Panel B.1: Bonds with mutual fund ownership in the top quartile			
	(1)	(2)	(3)
High-carbon	**0.002**** **(2.12)**	**0.160**** **(2.50)**	**0.013*** **(1.85)**
Time FE	Y	Y	Y
Bond FE	Y	Y	Y
Bond Controls	Y	Y	Y
Adj-R^2	0.533	0.570	0.619
# of obs	41852	37363	43604
Panel B.2: Bonds with mutual fund ownership in the bottom quartile			
	(1)	(2)	(3)
High-carbon	**0.001** **(0.62)**	**0.057** **(1.09)**	**0.008** **(0.84)**
Time FE	Y	Y	Y
Bond FE	Y	Y	Y
Bond Controls	Y	Y	Y
Adj-R^2	0.418	0.532	0.445
# of obs	39936	35593	41635

Table 14. Carbon emission and bond illiquidity around the Paris Agreement and Trump's election

This table reports bond-quarter panel regression results, over the sample period from 2014Q4 to 2016Q4 (2015Q4 is deleted) in Panel A, and 2015Q4 to 2017Q4 (2016Q4 is deleted) in Panel B. We perform tests in the sub-sample of bonds with mutual fund ownership in the top quartile. The dependent variables are the three illiquidity measures including the Amihud, Roll, and IRC measures in quarter t, and the deleted quarter is based on the time of dependent variable measurement. The independent variables are measured of quarter $t-1$ and defined in Appendix A. PA is a dummy equal to one for the time period after the Paris Agreement (after 2015Q4), and zero otherwise. TE is a dummy equal to one for the time period after Trump's election (after 2016Q4), and zero otherwise. We include time and bond fixed effects through all the columns. Bond controls include bond rating, maturity, and age. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Amihud	Roll	IRC
Panel A: Paris Agreement			
	(1)	(2)	(3)
High-carbon × PA	**0.006****	**0.390***	**0.044***
	(2.54)	**(1.80)**	**(1.80)**
High-carbon	-0.002	-0.256	-0.017
	(-1.00)	(-1.62)	(-0.68)
Bond Controls	Y	Y	Y
Adj-R^2	0.587	0.623	0.624
# of obs	7502	6641	7796
Panel B: Trump's election			
High-carbon × TE	**-0.005*****	**-0.383*****	**-0.071*****
	(-5.41)	**(-3.54)**	**(-4.52)**
High-carbon	0.003	0.238	0.053***
	(1.50)	(1.67)	(3.83)
Bond Controls	Y	Y	Y
Adj-R^2	0.633	0.685	0.671
# of obs	8233	7422	8539

Table A1. Summary statistics of fund characteristics

This table reports the average of funds characteristics from January 2007 to December 2019. The fund-month characteristics include fund flow, total net assets (TNA, in millions of dollars), fund age (time-since-issuance in months), fund turnover (minimum of aggregated sales or aggregated purchases of securities, divided by the average of total net assets of the fund over past 12 months, in percentage), expense ratio in percentage, fund return of last month in percentage, and fund carbon exposure. The fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon exposure within that fund as of the most recent quarter-end, with details provided in Appendix A. In Panel A, each month, we sort all the funds into quintiles based on the most recent quarter-end fund carbon exposure, and report the fund-month summary statistics for funds with different carbon exposure. P1(P5) is the quintile with the lowest (highest) carbon exposure. In Panel B, we classify all the funds into high-yield funds, investment-grade funds, and other funds, and report the fund-month summary statistics for funds with different investment styles.

