Carbon Emissions, Institutional Trading, and the Liquidity of Corporate Bonds[†]

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Abstract

This paper provides a detailed investigation on how firms' carbon emission levels affect trading behaviors of institutional investors and liquidity conditions of corporate bonds. Our analysis is conducted with a full sample from 2007 to 2019 and causality is further established by exploiting two carbon-related shocks: the Paris Agreement and the election of U.S. President Trump. We find that both mutual funds and insurance companies are more likely to sell corporate bonds in herds if the bonds' issuing firms have higher carbon emissions. We show that mutual fund flows negatively respond to the fund carbon exposures and that mutual funds are more likely to sell high-carbon bonds in the face of investor redemptions. We also find that bonds issued by high-carbon firms experience worse liquidity conditions.

Keywords: Carbon emissions, corporate bonds, mutual funds, insurance companies, herding, redemption, 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 large 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. Even if 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. Recent research shows that environmental and climate risks have become an important factor in institutional investors' portfolio decisions in the equity market (Krueger, Sautner, and Starks, 2020; Bolton and Kacperczyk, 2021; Cao, Titman, Zhan, and Zhang, 2021; Humphrey and Li, 2021; and Starks, Venkat, and Zhu, 2020).

However, there is little in the literature about how concerns for global warming and carbon emissions affect institutional investors' behaviors in the corporate bond market, while recent developments highlight growing awareness of carbon emissions by these investors. For example, AXA, a giant multinational insurance firm managing $790 billion assets, seeks to avoid portfolios with global warming potential by shifting away from corporate bonds issued by heavy polluters.[1] For the mutual fund industry, Wells Fargo Asset Management just 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] Moreover, one of the central banks, Bank of England, commits to use its $28 billion of corporate bond holdings to nudge companies to cut greenhouse gas emissions faster.[4]

Compared to the equity market, the corporate bond market has a larger presence of institutional investors and bears much higher trading costs. While mutual funds and ETFs hold

[1] Source: https://www.insurancejournal.com/news/international/2021/02/24/602568.htm
[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
[4] Source: https://www.reuters.com/world/uk/bank-england-plans-green-its-corporate-bond-holdings-2021-05-21/

about 29 percent of U.S. equities, mutual funds, ETFs, and insurance companies hold 44 percent of U.S. corporate bonds.[5] In addition, the over-the-counter nature of the corporate bond market renders it heavily reliant on dealer intermediation and a lot less liquid compared to the equity market (Bao, Pan, and Wang, 2011), and institutional investors are much more likely to trade in herds in the corporate bond market (Cai, Han, Li, and Li, 2019). Should institutional investors of corporate bonds react to concerns for carbon emissions, the impact would be reflected in both their trading patterns and market liquidity.

Our paper fills the notable gap in the literature by providing a detailed investigation on how firms' carbon emission levels affect institutional investors' trading behaviors and liquidity conditions of corporate bonds. In particular, we find that both mutual funds and insurance companies are more likely to sell corporate bonds in herds if the bonds' issuing firms have higher carbon emissions. We show that mutual fund flows react to the fund carbon exposures and that mutual funds are more likely to sell high-carbon bonds in response to investor redemptions. Consistent with institutional investors' trading behaviors, we also find that bonds issued by high-emission firms experience worse liquidity conditions. Our analysis is conducted with a full sample from 2007 to 2019 and causality is further established by exploiting two shocks: the Paris Agreement (December 2015) and the election of U.S. President Trump (November 2016).

Our main results are as follows. First, we use the full sample (with observations at the bond-quarter levels) to investigate the relationship between institutions' sell herding of a bond and carbon emission levels of the bond's issuer. Our definition of sell herding measure follows Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), and Cai, Han, Li, and Li (2019) and it gauges the extent to which a disproportionate number of institutions sell a certain security beyond the market-wide selling intensity in a given period. This comprehensive measure captures the direction and magnitude of collective trading among a group of institutional investors and adjusts for the market-wide trading trend.[6] We calculate sell herding measures for mutual funds and insurance companies separately. Firms' carbon emission scores are obtained from MSCI ESG rating, and higher scores indicate lower carbon emissions.[7] At each quarter end, bonds issued by

[5] Source for U.S. equity ownerships as of 2018: https://www.sifma.org/wp-content/uploads/2019/10/SIFMA-Insights-Who-Owns-Stocks-in-America.pdf (page 14). Source for U.S. corporate bond ownerships as of 2018: https://www.statista.com/statistics/1083823/ownership-us-corporate-bonds/.

[6] For example, if mutual funds on average tend to sell corporate bonds in a given quarter, our sell herding measure captures how a certain bond's sell herding level is beyond the general selling trend by mutual funds in that quarter.

[7] MSCI carbon emission scores are industry-adjusted and thus comparable for two firms from different industries.

firms in the lowest tercile of carbon emission scores are given the high carbon dummy equal to one. Our baseline panel regression controls for bond characteristics and time fixed effect and it generates a strongly positive association between next-quarter sell herding and the high carbon dummy. In particular, if a bond is issued by a high-emission firm, the sell herding level of mutual funds for that bond is 1 percentage point (or 7% of the standard deviation) higher compared to bonds issued by other firms. Our results change little when we further control for bond fixed effect, suggesting that for a given bond, the change of status in carbon emission of its issuer carries significant implications for its sell herding by mutual funds. We obtain similar patterns for insurance companies' sell herding behaviors.

We then utilize two shocks to test the causal effects of firms' carbon emissions on institutional investors' sell herding patterns. Specifically, we employ difference-in-differences analyses on the two eight-quarter windows around the Paris Agreement and Trump's presidential election, respectively. Intuitively, institutional investors' sell herding levels towards bonds with high-emission issuers should be greatly intensified after the Paris Agreement and lessened following the Trump's election. Our regression results confirm this hypothesis for both mutual funds and insurance companies, thus lending solid support for the causal relationship between firms' carbon emission and institutional investors' sell herding.

What are the potential contributing factors to insurance companies' decision to sell high-carbon bonds in herd? Insurance companies are subject to capital regulatory constraints and as a result can only hold a limited amount of lower-rated corporate bonds, especially those with high-yield (i.e., non-investment-grade) ratings. Thus, when an investment-grade corporate bond is downgraded to high-yield (called a "fallen angel"), this could trigger widespread selling from its insurance company investors (Ambrose, Cai, and Helwege, 2008; Ellul, Jotikasthira, and Lundblad, 2011; and Nanda, Wu, and Zhou, 2019). In light of this, we conjecture that when insurance companies significantly increase (decrease) their sell herding intensity of high-carbon bonds following the Paris Agreement (Trump's election), such effects should be even stronger for bonds on the verge of becoming "fallen angels", as they will carry much higher capital costs if downgraded by just one notch. Indeed, we find that insurance companies' capital constraints have amplifying effects on their reactions to bonds issued by high-carbon firms.

For mutual funds, what are the underlying mechanisms for our findings on the relationship between carbon emissions and sell herding? We analyze this question from the perspectives of both the end-investors of mutual funds and mutual fund managers. First, we hypothesize that end-investors of a corporate bond mutual fund react to the carbon exposure of the fund's portfolio. Prior literature has shown that investor flows of corporate bond funds are especially sensitive to bad performance of funds (Chen, Goldstein, and Jiang, 2010; and Goldstein, Jiang, and Ng, 2017), and it is plausible that investor flows are sensitive to funds' vulnerability to a potential risk source (i.e., carbon exposures). Our regression results show that mutual funds with higher carbon exposures indeed experience larger outflows, robust after controlling for past performance and other fund characteristics. Such flow-carbon relationships are especially strong after the Paris Agreement and attenuated following Trump's election. Second, we hypothesize that in the face of redemptions, mutual fund managers tend to sell high-carbon bonds. In other words, when negative shocks prompt investors to pull money out of corporate bond funds, fund managers may prioritize to sell bonds issued by high-carbon firms. To test this hypothesis, we follow the idea of Coval and Stafford (2007) and construct flow-induced selling pressure based on realized mutual fund trades conditional on large fund flows. This bond-level measure captures excessive sales of bonds by mutual funds experiencing large outflows (that are not mitigated by purchases from fund experiencing large inflows) in a given quarter. Our test results show that high-carbon bonds experience significantly larger flow-induced selling pressure, which is especially strong after the Paris Agreement and eased after Trump's election. Combined, we show that both mutual fund investors and managers are sensitive to fund's exposures to carbon emissions. Fund investors react with their redemption decisions, reinforced by fund managers' redemption-induced trading decisions. These findings reveal the underlying mechanism for the relationship between carbon emissions and mutual fund sell herding.

