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

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Abstract

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

JEL classification: G11, G20, G23, G41

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Abstract

This paper investigates how climate-related risks affect the trading behavior of bond mutual funds and tests the underlying mechanisms. We find that mutual funds collectively sell corporate bonds issued by firms with high carbon emissions, driven by funds' concerns about carbon-related redemption risks, rather than by a permanent shift in funds' investing preferences. Higher carbon exposures in mutual fund portfolios lead to more investor outflows, and bonds tend to experience more intensive selling if their holding mutual funds have higher flow-to-carbon sensitivity. Bonds issued by high-carbon firms experience worse liquidity conditions, especially when concerns about carbon-related risks heighten.

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1 Introduction

Over the past decade, institutional investors are increasingly aware of climate risks (Krueger, Sautner, and Starks (2020)). They strongly demand climate risk disclosures (Ilhan, Krueger, Sautner, and Starks (2023)), incorporate the Principles for Responsible Investment (PRI) into their portfolios (Gibson Brandon, Glossner, Krueger, Matos, and Steffen (2022)), and decarbonize their portfolios via portfolio re-weighting or firm engagement (Atta-Darkua, Glossner, Krueger, and Matos (2023)). Recent research shows that climate-related concerns have become an important consideration in equity mutual funds' portfolio decisions (Alekseev, Giglio, Maingi, Selgrad, and Stroebel (2022), Bolton and Kacperczyk (2021), Cao, Titman, Zhan, and Zhang (2022), Ceccarelli, Ramelli, and Wagner (2023), Humphrey and Li (2021), and Starks, Venkat, and Zhu (2023)). Nevertheless, there is little in the literature about how such concerns influence fixed-income mutual funds' behaviors and what factors drive their climate-related trading decisions.[1]

A few distinct features of the corporate bond market and bond mutual funds make them important subjects when studying 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), Bretscher, Schmid, Sen, and Sharma (2022), Falato, Goldstein, and Hortaçsu (2021), Haddad, Moreira, and Muir (2021), and Jiang, Li, Sun, and Wang (2022)). In addition, corporate bond mutual funds are much more likely to sell in herds than equity funds when facing common signals, and such collective selling can generate significant price distortions (Cai, Han, Li, and Li (2019)). Therefore,

[1]Open-end mutual funds are important investors in the corporate bond market, holding about 20 percent of outstanding U.S. corporate bonds.

when confronted with concerns about heightened climate risks, the aforementioned features of corporate bond mutual funds could distinctly affect their trading behaviors and have strong impacts on bond prices and liquidity conditions.

Our paper investigates how firms' carbon emission levels affect bond mutual funds' trading behaviors and tests the underlying mechanisms. Using a sample from January 2007 to December 2019, we find that mutual funds collectively sell corporate bonds issued by firms with high carbon emissions, and we establish causality by exploiting the shock of the Paris Agreement in December 2015. More importantly, we explore the underlying mechanism of this finding and show that it is driven by funds' concerns for carbon-related redemption risks, rather than by a permanent shift in funds' investment preferences or ethics. Consistent with the notion that mutual funds collectively sell high-carbon bonds under pressures 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 ownerships and during periods when carbon-related concerns heighten.

Our main results are as follows. First, we use the full sample (with observations at the bond-quarter levels) to investigate the relationship between mutual funds' collective selling of a bond and the carbon emission level of the bond's issuer. 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 institutions sell a certain security beyond the market-wide selling intensity in a given period. Firms' carbon emission scores are obtained from the MSCI ESG rating (with lower scores indicating higher carbon emissions), and bonds issued by firms in the lowest tercile of carbon emission scores at each quarter-end are defined as high-carbon bonds. Controlling for various bond/firm characteristics and fixed effects, we find a strong and positive association between the high-carbon dummy and mutual funds' collective selling in the subsequent quarter. In particular, the mutual fund sell herding measure of a high-carbon bond is one percentage point (or 7% of the standard deviation) higher compared to those of other bonds. Moreover, our results remain strong and robust when we employ an alternative mutual fund selling measure, outflow-induced selling pressure (Coval and Stafford (2007)), as the dependent variable.

We then utilize a shock to test the causal effect of firms' carbon emissions on mutual funds' collective selling. Specifically, we employ difference-in-differences analyses on the eight-quarter window around the Paris Agreement in December 2015, in which 196 signatories committed to combat global warming by reducing carbon emissions. The Paris Agreement is considered as a landmark step for actions regarding climate change, and more importantly, its adoption came as a surprise to most people. Thus, mutual funds' selling towards bonds with high-emission issuers should be greatly intensified after the announcement of the Paris Agreement. Our regression results confirm this hypothesis using both mutual fund selling measures, thus lending solid support to the causal effect of firms' carbon emissions on mutual funds' collective selling in the corporate bond market.

We also address a potential concern about utilizing the Paris Agreement as our identification strategy. Around the Paris Agreement, there was a simultaneous large decline in oil prices, which may 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 the alternative explanation that the increase in collective selling by mutual funds after the Paris Agreement is caused by negative oil price shocks rather than concerns for carbon emissions, we disentangle the effects of carbon emissions from those of oil price changes and show that our results are unaffected after controlling for bonds' individual exposures to oil price shocks.

What are the underlying mechanisms for the strong relationship between carbon emissions and mutual funds' collective selling? We test two potential channels: (i) driven by funds' concerns about carbon-related redemption risks; (ii) driven by a permanent shift in funds' investment preferences or ethics. The first channel emphasizes mutual funds' opportune assessment of potential investors' run risks associated with their asset exposures, while the second channel highlights mutual funds' long-term change in investment focus and strategies.

We find strong support for the first channel. In particular, higher carbon exposures in mutual fund portfolios lead to more investor outflows, and such a flow-to-carbon relationship is strongly enhanced after the Paris Agreement. Moreover, bonds tend to experience more collective selling if their holding mutual funds have higher carbon-induced redemption risks (measured as flow-to-carbon sensitivity), after controlling for bond issuers' carbon emissions.

For the second channel, we find that mutual funds' collective selling towards high-carbon bonds has a major reversal following the election of President Trump (November 2016), largely offsetting the intensified selling effects after the Paris Agreement. In addition, we find that the price impact of the Paris Agreement on high-carbon bonds is strong yet temporary. Specifically, high-carbon bonds experience much larger price depressions around the Paris Agreement relative to low-carbon bonds, but such price depressions quickly recover within half a year. This finding is more consistent with the effect of mutual fund fire sales due to heightened concerns about carbon-related risks. Taken together, the countervailing effect of Trump's election on mutual funds' collective selling and the short-lived price impact following the Paris Agreement suggest that our finding is unlikely driven by a permanent shift in mutual funds' preference for low-carbon bonds.

Finally, consistent with the notion that mutual funds tend to collectively sell high-carbon bonds under pressures from investor redemptions, we hypothesize that the liquidity condition of high-carbon bonds would on average deteriorate. Intuitively, if mutual funds collectively shy away from bonds with high carbon exposures, dealers will have a difficult time finding potential buyers to purchase such bonds, trading costs will increase, and liquidity will suffer. To test this conjecture, we calculate three commonly used illiquidity measures for the corporate bond market (namely, Amihud, Spread, and Roll) and test the relationship between these illiquidity measures and the high-carbon dummy for our full sample. Our regression results show that the coefficients of the high-carbon dummy are all positive and statistically significant, and results are more pronounced among bonds with higher mutual fund ownerships. Importantly, we find that the liquidity condition of high-carbon bonds substantially deteriorates after the Paris Agreement and improves after Trump's election.