Panel A: Fund carbon exposure and fund-month summary

Rank of fund carbon exposure	P1	P2	P3	P4	P5
Flow (%)	1.35	0.97	0.69	0.92	0.91
TNA	2539.73	3970.59	2544.43	1993.96	2018.21
Fund age (in months)	109.07	112.75	115.76	95.50	98.65
Turnover ratio (%)	107.86	112.16	114.30	100.13	92.65
Expense ratio (%)	0.80	0.72	0.89	1.01	1.09
Lagged return (%)	0.34	0.39	0.37	0.40	0.42
Fund carbon exposure	1.19	1.97	2.56	3.62	5.32

Panel B: Fund style and fund-month summary

Fund style	High-yield	Investment-grade	Other
Flow (%)	1.00	1.20	0.85
TNA	1753.91	3187.55	2522.88
Fund age (in months)	101.59	114.82	103.42
Turnover ratio (%)	65.70	128.36	102.80
Expense ratio (%)	0.94	0.63	1.03
Lagged return (%)	0.44	0.28	0.42
Fund carbon exposure	4.47	2.12	2.98

Table A2. Fund carbon exposure and quarterly mutual fund flow

This table reports fund-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is mutual fund flow in quarter t, expressed in percentage. The fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon exposure score within that fund in quarter $t-1$. Control variables include fund average bond rating, logarithm of TNA, lagged return, percentage of cash holding, expense ratio, turnover ratio, and fund age at the end of quarter $t-1$, and cumulative return from $t-4$ to $t-2$. We include quarter and style fixed effects in Column (1), and further include fund fixed effects from Columns (2) to (4). All variables are winsorized at the 0.5% level each month. Standard errors are clustered at the fund and month levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Quarterly mutual fund flow				
	(1)	(2)	(3)	(4)
Fund carbon exposure	**-0.420****	**-0.553*****	**-0.609*****	**-0.454****
	(-2.44)	**(-2.92)**	**(-3.28)**	**(-2.49)**
Fund average (bond) rating			0.086	0.022
			(0.50)	(0.14)
Ln(TNA)			-7.586***	-6.201***
			(-10.79)	(-8.89)
Lagged return			44.473***	47.453***
			(5.41)	(5.22)
Cash holding			0.039**	0.033**
			(2.53)	(2.06)
Expense ratio			-5.510***	-3.849*
			(-2.87)	(-1.92)
Turnover ratio			0.151	0.120
			(0.46)	(0.38)
Fund age			-0.030***	-0.029***
			(-4.30)	(-4.52)
Cumulative return				28.662***
				(6.30)
Time FE	Y	Y	Y	Y
Style FE	Y	Y	Y	Y
Fund FE	N	Y	Y	Y
Adj-R^2	0.039	0.221	0.285	0.250
# of obs	29229	29191	28095	25664

Table A3. Carbon emission intensity and mutual fund selling

This table reports bond-quarter panel regression results, over the sample period of 2007Q1 to 2019Q4. The dependent variable is the sell herding measure (SHM) of mutual funds measured in quarter t. The carbon emission intensity variable is defined as the logarithm of the sum of firm Scope 1 and Scope 2 emissions, scaled by firm revenue, from Trucost data. The independent variables are measured at the end of quarter $t-1$. Column (1) includes time and bond fixed effects, and controls for bond rating, maturity and age. Column (2) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Mutual fund SHM		
	(1)	(2)
Carbon emission intensity	**0.789****	**0.795****
	(2.35)	**(2.29)**
Rating	-0.026	0.027
	(-0.18)	(0.19)
Maturity	0.894***	0.897***
	(6.03)	(5.73)
Age	23.033***	22.839***
	(17.11)	(16.36)
Ln(ME)		0.594
		(1.26)
Ln(BM)		0.021
		(0.06)
Stock IVOL		6.554
		(1.45)
Institutional ownership		-0.983
		(-0.49)
Analyst		-0.000
		(-0.01)
Time FE	Y	Y
Bond FE	Y	Y
Adj-R^2	0.163	0.164
# of obs	37124	35164