Finally, since both mutual funds and insurance companies (the two largest institutional investors in the corporate bond market) are more likely to sell in herds the bonds with high carbon exposures, we expect liquidity conditions to deteriorate for such bonds. Intuitively, if the majority of investors tend to shy away from bonds with high carbon exposures, dealers will have a difficult time finding potential buyers when there is a sale of such bonds, trading costs will increase, and liquidity will suffer. To test this hypothesis, we calculate four commonly used illiquidity measures for the corporate bond market (namely, Amihud, IRC, 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 for three out of the four illiquidity measures. To address the concerns for endogeneity, we again use the Paris Agreement and Trump's election as two natural experiments and confirm our findings on the causal relationship between issuers' carbon emissions and bond illiquidity.

Our paper makes several unique contributions to the literature. First, we analyze how mutual funds and insurance companies respond to 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 examples, Bolton and Kacperczyk, 2021; Cao, Titman, Zhan, and Zhang, 2021; Humphrey and Li, 2021; and Starks, Venkat, and Zhu, 2020). While Duan, Li, Wen (2021) and Seltzer, Stark, and Zhu (2021) look at how aggregate institutional ownerships change for corporate bonds issued by firms with high carbon emissions, we are the first to study trading behaviors and the underlying mechanisms for mutual funds and insurance companies against the backdrop of increasing awareness of carbon emissions in the corporate bond market.[8] Our emphasis on institutional investors' sell herding towards high-carbon bonds further differentiates our paper from all existing ones.

Second, we are the first to investigate how concerns for firms' environmental performance could affect liquidity in the corporate bond market. The majority of studies on carbon emission effects have been focused on 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 in their pioneering study that market-level illiquidity overshadows the credit risk component in explaining prices of higher-rated corporate bonds. In addition, multiple papers have shown that the recent COVID-19 crisis essentially reflects itself as a liquidity crisis in the corporate bond market (see, for examples, 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 our findings on institutional herding in these bonds, but also deepens understanding of the pricing implications of carbon emissions. In

[8] In contrast to our primary focus on institutional trading dynamics, the focus of Duan, Li, and Wen (2021) and Seltzer, Stark, and Zhu (2021) is on the pricing implications of environmental risks in corporate bond market. Duan, Li, and Wen (2021) study whether carbon risks are priced in the cross-section of corporate bond return. Seltzer, Stark, and Zhu (2021) 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.

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.[9]

Third, we identify a new factor that drives corporate bond mutual fund flows, namely, the fund 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-carbon relationship for corporate bond mutual funds, after controlling for known factors driving fund flows.[10] This finding indicates that end-investors of corporate bond mutual funds are sophisticated enough to take into account the fund's exposures to carbon emissions and also provides a transmission channel for carbon emissions to affect mutual funds' trading decisions.

Finally, our paper emphasizes that constraints faced by institutional investors can amplify shocks for underlying markets. For mutual funds, we find that when facing investor redemptions, funds tend to sell more high-emission bonds.[11] For insurance companies, we find that they are more likely to sell high-emission bonds with higher risks of becoming "fallen angles", likely driven by their capital constraints.[12] While existing papers find that the effects of institutional investors' constraints (i.e., investor redemptions for mutual funds, and capital constraints for insurance companies) on the underlying markets are more evident during stress times, our paper complements the literature by showing that these effects can also be reinforced when a new shock, the awareness of climate changes and carbon emissions, is introduced to the market.

The rest of the paper is structured as follows. Section 2 describes our data and sample, and explains how we construct some of the key measures in the paper, including sell herding measure, flow-induced selling pressure, various illiquidity measures, MSCI carbon emission score, and high carbon dummy. Section 3 examines the relationship between firms' carbon emissions and institutional investors' sell herding in the corporate bond market, as well as how insurance

[9] Amiraslani, Lins, Servaes, and Tamayo (2021), Halling, Yu, and Zechner (2021), and Seltzer, Stark, and Zhu (2021) 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, 2020, 2021), and option market (Ilhan, Sautner, and Vilkov, 2021).

[10] 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).

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

[12] For papers on how insurance companies' capital constraints and the associated "fallen angel" concerns affect the corporate bond market, see, for examples, Ambrose, Cai, and Helwege (2008), Ellul, Jotikasthira, and Lundblad (2011), and Nanda, Wu, and Zhou (2019).

companies' capital constraints can amplify the effects. Section 4 analyzes the underlying mechanisms for our findings on the relationship between carbon emissions and mutual funds' selling, from the perspectives of both the end-investors of mutual funds and mutual fund managers. Section 5 investigates the relationship between bonds' liquidity conditions and their carbon exposures. Section 6 concludes.

2. Data, variables construction, and summary statistics

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

2.1. Data and sample

Our study combines data from several sources, spanning a sample period from January 2007 to December 2019. First, we obtain the MSCI carbon emission scores from 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. The data has been used in recent studies on carbon emission and climate changes, such as Choi, Gao, and Jiang (2020). After assembling the data from various resources, our largest sample for analysis contains 28,701 unique corporate bonds from 1,274 unique U.S. public firms over the period from January 2007 to December 2019.

Then we obtain data on institutional trading 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, and pension funds, and others. We focus on mutual funds and insurance companies as they are the major participants in the corporate bond market. Information of fixed income holdings for insurance companies is acquired through both National Association of Insurance Commissioners (NAIC) annual holdings files and the quarterly transaction reports to the state insurance commissioners that are used to interpolate the holdings each quarter. Data on mutual fund holdings are obtained from Thomson Reuters Lipper, which covers over 90% of the mutual fund universe. Thomson Reuters Lipper eMAXX is widely used in academic studies including Manconi, Rossi, and Yasuda (2012), Cai, Han, Li, and Li (2019) among others.

Next, for 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 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.

Our data of mutual fund characteristics and flows come from the Center for Research in Security Prices (CRSP) survivor-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 test results (Keswani and Stolin, 2008). Then we match CRSP mutual fund data with eMAXX fund data according to 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 age less than one year to mitigate data biases associated with young funds, or if none of the bonds held by the mutual fund has an 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 measures (SHM)

Following Lakonishok, Shleifer, and Vishny (1992) and Cai, Han, Li, and Li (2019), we estimate the extent of herding by institutional investors in trading corporate bonds. It captures whether a disproportionate number of institutions are buying/selling a certain security beyond the market-wide buying/selling intensity in a given period. Specifically, we calculate the herding measure of bond i in quarter t for mutual funds, and insurance companies separately, using following equation:

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

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

$$\overline{p_t} = \frac{\sum_i \# \; of \; Buy_{i,t}}{\sum_i \# \; of \; Buy_{i,t} + \sum_i \# \; of \; Sell_{i,t}} \tag{2}$$

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 $\left|p_{i,t} - E\left[p_{i,t}\right]\right|$ is always 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 is zero.[13]

Next, we follow Wermers (1999) to define a sell herding measure (SHM) for bonds with a lower proportion of buyers than the market average.[14]

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

We focus on the sell herding measure in this paper, investigating whether sell herding of different institutions in the corporate bond market is associated with the carbon emission of issuers.

[13] We follow Laknishock, 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 $\overline{p_t}$, the absolute value of $p_{i,t} - E\left[p_{i,t}\right]$ is greater than zero. The adjustment factor is, therefore, the expected value of $p_{i,t} - E\left[p_{i,t}\right]$ under the null hypothesis of no herding. Since $Buy_{i,t}$ follows a binomial distribution with probability $\overline{p_t}$ of success, the adjustment factor is easily calculated given $\overline{p_t}$ and the number of institutions active on that bond in that quarter.