Our paper makes several contributions to the literature. First, 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), Cao, Titman, Zhan, and Zhang (2022), Humphrey and Li (2021), and Starks, Venkat, and Zhu (2023)). While Duan, Li, and Wen (2023) and Seltzer, Stark, and Zhu (2022) study aggregate institutional ownerships 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.[2]

Second, we are the first to investigate how concerns about firms' environmental performance 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 (2022), 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 deepens the understanding of the pricing implications of carbon emissions. In particular,

[2] In contrast to our primary focus on mutual fund trading dynamics, the focus of Duan, Li, and Wen (2023) and Seltzer, Stark, and Zhu (2022) 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, Stark, and Zhu (2022) 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.

our finding implies that the effects of carbon emissions on corporate bond prices could also be driven by changes in bonds' liquidity condition, rather than by credit risks alone.[3]

Third, 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. We provide the first evidence on the negative flow-to-carbon relationship for corporate bond mutual funds, after controlling for known factors driving fund flows.[4] This finding indicates that end-investors of corporate bond mutual funds are sophisticated enough to take into account the funds' exposures to carbon emissions and also provides a transmission channel for firms' carbon emissions to affect mutual funds' trading decisions.

Finally, our paper emphasizes that constraints faced by institutional investors (like mutual funds' redemption risks) can amplify shocks for underlying markets.[5] 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 firms' carbon emissions and mutual funds' collective selling in the corporate bond market. Section 4 tests two potential mechanisms for our findings. Section 5 investigates the implications of bonds' carbon exposures on their liquidity conditions. Section

[3] Amiraslani, Lins, Servaes, and Tamayo (2022), Halling, Yu, and Zechner (2021), and Seltzer, Stark, and Zhu (2022) 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)).

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

[5] 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 (2023), Choi, Hoseinzade, Shin, and Tehranian (2020), Chen, Du, and Sun (2022), and Ma, Xiao, and Zeng (2022).

6 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 the sell herding measure and bond illiquidity measures). Finally, we provide summary statistics for the main variables.

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 exposures. 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; 3) rank and rate each company against its industry peers.[6]

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 not available, MSCI uses GHG (greenhouse gas) data reported by the Carbon Disclosure Project (CDP) or government databases.[7] 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 score is on a scale of 0–10 and generally updated annually while

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

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

sometimes updated more than once within a year. The MSCI carbon emission score covers all the companies in the MSCI World Index. Corporate bonds issued by these firms take more than 70% of the total corporate bond market cap.

Next, for the corporate bond transaction and price data, we rely on the enhanced Trade 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; and (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, and equity-linked securities, Yankees, Canadians, structured notes, issues denominated in foreign currency, and issues offered globally. Besides, following the prior literature, we exclude newly-issued and about-to-mature bonds (i.e., with age and 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. After assembling the data from the above resources, our largest sample for analysis contains 27,146 unique corporate bonds from 1,254 unique U.S. public firms over the sample period from January 2007 to December 2019.

We obtain data on institutional holdings of fixed-income securities from Thomson Reuters Lipper eMAXX. This dataset is survivorship-bias free and contains quarter-end security level corporate bond holdings of about 20,000 institutional investors, including insurance companies, mutual funds, pension funds, and others. 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). 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. 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.

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. We drop a fund if none of its holding bonds has a MSCI carbon emission score. Finally, our mutual fund sample for flow-related analysis contains 1,698 unique mutual funds, with 98,018 fund-month observations.

2.2 Variable construction

2.2.1 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.[8] It captures whether a disproportionate number of institutions are buying/selling a certain security beyond the market-wide buying/selling intensity in a given period. Specifically, we calculate the herding measure of bond i in quarter t for mutual funds, using the following equation:

$$HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]| \tag{1}$$

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 buy intensity, estimated using the market-wide intensity of buying $\bar{p}_t$,

$$\bar{p}_t = \frac{\sum_i \#\ of\ Buy_{i,t}}{\sum_i \#\ of\ Buy_{i,t} + \sum_i \#\ of\ Sell_{i,t}} \tag{2}$$

Therefore, the first term in Equation (1) 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 (1) as an adjustment factor, to make the expected value of herding measure under null hypothesis zero.[9]

Next, we follow Wermers (1999) to define the sell herding measure (SHM) for bonds with a lower proportion of buyers than the market average.[10]

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

We focus on the sell herding measure in this paper, investigating whether the collective

[8] To show the robustness of our findings, we also use an alternative measure to quantify mutual funds' selling activities, namely, outflow-induced selling pressure, which is detailed in Section 3.

[9] We follow Lakonishok, Shleifer, and Vishny (1992) to calculate the adjustment factor in Equation (1). 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.

[10] 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.

selling among mutual funds in the corporate bond market is associated with bond issuers' carbon emission levels.

2.2.2 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 Spread is the same-bond-same-day effective spread proposed by Hong and Warga (2000) and Jiang, Li, Sun, and Wang (2022), which is the dollar-volume-weighted average buy prices minus the dollar-volume-weighted average sell prices of all transactions on the same day for the same bond; and 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. The construction methodologies 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 bond and firm characteristics. Panel A (B) is based on bond-quarter (firm-quarter) observations. Mutual funds have an average sell herding measure of 6.62%. This implies that if 100 institutions trade a given bond in a given quarter, there are approximately 7 more mutual funds that herd to sell than expected if each institution trades bonds independently.

The average bond illiquidity measure based on Amihud is 0.05% per thousand dollars. The average same-day bid-ask spread and Roll illiquidity measures are 1.36% and 2.08%, respectively. The distributions of the bond illiquidity measures are all right skewed. The summary statistics are comparable to previous literature. Bonds in our sample on average have a credit rating of 7.6 (equivalently, nearly BBB+ for S&P or Baa1 for Moody's), time-to-maturity of 9.8 years, and time-since-issuance of 6.4 years.

[Insert Table 1 about here]

Bond issuers (i.e., firms) on average have a carbon score of 5.8. At the end of each quarter, we sort all firms into three equal groups according to their average MSCI carbon emission scores across the quarter. Bonds issued by firms with carbon emission scores in the bottom tercile are assigned with the high-carbon dummy equal to one, and zero otherwise. For other firm-level characteristics, bond issuers are on average large firms with high institutional ownership (an average of 76%) and are followed by 15 financial analysts.

In Panel C of Table 1, we provide distribution information on the raw MSCI carbon emission scores of firms issuing actively traded corporate bonds for each of the Fama-French 12 industries. The average carbon emission scores are comparable across industries, except for the relatively low score of the "Energy" industry, which includes "Oil, Gas, and Coal Extraction and Products" and typically has high carbon emissions.[11] This observation is largely consistent with the manual of MSCI that the emission score 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 D of Table 1 we compare the Fama-French 12 industry distributions of all issuers with actively traded corporate bonds and those with non-missing 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.

[11]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 Carbon emission and mutual fund selling of corporate bonds

In this section, we analyze whether the carbon emission performance of a corporate bond issuer has an impact on the mutual fund trading of its bonds. 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. 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 in December 2015. We also rule out an alternative explanation of negative oil price shocks for our findings.

3.1 Baseline results

To start, we investigate the relationship between mutual funds' collective selling and carbon emission score of bonds' issuers, running panel regression as follows:

$$SHM_{i,t} = \alpha + \beta \times High\ carbon_{i,t-1} + \delta \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \tag{4}$$

where $SHM_{i,t}$ is the sell herding measure of mutual funds for bond i over quarter t. $High\ carbon_{i,t-1}$ is a dummy variable measured at the previous quarter end, indicating whether the issuer's carbon emission level falls into the top one-third among all firms, i.e., with a carbon score in the lowest tercile.[12]

In the baseline 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.[13] We further control for stock characteristics

[12] 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 such as quintiles.

[13] Note that the inclusion of bond fixed effects renders the coupon size and logarithm of bond issue size

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), institutional ownership and the number of analysts following that stock.[14] Standard errors are calculated using two-way clustering at the bond and quarter levels. The results are reported in Table 2.

[Insert Table 2 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 2. 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 2. 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 1.3 percentage points when its issuer's carbon emission level changes from normal to high.[15] The results remain robust if we additionally control for bonds' lagged sell herding levels and lagged abnormal returns

redundant in our regression.

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

[15] 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 2 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.

(not reported).

3.2 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 emission 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 emission to the mutual funds' collective selling of its bonds, we utilize an exogenous shock, namely, the Paris Agreement, which has a considerable impact on carbon-related policy uncertainty and regulatory risks.

