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

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Abstract

This paper investigates how firms' carbon emission levels affect the trading behavior of bond mutual funds. We find that mutual funds collectively sell corporate bonds issued by firms with high carbon emissions, driven by funds' concerns for carbon-related redemption risks and regulatory 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 for carbon-related risks heighten.

Keywords: Carbon emissions, corporate bonds, mutual funds, collective selling, redemption risks, liquidity

JEL classification: G11, G20, G23, G41

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1 Introduction

In recent years, concerns and debates over global warming being linked to carbon dioxide (CO_2) emissions have drawn high attention. In December 2015, 196 signatories adopted a legally binding international treaty on climate change, namely the Paris Agreement, and committed to limit global warming to well below 2°C compared to pre-industrial levels. Although the U.S. has pulled out of the Paris Agreement under the Trump administration, institutional investors are increasingly aware of the relationship between carbon emissions and global warming, and some of them form coalitions such as Climate Action 100+ (the participants of which in total manage over $54 trillion of assets) to track large companies' carbon emissions.

While recent research shows that climate-related concerns have become an important factor in equity mutual funds' portfolio decisions (Krueger, Sautner, and Starks (2020); Bolton and Kacperczyk (2021); Cao, Titman, Zhan, and Zhang (2022); Humphrey and Li (2021); and Starks, Venkat, and Zhu (2020)), there is little in the literature about how such concerns influence fixed-income mutual funds' behaviors and what factors drive mutual funds' carbon-related trading decisions.[1] Meanwhile, recent developments highlight the growing awareness of carbon emissions among bond mutual funds. For example, Wells Fargo Asset Management launched a climate transition credit strategy in June 2021 with the intention to decarbonize their fixed-income portfolios.[2] State Street also recently announced the launch of the State Street Sustainable Climate Bond Funds, which aim to significantly reduce investors' exposure to carbon emissions.[3]

A few distinct features of the corporate bond market and bond mutual funds make them important subjects when studying the effects of carbon emissions. First, the over-the-counter

[1] Open-end mutual funds hold about 20 percent of U.S. corporate bonds. Source for U.S. corporate bond ownerships as of 2018: https://www.statista.com/statistics/1083823/ownership-us-corporate-bonds/.

[2] Source: https://www.abfjournal.com/dailynews/wells-fargo-asset-management-launches-climate-transition-credit-strategy/.

[3] Source: https://newsroom.statestreet.com/press-releases/press-release-details/2021/State-Street-Global-Advisors-Launches-Climate-Bond-Funds/default.aspx.

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 (holding illiquid corporate bonds while allowing their investors to redeem shares on a daily basis), which could trigger large-scale investor redemptions in the face of a negative shock and is shown to pose fragility to the mutual fund industry and the underlying markets (Goldstein, Jiang, and Ng (2017); Jiang, Li, Sun, and Wang (2022)). In addition, corporate bond mutual funds are much more likely to trade in herds than equity funds, and such collective trading on the selling side can generate significant price distortions (Cai, Han, Li, and Li (2019)). Therefore, when confronted with concerns about carbon emissions, the aforementioned features of the corporate bond mutual funds could distinctly affect their trading behaviors and pose impacts on bond prices and liquidity conditions.

Our paper provides a detailed investigation of how firms' carbon emission levels affect bond mutual funds' trading behaviors and liquidity conditions of corporate bonds. 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 and regulatory 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 and regulations, 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. Our panel regressions control for various bond/firm characteristics and fixed effects, and 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 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. Intuitively, mutual funds' selling towards bonds with high emission issuers should be greatly intensified after the passage 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.

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 for carbon-related redemption and regulatory risks; (ii) driven by a permanent shift in funds' investment preferences or ethics. The first channel emphasizes mutual funds' opportune assessment of potential risks (posed by end investors and regulators) associated with their asset exposures, and 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 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 effects of regulatory risks, we find that high carbon bonds undergo higher mutual funds' collective selling if they are issued by firms subject to stricter environmental regulations. Combined, these findings suggest that the relationship between mutual funds' collective selling and carbon emissions is likely driven by funds' concerns for carbon-related redemption and regulatory risks.