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

2.2.2. Flow-induced selling pressure from mutual funds

Following Coval and Stafford (2007), we construct a flow-induced selling pressure measure based on realized fund trades conditional on large fund flows:[15]

$$Sell\ Pressure_{i,t} = \frac{\sum_{j=1}^{J}\left(Sell\ Amt_{j,i,t} \middle| Flow_{\ j,t} < 25^{th} Pctl - Buy\ Amt_{j,i,t} \middle| Flow_{j,t} > 75^{th} Pctl\right)}{Initial\ Amount\ Outstanding_i} \quad (4)$$

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 captures the difference between sales and purchases of bonds by mutual funds that experience extreme outflows and inflows, respectively. A large positive value indicates strong flow-induced selling pressure that is not mitigated by other funds' purchase.

2.2.3. Illiquidity measures

We construct four widely used corporate bond illiquidity measures at the quarterly frequency: the Amihud measure gauges the price impact of a given trading size; the IRC computes the round-trip transaction cost and is calculated following Dick-Nielsen, Feldhutter, and Lando (2012); the Spread is the same-bond-same-day effective spread proposed by Hong and Warga (2000), which is the dollar-volume-weighted average ask prices minus the dollar-volume-weighted average bid prices of all transactions on the same day and 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. We exclude interdealer transactions when constructing these illiquidity measures except for the IRC measure. The construction methodologies are detailed in the Appendix. 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.

2.2.4. 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 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

[15] 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.

comparable for two firms from different industries. The coverage of MSCI grows over time. In our sample, the number of unique firms with emission score is around 400 in the earlier period and around 800 in the later period. For bonds actively traded by mutual funds or insurance companies (i.e., those with non-missing herding measures for at least one type of institutions), on average 57.5% of them are matched with the MSCI emission scores (62.4% in terms of issuance amount).

To address the concern that MSCI may focus on carbon emissions by certain industries and that the matched sample may not be representative enough for the overall corporate bond market, in Panel C of Table 1 we compare the Fama-French 12 industry distribution for all issuers (with actively traded corporate bonds) and that for issuers with non-missing MSCI emission scores. The comparison shows that industry compositions for the two samples are similar, indicating that our matched sample is representative of the general corporate bond market.

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. From Panel A, the level of sell herding varies by investor type. Insurance companies, the largest investor group for corporate bonds, exhibit a greater tendency of herding to sell than mutual funds, with an average sell herding measure of 8.88%. Intuitively, this implies that if 100 institutions trade a given bond in a given quarter, there are approximately 9 more insurance companies herd to sell in the market than there would be expected if each institution trades bonds independently.

The flow-induced selling pressure from mutual funds has an average of 0.01%, implying a fairly selling pressure for bonds in the sample by mutual funds that experience extreme fund flows. The average bonds' illiquidity measure based on Amihud is 0.05% per thousand dollars. The average illiquidity based on IRC, same-day bid-ask spread, and Roll is 0.53%, 1.31%, and 2.01, respectively. The distributions of the four bond illiquidity measures are all right skewed, with larger means than medians. The summary statistics are comparable to previous literature.

[Insert Table 1 about here]

Bonds in our sample on average have the rating of 7.54 (equivalently, nearly BBB+ for S&P or Baa1 for Moody's), time-to-maturity of 9.46 years, time-since-issuance of 6.12 years. The issuers are on average large firms with high institutional ownership (an average of 76%) and are followed by 15 financial analysts.

3. Carbon emission and institutional selling in corporate bond market

In this section, we analyze in details whether carbon emission performance of a corporate bond issuer has an impact on institutional trading of its bonds. We focus on sell herding behaviors of mutual funds and insurance companies, which have been shown to exert large destabilizing effects on the corporate bond market (Cai, Li, Li, and Han, 2019). Our sell herding measure comprehensively captures the direction and magnitude of collective trading among a group of institutional investors and adjusts for the market-wide trading trend. The analysis is first conducted with a full sample from 2007 to 2019 and causality is further established by exploiting two carbon-related shocks: the Paris Agreement and the election of U.S. President Trump.

3.1. Baseline results

To start, we investigate the relationship between institutional sell herding and carbon rating of bonds' issuer, running panel regression as follows:

$$Sell\ herding_{i,j,t} = \alpha + \beta \times High\ carbon_{i,t-1} + \delta \times controls_{i,t-1} + \mu_t + \epsilon_{i,t} \qquad (5)$$

where $Sell\ herding_{i,j,t}$ is the sell herding measure for bond i over quarter t of institution type j, with j being either mutual funds or insurance companies. We study these two types of institutions because they are the largest institutional investors in the corporate bond market. $High\ carbon_{i,t-1}$ is a dummy variable defined at the end of previous quarter, indicating whether issuer i's carbon emission level falls into the top one-third of all firms, i.e., carbon score in the lowest tercile. We control for various bond-level characteristics and stock characteristics of the issuer. Bond level controls include bond rating, time to maturity, age, coupon rate and logarithm of bond issue size.[16] Issuing firm's stock controls 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

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

equity returns), institutional ownership and number of analysts covering that stock.[17] We also control for year-quarter time fixed effects. 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]

Columns (1) to (3) show the results for mutual funds' sell herding. Controlling for bond characteristics and time fixed effect, high carbon dummy is positively associated with mutual funds' sell herding, significant at the 1% level, as reported in Column (1). The coefficient indicates that if a bond is issued by a firm identified as having a high carbon business model, the sell herding level by mutual funds is 1.029-percentage-point higher compared to bonds issued by other firms. The increase is economically significant and equivalent to 7% of the standard deviation of mutual funds' sell herding measures. It is possible that the high carbon dummy is correlated with other non-observable bond characteristics and same-firm stock characteristics, which might confound the relationship between sell herding measure and high carbon dummy. Therefore, we include bond fixed effect in Column (2) and further control for stock characteristics in Column (3). The effect of high carbon dummy on sell herding level remains significant, both statistically and economically. In particular, Column (3) shows that for a given bond, its sell herding level by mutual funds increases by 1.148 percentage points when its issuer's carbon emission level changes from normal to high.

Columns (4) to (6) show consistent results for insurance companies' sell herding pattern. Similar to mutual funds, insurance companies are more likely to sell a bond in herds if the bond's issuer has a carbon intensive business model. The finding is robust to the inclusion of bond fixed effects and additional stock controls.

3.2. Establishing causality: evidence from Paris Agreement and Trump's election

Though we have included bond fixed effect and various control variables in our baseline regressions, we recognize there are still endogeneity concerns for the documented relationship between a firm's carbon emission and institutional trading behaviors in the corporate bond market. For example, unobservable firm-level risks might be omitted variables that confound this relationship. To establish a causal link from the issuer's carbon emission to institutional sell

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

herding levels in its bonds, we utilize two exogenous shocks that have a notable impact on the general awareness of climate change and carbon emissions.

The first shock we exploit is Paris Agreement in December 2015, under which 196 signatories have agreed to take actions to limit global temperature increases. On December 12th, 2015, the Paris Agreement was announced at the 21st Conference of the Parties (or COP21) to the United Nations Framework Convention on Climate Change (UNFCCC) in Paris.[18] It is broadly considered as a landmark step for global climate change mitigation and adaptation action, and more importantly, it came as a surprise.[19] 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 to be 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 sell herding measure to be intensified.

Our second exogenous shock is the election of President Trump in November 2016, which is generally considered to offset the Paris Agreement effects. The outcome of the election was unexpected to the market. Moreover, the two candidates' positions on environmental issues are very different. President Trump, who repeatedly denied that climate change is caused by humans, was inclined to weaker 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-emission firms. We

[18] 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.

[19] 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."

therefore expect the sell herding level on high-carbon bonds to decrease after the election of President Trump.

To test the hypothesis that the effect of carbon emission on institutional sell herding in corporate bonds would be strengthened after Paris Agreement and attenuated after Trump's election, we employ difference-in-differences approaches. For each shock, we focus on an event window of [-4, +4] quarters, excluding the event quarter. For example, to identify effects of carbon emission on sell herding before and after Paris Agreement, we focus on the period from 2014Q4 to 2016Q4, excluding the 4th quarter of 2015 based on the time of dependent variable measurement. Specifically, we run the following regressions for Paris Agreement event and Trump's election event, respectively:

$$Sell\ herding_{i,j,t} = \alpha_1 + \beta_1 High\ carbon_{i,t-1} \times PA_t + \gamma_1 High\ carbon_{i,t-1} + \delta_1 controls_{i,t-1} + \mu_t + \epsilon_{i,t} \quad (6)$$

$$Sell\ herding_{i,j,t} = \alpha_2 + \beta_2 High\ carbon_{i,t-1} \times TE_t + \gamma_2 High\ carbon_{i,t-1} + \delta_2 controls_{i,t-1} + \mu_t + \epsilon_{i,t} \quad (7)$$

where PA_t is a time dummy equals one for the period after the announcement of Paris Agreement and TE_t is a time dummy equals one for the period after Trump was elected as the U.S. President.[20]

Our variables of interest are the interaction terms $High\ carbon_{i,t-1} \times PA_t$ and $High\ carbon_{i,t-1} \times TE_t$. If our conjecture is correct, we would find a positive β_1 and a negative β_2, which capture how the effect of carbon emission on institutional sell herding level changes due to Paris Agreement and Trump's election in a relatively short window, respectively.