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.[16] 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.[17] For firms with higher carbon exposures, 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, institutional investors may have higher incentives to sell bonds issued by high-carbon firms, thus we expect the effect of the high-carbon dummy on the mutual funds' collective selling to be

[16] 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/the-paris-agreement/key-aspects-of-the-paris-agreement.

[17] 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."

intensified.

To test the hypothesis that the effect of carbon emission on mutual funds' sell herding of corporate bonds is strengthened following the Paris Agreement, 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:

$$SHM_{i,t} = \alpha_1 + \beta_1 \times High\ carbon_{i,t-1} \times PA_t + \gamma_1 \times High\ carbon_{i,t-1} + \delta_1 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \tag{5}$$

where PA_t is a time dummy equal to one for the period after the announcement of the Paris Agreement.[18] Our variable of interest is the interaction term $High\ carbon_{i,t-1} \times PA_t$.[19] If the conjecture is correct, we would find a positive β_1, which captures how the effect of carbon emission on mutual funds' collective selling changes after the Paris Agreement.

[Insert Table 3 about here]

In Table 3, 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 3-percentage-point increase (21% 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 emissions and mutual funds' collective selling, we verify the premise of pre-PA parallel trends following the methodology of Borusyak and Jaravel (2022). Specifically, we define the dummies Pre_PA(-3) and Pre_PA(-2), which

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

[19] 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.

equal one for the third to last quarter (2015Q1) and second to last quarter (2015Q2) before the Paris Agreement, respectively. We interact these two dummies with the high-carbon dummy. The interactions capture whether the sensitivity of mutual funds' collective selling to carbon emission 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 (5). 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 Table A1 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.

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

3.3 Robustness: alternative mutual fund selling measure

Our baseline results 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:[20]

[20] We manually match our eMAXX sample funds to the mutual funds covered in the CRSP survivor-bias free mutual fund databased based on fund names, to obtain fund returns, and the total net asset to calculate

$$Selling\,pressure_{i,t} = \frac{\sum_{j=1}^{J}(Sell\ Amt_{j,i,t}|Flow_{j,t} < 25^{th}Pctl - Buy\ Amt_{j,i,t}|Flow_{j,t} > 75^{th}Pctl)}{Bond\ issue\ size_i} \tag{6}$$

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. 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 exposures, 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 4 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 (4). The results are shown in Table 4. 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 0.33 percentage points (56% of the standard deviation) higher relative to other bonds, indicating a nontrivial economic magnitude. 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 (5). The results presented in Table 5 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

fund flows. Following the prior literature, fund-level flow is aggregated from CRSP share-class level.

mutual funds.

[Insert Table 5 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.

3.4 Alternative explanation: 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 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;[21] second, about 10% of bonds in our sample belong to the energy industry which are more likely to be in the high-carbon category and exposed to oil price shocks. Issuers with high exposures to negative oil shocks would suffer from the sharp oil price decline, and the underlying bonds would experience collective selling from mutual funds.[22]

[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

[21] 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.

[22] Admittedly, issuers with low exposures 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.

bonds' individual exposures 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:

$$R_{i,t,w} = \alpha_{i,t} + \mu_{i,t} \times R_{m,t,w} + \beta_{i,t} \times R_{oil,t,w} + \epsilon_{i,t,w} \tag{7}$$

where $R_{i,t,w}$ 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.[23] $\beta_{i,t}$ is the loading on the oil factor, i.e., oil exposure, for firm i in quarter t.[24] $\beta_{i,t}$ measures the sensitivity of a firm's stock prices to the movement of oil prices in a given quarter, thus serving as a time-varying proxy for a firm's exposure to oil price shocks.

We then augment the specification of Equation (5) (i.e., the difference-in-differences test) by including $\beta_{i,t}$ (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 6.

[Insert Table 6 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 3. Bond issuers' oil exposures do not have much impact on mutual funds' collective selling. In addition, results in Table 6 are robust if we use alternative measures of firm's oil exposure: 1) using

[23]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)).

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

WTI oil prices, 2) using daily returns or monthly returns as specified in Ilhan, Sautner, and Vilkov (2021), 3) using the absolute value of oil exposure $\beta_{i,t}$, and 4) taking 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 exposures rather than their oil exposures.

4 Explore the mechanism: why do mutual funds sell high-carbon bonds?

Our results so far show that the carbon emission intensity of bond issuers has an impact on mutual funds' trading patterns of corporate bonds. Such effects are strengthened following the Paris Agreement. In this section, we conduct a detailed investigation of the drivers for mutual funds' selling behaviors towards high-carbon bonds. Specifically, we test two potential mechanisms: (i) mutual funds' concerns about redemption risks; (ii) permanent shifts in mutual funds' investment preferences or ethics.

4.1 Channel I: driven by concerns about redemption risks

4.1.1 Redemption risks from mutual fund end-investors

Redemption by end-investors carries substantial stability concerns for bond mutual funds. The corporate bond market is known for its illiquidity and high transaction costs. Meanwhile, bond mutual funds offer daily redemptions to their investors as equity funds do. Such substantial liquidity transformation performed by bond mutual funds can generate a first-mover advantage among their investors and trigger amplified redemptions in the face of a negative shock (see, e.g., Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017)). If end-investors care about bond mutual funds' carbon exposures and make their redemption decisions accordingly, 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 should their investors care about carbon exposures.

Do investors care about the carbon exposures of corporate bond mutual funds? Hartzmark and Sussman (2019) document that equity fund flows are higher towards funds being categorized as high sustainability. However, little is known about bond fund investors. We aim to fill this gap and provide the first empirical evidence to understand the relationship between bond mutual fund flows and carbon exposures of their portfolios.

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

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t})}{TNA_{j,t-1}} \tag{8}$$

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.

To measure fund-level carbon exposures, we follow the methodology in Cao, Titman, Zhan, and Zhang (2022) 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:

$$Fund\ carbon\ exposure_{j,t} = \sum_i \omega_{i,j,t} Carbon\ exposure_{i,t} \tag{9}$$

where $Carbon\ exposure_{i,t}$ is the average of carbon exposure for bond i in the quarter t. Here, we take the negative value of MSCI carbon emission scores as carbon exposure, such that a higher value of carbon exposure (lower MSCI carbon emission score) indicates higher carbon emission by the issuing firm. $\omega_{i,j,t}$ is the weight of bond i in mutual fund j's portfolio 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.

Using a fund-month sample, we test whether flows are sensitive to bond mutual funds' carbon exposure by regressing the percentage flow of fund j in month t on fund carbon exposure as of the most recent quarter-end:

$$Flow_{j,t} = \alpha + \beta \times Fund\ carbon\ exposure_{j,t-1} + \delta \times controls_{i,t-1} + \mu_t + \theta_s + \epsilon_{i,t} \quad (10)$$

where μ_t represents the year-month fixed effects and θ_s is the fund style fixed effects. Here, we use Lipper Objective Code to identify the style of mutual funds. We control for a set of lagged fund characteristics, including logarithm of TNA, 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 7 about here]

Results in Table 7 show that funds with higher fund carbon exposures experience larger outflows, robust across different specifications. With time and style fixed effects included in Column (1), a one-standard-deviation increase in fund carbon exposure is associated with a 0.25-percentage-point increase in fund outflow. The effect of fund carbon exposures on investor flows remains prominent after controlling for various fund characteristics and fund fixed effects, as shown in Columns (2) and (3).

Next, we test whether the relationship between fund flows and fund carbon exposures is causal. Specifically, we investigate how the flow-carbon relationship changes around the Paris Agreement on the event window of [-6, +6] months (excluding the event month based on the time of fund flow). As the Paris Agreement draws public attention to climate changes and carbon emissions, we expect the negative relation between fund flows and fund carbon exposures to be strengthened after the Paris Agreement. We again run difference-in-differences regressions to test our hypotheses and report the results in Table 8.