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 for carbon-related risks. Therefore, the countervailing effect of the 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 and regulations, 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 while improves after the 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 (2020)). While Duan, Li, and Wen (2022) 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 for redemption and regulatory risks as the underlying mechanism.[4]

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 higher-rated corporate bonds. In addition, multiple papers have shown that the recent COVID-19 crisis essentially reflects itself

[4]In contrast to our primary focus on mutual fund trading dynamics, the focus of Duan, Li, and Wen (2022) and Seltzer, Stark, and Zhu (2022) is on the pricing implications of environmental risks in corporate bond market. Duan, Li, and Wen (2022) 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.

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); 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, 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.[5]

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.[6] 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.[7] 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.

[5] 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)), municipal bond market (Painter (2020)), equity market (Bolton and Kacperczyk (2021); and Bolton and Kacperczyk (2022)), and option market (Ilhan, Sautner, and Vilkov (2021)).

[6] For a review on equity mutual fund flows, see Christoffersen, Musto, and Wermers (2014). For corporate bond mutual fund flows, see, for examples, Chen, Goldstein, and Jiang (2010); and Goldstein, Jiang, and Ng (2017).

[7] For papers on how investor redemptions of fixed-income mutual funds introduce fragility risks to the underlying markets, see Jiang, Li, Sun, and Wang (2022); Li, O'hara, and Zhou (2022); and Ma, Xiao, and Zeng (2021).

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, including the sell herding measure, illiquidity measures, and the high carbon dummy. 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 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, bond illiquidity measures, and high-carbon dummy). Finally, we provide summary statistics for 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. MSCI collects 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 or government databases.

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, Rossi, and Yasuda (2012), and Cai, Han, Li, and Li (2019) among others. Following 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 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 previous literature, we aggregate share-class level information to fund-level. Different from the 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:

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

[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.

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 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,

[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.

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 the 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.

2.2.3 MSCI emission score and high carbon dummy

The MSCI carbon emission scores are obtained from MSCI ESG rating. A MSCI carbon emission score is given to each firm monthly since January 2007 (the score is normally updated annually while sometimes it is updated more than once within a year), on a scale of 0–10. Companies with better performance on this issue score higher. For bonds actively traded by mutual funds, i.e., those with non-missing sell herding measure, on average 66.6% of them have MSCI emission scores (62.4% in terms of issuance amount).

To calculate our key high-carbon measure, 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.

2.3 Summary statistics

Table 1 presents summary statistics of time-series average of cross-sectional variables in our sample. 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 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.

[Insert Table 1 about here]

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. The 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 the time-series averages of cross-sectional distribution of the raw 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. The cross-sectional means and medians are comparable across the 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 emission.[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.

[11] To make sure that the results are not driven by this certain industry, we replicate our main tests after excluding bond issuers in the "Energy" industry. Results are reported in Table A.1 and are consistent with our baseline analysis.

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 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.

3.1 Baseline results

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

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

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.

In the baseline model, we control for various bond-level characteristics and quarter fixed effects, with bond level controls including bond rating, time to maturity, age, coupon rate and logarithm of the bond issue size.[12] We further control for stock characteristics of the issuer in later specifications, which include firm's equity size (the logarithm of market value of the firm's equity), logarithm of book-to-market ratio, stock IVOL (the standard deviation of daily residual equity returns), institutional ownership and the number of analysts following

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

that stock.[13] 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 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.

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 for 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

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

the mutual funds' collective selling of its bonds, we utilize an exogenous shock that has a considerable impact on the future regulation and general awareness of climate change.

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.[14] 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.[15] For firms with higher carbon exposures, regulatory risks and litigation risks would increase, as regulations against climate changes (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 high carbon dummy on the mutual funds' collective selling to be 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:

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

[14] 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.

[15] 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."

where PA_t is a time dummy equal to one for the period after the announcement of the Paris Agreement.[16] Our variable of interest is the interaction term $High\ carbon_{i,t-1} \times PA_t$. 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 (2017). Specifically, we define the dummies Pre_PA(-3) and Pre_PA(-2), which 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 high carbon dummy support the parallel trend assumption before the Paris Agreement.

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

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

a firm's carbon emission and mutual funds' collective selling of its bonds.

3.3 Robustness: alternative mutual fund trading 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:[17]

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

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

[17] 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 total net asset to calculate fund flows. Following the prior literature, fund-level flow is aggregate from CRSP share-class level.

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 establishing 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 high carbon dummy and the post-Paris Agreement dummy, providing evidence for the causal effect of carbon emission on outflow-induced selling from mutual funds.