[Insert Table 3 about here]

We first report the results on mutual funds' sell herding around Paris Agreement and Trump's election in Table 3. In Panel A, we find that mutual funds' sell herding in 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 passage of Paris Agreement, a high-carbon bond experiences an additional 2.6-percentage-point increase (18% of standard deviation) in its mutual fund sell herding level following the Paris Agreement, nearly three times of the corresponding magnitude in the full sample. Such effect is reversed after

[20] Note that effects of *PA* and *TE* dummies are absorbed by time fixed effects.

the election of President Trump, as demonstrated in Panel B. Specifically, Column (1) shows that a high-carbon bond experiences an additional 2.3-percentage-point decline in its mutual fund sell herding level following the election of President Trump. In sum, these two tests show that the effects of carbon emission on institution sell herding of corporate bonds get amplified when there are exogenous shocks that lead to higher awareness of climate challenges and more stringent potential regulations, and that such effects are attenuated when there is a potential reversal on climate-related policies. The offsetting effect of the Trump's election on sell herding suggests that the effect of Paris Agreement is largely driven by investors' expectations for increased carbon-related regulatory risks rather than by a permanent change in investors' preference for lower-carbon bonds. We further explore the mechanisms of why mutual funds herd to sell high-carbon bonds in detail in Section 4.

[Insert Table 4 about here]

Table 4 shows similar results on insurance companies' sell herding changes following the passage of the Paris Agreement and the election of President Trump. Panel A shows that insurance companies herd to sell bonds issued by firms with high carbon emission to a greater extent after the Paris Agreement. Specifically, Column (1) shows that a high-carbon bond experiences an additional 5.7-percentage-point increase (36% of standard deviation) in its sell herding by insurers following the Paris Agreement. Panel B demonstrates that the effect of high carbon emission on insurance company sell herding reverses after the election of President Trump, which is more consistent with a reduction in carbon-related regulatory risks than a permanent change in investment preferences by insurance companies.

To lend more support to our argument that insurance companies' sell herding in high-carbon bonds is mainly driven by insurers' concerns for regulatory risks associated with high-carbon bonds (rather than by a shift in insurers' investment preference), we exploit a unique regulatory constraint for insurance companies and conduct a triple-difference test. One important feature for insurance companies is that they are subject to risk-based capital requirements prescribed by National Association of Insurance Commissioners (NAIC) and as a result can only hold a limited amount of lower-rated corporate bonds, especially those with high-yield (i.e., non-investment grade) ratings.[21] Thus, when an investment-grade corporate bond is downgraded to be high-yield

[21] See: https://content.naic.org/cipr_topics/topic_riskbased_capital.htm

(called a “fallen angel”), this could trigger widespread selling from its insurance company investors to avoid breaching their capital requirements (Ambrose, Cai, and Helwege, 2008; Ellul, Jotikasthira, and Lundblad, 2011; and Nanda, Wu, and Zhou, 2019).

In light of this, we examine whether insurance companies’ increased (decreased) sell herding on high-carbon bonds is further magnified (mitigated) post Paris Agreement (Trump’s election) for bonds on the verge of becoming “fallen angels” (i.e., bonds with BBB ratings, which are investment-grade but one step away from being downgraded to high-yield), as such bonds will carry much higher capital costs if downgraded by just one notch. Specifically, we introduce a triple interaction between a BBB dummy, high carbon dummy, and post-event dummy on top of the difference-in-differences analyses. Supporting evidence is presented in Table 5, with the triple interaction term attracting a positive coefficient for the Paris Agreement test and a negative coefficient for the Trump’s election test. These findings suggest that when insurance companies change their sell herding behaviors for high-carbon bonds following the two shocks, they pay extra attention to bonds with higher potential regulatory costs.

[Insert Table 5 about here]

4. Why do mutual funds herd to sell high-carbon bonds?

The earlier results support our hypothesis that carbon emission intensity of the issuers has an impact on institutional sell herding levels in the corporate bond market. Such pattern is strengthened when there is more (potential) stringent regulatory force against climate changes and is weakened when such regulation is expected to be less rigid. In this section, we take a deeper investigation of the drivers for mutual funds’ sell herding behaviors, from the perspectives of both the end investors of mutual funds and mutual fund managers. We first examine whether mutual fund flows are sensitive to fund-level carbon exposures, and then investigate the relationship between flow-induced selling pressure and carbon ratings of the bonds. We again use the two shocks, i.e., Paris Agreement and Trump’s election, to establish causality.

4.1. Do mutual funds’ carbon exposures drive investor flows?

Do investors care about carbon exposures of corporate bond mutual funds? As documented by Hartzmark and Sussman (2019), equity fund flow is higher towards funds being categorized as high sustainability, because sustainability is viewed as positively predicting future performance and investors have nonpecuniary motives. However, little is known about the bond mutual fund industry. We aim to fill this gap and provide some of the first empirical evidence to understand the mechanisms underlying mutual funds' sell herding in high-carbon corporate bonds. Unlike equity market, 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 first-mover advantage among their investors and trigger amplified redemptions in the face of a negative shock (see Chen, Goldstein, and Jiang, 2010; and Goldstein, Jiang, and Ng, 2017). Therefore, redemption by end investors carry more financial stability implications for bond mutual funds than for equity mutual funds. If end investors care about bond mutual funds' carbon exposures and their flows are sensitive to the mutual fund carbon performance, we can better understand the results we have previously documented. Intuitively, if flows by end investors are negatively related to mutual fund carbon exposures, to attract more inflows and avoid potential redemption, mutual fund managers might shift their portfolios away from high-carbon bonds, leading to a higher sell herding level.

Following 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.

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

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

To measure fund-level carbon exposures, we follow Cao, Titman, Zhan, and Zhang (2021) 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:

$$Fund\ carbon\ exposure_{j,t} = \sum\nolimits_{i \text{ held by } j} w_{i,t} Carbon\ Exposure_{i,t} \tag{9}$$

where $Carbon\ Exposure_{i,t}$ is the average of carbon exposure for bond i in the quarter t. Here, we take the negative value of MSCI carbon emission scores as carbon exposure, such that a higher value of carbon exposure (lower MSCI carbon emission score) indicates higher carbon emission by the issuing firm. $w_{i,t}$ 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.

To test whether flows are sensitive to bond mutual funds' carbon exposure, we regress the percentage flow of fund j in month t on fund carbon exposure of the most recent quarter-end:

$$Mutual\ fund\ flow_{j,t} = \alpha + \beta Fund\ carbon\ exposure_{j,t-1} + \delta controls_{i,t-1} + \mu_t + \theta_s + \epsilon_{i,t} \qquad (10)$$

where μ_t represents the year-month fixed effects and θ_s the style fixed effect.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 last month, and percentage of cash holding, expense ratio, turnover ratio, and fund age, measured at the end of most recent quarter.

[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 effect as shown in Columns (2) and (3).

Next, we test causality for our findings on the relationship between fund flows and fund carbon exposures. Specifically, we investigate how the flow-carbon relationship changes around the Paris Agreement and Trump's election for the event window of [-6, +6] months (excluding the event month based on the time of fund flow). As Paris Agreement draws public attention to climate changes and potentially leads to more rigid regulations against high-carbon firms, we expect the negative relation between fund flows and fund carbon exposures to be strengthened after the Paris Agreement. In contrast, the election of Trump should alleviate carbon-related regulatory concerns, therefore attenuating the negative relation. We again run difference-in-differences regressions to test our hypotheses and report our results in Table 7.