[Insert Table 8 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 fund's carbon exposures is magnified notably after the Paris Agreement, not only supporting the causal effects of fund carbon exposures 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.[25]

4.1.2 Flow sensitivity to carbon exposure and mutual fund selling

We show that on average higher carbon exposures of mutual funds lead to more investor outflows, which echoes the results documented in Hartzmark and Sussman (2019) for equity mutual funds. Next, we provide evidence that fund managers' selling of high-carbon bonds is associated with such carbon-driven redemption risks. To test this channel, we exploit the fact that the sensitivity of investor flows to fund carbon exposures varies significantly across different mutual funds. Thus, corporate bonds with similar carbon scores may bear different levels of carbon-driven redemption risks due to their mutual fund ownerships. 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 exposures.

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.

$$Flow_{j,t} = \alpha + \beta_{j,t} \times Fund\ carbon\ exposure_{j,t-1} + \delta \times controls_{j,t-1} + \epsilon_{j,t} \qquad (11)$$

[25] While we provide strong evidence that funds' carbon exposures lead 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.

where $\beta_{j,t}$ is estimated based on the past 12-month observations of fund j. $Fund\ carbon\ exposure_{j,t-1}$ is the value-weighted carbon exposure of bonds in the portfolio of fund j. We control for the logarithm of TNA, monthly return, percentage of cash holding, expense ratio, turnover ratio, and fund age in the regression. A higher $\beta_{j,t}$ indicates that flows are more sensitive to the carbon exposure of that mutual fund.[26] Based on a quarterly average of $\beta_{j,t}$, we divide all the mutual funds into two equally sized subgroups according to the cross-sectional median, high-carbon sensitivity funds, and low-carbon sensitivity funds. 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 with high flow-to-carbon sensitivity, as demonstrated in Equation (11), and is named as (bond level) flow sensitivity to carbon.

$$(Bond\ level)\ flow\ sensitivity\ to\ carbon_{i,t} = \sum_j \omega_{i,j,t} High\ carbon{-}sensitivity\ fund_{j,t} \tag{12}$$

where $\omega_{i,j,t}$ represents the par amount of corporate bond i held by fund j divided by the total amount of corporate bond i held by all mutual funds at the end of quarter t. $High\ carbon{-}sensitivity\ fund_{j,t}$ 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 flow-to-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 exposures. To test such a conjecture, in our baseline regression with the sell herding measure as the dependent variable, we interact the high-carbon dummy with the bond-level flow sensitivity to carbon and test

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

whether the interaction has a significant positive coefficient.

$$
\begin{aligned}
SHM_{i,t} = & \alpha_2 + \beta_2 \times High\ carbon_{i,t-1} \times (Bond\ level)\ flow\ sensitivity\ to\ carbon_{i,t-1} \\
& + \gamma_2 \times High\ carbon_{i,t-1} + \vartheta_2 \times (Bond\ level)\ flow\ sensitivity\ to\ carbon_{i,t-1} \\
& + \delta_2 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t}
\end{aligned}
\tag{13}
$$

[Insert Table 9 about here]

We show the supporting evidence in Table 9. 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 high-carbon sensitivity funds experiences significantly higher collective selling among mutual funds (12% of standard deviation) than the bond held by low-carbon sensitivity funds. This finding shows that conditional on bonds' own carbon emission levels, 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.

4.2 Channel II: driven by permanent shifts in investment preferences or ethics

While we provide 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' permanent shifts in their investment preferences or ethics against bonds issued by firms with high carbon emissions. Such changes represent funds' long-term investment attitudes and are likely to be long-lasting and irreversible.[27]

[27]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

4.2.1 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 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. President 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.

$$SHM_{i,t} = \alpha_4 + \beta_4 \times High\ carbon_{i,t-1} \times TE_t + \gamma_4 \times High\ carbon_{i,t-1} + \delta_4 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \tag{14}$$

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).

launch of the State Street Sustainable Climate Bond Funds, which aim to significantly reduce investors' exposure to carbon emissions.

[Insert Table 10 about here]

Panel A of Table 10 reports the results. We find that the coefficients on $High\ carbon_{i,t-1} \times TE_t$ 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 2.65-percentage-point decline in its mutual funds' collectively selling following the election of President Trump, comparable in magnitude to the amplifying effect following the Paris Agreement. Thus, the effects of carbon emission 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.

These results are robust to the alternative measure of mutual fund selling. Specifically, the effect of carbon emissions on mutual funds' outflow-induced selling pressure is also reversed following Trump's election, as presented in Panel B of Table 10. The significantly negative coefficients for the interaction terms imply that the positive relationship between outflow-induced selling and fund carbon exposures is notably weakened after Trump's election.

4.2.2 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 risks (i.e., panic sales), the high-carbon bonds should experience temporary price depressions and subsequent reversals. [28] To investigate bond return patterns around the Paris Agreement, we focus on monthly corporate

[28] 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.

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 11, 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 emission level falls 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 terciles based on their ownerships by mutual funds (calculated as the total par value of mutual fund holdings scaled by bond issue size), and those in the top tercile are considered heavily held by mutual funds.[29] 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 11 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 return differences observed in the month of the Paris Agreement announcement and the

[29] Results are essentially unchanged if we rebalance the portfolios based on bonds' carbon emission levels and mutual fund ownerships at the end of each month.

month following (-1.15% and -0.67%, respectively). 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 indicates 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 11 repeats the analysis for bonds lightly held by mutual funds (i.e., bonds with mutual fund ownerships in the bottom tercile at each quarter-end). Panel B shows that the return differences between high- and low-carbon bonds lightly held by mutual funds are only significant in the month of the Paris Agreement announcement, and the return difference is also much smaller (-0.71%) compared with that for bonds heavily held by mutual funds. There are generally no significant return differences in other months, suggesting that carbon emissions have limited price impacts on bonds with low mutual fund ownerships, 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 ownerships 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 ownerships in the top and bottom terciles. Portfolios are constructed based on carbon emission levels in November 2015 and mutual fund ownerships 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 11 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.

To summarize, the countervailing effects of Trump's election on mutual fund selling (documented in Section 4.2.1) and the short-lived price impacts in Section 4.2.2 challenge the hypothesis of a permanent shift in mutual funds' investment preference for low carbon-emission issuers.

5 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 behavior 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 emission levels and also explore the role played by mutual funds in this relation. We exclude bonds not held by any mutual fund.

To examine whether the issuer's carbon emissions affect subsequent bond illiquidity, we first run the panel regressions for our full sample, using three bond illiquidity measures defined in Section 2.2.2, namely Amihud, Spread, and Roll, as dependent variables. Our key independent variable is lagged high-carbon dummy, and other control variables are defined as in Equation (4).

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

Panel A of Table 12 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 both bond and issuer's stock characteristics, supporting the robust impact of the high-carbon dummy on future bond illiquidity. The economic significance is also sizable. For instance, the Spread illiquidity measure for a high-carbon bond is 0.065-percentage-point (6% of the standard deviation) higher, compared with other bonds. The effects of control variables are consistent with the findings in the existing literature.

[Insert Table 12 about here]

To provide supporting evidence that the effects of bonds' carbon exposures on liquidity are largely driven by mutual fund trading, in Panel B we perform regressions for bonds with high (above the median) and low (below the median) mutual fund ownerships, respectively.[30] We find the positive impacts 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 effects of carbon emissions on bond liquidity around the two carbon-related shocks. Specifically, we analyze whether the positive relationship between high carbon 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 (5), using bond illiquidity measures as the dependent variables, and present the empirical findings in Table 13.

[Insert Table 13 about here]

[30] Results are largely consistent if we assign high and low mutual fund ownerships based on terciles.

Consistent with our documented results that the announcement of the Paris Agreement amplifies the effects of carbon emission on mutual fund selling, it also increases the adverse effects of carbon emission on corporate bond liquidity. Panel A shows that the coefficients on interaction terms are significantly positive for all three illiquidity measures that we examine, and results are robust across different specifications. In Panel B, we find that the negative effect of issuers' high carbon emissions on bond liquidity is substantially alleviated following the election of President Trump. The interaction terms have significantly negative coefficients, robust across illiquidity measures and different specifications. These findings support the causal effects of carbon exposures on bond liquidity.