[Insert Table 5 about here]

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

4 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 for redemption and regulatory risks; (ii) permanent changes in mutual funds' investment preferences or ethics.

4.1 Channel I: driven by concerns for redemption and regulatory risks

4.1.1 Redemption risks from mutual fund end-investors

Do investors care about 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, as sustainability is viewed as positively predicting future performance and investors have nonpecuniary motives. However, little is known about the bond mutual 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 the bonds in their portfolios.

Compared with the equity market, 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 Chen, Goldstein, and Jiang (2010); Goldstein, Jiang, and Ng (2017)). Therefore, redemption by end investors carries more stability concerns for bond mutual funds than for equity mutual funds. 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 redemptions, mutual fund managers might shift their portfolios away from high carbon bonds should their investors care about carbon exposures.

Following the previous literature (e.g., Chevalier and Ellison (1997); 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.

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t})}{TNA_{j,t-1}} \tag{7}$$

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:

$$Fund\ carbon\ exposure_{j,t} = \sum_i \omega_{i,t} Carbon\ exposure_{i,t} \tag{8}$$

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. $\omega_{i,t}$ 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 of the most recent quarter-end:

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

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), percentage of cash holding, expense ratio, turnover ratio, and fund age.

[Insert Table 6 about here]

Results in Table 6 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 7.

[Insert Table 7 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.

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.

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

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. 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.

$$(Bond\ level)\ flow\ sensitivity\ to\ carbon_{i,t} = \sum_j \omega_{i,j,t} High\ carbon{-}sensitivity\ fund_{j,t} \tag{11}$$

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 whether the interaction has a significant positive coefficient.

$$\begin{aligned} SHM_{i,t} &= \alpha_2 + \beta_2 \times High\ carbon_{i,t-1} \times (Bond\ level)\ flow\ sensitivity\ to\ carbon_{i,t-1} \\ &+ \gamma_2 \times High\ carbon_{i,t-1} + \vartheta_2 \times (Bond\ level)\ flow\ sensitivity\ to\ carbon_{i,t-1} + \delta_2 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \end{aligned} \tag{12}$$

[Insert Table 8 about here]

We show the supporting evidence in Table 8. 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.

4.1.3 Regulatory risks

Another source of risk associated with firms' carbon emission is regulatory risks. As shown by Seltzer, Stark, and Zhu (2022), bonds issued by firms with poor environmental performances tend to have lower credit ratings and higher yield spreads. If mutual funds are concerned about such regulatory risks associated with bond issuers, we should expect high carbon bonds issued by firms facing higher regulatory costs to experience stronger mutual funds'collective selling compared to other high carbon bonds.

To quantify the different levels of regulatory costs faced by bond issuers, we follow Seltzer, Stark, and Zhu (2022) to construct the regulatory stringency measure (namely, Reg) and focus on the "Air" part related to carbon emission, with the EPA enforcement data provided in the Integrated Compliance Information System for Federal Civil Enforcement Case Data. The measure of regulatory stringency captures enforcement actions for the Clean Air Act (CAA) in a given state in a given year. Specifically, we divide the number of enforcement actions, which includes both informal enforcement actions (notifications of violation) and formal actions (fines and administrative orders), by the total number of manufacturing facilities at the state-year level. Thus, a bond is subject to higher regulatory stringency if its issuing firm is headquartered in a state with more stringent environmental regulations. To test our hypothesis for regulatory risk, we run the following regression.

$$\begin{aligned} SHM_{i,t} = \alpha_3 &+ \beta_3 \times High\ carbon_{i,t-1} \times Reg_{s,t-1} \\ &+ \gamma_3 \times High\ carbon_{i,t-1} + \vartheta_3 \times Reg_{s,t-1} + \delta_3 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \quad (13) \end{aligned}$$

where $Reg_{s,t-1}$ is the regulatory stringency for the issuing firm's headquarter state s in year $t-1$.

Coefficients on the interaction term of high carbon dummy and regulatory stringency are significantly positive across all specifications in Table 9, indicating that mutual funds are more likely to collectively sell high carbon bonds if the bonds are issued by firms subject to stricter environmental regulations. When bond characteristics and time fixed effects are controlled for in Column (3), for high carbon bonds, a one-standard-deviation increase in the regulatory stringency (1.61%) is associated with a 1.46-percentage-point (10% of the standard deviation) increase in the collective selling by mutual funds.