[Insert Table 7 about here]

After Paris Agreement, there are even larger outflows for funds that hold more carbon-intensive bonds as evidenced in Panel A. The effect is statistically significant at the 1% level when various fund characteristics and fund fixed effect are controlled for (Column (3)). The negative relationship between fund flows and fund carbon exposures is reversed shortly after Trump's election, as Panel B shows significantly positive coefficients for the interaction terms across different specifications. Our results demonstrate that the sensitivity of investor flows to the fund's carbon exposures changes notably following the two climate-related shocks, not only validating 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.

4.2. Flow-induced selling pressure on high-carbon bonds

After establishing the fact that end-investor flows are sensitive to carbon exposures of bond mutual funds, we test whether such flow pattern creates selling pressure on corporate bonds issued by high-carbon companies, which complements our study on the mechanism for higher levels of sell herding in these bonds. Intuitively, knowing that investors react to funds' carbon exposures, in the face of outflows fund managers have the incentive to prioritize dumping high-carbon bonds to meet redemptions, leading to potentially higher selling pressure on high-carbon bonds. To explore this channel, we use (out)flow-induced selling pressure (the construction of which detailed in section 2.2.2) as the dependent variable and run our full sample panel regression, with explanatory variables and controls detailed in Equation (5). The results are shown in Table 8.

[Insert Table 8 about here]

As shown in Table 8, the positive coefficient on the $High\ carbon$ dummy confirms our conjecture that bonds issued by firms with carbon intensive business are subject to stronger flow-induced selling pressure from mutual funds. In Column (1), when bond characteristics and time fixed effect are controlled for, high-carbon bonds experience outflow-induced selling pressure that is 0.33-percentage-point (56% of the standard deviation) higher relative to other bonds, indicating a nontrivial economic magnitude. Turning to establishing causality, we again focus on the two exogenous shocks, i.e., Paris Agreement and Trump's election and expect an intensifying (offsetting) effect for the former (latter). Specifically, we use outflow-induced selling pressure as the dependent variable and run similar difference-in-differences regressions as in Equation (6) and (7). We report the results in Table 9.

[Insert Table 9 about here]

After the announcement of Paris Agreement (Panel A of Table 9), in the face of redemptions possibly driven by funds' carbon exposures, the tendency for mutual fund managers to sell high-carbon bonds increases, leading to an additional increase in flow-induced selling pressure for high-carbon bonds relative to other bonds. Consistent with the reversed effects of fund carbon exposure on outflows after the election of Trump, mutual funds' selling pressure on high-carbon bonds decreases in the year following Trump's election The supporting evidence is tabulated in Panel B of Table 9.

Taken together, the evidence in section 4.1 and 4.2 shows that bond mutual fund flows are sensitive to fund carbon exposures, creating incentives for fund managers to prioritize selling high-carbon bonds to avoid redemption and thus a higher selling pressure for these bonds. Such redemption-induced selling pressure is shown to be a plausible transmission channel for carbon emissions to affect sell herding of mutual funds.

5. Carbon emission and corporate bond liquidity

Our previous results show that both mutual funds and insurance companies (the two largest institutional investors in the corporate bond market) are more likely to sell in herds bonds with high carbon exposures. Such trading dynamics could carry liquidity implications for these high-carbon bonds. Intuitively, if the majority of investors tend to shy away from bonds with high-carbon exposures, dealers will have a difficult time finding potential buyers when there's a sale of 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.

To examine whether issuer's carbon emissions affect future bond illiquidity, we first run the panel regressions for our full sample, using the four bond illiquidity measures, (namely Amihud, IRC, Spread, and Roll) as dependent variables. Our key independent variable is lagged high carbon dummy, and other control variables are defined as in Equation (5).

$$Bond\ illiquidity_{i,t} = \alpha + \beta \times High\ carbon_{i,t-1} + \delta \times controls_{i,t-1} + \mu_t + \sigma_i + \epsilon_{i,t} \qquad (11)$$

Table 10 reports the regression results. The coefficients of the high carbon dummy are positive for all regressions and are statistically significant for three out of the four illiquidity measures (except for the Roll measure) even after controlling for both bond and issuer's stock characteristics.

[Insert Table 10 about here]

For the three illiquidity measures that carry significant results, magnitudes of the coefficients on the high carbon dummy are comparable across different specifications, supporting the robust impact of high emission dummy on future bond illiquidity. The economic significance is also sizable. For instance, being a high-carbon bond is associated with an increase of 0.087 percentage point (8% of the standard deviation) in the Spread illiquidity measure with bond controls over the next quarter. The effects of control variables are consistent with the findings in the existing literature. For instance, bonds tend to experience deterioration in liquidity if they bear lower credit rating or their issuers have higher stock return volatility.

With the full-sample test, we demonstrate a robust positive association between issuer's carbon emissions and bond illiquidity. Next, we again resort to the two carbon-related shocks and test for the causal effect of carbon emissions on bond liquidity. Specifically, we analyze whether the illiquidity-carbon relationship intensifies after the announcement of the Paris Agreement and whether such pattern is reversed after the election of President Trump. Specifically, we conduct difference-in-differences analyses similar to Equations (6) and (7), using bond illiquidity measures as dependent variables. We present the empirical findings in Table 11.

[Insert Table 11 about here]

Consistent with our documented results that the passage of Paris Agreement amplifies the effects of carbon emission on institutional sell herding and flow-induced selling pressure from mutual funds, it also enhances the adverse effects of carbon emission on corporate bond liquidity. The coefficients on interaction terms are significantly positive for all four illiquidity measures that we examine and results are robust across specifications, as demonstrated in Panel A. In Panel B, we again find corroborating results from the investigation of Trump's election. The negative effect of issuers' high carbon emissions on bond liquidity is substantially alleviated in the period after the election of Trump. The interaction terms have significantly negative coefficients, robust across illiquidity measures and across different specifications.

Taken together, this section shows how concerns for firms' carbon performance could affect liquidity conditions in the corporate bond market. We start with a full-sample panel regression to show a positive relationship between issuer's carbon emissions and bond illiquidity levels and follow up with a difference-in-differences approach to establish causality. Our findings on the impact of carbon emissions on bond liquidity are consistent with the trading patterns of insurance companies and mutual funds towards high-carbon bonds.

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 institutional sell herding in these bonds, but also deepens 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.[22]

6. Conclusion

Concerns and debates over global warming and carbon emissions have repeatedly hit 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 become increasingly aware of firms' carbon emission. While recent research shows that climate risks have become an important factor in institutional investors' portfolio decisions in the equity market, little is known about how concerns for carbon emissions affect institutional investors' behaviors in the corporate bond market, which has a larger presence of institutional investors and bears much higher trading costs.

In this paper, we fill the gap in the literature by providing a detailed study on how firms' carbon emission levels affect institutional investors' trading behaviors and liquidity conditions of corporate bonds. We conduct our analyses with a full sample from 2007 to 2019 and further establish causality by exploiting two shocks: the Paris Agreement (December 2015) and the election of U.S. President Trump (November 2016). We find that both mutual funds and insurance companies are more likely to sell corporate bonds in herds if the bonds' issuing firms have higher carbon emissions. Using the difference-in-differences approach, we show that such effects are

[22] 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 (2021); Halling, Yu, and Zechner (2021); and Seltzer, Stark, and Zhu (2021).

much stronger after the Paris Agreement and weakened following Trump's election. Applying a similar methodology, we show that mutual fund flows react to the fund carbon exposures and mutual funds are more likely to sell high-carbon bonds in response to investor redemptions. We also find that bonds issued by high-emission firms experience worse liquidity conditions.

Our paper is the first to study trading behaviors (especially sell herding) and the underlying mechanisms for mutual funds and insurance companies against the backdrop of increasing awareness of carbon emissions in the corporate bond market. We are also the first to investigate how concerns for firms' carbon emissions could affect liquidity in the corporate bond market, and 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. In addition, our finding that mutual funds' carbon exposures drive investor flows suggests that end-investors of corporate bond mutual funds care about the funds' exposures to carbon emissions. Finally, our paper emphasizes that constraints faced by institutional investors (i.e., investor redemptions for mutual funds, and capital constraints for insurance companies) can amplify shocks for the underlying markets.