Table A4. Carbon emission and flow-adjusted mutual fund selling

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is the flow-adjusted sell herding measure (SHM) of mutual funds measured in quarter t. We first follow Jiang, Li, and Wang (2021) to get the flow-adjusted trading of each bond held by each fund at each quarter-end. For each bond at each quarter-end, we then aggregate the number of flow-adjusted buyers and sellers across all the mutual funds holding the bond, which are finally used as the inputs to calculate the flow-adjusted SHM. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. Column (1) includes time and bond fixed effects, and controls for bond rating, maturity, and age. Column (2) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Flow-adjusted mutual fund SHM		
	(1)	(2)
High-carbon	**1.603****	**1.563****
	(2.03)	**(2.02)**
Rating	-0.049	-0.275
	(-0.32)	(-1.51)
Maturity	0.177	-0.122
	(0.67)	(-0.47)
Age	0.575	0.290
	(0.40)	(0.20)
Ln(ME)		0.862**
		(1.99)
Ln(BM)		1.035***
		(3.70)
Stock IVOL		35.766**
		(2.53)
Institutional ownership		-0.825
		(-0.88)
Analyst		-0.006
		(-0.31)
Time FE	Y	Y
Bond FE	Y	Y
Adj-R^2	0.139	0.140
# of obs	86423	81083

Table A5. Carbon emission and mutual fund selling: Placebo test

This table reports bond-quarter panel regression results, over the eight quarters around the placebo event (four quarters before and four quarters after), excluding the event quarter. The dependent variable is the sell herding measure of mutual funds measured in quarter t. The independent variables are measured at the end of quarter $t-1$ and defined in Appendix A. Post-Event is a dummy equal to one for the time period after the placebo event, and zero otherwise. Control variables and fixed effects are as defined in Table 5. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Mutual fund SHM		
	(1)	(2)
	2011Q4	2012Q4
High-carbon × Post-Event	**1.999**	**-2.537**
	(1.39)	**(-1.08)**
High-carbon	2.412	2.405***
	(1.48)	(2.65)
Bond Controls	Y	Y
Time FE	Y	Y
Bond FE	N	Y
Adj-R^2	0.175	0.185
# of obs	3658	4262

Table A6. Carbon emission and mutual fund ownership change

This table reports bond-quarter panel regression results over the sample period of 2007Q1 to 2019Q4. The dependent variable is the bond mutual fund selling in quarter t, proxied by the mutual fund ownership change ($\Delta Mut_{i,t} = Mut_{i,t} - Mut_{i,t-1}$) in percentage. The independent variables are measured at the end of the quarter $t-1$. Column (1) includes time and bond fixed effects and controls for bond rating, maturity, and age. Column (2) additionally controls for Ln(ME), Ln(BM), stock IVOL, institutional ownership, and analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: ΔMut		
	(1)	(2)
High-carbon	**-0.098****	**-0.107****
	(-2.10)	**(-2.32)**
Rating	0.002	0.010
	(0.19)	(0.67)
Maturity	-0.003	-0.003
	(-1.52)	(-1.44)
Age	-0.078	-0.059
	(-0.97)	(-0.80)
Ln(ME)		-0.092*
		(-1.71)
Ln(BM)		-0.041
		(-1.22)
Stock IVOL		-1.728
		(-1.44)
Institutional ownership		-0.095
		(-0.91)
Analyst		-0.002
		(-1.20)
Time FE	Y	Y
Bond FE	Y	Y
Adj-R^2	0.067	0.067
# of obs	173135	159767