[Insert Table 9 about here]

Taken together, the evidence in Section 4.1 lends strong support to the first channel, that is, mutual funds' collective selling of high carbon bonds is driven by their concerns for carbon-related redemption and regulatory risks. We show that bond mutual fund flows are sensitive to fund carbon exposures, motivating fund managers to prioritize selling high carbon bonds held by funds with larger redemption risks. Moreover, we show that regulatory risks related to environment and climate also matter for mutual funds' trading decisions. They herd to sell high carbon bonds more if these bonds are issued by firms exposed to more stringent regulations.

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 for redemption and regulatory 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. To test this alternative hypothesis, we 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.

4.2.1 Reversal of mutual fund selling following Trump's election

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 president 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 cost 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.

$$
\begin{aligned}
SHM_{i,t} = \alpha_4 + \beta_4 \times High\ carbon_{i,t-1} \times TE_t \\
+ \gamma_4 \times High\ carbon_{i,t-1} + \delta_4 \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \quad (14)
\end{aligned}
$$

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

[Insert Table 10 about here]

Panel A of Table 10 reports the results. 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 for 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 wide-spread concerns for carbon-related risks (i.e., panic sales), the high carbon bonds should experience temporary price depressions and subsequent reversals. To investigate bond return patterns around the Paris Agreement, we focus on monthly corporate bond returns. We first calculate raw monthly bond returns, following Gebhardt, Hvidkjaer, and Swaminathan (2005):

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

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

In Table 11, we examine monthly abnormal returns around the Paris Agreement for high and low carbon bonds, as well as their difference. 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 a given month, 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 each quarter, 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. 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 month following (-1.15% and -0.56%, 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 indicate that mutual funds' selling of high carbon bonds is unlikely driven by permanent shifts in funds' investment preferences or ethics.

To provide further support that the price patterns documented above are dominantly driven by mutual fund trading, Panel B of Table 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 (-0.77%) compared with that for bonds heavily held by mutual funds. There are 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 better 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 medians of cumulative monthly abnormal returns (from June 2015 to June 2016) in Figure 1, for bonds with mutual fund ownerships in the top and bottom terciles. Portfolios are constructed based on carbon emission levels and mutual fund ownerships at the end of 2015.

[Insert Figure 1 about here]

Figure 1 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 -5.35%. 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 1 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 for carbon-related redemption and regulatory 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 due to heightened concerns for carbon-related redemption and regulatory risks. Such trading behavior could affect bond liquidity, which has significant implications for bond pricing and market stability. In particular, if most mutual funds tend to shy away from high carbon bonds at the same time, dealers will have difficulty finding 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 issuer's carbon emission levels in both the full sample and the difference-in-differences frameworks. We exclude bonds not held by any mutual fund.

To examine whether 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 the three illiquidity measures after controlling for both bond and issuer's stock characteristics. Magnitudes of the coefficients on the high carbon dummy are comparable across different specifications, supporting the robust impact of the high emission 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]

In Panel B, we perform similar regressions for bonds with high (above the median) and low (below the median) mutual fund ownerships, respectively.[18] We find the positive impacts of 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 for 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 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]

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 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 Trump. The interaction terms have significantly negative coefficients, robust across illiquidity measures and different specifications.

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

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 for 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 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.[19]

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. 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 for 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 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.

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

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. 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.

Furthermore, we explore the underlying mechanism of this finding and show that it is driven by funds' concerns for carbon-related redemption risks and regulatory risks, rather than by a permanent shift in funds' investment preferences or ethics. 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 and regulations, 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.

Importantly, 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 changes by governments and policymakers can introduce carbon-related redemption and regulatory risks to assets with high carbon exposures, making mutual funds collectively reduce their exposures to such risks. Our findings do not support the channel of permanent shifts in mutual funds' investment preferences or ethics. In particular, 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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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: $HM_{i,t} = \|p_{i,t} - E[p_{i,t}]\| - E\|p_{i,t} - E[p_{i,t}]\|$, 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 $\bar{p_t} = \frac{\sum_i \#\ of\ Buy_{i,t}}{\sum_i \#\ of\ Buy_{i,t} + \sum_i \#\ of\ Sell_{i,t}}$. Finally, sell herding measure (SHM) is defined for bonds with a lower proportion of buyers than the market average: $SHM_{i,t} = HM_{i,t}\|[p_{i,t} < E[p_{i,t}]]$.
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: $Selling\ pressure_{i,t} = \frac{\sum_{j=1}^{J}(Sell\ Amt_{j,i,t}\|Flow_{j,t}<25^{th}Pctl - Buy\ Amt_{j,i,t}\|Flow_{j,t}>75^{th}Pctl)}{Bond\ issue\ size_i}$, 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. A large positive (negative) value indicates strong selling (buying) pressure.
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. $Fund\ carbon\ exposure_{j,t} = \sum_i \omega_{i,t} Carbon\ exposure_{i,t}$, 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. $\omega_{i,t}$ is the weight of bond i in mutual fund j's portfolio at the end of quarter t. This fund-level carbon exposure reflects the overall exposure to carbon emissions for a fund's corporate bond holdings.