Results in our paper also add color to the ongoing debate on the fundamental reasons for institutional investors to take account of carbon emissions when making investment decisions. One potential reason is that the increasing awareness of global warming and environmental issues generates permanent changes in institutional investors' preferences towards polluting firms. Another explanation is that the growing emphasis on global warming by policy makers has introduced carbon-related regulatory risks to assets with high carbon exposures, making institutional investors (and their end investors) more likely to reduce their exposures to such risks. While our findings cannot rule out the first explanation (and it may well be true in the long run), they do provide strong support for the second view. In particular, all impacts of carbon emissions on sell herding, mutual fund flows, and bond liquidity are strongly amplified following the passage of the Paris Agreement and notably offset following the election of President Trump, suggesting the time-varying nature of institutional investors' attitudes towards carbon emissions.

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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: $$HM_{i,t} = \lvert p_{i,t} - E[p_{i,t}] \rvert - E\lvert p_{i,t} - E[p_{i,t}] \rvert,$$ Where $p_{i,t}$ is the proportion of buyers to all active traders of bond i in quarter t. The term $E[p_{i,t}]$ is the expected level of buy intensity, estimated using market-wide intensity of buying $\overline{p}_t$, $$\overline{p}_t = \frac{\sum_i \#\ of\ Buy_{i,t}}{\sum_i \#\ of\ Buy_{i,t} + \sum_i \#\ of\ Sell_{i,t}}$$ Finally, sell herding measure (SHM) is defined for bonds with a lower proportion of buyers than the market average. $$SHM_{i,t} = HM_{i,t} \vert p_{i,t} < E[p_{i,t}]$$
Mutual funds' selling pressure	Following Coval and Stafford (2007), we construct flow-induced selling pressure based on realized fund trades conditional on large fund flows: $$Sell\ Pressure_{i,t} = \frac{\sum_{j=1}^{J}(Sell\ Amt_{j,i,t} \vert Flow_{j.t} < 25^{th} Pctl - Buy\ Amt_{j,i,t} \vert Flow_{j.t} > 75^{th} Pctl)}{Initial\ Amount\ Outstanding_i}$$ 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. $$Fund\ carbon\ exposure_{j,t} = \frac{\sum_{i=1}^{I} holding\ amount_{j,i,t} \times bond\ carbon\ expsoure_{i,t}}{\sum_{i=1}^{I} holding\ amount_{j,i,t}}$$ where $bond\ carbon\ expsoure_{i,t}$ is the negative value of MSCI carbon emission score as its carbon emission exposure of bond i in quarter t, such that bonds with higher carbon emission exposure are issued by firms with more carbon intensive business models. $holding\ amount_{j,i,t}$ is the par amount of corporate bond i held by fund j as of the end of quarter t. This fund-level carbon exposure reflects the overall exposure to carbon emissions for a fund's corporate bond holdings.
Amihud (% per thousand $)	Quarterly Amihud illiquidity measure for a bond. 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.
IRC (%)	Quarterly Imputed Round-trip Costs (IRC) is calculated following Dick-Nielsen, Feldhutter, and Lando (2012). We include intraday interdealer transactions.

Spread (%)	Same-bond-same-day Effective Bid-Ask Spread (Spread) is calculated following Hong and Warga (2000), which equals the dollar-volume-weighted average ask prices minus the dollar-volume-weighted average bid prices of all transactions on the same day and same bond. We first calculate the measure for each bond each day, then average for each bond for all days within a quarter.
Roll	Quarterly implicit bid-ask spread following Roll (1984), which 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 dummy	The dummy which equals to 1 if the firm's (issuer's) MSCI emission score is among the lowest group when we divide all stocks into three groups based on their average MSCI carbon emission score across each quarter.
Control Variables	
Rating	The average of ratings provided by S&P and Moody's when both are available, or the 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 ratings from 1 to 10. Non-investment-grade (high yield) bonds have ratings above 10. A larger number indicates higher credit risk or lower credit quality.
Maturity	Years to maturity.
Age	Years since issuance.
Coupon (%)	Individual bond's coupon rate.
Ln(Size)	Logarithm of the offering amount of individual bond.
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 book equity for the fiscal year-end in a calendar year divided by market equity at the end of December of that year, as in Fama and French (1992).
Stock IVOL	The standard deviation of the regression residual of individual stock returns on the Fama and French (1993) three factors using daily data in the previous month, as in Ang, Hodrick, Xing, and Zhang (2006). We then average monthly stock IVOL in a quarter to get quarterly IVOL measure.
Institutional ownership	The percentage of common stocks owned by institutions in the previous quarter.
Analyst	The number of analysts following the firm in the previous quarter.

Table 1. Summary statistics

This table provides descriptive statistics of the data used in our empirical analysis over the 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 measures (SHM) of insurance companies and mutual funds, selling pressure for mutual funds, corporate bond illiquidity measures including the Amihud, IRC, effective spread (Spread) and Roll measures, and other bond characteristics including bond rating, time-to-maturity (Maturity), time-since-issuance (Age), coupon rate in percentage terms and logarithm of bond issuesize (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. Panel C reports time-series average of the industry distribution (in percentage terms) of firms issuing actively traded bonds (i.e., bonds with at least one non-missing SHM of insurance companies and mutual funds), for all issuers and 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. All variables are winsorized each quarter at the 0.5% level.

	N	Mean	Std	Q1	Median	Q3
Panel A: Bond-quarter variables						
SHM of insurance companies (%)	68,113	8.88	15.66	-5.30	5.91	19.36
SHM of mutual funds (%)	64,659	6.43	14.23	-5.66	3.07	14.23
Selling pressure (%)	138,371	0.01	0.59	-0.10	0.01	0.10
Amihud (% per K)	150,433	0.05	0.05	0.01	0.03	0.07
IRC (%)	150,433	0.53	0.42	0.22	0.41	0.73
Spread (%)	150,433	1.31	1.13	0.46	0.99	1.89
Roll	150,433	2.01	2.18	0.62	1.37	2.66
Rating	467,450	7.54	3.10	5.60	7.19	9.08
Maturity (in years)	550,105	9.46	8.14	3.18	6.97	13.82
Age (in years)	550,105	6.12	4.84	2.50	5.06	8.42
Coupon (%)	550,105	5.42	1.54	4.43	5.42	6.34
Ln(Size)	550,105	11.23	2.31	9.30	11.67	13.09
Panel B: Firm-quarter variables						
Carbon emission score	28,420	5.77	2.56	4.14	5.90	7.99
High carbon	28,420	0.33	0.47	0.00	0.00	1.00
Ln(ME)	26,436	9.22	1.33	8.34	9.22	10.09
Ln(BM)	26,423	-0.58	1.10	-1.17	-0.65	-0.17
Stock IVOL	28,412	0.07	0.04	0.04	0.06	0.08
Institutional ownership	28,137	0.76	0.17	0.67	0.78	0.87
Analyst	26,049	14.73	7.74	8.76	14.66	19.89

Panel C: Comparison of bond issuers' industry distribution		
Industry	Industry share (for all issuers in the sample)	Industry share (for issuers with MSCI scores)
1 Consumer Nondurables	5.52	5.54
2 Consumer Durables	2.22	2.00
3 Manufacturing	7.55	7.23
4 Energy	9.48	9.43
5 Chemicals and Allied Products	3.01	2.50
6 Business Equipment	4.94	5.31
7 Telephone and Television Transmission	9.22	9.58
8 Utilities	11.54	10.80
9 Shops	6.15	5.80
10 Healthcare	6.09	5.88
11 Finance	24.34	24.71
12 Other	9.93	11.22

Table 2. High carbon dummy and SHM of mutual funds and insurance companies

This table reports quarterly panel regression results, over the sample period of 2007Q1 to 2019Q4. The dependent variable is the sell herding measure of mutual funds or insurance companies measured in quarter t. The independent variables are measured at the end of quarter $t-1$ and defined in the Appendix. Columns (1) and (4) include time fixed effect and control for bond rating, maturity, age, bond coupon and Ln(Size). Columns (2) and (5) include time fixed effect and bond fixed effect, and control for bond rating, maturity and age. Columns (3) 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% level, respectively.