Appendix A Variable Definitions

Key Variables	
Flow	Following the majority of the prior literature on fund flows, we calculate flows for fund j in month t as the percentage growth of new assets, assuming that all flows take place at the end of the month: $Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1} \times (1+R_{j,t})}{TNA_{j,t-1}}$ where $TNA_{j,t-1}$ is the total net assets under management of fund j at the end of month $t-1$, and $R_{j,t}$ is the total return of fund j in month t.
Sell herding measure (SHM)	Following Lakonishok, Shleifer, and Vishny (1992) and Cai, Han, Li, and Li (2019), we estimate the herding measure of bond i in quarter t using following equation: $HM_{i,t} = \lvert p_{i,t} - E[p_{i,t}]\rvert - E\lvert p_{i,t} - E[p_{i,t}]\rvert$, where $p_{i,t}$ is the proportion of buyers to all active traders of bond fund i in quarter t. The term $E[p_{i,t}]$ is the expected level of buying intensity, estimated using the market-wide intensity of buying $\bar{p}_t$, and $\bar{p}_t = \frac{\sum_i \#\ of\ Buy_{i,t}}{\sum_i \#\ of\ Buy_{i,t} + \sum_i \#\ of\ Sell_{i,t}}$. Sell herding measure (SHM) is defined for bonds with a lower proportion of buyers than the market average: $SHM_{i,t} = HM_{i,t} \lvert [p_{i,t} < E[p_{i,t}]]$.
Outflow-induced selling pressure	Following Coval and Stafford (2007), we construct outflow-induced selling pressure based on realized fund trades conditional on large fund flows: $Selling\ pressure_{i,t} = \frac{\sum_{j=1}^{J} (Sell\ Amt_{j,i,t} \lvert Flow_{j,t} < 20^{th} Pctl - Buy\ Amt_{j,i,t} \lvert Flow_{j,t} > 80^{th} Pctl)}{Bond\ issue\ size_i}$, where $Sell\ Amt_{j,i,t}$ is the selling amount of mutual fund j on bond i in quarter t, and $Buy\ Amt_{j,i,t}$ is similarly defined.
Oil exposure	Following Demirer, Jategaonkar, and Khalifa (2015), we calculate a firm-level exposure to oil price shocks by running the following regression within each quarter: $R_{f,t,w} = \alpha_{f,t} + \mu_{f,t} \times R_{m,t,w} + \beta_{f,t} \times R_{oil,t,w} + \epsilon_{f,t,w}$, where $R_{f,t,w}$ and $R_{m,t,w}$ are the excess return for firm i and stock market of week w in quarter t, respectively. $R_{oil,t,w}$ is the return of Brent crude oil price of week w in quarter t. $\beta_{f,t}$ is the loading on the oil factor, i.e., oil exposure, for firm f in quarter t. We assign the firm level oil exposure to all the bonds issued by that firm
Fund carbon exposure	A carbon score is assigned to each fund based on the par amount of holding-weighted average of bond carbon exposure within that fund. $Fund\ carbon\ exposure_{j,t} = \sum_i \omega_{i,j,t} Carbon\ exposure_{i,t}$, where $Carbon\ exposure_{i,t}$ is the carbon exposure score for bond i in quarter t. $\omega_{i,j,t}$ is the weight of bond i in mutual fund j's portfolio at the end of quarter t.