(Bond level) flow sensitivity to carbon	Firstly, we regress mutual funds' investor inflow on fund carbon exposure in the rolling window of 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 dummy" = 1 (0). Finally, the (bond level) flow sensitivity to carbon is calculated as fund-ownership weighted sum of the high carbon sensitivity fund dummy.
Regulatory stringency	We use EPA enforcement data provided in the Integrated Compliance Information System for Federal Civil Enforcement Case Data to measure firms' exposures to environmental regulatory actions. The measure of regulatory stringency we employ captures enforcement actions, which include both informal enforcement actions (notifications of violation) and formal actions (fines and administrative orders), for the Clean Air Act (CAA) in a given state in a given year. We divide the number of enforcement actions by the total number of manufacturing facilities at the state-year level. This state-year measure is then connected with the bond data by issuer's state and year.
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 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.
MSIC carbon emission score	The MSCI carbon emission score is obtained from MSCI ESG rating. A MSCI carbon emission score is given to each firm monthly since 2007 (the score is normally updated annually while sometimes it is updated more than one time within a year), on a scale of 0–10. Companies with better performance on this issue score higher. The score is adjusted by industry and is thus comparable for two firms from different industries.
High carbon	A dummy equals to 1 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.
Control Variables	
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.
Maturity	Time-to-maturity in years.
Age	Time-since-issuance in years.
Coupon (%)	Individual bond coupon rate.
Ln(Size)	The natural logarithm of 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.

Figure 1. Cumulative monthly abnormal returns around the Paris Agreement

This figure shows the medians of cumulative monthly abnormal returns around the Paris Agreement, over the sample period from June 2015 to June 2016. High and low carbon groups are based on the carbon emission ranks in December 2015, and bonds with mutual fund ownerships in the top and bottom terciles are based on the ranks in the quarter of 2015Q4. (High – Low) carbon shows differences between the medians of cumulative monthly abnormal returns of the High and Low carbon groups.