	Mutual funds' sell herding			Insurance companies' sell herding		
	(1)	(2)	(3)	(4)	(5)	(6)
High carbon	**1.029***** **(3.86)**	**1.115***** **(2.70)**	**1.148**** **(2.56)**	**0.879**** **(2.40)**	**1.081**** **(2.66)**	**1.070**** **(2.51)**
Rating	0.299*** (5.88)	0.435*** (4.74)	0.480*** (4.21)	0.728*** (13.55)	0.993*** (11.58)	1.038*** (10.10)
Maturity	-0.139*** (-7.06)	0.308 (0.70)	0.451 (1.02)	-0.258*** (-11.90)	-10.816*** (-4.15)	-9.148*** (-3.46)
Age	0.227*** (3.83)	1.131 (1.19)	1.181 (1.00)	0.609*** (8.64)	-8.341* (-1.85)	-11.761** (-2.39)
Coupon	0.445*** (4.92)			-0.260** (-2.28)		
Ln(Size)	-13.789*** (-3.46)			6.888** (2.15)		
Ln(ME)			0.608 (1.24)			-0.211 (-0.46)
Ln(BM)			0.247 (0.72)			0.323 (0.94)
Stock IVOL			1.461 (0.25)			24.144*** (5.73)
Institutional Ownership			1.419 (1.10)			0.074 (0.11)
Analyst			-0.062* (-1.98)			-0.020 (-0.66)
Time FE	Y	Y	Y	Y	Y	Y
Bond FE	N	Y	Y	N	Y	Y
Adj-R^2	0.069	0.181	0.184	0.089	0.260	0.267
# of obs	54,494	52,531	42,364	56,817	54,643	45,803

Table 3. High carbon dummy and SHM of mutual funds, around Paris Agreement and Trump's election

This table reports quarterly panel regression results, over the sample period of 2014Q4 to 2016Q4 (2015Q4 is deleted) in Panel A, and 2015Q4 to 2017Q4 (2016Q4 is deleted) in Panel B. The dependent variable is the sell herding measure of mutual funds measured in quarter t, and the deleted quarters are based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in the Appendix. PA is a dummy indicating time period after Paris Agreement (after 2015Q4). TE is a dummy indicating time period after Trump's election (after 2016Q4). Column (1) includes time fixed effect and controls for bond rating, maturity, age, bond coupon and Ln(Size). Column (2) includes time fixed effect and bond fixed effect, 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% level, respectively.

Panel A: Mutual funds' sell herding around Paris Agreement			
	(1)	(2)	(3)
High carbon × PA	**2.566*****	**1.798****	**1.939****
	(4.83)	**(3.06)**	**(2.29)**
High carbon	-0.252	-1.138	-1.350
	(-0.50)	(-1.43)	(-1.50)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.046	0.211	0.211
# of obs	10,850	9,242	8,283

Panel B: Mutual funds' sell herding around Trump's election			
	(1)	(2)	(3)
High carbon × TE	**-2.347*****	**-2.782****	**-2.106****
	(-4.89)	**(-3.40)**	**(-2.42)**
High carbon	2.432***	-0.259	-0.209
	(6.21)	(-0.21)	(-0.16)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.050	0.256	0.249
# of obs	11,379	9,491	8,630

Table 4. High carbon dummy and SHM of insurance companies, around Paris Agreement and Trump's election

This table reports quarterly panel regression results, over the sample period of 2014Q4 to 2016Q4 (2015Q4 is deleted) in Panel A, and 2015Q4 to 2017Q4 (2016Q4 is deleted) in Panel B. The dependent variable is the sell herding measure of insurance companies measured in quarter t, and the deleted quarters are based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in the Appendix. PA is a dummy indicating time period after Paris Agreement (after 2015Q4). TE is a dummy indicating time period after Trump's election (after 2016Q4). Column (1) includes time fixed effect and controls for bond rating, maturity, age, bond coupon and Ln(Size). Column (2) includes time fixed effect and bond fixed effect, 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% level, respectively.

Panel A: Insurance companies' sell herding around Paris Agreement

	(1)	(2)	(3)
High carbon × PA	**5.717*****	**5.858*****	**5.072****
	(3.73)	**(3.85)**	**(3.47)**
High carbon	-0.353	-1.731	-1.171
	(-0.42)	(-1.07)	(-0.77)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.063	0.321	0.314
# of obs	11,800	10,297	9,453

Panel B: Insurance companies' sell herding around Trump's election

	(1)	(2)	(3)
High carbon × TE	**-4.786*****	**-5.840*****	**-3.912****
	(-4.19)	**(-4.09)**	**(-2.40)**
High carbon	5.260***	3.882	2.970
	(6.47)	(1.81)	(1.44)
Bond Controls	Y	Y	Y
Stock Controls	N	N	Y
Time FE	Y	Y	Y
Bond FE	N	Y	Y
Adj-R^2	0.082	0.383	0.376
# of obs	11,003	9,381	8,637

Table 5. High carbon dummy, rating BBB bonds, and SHM of insurance companies, around Paris Agreement and Trump's election

This table reports quarterly panel regression results excluding bonds with ratings lower than BB, over the sample period of 2014Q4 to 2016Q4 (2015Q4 is deleted) in Panel A, and 2015Q4 to 2017Q4 (2016Q4 is deleted) in Panel B. The dependent variable is the sell herding measure of insurance companies measured in quarter t, and the deleted quarters are based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in the Appendix. PA is a dummy indicating time period after Paris Agreement (after 2015Q4). TE is a dummy indicating time period after Trump's election (after 2016Q4). Column (1) includes time fixed effect and bond fixed effect, and controls for bond rating, maturity and age, as well as dummies for High carbon and Rating BBB. Column (2) additionally controls for Ln(ME), Ln(BM), Stock IVOL, Institutional Ownership and Analyst. All variables are winsorized at the 0.5% level each quarter. Standard errors are clustered at the bond and quarter levels, with corresponding t-values in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Insurance companies' sell herding and BBB rated bonds around Paris Agreement

	(1)	(2)
High carbon × Rating BBB × PA	**3.025**	**4.385****
	(1.52)	**(2.04)**
High carbon × Rating BBB	0.896	0.676
	(0.47)	(0.34)
High carbon × PA	5.455*	4.167
	(2.32)	(1.80)
Rating BBB × PA	2.047*	1.737*
	(2.30)	(1.95)
Bond controls	Y	Y
Stock controls	N	Y
Time FE	Y	Y
Bond FE	Y	Y
Adj-R^2	0.316	0.311
# of obs	9,877	9,168

Panel B: Insurance companies' sell herding and BBB rated bonds around Trump's election

	(1)	(2)
High carbon × Rating BBB × TE	**-3.802***	**-5.920****
	(-1.93)	**(-2.78)**
High carbon × Rating BBB	3.826	5.695*
	(1.71)	(2.33)
High carbon × TE	-4.148**	-1.328
	(-2.52)	(-0.80)
Rating BBB × TE	2.469	3.174*
	(1.70)	(2.01)
Bond controls	Y	Y
Stock controls	N	Y
Time FE	Y	Y
Bond FE	Y	Y
Adj-R^2	0.535	0.533
# of obs	8,768	8,187

Table 6. Mutual fund flow and fund carbon exposure

This table reports monthly panel regression results, over the sample period of January 2007 to December 2019. The dependent variable is mutual fund flow in month *t*. Quarterly fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon emission exposure within that fund, with details provided in the Appendix. Other 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. We include month and style fixed effects in Columns (1) and (2), and further include fund fixed effect in Columns (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% level, respectively.

	(1)	(2)	(3)
Fund carbon exposure	**-0.136*****	**-0.082****	**-0.165*****
	(-3.35)	**(-2.11)**	**(-3.71)**
Ln(TNA)		-0.263***	-2.519***
		(-7.55)	(-12.78)
Lagged return		19.520***	15.705***
		(4.04)	(3.53)
Cash holding		0.008*	0.018***
		(1.75)	(3.07)
Expense ratio		-1.595***	-1.898***
		(-8.44)	(-2.75)
Turnover ratio		-0.104**	-0.007
		(-2.08)	(-0.06)
Fund age		-0.010***	-0.010***
		(-12.58)	(-4.54)
Time FE	Y	Y	Y
Style FE	Y	Y	Y
Fund FE	N	N	Y
Adj-R^2	0.028	0.059	0.170
# of obs	92,428	88,028	88,028

Table 7. Mutual fund flow and fund carbon exposure, around Paris Agreement and Trump's election

This table reports monthly panel regression results, over the sample period of June 2015 to June 2016 (December 2015 is deleted) in Panel A, and May 2016 to May 2017 (November 2016 is deleted) in Panel B. The dependent variable is mutual fund flow in month *t*, and the deleted months are based on the time of dependent variable measurement. Quarterly fund carbon exposure is calculated as the par amount of holding-weighted average of bond carbon emission exposure within that fund, with details provided in the Appendix. Other 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. PA is a dummy indicating time period after Paris Agreement (after December 2015). TE is a dummy indicating time period after Trump's election (after November 2016). We include style fixed effect in Columns (1) and (2), and include style fixed effect and bond fixed effect in Columns (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% level, respectively.