(Bond level) flow-sensitivity-to-carbon	First, we regress mutual funds' investor (out)flow on fund carbon exposure in the rolling window of the past 12 months with fund controls (as in Table 2, and get the flow-to-carbon sensitivity (β) for each fund. Then, based on the cross-sectional median of β in each quarter, we sort all funds into 2 groups by the cross-sectional median and define the bottom (top) half group with "high-carbon-sensitivity fund" = 1 (0) given that we measure fund outflows. At last, the (bond level) flow-sensitivity-to-carbon is calculated as the fund-ownership weighted sum of the high-carbon-sensitivity fund dummy.
Amihud (% per thousand \$)	First, we remove a trade if its price change is more than 20% from the previous trade within the same day. Then, we compute per transaction the Amihud measure as the absolute value of return divided by the trading volume and then average across all trades of a bond within a quarter. We require at least 2 trades per quarter to report the measure.
Roll (%)	Following Roll (1984), the quarterly implicit bid-ask spread is estimated as the serial covariance of returns of bond j in quarter t. Specifically, $Roll_{j,t} = 2\sqrt{\max(0, -cov(\Delta p_{t,d}, \Delta p_{t,d-1}))}$, where $p_{t,d}$ is the logarithm of the daily clean price on day d in quarter t, $\Delta p_{t,d}$=$p_{t,d} - p_{t,d-1}$ is the price change from day $d-1$ to d in quarter t. We follow Bao, Pan, and Wang (2011) to limit the difference in days to 1 week.
IRC (%)	Imputed Round-trip Costs (IRC) is calculated following Dick-Nielsen, Feldhütter, and Lando (2012). Specifically, if two or three trades in a given bond with the same trade size take place on the same day, and there are no other trades with the same size on that day, the transactions are defined as part of an Imputed Roundtrip Trades (IRT). For an IRT, the imputed roundtrip cost (IRC) is calculated as $(P_{max} - P_{min})/P_{max}$, where P_{max} is the largest price in the IRT and P_{min} is the smallest price in the IRT. A daily estimate of roundtrip costs is the average of roundtrip costs on that day for different trade sizes. We then estimate the quarterly roundtrip costs by averaging over daily estimates.
Carbon exposure score	We first obtain MSCI carbon emission score from MSCI ESG rating. MSCI follows the ESG IVA approach to get the MSCI carbon emission score, on a scale of 0–10. The score is adjusted by industry and is thus comparable for two firms from different industries. Companies with better performance on this issue score higher. The score is normally updated annually while sometimes it is updated more than one time within a year. We invert the original MSCI carbon emission score to get carbon exposure score, which is calculated as 10 minus the original score, to ensure that a higher carbon exposure score reflects a higher level of carbon emissions.