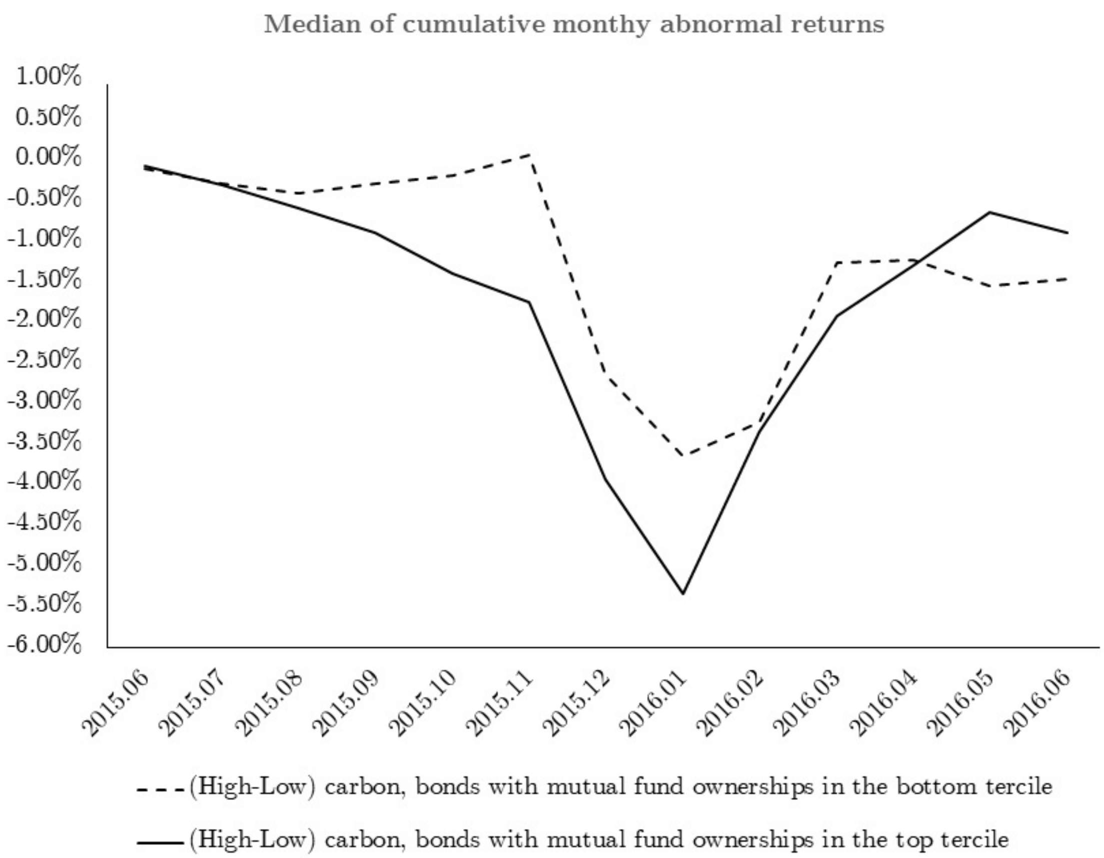

Table 1. Summary statistics

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)), 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-month. 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 (%)	124,402	0.02	0.59	-0.09	0.02	0.09
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. High carbon dummy and SHM

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. 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 the 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. High carbon dummy and SHM 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 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 the 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 to 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***** **(4.75)**	**2.247***** **(2.94)**	**2.220**** **(2.20)**	**2.385**** **(2.24)**
High carbon × Pre_PA(-3)				0.129 (0.15)
High carbon × Pre_PA(-2)				0.486 (0.65)
High carbon	-0.525 (-1.05)	−1.683* (-1.91)	−1.822* (-1.87)	−1.999* (-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. Outflow-induced selling pressure and high carbon dummy

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 the 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. Outflow-induced selling pressure and high carbon dummy 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 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 the 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. 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 the 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	**-0.136^{***}**	**-0.083^{**}**	**-0.166^{***}**
	(-3.36)	**(-2.15)**	**(-3.73)**
Ln(TNA)		-0.262^{***}	-2.524^{***}
		(-7.53)	(-12.79)
Lagged return		17.173^{***}	13.702^{***}
		(3.52)	(3.08)
Cash holding		0.008^{*}	0.014^{**}
		(1.82)	(2.58)
Expense ratio		-1.570^{***}	-1.791^{***}
		(-8.33)	(-2.72)
Turnover ratio		-0.106^{**}	-0.014
		(-2.17)	(-0.14)
Fund age		-0.010^{***}	-0.010^{***}
		(-12.62)	(-4.50)
Time FE	Y	Y	Y
Style FE	Y	Y	Y
Fund FE	N	N	Y
Adj. R^2	0.028	0.058	0.171
# of obs	92,428	88,028	88,028

Table 7. 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 the 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 8. High carbon dummy, (bond level) flow sensitivity to carbon, and SHM

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is the sell herding measure 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. Definition is provided in the 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 9. High carbon dummy, regulatory stringency, and SHM

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. The dependent variable is the sell herding measure of mutual funds measured in quarter t. Regulatory stringency (Reg) is the number of enforcement actions for the Clean Air Act (CAA) divided by total number of manufacturing facilities, of the issuer's headquarter state in year $t-1$. 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. Definition is provided in the Appendix A. 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 × Reg	**65.572*****	**107.349*****	**90.897*****
	(3.29)	**(3.55)**	**(2.90)**
High carbon	-0.081	-0.469	-0.191
	(-0.22)	(-0.73)	(-0.31)
Reg	28.332***	10.485	25.545
	(-2.95)	(0.52)	(1.11)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.073	0.191	0.194
# of obs	44,880	43,135	34,352

Table 10. High carbon dummy and SHM 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 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 the Appendix A. TE is a dummy equal to one for the time period after Trump's election (after 2016Q4), and zero otherwise. Column (1) includes time fixed effects and controls for bond rating, maturity, age, bond coupon and Ln(Size). Column (2) includes time and bond fixed effects, and controls for bond rating, maturity and age. Column (3) additionally controls for Ln(ME), Ln(BM), Stock IVOL, institutional ownership and Analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: mutual fund SHM around Trump's election			
	(1)	(2)	(3)
High carbon × TE	**-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 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 returns around the Paris Agreement