Panel A: Mutual fund flow around Paris Agreement

	(1)	(2)	(3)
Fund carbon exposure × PA	**-0.159**	**-0.201***	**-0.523*****
	(-1.43)	**(-1.80)**	**(-3.94)**
Fund carbon exposure	-0.165	-0.106	0.364**
	(-1.56)	(-0.96)	(2.84)
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

Panel B: Mutual fund flow around Trump's election

	(1)	(2)	(3)
Fund carbon exposure × TE	**0.192****	**0.251*****	**0.306*****
	(2.41)	**(3.58)**	**(3.46)**
Fund carbon exposure	-0.082	-0.085	-0.151
	(-1.26)	(-1.25)	(-1.49)
Fund controls	N	Y	Y
Time FE	Y	Y	Y
Style FE	Y	Y	Y
Fund FE	N	N	Y
Adj-R^2	0.023	0.047	0.230
# of obs	10,145	9,526	9,487

Table 8. High carbon dummy and flow-induced mutual funds' selling pressure

This table reports quarterly panel regression results, over the sample period of 2007Q1 to 2019Q4. The dependent variable is the flow-induced mutual funds' selling pressure measured in quarter t. The independent variables are measured at the end of quarter $t-1$ and defined in the Appendix. Column (1) includes time fixed effect and control for bond rating, maturity, age, bond coupon and Ln(Size). Column (2) includes time fixed effect and bond fixed effect, and control 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% level, respectively.

	(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(bond 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 9. High carbon dummy and flow-induced mutual funds' selling pressure, around Paris Agreement and Trump's election

This table reports quarterly panel regression results, over the sample period of 2014Q4 to 2016Q4 (2015Q4 is deleted) in Panel A, and 2015Q4 to 2017Q4 (2016Q4 is deleted) in Panel B. The dependent variable is the flow-induced mutual funds' selling pressure measured in quarter t, and the deleted quarters are based on the time of dependent variable measurement. The independent variables are measured at the end of quarter $t-1$ and defined in the Appendix. PA is a dummy indicating time period after Paris Agreement (after 2015Q4). TE is a dummy indicating time period after Trump's election (after 2016Q4). Column (1) includes time fixed effect and controls for bond rating, maturity, age, bond coupon and Ln(Size). Column (2) includes time fixed effect and bond fixed effect, 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% level, respectively.

Panel A: Flow-induced mutual funds' selling pressure around Paris Agreement

	(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

Panel B: Flow-induced mutual funds' 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 10. High carbon dummy and bond illiquidity

This table reports quarterly panel regression results over the period from 2007Q1 to 2019Q4. The dependent variables are four illiquidity measures including the Amihud, IRC, Spread and Roll measure in quarter t. The independent variables are measured of quarter $t-1$ and defined in the Appendix. Specification (1) controls for bond rating, Maturity and Age. Columns (1), (3), (5) and (7) include time fixed effect and bond fixed effect, and control for bond rating, maturity and age. Columns (2), (4), (6), (8) 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% level, respectively.

	Amihud		IRC		Spread		Roll	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High carbon	**0.004*****	**0.002****	**0.017****	**0.018****	**0.087*****	**0.092*****	**0.154***	**0.065**
	(3.14)	**(2.27)**	**(2.08)**	**(2.21)**	**(3.49)**	**(3.74)**	**(1.97)**	**(0.92)**
Rating	0.000	-0.003***	-0.000	-0.020***	-0.028***	-0.050***	0.123**	-0.076***
	(0.82)	(-5.08)	(-0.10)	(-6.14)	(-2.88)	(-5.23)	(2.39)	(-2.95)
Maturity	0.000	0.000	-0.004	-0.010**	0.038**	0.044*	-0.039	-0.088*
	(0.43)	(0.01)	(-1.42)	(-2.13)	(2.33)	(2.01)	(-1.35)	(-1.85)
Age	0.001	0.005	0.038	0.065**	0.333***	0.353***	-0.451*	-0.174
	(0.16)	(1.09)	(1.40)	(2.42)	(3.42)	(3.39)	(-1.95)	(-0.89)
Ln(ME)		-0.006***		-0.023*		-0.008		-0.333**
		(-3.32)		(-2.00)		(-0.24)		(-2.66)
Ln(BM)		-0.005***		-0.014		-0.035		-0.250**
		(-3.34)		(-1.48)		(-1.29)		(-2.29)
Stock IVOL		0.153***		0.807***		2.742***		7.763***
		(6.27)		(4.17)		(9.59)		(5.66)
Institutional Ownership		-0.004		-0.123***		-0.391***		0.620
		(-0.68)		(-2.89)		(-3.45)		(0.88)
Analyst		-0.000		-0.000		0.003		0.008
		(-1.02)		(-0.43)		(1.44)		(1.52)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj-R^2	0.569	0.581	0.683	0.691	0.617	0.624	0.419	0.425
# of obs	141,125	118,447	141,125	118,447	141,125	118,447	141,125	118,447

Table 11. High carbon dummy and bond illiquidity, around Paris Agreement and Trump's election

This table reports quarterly panel regression results, over the sample period of 2014Q4 to 2016Q4 (2015Q4 is deleted) in Panel A, and 2015Q4 to 2017Q4 (2016Q4 is deleted) in Panel B. The dependent variables are four illiquidity measures including the Amihud, IRC, Spread and Roll measure in quarter t, and the deleted qaurters are based on the time of dependent variable measurement. The independent variables are measured of quarter $t-1$ and defined in the Appendix. PA is a dummy indicating time period after Paris Agreement (after 2015Q4). TE is a dummy indicating time period after Trump's election (after 2016Q4). Columns (1), (3), (5) and (7) include time fixed effect and bond fixed effect, and control for bond rating, maturity and age. Columns (2), (4), (6), (8) 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% level, respectively.

Panel A: Bond illiquidity around Paris Agreement								
	Amihud		IRC		Spread		Roll	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High carbon× PA	**0.007****	**0.006*****	**0.075****	**0.061*****	**0.098***	**0.122****	**0.273***	**0.192***
	(3.17)	**(3.67)**	**(3.49)**	**(3.91)**	**(2.20)**	**(2.93)**	**(1.78)**	**(1.99)**
High carbon	-0.004**	-0.003**	-0.051*	-0.043*	-0.092**	-0.099**	-0.187*	-0.139*
	(-2.94)	(-2.79)	(-2.32)	(-2.34)	(-2.63)	(-2.60)	(-1.94)	(-2.08)
Bond controls	Y	Y	Y	Y	Y	Y	Y	Y
Stock controls	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj-R^2	0.586	0.583	0.686	0.690	0.678	0.681	0.506	0.541
# of obs	22,319	20,943	22,319	20,943	22,319	20,943	22,319	20,943

Panel B: Bond illiquidity around Trump's election								
	Amihud		IRC		Spread		Roll	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High carbon × TE	**-0.005*****	**-0.004*****	**-0.056*****	**-0.033****	**-0.095****	**-0.098*****	**-0.184*****	**-0.181****
	(-4.61)	**(-3.50)**	**(-5.18)**	**(-2.59)**	**(-3.23)**	**(-3.53)**	**(-3.81)**	**(-3.48)**
High carbon	0.000	-0.000	0.032*	0.019	0.044	0.044	0.050	0.073
	(0.13)	(-0.24)	(2.27)	(1.28)	(1.60)	(1.38)	(0.78)	(1.27)
Bond controls	Y	Y	Y	Y	Y	Y	Y	Y
Stock controls	N	Y	N	Y	N	Y	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj-R^2	0.606	0.601	0.705	0.707	0.710	0.710	0.581	0.574
# of obs	23,375	21,899	23,375	21,899	23,375	21,899	23,375	21,899