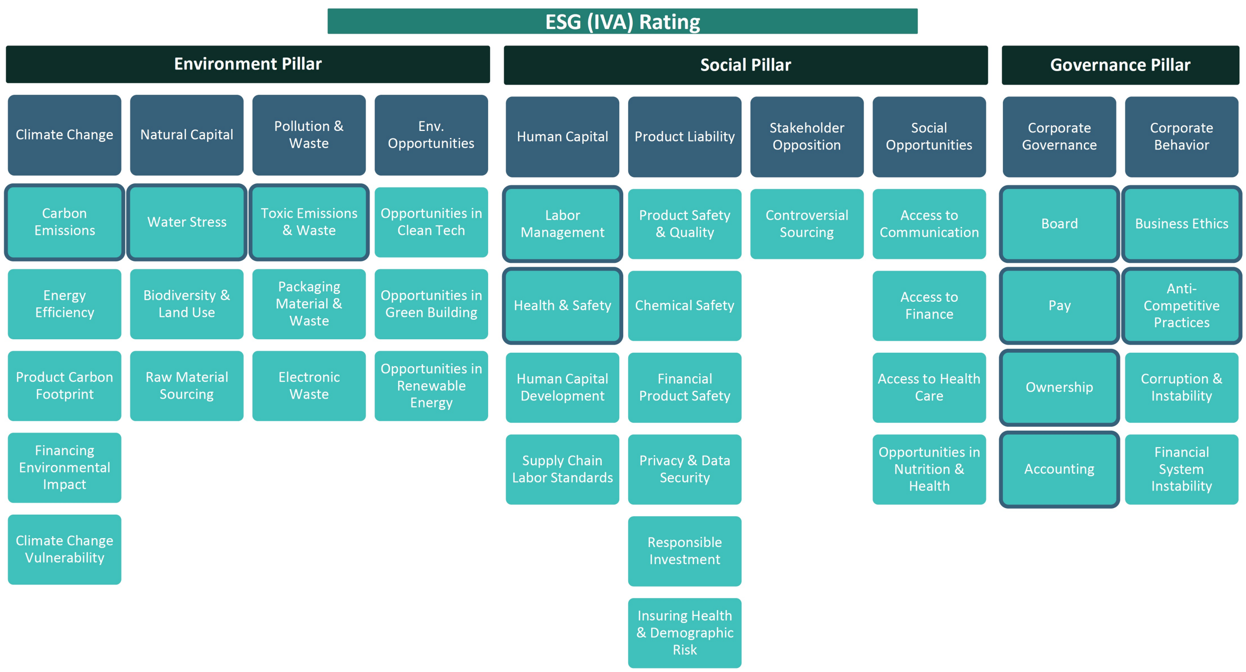
High-carbon dummy	The high-carbon dummy is equal to one if the firm's (issuer's) carbon exposure score is among the highest group when we divide all firms into three groups each quarter, and zero otherwise.
Rating	Rating is the average of credit ratings provided by S&P and Moody's when both are available, or the credit rating provided by one of the two rating agencies when only one rating is available. A numerical score of 1 refers to AAA rating by S&P and Aaa rating by Moody. A numerical score of 21 refers to C for both S&P and Moody. Investment-grade (low yield) bonds have credit ratings from 1 to 10. Non-investment-grade (high-yield) bonds have credit ratings above 10. A larger number indicates higher credit risk or lower credit quality.
Control Variables	
Maturity	Time-to-maturity in years.
Age	Time-since-issuance in years.
Coupon (%)	Individual bond coupon rate.
Ln(Size)	The natural logarithm of the individual bond issue size.
Ln(ME)	The natural logarithm of the market value of the firm's equity at the end of last year.
Ln(BM)	The natural logarithm of firm's book equity for the fiscal year-end in a calendar year divided by its market equity at the end of December of that year, as in Fama and French (1992).
Stock IVOL	The standard deviation of the regression residual of individual stock returns on the Fama and French (1993) three factors using daily data in the previous month, as in Ang, Hodrick, Xing, and Zhang (2006). We then average monthly stock IVOL within a quarter to get the quarterly IVOL measure.
Institutional ownership	The percentage of common stocks owned by institutions.
Analyst	The number of analysts following the firm.
Fund average bond rating	Fund average bond rating is calculated based on holding-weighted average of bond rating within that fund. $\textit{Fund average bond rating}_{j,t} = \sum_i \omega_{i,j,t} \textit{bond rating}_{i,t}$, where $\textit{bond rating}_{i,t}$ is the bond rating for bond i in quarter t. $\omega_{i,j,t}$ is the weight of bond i in mutual fund j's portfolio at the end of quarter t.
Ln(TNA)	The natural logarithm of the fund's total net asset.
Lagged return	Fund return in the last month.
Cash holding	Amount of fund invested in cash.
Expense ratio	Expense ratio as of the most recently completed fiscal year.
Turnover ratio	Turnover ratio is the minimum (of aggregated sales or aggregated purchases of securities), divided by the average 12-month Total Net Assets of the fund. Provided by CRSP Open-end Mutual Fund database.
Fund age	Fund age measures the time since fund issuance in months.
ST cumulative return	Short-term cumulative monthly return from month $t-6$ to $t-1$.
LT cumulative return	Long-term cumulative monthly return from month $t-12$ to $t-1$.

Appendix B MSCI Carbon Emission Score

B.1 Steps for MSCI ESG IVA

MSCI ESG IVA applies a three-stage approach.[43]

Step 1: Identify key ESG drivers of risks and opportunities for each industry. MSCI ESG IVA identifies four to seven key ESG trends and issues where companies in that industry currently generate large environmental or social externalities. These are issues where some companies in those industries may be forced to internalize unanticipated costs associated with those externalities in the future. Once the key issues have been selected for a GICS subindustry, the weights that determine each key issue's contribution to the overall rating are set. Each key issue typically comprises 5-30% of the total IVA rating. The following shows related ESG issues.