This table reports medians of monthly abnormal returns 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. At the end of each quarter, bonds are sorted into terciles based on the mutual fund ownerships, i.e., the total par value of mutual fund holdings scaled by bond issue size. Panel A and B show monthly abnormal returns for bonds with mutual fund ownerships in the top and bottom terciles, respectively. High (Low) carbon bonds are those whose issuers' carbon emission level falls into the top tercile (otherwise) among all firms each month. (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	0.25	0.33	0.21	0.09	0.30	0.73	0.86	0.13	-0.95	-0.61	-0.14	-0.54
High carbon	0.42	0.08	-0.02	0.26	-0.25	0.12	-0.42	0.30	0.47	0.47	0.22	-0.15	-0.74
(High − Low) carbon	**0.21***	**-0.17**	**−0.35*****	**0.05**	**−0.34*****	**-0.18**	**−1.15*****	**−0.56*****	**0.34****	**1.42*****	**0.84*****	**-0.01**	**-0.20**
Panel B: bonds with mutual fund ownerships in the bottom tercile													
Low carbon	0.04	0.14	0.10	0.14	-0.19	0.04	0.32	0.47	0.02	-0.66	-0.40	0.06	-0.24
High carbon	0.03	0.20	-0.16	0.19	-0.12	-0.20	-0.44	0.36	0.14	-0.66	-0.18	0.12	-0.43
(High − Low) carbon	**-0.01**	**0.06**	**-0.26**	**0.04**	**0.07**	**-0.24**	**−0.77*****	**-0.11**	**0.12**	**-0.01**	**0.22**	**0.06**	**-0.18**

Table 12. High carbon dummy 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 the Appendix A. We limit the sample to bonds held by at least one mutual fund in each quarter. 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 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: all bonds

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)**
Rating	0.001***	0.001	-0.007	−0.016**	0.079***	0.029
	(3.53)	(1.35)	(-1.05)	(-2.11)	(3.65)	(1.65)
Maturity	0.000	0.000	0.04	0.035	−0.092**	−0.136**
	(0.29)	(-0.06)	(1.66)	(1.34)	(-2.36)	(-2.46)
Age	0.001	0.004	0.393***	0.404***	0.033	0.051
	(0.23)	(0.64)	(2.96)	(2.76)	(0.16)	(0.24)
Ln(ME)		-0.003***		0.003		−0.194***
		(-3.02)		(0.08)		(-2.81)
Ln(BM)		−0.002*		-0.031		-0.071
		(-1.91)		(-1.25)		(-1.53)
Stock IVOL		0.064***		1.581***		5.243***
		(5.99)		(3.65)		(4.45)
Institutional ownership		0.001		−0.236**		0.074
		(0.23)		(-2.36)		(0.26)
Analyst		−0.000*		-0.003		0.006**
		(-1.98)		(-1.62)		(2.08)
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						
Dependent variable	Amihud		Spread		Roll	
	(1)	(2)	(3)	(4)	(5)	(6)
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. High carbon dummy 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 the 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 limit the sample to bonds held by at least one mutual fund in each quarter. 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 A.1. High carbon dummy and SHM, excluding firms in the "Energy" industry

This table reports bond-quarter panel regression results, over the sample period from 2007Q1 to 2019Q4. We exclude bond issuers in the "Energy" industry based on Fama-French 12 industry identification. 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 the 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	**0.482***	**0.952****	**1.067****
	(1.73)	**(2.35)**	**(2.31)**
Rating	0.315***	0.441***	0.489***
	(5.67)	(4.85)	(4.20)
Maturity	−0.136***	0.225	0.393
	(-6.35)	(0.72)	(1.35)
Age	0.219***	1.794**	1.820*
	(3.64)	(2.11)	(1.84)
Coupon	0.395***		
	(4.19)		
Ln(Size)	−15.030***		
	(-3.63)		
Ln(ME)			0.982
			(1.67)
Ln(BM)			0.355
			(0.78)
Stock IVOL			0.604
			(0.08)
Institutional ownership			0.462
			(0.32)
Analyst			−0.065*
			(-1.71)
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj. R^2	0.067	0.186	0.188
# of obs	44,720	42,860	34,582