Taken together, this section shows that on average issuing firms' carbon emissions have significant negative impacts on corporate bond liquidity, especially for bonds held more heavily 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 emissions. Importantly, our finding implies that the effects of carbon emissions on corporate bond pricing could also be driven by changes in bonds' liquidity condition, rather than by credit risks alone.[31]

6 Conclusion

Concerns and debates over global warming and carbon emissions have repeatedly hit the headlines over the past few years: 196 signatories signed the Paris Agreement in 2015 and the U.S. subsequently pulled out of the Paris Agreement under the Trump administration.

[31] 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 (2022), Halling, Yu, and Zechner (2021), and Seltzer, Stark, and Zhu (2022).

Amid these developments, institutional investors like mutual funds have become increasingly aware of their exposures to carbon-related risks. While recent research shows that climate risks have become an important factor in equity mutual funds' portfolio decisions, little is known about how concerns about carbon emissions affect mutual funds' behaviors in the corporate bond market, where liquidity is low, trading costs are high, and the price impact of mutual fund selling is strong. These distinct features of the corporate bond market, combined with the fact that bond mutual funds conduct drastic liquidity transformation and are thus subject to major redemption risks, warrant a careful analysis of carbon implications for corporate bond mutual funds.

In this paper, we fill the gap in the literature by providing a detailed study on how firms' carbon emission levels affect mutual funds' trading behaviors and liquidity conditions of corporate bonds. We conduct our analyses with a full sample from January 2007 to December 2019 and also exploit the shock of the Paris Agreement in December 2015 to establish causality. We find that mutual funds are more likely to sell corporate bonds collectively if the bonds' issuing firms have higher carbon emissions, and that such effects are much stronger after the Paris Agreement.

Importantly, we explore the underlying mechanism of this finding and show that it is driven by funds' concerns about carbon-related redemption risks. In particular, higher carbon exposures in mutual fund portfolios lead to more investor outflows, and bonds tend to experience more intensive selling if their holding mutual funds have higher flow-to-carbon sensitivity. Consistent with the notion that mutual funds collectively sell high-carbon bonds under pressures 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 ownerships and during periods when carbon-related concerns heighten. Our finding indicates that pricing implications of carbon emissions for corporate bonds could also be driven by the bonds' liquidity conditions, rather than by credit risks alone.

Results in our paper shed new light on the ongoing debate on the fundamental reasons for mutual funds to take account of carbon emissions when making investment decisions. Our findings support the view that the emphasis on climate change by governments and policymakers can introduce carbon-related redemption risks to assets with high carbon exposures, making mutual funds collectively reduce their exposures to such risks. Our findings do not lend strong support to the channel of permanent shifts in mutual funds' investment preferences or ethics. In particular, the impacts of carbon emissions on mutual fund selling and bond liquidity are notably offset following the election of President Trump, suggesting the time-varying nature of mutual funds' attitudes towards carbon emissions.

Moreover, the price depression effect on high-carbon bonds around the Paris Agreement is drastic yet transient, consistent with the price pattern of non-fundamental-driven fire sales by mutual funds rather than a shift in their overall investment focus.

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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.

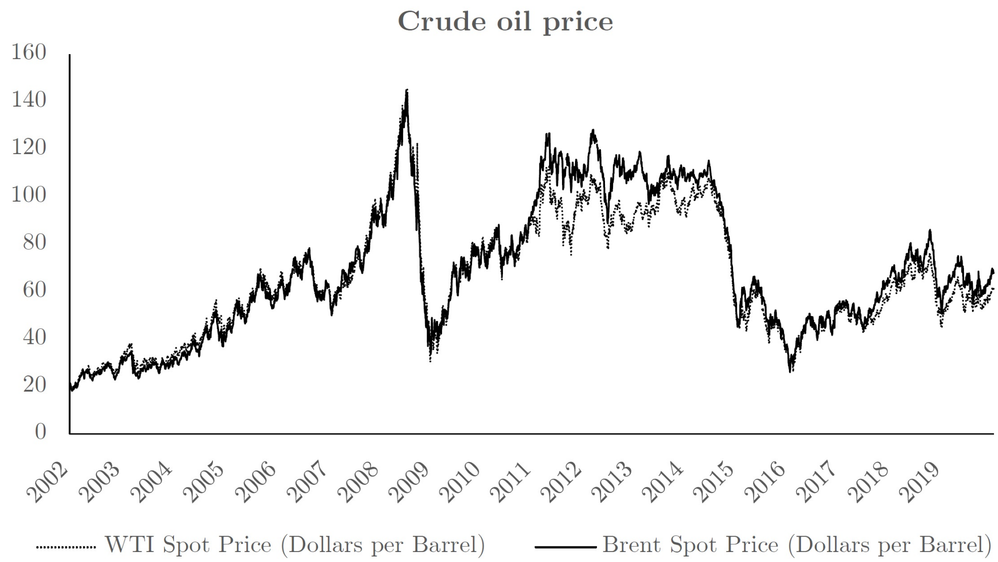


Figure 2. Cumulative monthly abnormal returns around the Paris Agreement

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

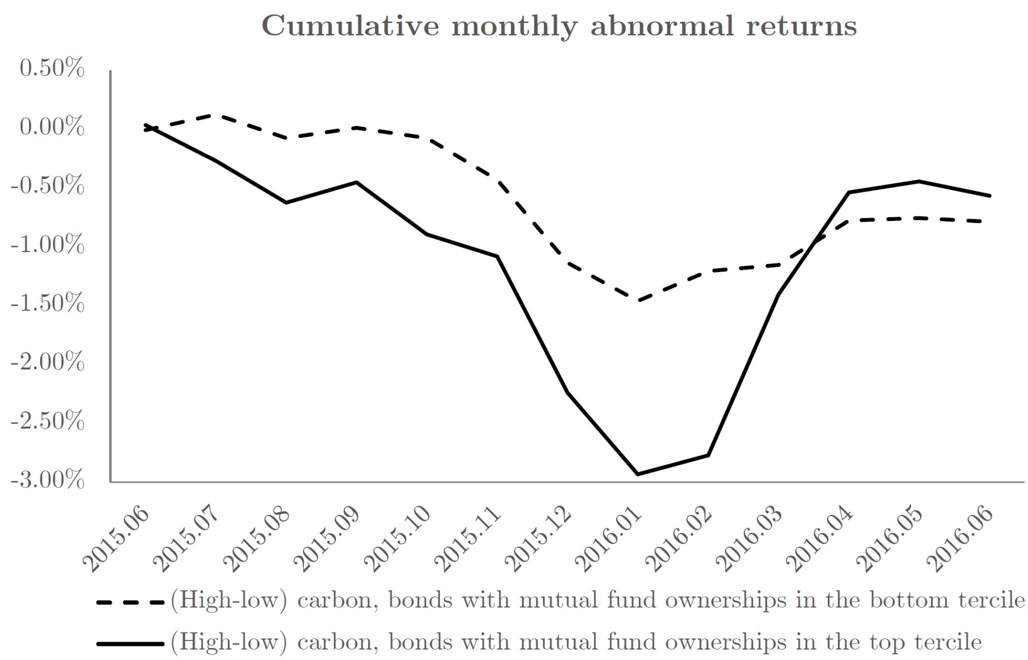


Table 1. Summary statistics

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 bond-quarter observations (N), the time-series average of cross-sectional 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, corporate bond illiquidity measures including the Amihud, effective spread (Spread), and Roll measures, and other bond characteristics including bond rating, time-to-maturity in years (Maturity), time-since-issuance in years (Age), coupon rate in percentage and logarithm of bond issue size (Ln(Size)). Panel B reports summary statistics for firm-quarter variables including the MSCI carbon emission score, high-carbon dummy, logarithm of firm size (Ln(ME)), the logarithm of book-to-market ratio (Ln(BM)), Stock IVOL, institutional ownership and number of analysts (Analyst). The variables' definitions are provided in the Appendix A. Panel C reports the time-series average of cross-sectional mean, median, and standard deviation (Std) of the MSCI emission score for firms issuing actively traded corporate bonds (i.e., bonds with non-missing mutual fund SHM), across the Fama-French 12 industries. Panel D reports the time-series averages of the industry distributions (in percentage) for all issuers with actively traded bonds, and the issuers with non-missing MSCI emission 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, issues denominated in foreign currency, and issues offered globally. We only consider observations with Age and Maturity longer than 6 months. All variables are winsorized each quarter at the 0.5% level.