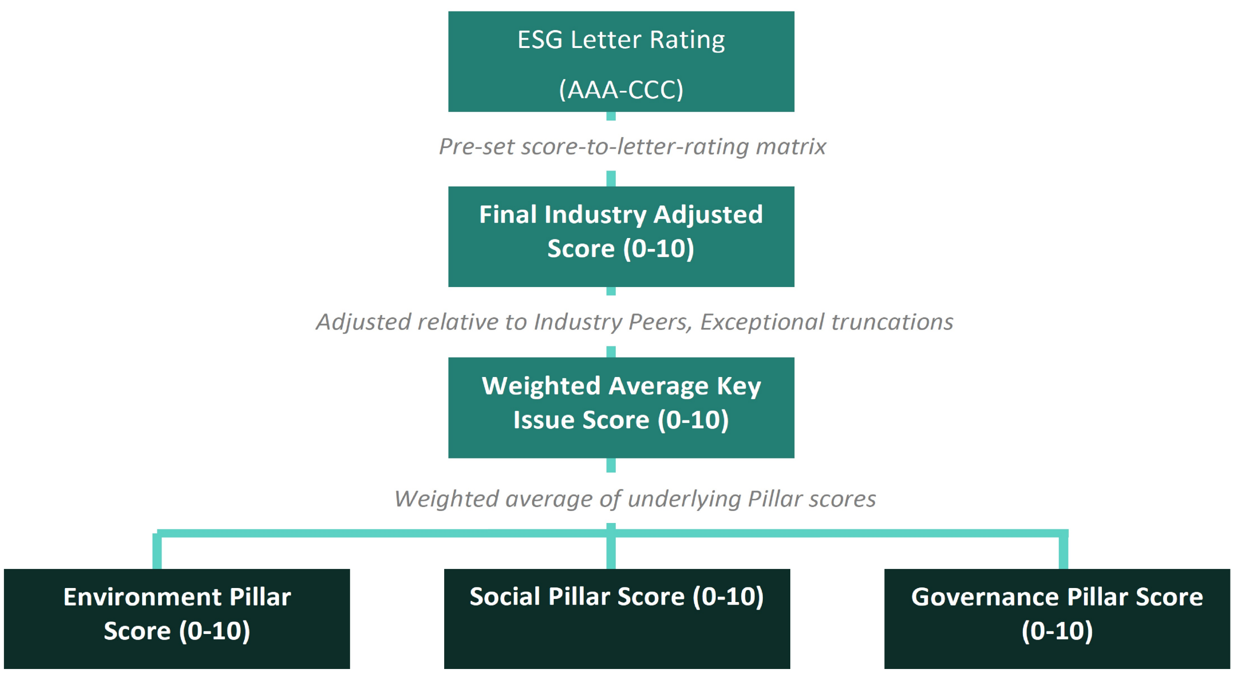


Step 2: Evaluate risk exposure and risk management. MSCI ESG IVA analysts calculate the size of each company's exposure to key ESG risks based on a granular breakdown of a company's business: its core product segments or business activities, the locations of its assets or revenues, and other relevant measures for specific issues such as the percentage of production outsourced to a supply chain. The analysis then takes into account the extent to which a company has developed robust strategies and demonstrated a strong track record of performance in managing its specific level of risks or opportunities. By weighing a company's

[43]Source of the executive summary IVA methodology description: https://silo.tips/download/executive-summary-intangible-value-assessment-iva-methodology. Source of the full IVA methodology description: https://docplayer.net/52563642-Intangible-value-assessment-iva-methodology.html.

strategy and performance against its specific level of risk or opportunities, MSCI ESG IVA rating model is designed to measure any gaps in companies' risk management systems.