	N	Mean	Std	Q1	Median	Q3
Panel A: Bond-quarter variables						
SHM of mutual funds (%)	57,579	6.62	14.52	-5.72	3.10	14.84
Selling pressure (%)	138,371	0.01	0.59	-0.10	0.01	0.10
Amihud (% per thousand $)	136,851	0.05	0.05	0.01	0.03	0.07
Spread (%)	136,851	1.36	1.13	0.50	1.05	1.94
Roll (%)	136,851	2.08	2.21	0.67	1.44	2.76
Rating	421,000	7.55	3.11	5.64	7.20	9.10
Maturity (in years)	491,620	9.83	8.00	3.57	7.29	14.70
Age (in years)	491,620	6.43	4.80	2.85	5.32	8.62
Coupon (%)	491,620	5.50	1.49	4.55	5.49	6.39
Ln(Size)	491,620	11.19	2.32	9.24	11.62	13.04
Panel B: Firm-quarter variables						
Carbon emission score	27,747	5.79	2.56	4.17	5.93	8.01
High carbon	27,747	0.33	0.47	0.00	0.00	1.00
Ln(ME)	25,806	9.23	1.34	8.35	9.23	10.09
Ln(BM)	25,798	-0.58	1.10	-1.16	-0.65	-0.16
Stock IVOL	27,739	0.07	0.04	0.04	0.06	0.08
Institutional ownership	27,473	0.76	0.17	0.67	0.78	0.87
Analyst	25,407	14.74	7.72	8.78	14.71	19.91

Panel C: Time-series averages of cross-sectional distribution of the MSCI emission score			
Industry	Mean	Median	Std
1 Consumer Nondurables	6.96	7.37	1.84
2 Consumer Durables	7.28	7.64	1.95
3 Manufacturing	5.79	6.13	2.89
4 Energy	3.48	3.12	2.15
5 Chemicals and Allied Products	6.19	6.25	2.60
6 Business Equipment	7.15	7.61	2.06
7 Telephone and Television Transmission	6.32	6.47	1.66
8 Utilities	5.78	5.76	2.49
9 Shops	6.60	7.04	1.96
10 Healthcare	7.42	7.87	1.73
11 Finance	6.60	6.90	1.85
12 Other	5.26	5.43	2.30

Panel D: Comparison of bond issuers' industry distribution		
Industry	Industry share (for all issuers)	Industry share (for issuers with MSCI scores)
1 Consumer Nondurables	5.17	5.16
2 Consumer Durables	2.19	2.60
3 Manufacturing	6.98	6.92
4 Energy	10.29	10.72
5 Chemicals and Allied Products	2.25	2.62
6 Business Equipment	5.02	4.60
7 Telephone and Television Transmission	10.24	10.52
8 Utilities	10.86	12.01
9 Shops	5.63	5.60
10 Healthcare	5.62	5.61
11 Finance	23.26	23.08
12 Other	12.49	10.56

Table 2. 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	**0.954*** **	**1.209*** **	**1.289*** **
	(3.21)	**(2.75)**	**(2.70)**
Rating	0.330***	0.460***	0.506***
	(5.60)	(4.60)	(4.28)
Maturity	−0.144***	0.227	0.341
	(-6.48)	(0.51)	(0.75)
Age	0.209***	1.432	1.506
	(3.54)	(1.37)	(1.25)
Coupon	0.401***		
	(4.47)		
Ln(Size)	−15.172***		
	(-3.72)		
Ln(ME)			0.755
			(1.37)
Ln(BM)			0.221
			(0.58)
Stock IVOL			1.650
			(0.25)
Institutional ownership			0.894
			(0.67)
Analyst			−0.080**
			(-2.32)
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.069	0.190	0.192
# of obs	47,229	45,362	38,069

Table 3. 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. Pre_PA(-3) and Pre_PA(-2) equal one for the third to last quarter (2015Q1) and second to last quarter (2015Q2) before the Paris Agreement, 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	**3.064*** **	**2.247*** **	**2.220** **	**2.385** **
	(4.75)	**(2.94)**	**(2.20)**	**(2.24)**
High carbon × Pre_PA(-3)				0.129
				(0.15)
High carbon × Pre_PA(-2)				0.486
				(0.65)
High carbon	-0.525	−1.683*	−1.822*	−1.999*
	(-1.05)	(-1.91)	(-1.87)	(-1.95)
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	0.043	0.210	0.210	0.209
# of obs	10,358	8,892	7,965	7,965

Table 4. 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: Outflow-induced selling pressure			
	(1)	(2)	(3)
High carbon	**0.330****	**0.315***	**0.448*****
	(2.47)	**(1.79)**	**(3.02)**
Rating	0.010	0.092	0.084
	(0.64)	(1.52)	(1.08)
Maturity	0.008	4.711***	5.577***
	(0.87)	(4.92)	(4.92)
Age	0.192***	0.379**	0.324*
	(6.97)	(2.46)	(1.70)
Coupon	0.267***		
	(4.75)		
Ln(Size)	5.429***		
	(5.31)		
Ln(ME)			0.157
			(0.94)
Ln(BM)			0.080
			(0.58)
Stock IVOL			-2.849
			(-0.89)
Institutional ownership			0.626
			(1.15)
Analyst			0.013
			(1.23)
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.044	0.113	0.121
# of obs	127,192	126,186	107,088

Table 5. 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: Outflow-induced selling pressure			
	(1)	(2)	(3)
High carbon × PA	**1.559****	**1.779*****	**1.676****
	(2.41)	**(3.25)**	**(2.28)**
High carbon	-0.034	-0.360	-0.691
	(-0.06)	(-0.66)	(-0.89)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.045	0.147	0.148
# of obs	30,317	29,524	27,522

Table 6. Carbon emission, oil exposure, and mutual fund selling around the Paris Agreement

This table reports quarterly panel regression results controlling for effects of oil exposures, 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 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	**3.035*** **	**2.022** **	**2.077** **
	(3.65)	**(2.34)**	**(2.09)**
Oil exposure × PA	0.452	1.491	1.711
	(0.34)	(1.10)	(1.04)
High carbon	-0.557	−1.691**	−1.724*
	(-1.25)	(-2.01)	(-1.85)
Oil exposure	0.364	-0.535	-0.894
	(0.48)	(-0.73)	(-1.35)
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	0.211	0.21
# of obs	10,138	8,702	7,965

Table 7. 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 emission exposure within that fund as of the most recent quarter-end before month t, with details provided in Appendix A. Control variables include 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 $t-1$, and 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 (2), and further include fund fixed effects in Column (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)	(4)
Fund carbon exposure	**−0.136***** **(-3.36)**	**−0.083**** **(-2.15)**	**−0.166***** **(-3.73)**	**−0.110**** **(-2.45)**
Ln(TNA)		−0.262*** (-7.53)	−2.524*** (-12.79)	−1.571*** (-9.23)
Lagged return		17.173*** (3.52)	13.702*** (3.08)	-1.480 (-0.32)
ST cumulative return				7.003*** (3.61)
LT cumulative return				8.758*** (6.75)
Cash holding		0.008* (1.82)	0.014** (2.58)	0.011** (2.24)
Expense ratio		−1.570*** (-8.33)	−1.791*** (-2.72)	−0.990* (-1.68)
Turnover ratio		−0.106** (-2.17)	-0.014 (-0.14)	0.017 (0.18)
Fund age		−0.010*** (-12.62)	−0.010*** (-4.50)	−0.009*** (-4.66)
Time FE	Y	Y	Y	Y
Style FE	Y	Y	Y	Y
Fund FE	N	N	Y	Y
Adj. R^2	0.028	0.058	0.171	0.145
# of obs	92,428	88,028	88,028	79,468