Step 3: Rank and rate each company against industry peers. Using an industry-specific key issue weighting model, companies are rated and ranked in comparison to their industry peers. Specifically, each company receives an Industry-Adjusted Score (IAS), which is defined by the weighted average of the Environmental and Social Key Issue Scores and the Governance Pillar Score and normalized based on score ranges set by benchmark values in the peer set. The highest-scoring benchmark company receives a 10 as its preliminary IAS and the lowest-scoring benchmark company receives a 0. After any override considerations are factored in, each company's final IAS corresponds to a rating between best (AAA) and worst (CCC). These assessments of company performance are not absolute but are explicitly intended to be relative to the standards and performance of a company's industry peers. The companies in each industry undergo an annual review and are updated on a rolling basis as well as in response to major events with their industry peers. The following shows the hierarchy of MSCI ESG IVA scores.



B.2 The key issue of carbon emissions

The key issue of carbon emissions evaluates the extent to which companies face increased costs linked to carbon pricing or regulatory caps. Companies that proactively invest in low-carbon technologies and increase the carbon efficiency of their facilities or products score higher on this key issue. Companies that allow legal compliance to determine product strategy, focus exclusively on activities to influence policy setting, or rely heavily on exploiting differences in regulatory frameworks score lower. The following shows the related considerations for this key issue.

<table>
<tr><td>Social or Environmental Impact</td><td>Contribution to climate change</td></tr>
<tr><td>Risk/Opportunity to Company</td><td>Increased costs linked to carbon pricing or trading
Facility retrofits
Potential operational disruptions related to regulatory caps</td></tr>
<tr><td>Exposure Metrics</td><td>Extent to which companies emit GHG in jurisdictions where regulations on carbon emissions are stringent or becoming more stringent
Extent to which companies' main business activities are carbon-intensive based on economic input-output model estimating total GHG emissions relative to sales</td></tr>
<tr><td>Management Metrics</td><td>Efforts to reduce exposure through comprehensive carbon policies and implementation mechanisms, including carbon reduction objectives, production process improvements, installation of depollution or emissions capture equipment, and/or switch to cleaner energy sources.

<table>
<tr><th>Category</th><th>Management Metrics</th></tr>
<tr><td>Targets*</td><td>Aggressiveness of target in the context of current performance*
Carbon Improvement Targets*
Target Year*
Target Reduction (%)*
Baseline, Baseline Year*
Target Description*
Highest Overall Target Year
Highest Overall Carbon Improvement Target
Highest Overall Target Description
Highest Overall Target Percentage
Demonstrated track record of achieving carbon reduction targets</td></tr>
<tr><td>Mitigation*</td><td>Programs or actions to reduce the emissions intensity of core operations*
Use of cleaner sources of energy*
Capture GHG emissions
Energy consumption management and operational efficiency enhancements*
Reduce future energy consumption (e.g. demand-side management programs)</td></tr>
</table>
</td></tr>
</table>

	Other initiatives (e.g. carbon offsets) CDP disclosure
Performance*	**Trend in GHG emissions intensity*** **GHG emissions intensity vs. peers*** *GHG Emissions - metric tons CO2e** *Year** *Scope 1 GHG emissions** *Scope 2 GHG emissions** *Scope 1 plus 2 GHG emissions** *Scope 3 (upstream) GHG emissions** *Scope 3 (downstream) emissions** *Scope 3 (undefined) emissions** *GHG emissions details** *Scope 1 Estimated* *Scope 2 Estimated* *Scope 1+2 Estimated* *Estimate Key* *GHG Emissions Intensity - metric tons CO2e / USD million sales** *Year** *Company Sales** *GHG Intensity** *GHG Intensity Details** *Intensity Key* *GHG Intensity – Reported* *GHG Intensity – Reported Details*

* Baseline Indicators. Please see the **Variations in Disclosure** section above for information on Baseline Indicators.

Industry Groups Using Key Issue	• Energy • Materials • Capital Goods • Commercial & Professional Services • Transportation • Food Beverage & Tobacco • Diversified Financials • Real Estate • Utilities
Data Sources	• Company disclosure and news searches • Carbon Disclosure Project (CDP) • Environment regulatory agencies (EPA, EEA) • Comprehensive Environmental Data Archive (CEDA) • Eurostat – Air Emissions Accounts by Activity