Table 8. 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 logarithm of TNA, lagged return, as of month $t-1$, and 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 (2), and further include fund fixed effects in Column (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	**-0.166**	**-0.208^{*}**	**-0.522^{***}**
	(-1.51)	**(-1.86)**	**(-3.98)**
Fund carbon exposure	-0.156	-0.100	0.358^{***}
	(-1.48)	(-0.92)	(2.83)
Fund Controls	N	Y	Y
Time FE	Y	Y	Y
Style FE	Y	Y	Y
Fund FE	N	N	Y
Adj. R^2	0.027	0.061	0.235
# of obs	11,080	10,639	10,613

Table 9. Mutual funds' selling response to carbon emission: amplified by flow 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. 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) flow sensitivity to carbon	**3.590***	**2.641****	**3.123****
	(1.94)	**(2.14)**	**(2.28)**
High carbon	-0.687	0.164	0.089
	(-0.67)	(0.22)	(0.11)
(Bond level) flow sensitivity to carbon	-1.859	-1.290^{*}	-2.379^{***}
	(-1.00)	(-1.89)	(-3.10)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.058	0.188	0.190
# of obs	43,006	41,146	32,865

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 President Trump's election			
	(1)	(2)	(3)
High carbon × TE	**−2.646*****	**−3.256*****	**−2.696*****
	(-4.27)	**(-4.13)**	**(-3.02)**
High carbon	2.658***	1.171	1.239
	(6.54)	(0.89)	(0.96)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.052	0.283	0.278
# of obs	10,455	8,805	7,979
Panel B: Outflow-induced selling pressure around President Trump's election			
	(1)	(2)	(3)
High carbon × TE	**−1.783****	**−1.728***	**−1.639****
	(-2.41)	**(-1.96)**	**(-2.06)**
High carbon	1.888***	1.639**	1.634***
	(5.91)	(3.07)	(2.82)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.030	0.140	0.141
# of obs	32,326	30,345	28,333

Table 11. 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 terciles based on the mutual fund ownerships 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 emission level falls into the top tercile (otherwise) among all firms in November 2015. Panel A and B show monthly abnormal returns for bonds with mutual fund ownerships in the top and bottom terciles, 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 ownerships in the top tercile													
Low-carbon	0.21	0.27	0.31	0.18	0.10	0.30	0.73	0.83	0.08	-0.94	-0.42	-0.07	-0.50
High-carbon	0.25	-0.04	-0.05	0.35	-0.34	0.12	-0.42	0.16	0.24	0.39	0.44	0.02	-0.63
(High – Low) carbon	**0.03**	**−0.30****	**−0.35*****	**0.17**	**−0.44*****	**-0.18**	**−1.15*****	**−0.67****	**0.16**	**1.34*****	**0.86*****	**0.09**	**-0.12**
Panel B: Bonds with mutual fund ownerships in the bottom tercile													
Low-carbon	0.10	0.14	0.10	0.14	-0.17	0.04	0.32	0.54	0.08	-0.68	-0.32	0.04	-0.16
High-carbon	0.09	0.27	-0.10	0.23	-0.26	-0.32	-0.39	0.23	0.34	-0.63	0.06	0.06	-0.19
(High – Low) carbon	**-0.01**	**0.13**	**-0.20**	**0.09**	**-0.09**	**-0.35**	**−0.71*****	**-0.32**	**0.26**	**0.04**	**0.38****	**0.02**	**-0.03**

Table 12. 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, Spread, and Roll measure in quarter t. The independent variables are measured of quarter $t-1$ and defined in Appendix A. We exclude bonds not held by any mutual fund. Panel A reports regression coefficients for all bonds in the sample. In Panel B, we show regression coefficients for bonds with mutual fund ownerships above and below the median separately. We include time and bond fixed effects through all the columns. Columns (1), (3), and (5) control for bond rating, maturity, and age. Columns (2), (4), and (6) 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.

Panel A: Bonds excluding those not held by any mutual fund						
Dependent variable	Amihud		Spread		Roll	
	(1)	(2)	(3)	(4)	(5)	(6)
High carbon	**0.002******	**0.002******	**0.065******	**0.064******	**0.135******	**0.082****
	(3.44)	**(3.09)**	**(3.71)**	**(3.55)**	**(2.83)**	**(2.38)**
Bond Controls	Y	Y	Y	Y	Y	Y
Stock Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.485	0.463	0.559	0.550	0.442	0.437
# of obs	78,313	67,286	78,313	67,286	78,313	67,286
Panel B: Bonds with mutual fund ownerships above and below median						
Panel B.1: Bonds with mutual fund ownerships above median						
High carbon	**0.004******	**0.003******	**0.078******	**0.078******	**0.187****	**0.100***
	(3.52)	**(3.50)**	**(2.91)**	**(2.86)**	**(2.53)**	**(1.68)**
Bond Controls	Y	Y	Y	Y	Y	Y
Stock Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.538	0.532	0.607	0.598	0.464	0.450
# of obs	32,745	27,099	32,745	27,099	32,745	27,099
Panel B.2: Bonds with mutual fund ownerships below median						
High carbon	**0.001**	**0.000**	**0.032**	**0.038**	**0.085***	**0.051**
	(1.15)	**(0.57)**	**(1.32)**	**(1.55)**	**(1.85)**	**(1.35)**
Bond Controls	Y	Y	Y	Y	Y	Y
Stock Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.467	0.439	0.536	0.527	0.449	0.439
# of obs	45,044	39,700	45,044	39,700	45,044	39,700

Table 13. 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. The dependent variables are the three illiquidity measures including the Amihud, Spread, and Roll measure 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 exclude bonds not held by any mutual fund. We include time and bond fixed effects through all the columns. Columns (1), (3), and (5) control for bond rating, maturity, and age. Columns (2), (4), and (6) 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	Amihud		Spread		Roll	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bond illiquidity around the Paris Agreement						
High carbon × PA	**0.007*****	**0.004*****	**0.076****	**0.065****	**0.346****	**0.194****
	(3.15)	**(2.85)**	**(2.13)**	**(2.00)**	**(2.47)**	**(2.38)**
High carbon	−0.003***	−0.003**	-0.028	-0.026	−0.168*	-0.140
	(-2.87)	(-2.60)	(-0.65)	(-0.59)	(-1.73)	(-1.63)
Bond Controls	Y	Y	Y	Y	Y	Y
Stock Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.567	0.550	0.629	0.627	0.432	0.490
# of obs	11,227	10,401	11,227	10,401	11,227	10,401
Panel B: Bond illiquidity around Trump's election						
High carbon × TE	**−0.004*****	**−0.003*****	**−0.086*****	**−0.091*****	**−0.156*****	**−0.133****
	(-5.20)	**(-3.60)**	**(-2.65)**	**(-2.93)**	**(-3.15)**	**(-2.52)**
High carbon	0.001	0.001	0.041	0.051	0.067	0.080
	(1.09)	(1.04)	(1.38)	(1.68)	(0.82)	(1.07)
Bond Controls	Y	Y	Y	Y	Y	Y
Stock Controls	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.596	0.577	0.656	0.657	0.566	0.548
# of obs	12,798	11,787	12,798	11,787	12,798	11,787

Table A1. 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 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 SHM		
	(1)	(2)
Placebo event quarter	2011Q4	2012Q4
High carbon × Post-Event	**0.637**	**-1.549**
	(0.43)	**(-0.85)**
High carbon	4.415***	3.494***
	(3.58)	(3.68)
Bond Controls	Y	Y
Stock Controls	Y	Y
Time FE	Y	Y
Bond FE	Y	Y
Adj. R^2	0.197	0.242
# of obs	3,937	4,731

Appendix A Variable Definitions

Key Variables	
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 buy 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: $Selling\ pressure_{i,t} = \frac{\sum_{j=1}^{J}(Sell\ Amt_{j,i,t} \lvert Flow_{j,t} < 25^{th} Pctl - Buy\ Amt_{j,i,t} \lvert Flow_{j,t} > 75^{th} Pctl)}{Bond\ issue\ size_i}$, 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.
Firm 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: $R_{i,t,w} = \alpha_{i,t} + \mu_{i,t} \times R_{m,t,w} + \beta_{i,t} \times R_{oil,t,w} + \epsilon_{i,t,w}$, where $R_{i,t,w}$ 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. $\beta_{i,t}$ is the loading on the oil factor, i.e., oil exposure, for firm i in quarter t.
Fund carbon exposure	A carbon score is assigned to each fund based on the par amount of holding-weighted average of bond carbon emission 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 negative value of MSCI carbon emission score as its carbon emission exposure for bond i in the quarter t, such that bonds with higher carbon emission exposure are issued by firms with more carbon-intensive business models. $\omega_{i,j,t}$ 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 inflow on fund carbon exposure in the rolling window of the past 12 months with fund controls (as in Table 4, 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 and define the top (bottom) half group with "high carbon sensitivity fund" = 1 (0). 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.
Spread (%)	Same-bond-same-day effective bid-ask spread is calculated following Hong and Warga (2000) and Jiang, Li, Sun, and Wang (2022), which equals the dollar-volume-weighted average buy prices minus the dollar-volume-weighted average sell prices of all transactions on the same day and for the same bond. We first calculate the measure for each bond each day, then take the average for each bond for all days within a quarter.
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.
MSCI carbon emission score	The MSCI carbon emission score is obtained 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.
High carbon dummy	The high carbon dummy is equal to one if the firm's (issuer's) MSCI emission score is among the lowest group when we divide all firms into terciles based on their average MSCI carbon emission score within 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. Numerical score of 1 refers to AAA rating by S&P and Aaa rating by Moody. 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.

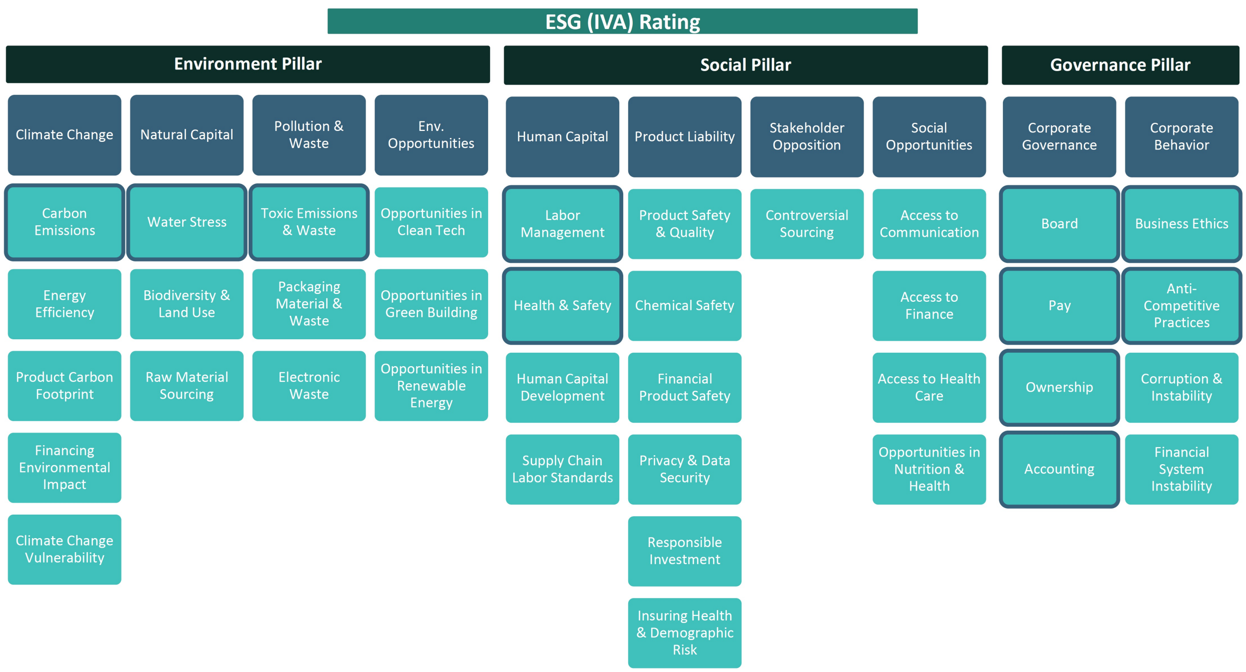
Control Variables	
Maturity	Time-to-maturity in years.
Age	Time-since-issuance in years.
Coupon (%)	Individual bond coupon rate.
Ln(Size)	The natural logarithm of the individual bond issue size.
Ln(ME)	The natural logarithm of the market value of the firm's equity at the end of last year.
Ln(BM)	The 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 (1993).
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.

Appendix B MSCI Carbon Emission Score

B.1 Steps for MSCI ESG IVA

MSCI ESG IVA applies a three-stage approach.[32]

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.

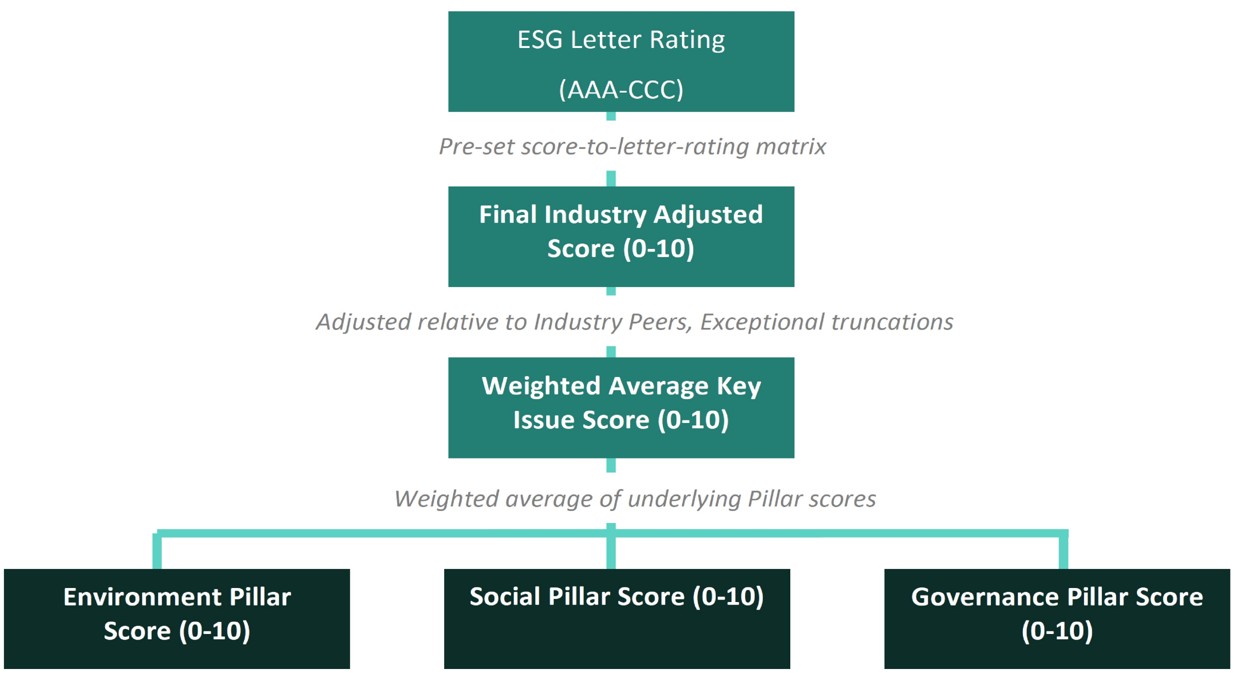


Step 2: Evaluate risk exposure and risk management. MSCI ESG IVA analysts calculate the size of each company's exposure to key ESG risks based on a granular breakdown of a company's business: its core product segments or business activities, the locations of its assets or revenues, and other relevant 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

[32]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.

Social or Environmental Impact	• Contribution to climate change
Risk/Opportunity to Company	• Increased costs linked to carbon pricing or trading • Facility retrofits • Potential operational disruptions related to regulatory caps
Exposure Metrics	• 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
Management Metrics	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.

Category	Management Metrics
Targets*	**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**
Mitigation*	**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)

		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	