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ARE GREEN BONDS MORE RESILIENT TO ASSET FIRE SALES THAN THEIR NON-GREEN COUNTERPARTS?

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Abstract

The global need to fund sustainable development toward the green energy transition underlines the significance of understanding the factors that drive green investment decisions. Based on a sample data set of US corporate bond mutual funds over 2013Q – 2023Q1, I show that asset fire sales impact green bonds differently than non-green bonds. My findings suggest that fund managers prefer to retain green bonds over non-green bonds. In addition, although investors can use green bonds as a hedge against non-green bonds during normal times when an asset fire sale occurs, green bonds deteriorate and underperform relatively to non-green bonds. Policy implications may include strengthening the green bond market through government-backed issuance, which could enhance market liquidity.

Keywords: "Asset Fire Sale", "Green Bonds", "Sustainable Investment", "Mutual Funds", "Corporate Bonds"

Preface and Acknowledgements

I would like to thank my supervisor, Rex Wang, for the help he gave me during the process. Even more, for picking up the process this year with me after some personal circumstances. In addition, I thank my family who supported me and challenged my reasoning. Moreover, I want to thank my friends, roommates (Eline, Rosa) and Leon for helping me in the process.

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1 Introduction

In 2015, the 2030 Sustainable Development Goals (SDG) were universally signed by United Nations member states. The SDG goals outline a short- and long-term strategy for our people and planet (Salvia et al., 2019). Already in 1987, sustainable development was defined by the World Commission on Environment and Development (Klarin, 2018) as meeting current needs without compromising those of future generations. Of particular concern is the fact that there is not enough money to implement these goals (Cabezas et al., 2012). António Guterres, UN Secretary-General, argues that innovative financial instruments could be the answer, especially green bonds (United Nations, 2019).

According to the Green Bond Principles (GBP), green bonds are fixed-income, liquid instruments from which the proceeds are exclusively used for (re-)financing green projects. In addition, the International Capital Markets Association (ICMA) defines green projects as climate-mitigating, -adapting, or environment-friendly (ICMA, 2017). In 2007, the European Investment Bank (EIB) issued its first green bond in order to finance projects for energy efficiency and renewable energy (Flammer, 2020). Since the first issuance, green bonds have become popular among investors and issuers. Zhou and Cui (2019) show that for issuers, after a public issuance notice of green bonds, stock prices increase considerably. Therefore, governmental institutions and companies have beneficially incorporated this debt instrument to finance their transitions toward renewable energy (Flammer, 2020). At the same time, for investors, this is a safe financial instrument that endorses commitment to climate-friendly regulations (see, e.g., Maltais & Nykvist, 2020; Agliardi & Agliardi, 2019; Pasework & Riley, 2009). Often, retail investors invest in green bonds via mutual funds or ETFs primarily because they cannot afford to invest in debt instruments (Ibunkle & Steffen, 2015).

Massa et al. (2013) highlight that since the Great Financial Crisis (GFC) of 2008, remarkable investments have been made in corporate bond mutual funds (CBMFs). Generally, a growing corporate bond market is seen as positive for green bonds due to its potential to expand the investor base, enhance liquidity, and stimulate interest in sustainable investments (Deschryver & De Mariz, 2020). Currently, institutional investors (such as mutual funds) provide two-thirds of the total debt for large representative corporates via corporate bonds or securitized loans. In addition, mutual funds are shifting their portfolios towards corporate bonds with higher risks (Feroli et al., 2014). At the same time, stricter capital requirements lead to limited balance sheet capacity of dealer banks, thus resulting in lower liquidity in the total corporate bond market (see, e.g., Bao et al., 2011; Bessembinder et al., 2018).

Additionally, amid the current commodity and energy price shocks, inflated by the Russian-Ukrainian conflict, increased exposure to high inflation, post-pandemic growth, and uncertain financial conditions globally, concerning is the potential impact of these crises on debt stability and financial fragility. Price pressures and shortages associated with energy sanctions and an uneven green transition could further increase inflation and entrench the price-wage spiral (IMF, 2022). Eurozone sovereigns, corporates, and households face higher interest rates and cost pressures that could test debt sustainability (Canale & Mirdala, 2019). Therefore, concerns rise about the financial stability of bond markets in the event of large redemptions, foremost under the assumption that liquidation costs are of considerable size for illiquid asset sales that are flow-driven (Choi et al., 2020).

During the GFC, liquidity-constrained mutual funds holding illiquid securitized bonds shifted the crisis from the securitized bond market to the corporate bond market. Through that crisis, investors reacted in an emotional way, which led to running behavior (Seo & Barrett, 2007). Retail investors took their money quickly out of mutual funds (Schmidt et al., 2016). As a result, mutual funds with a higher share of illiquid assets were affected the most because they faced higher transaction costs in liquidating those assets (Pástor & Stambaugh, 2003). These redemptions triggered fire sales that often lasted multiple days as investors needed to liquidate their holdings until the stock price fell to the correction point (Bernardo & Welch, 2004). Coval and Stafford (2007) argue that there is negative price pressure for equity mutual funds during such an asset fire sale.

Similarly, this negative price pressure occurs for asset fire sales in the corporate bond market following regulatory constraints (Ellul et al., 2011). On the contrary, Choi et al. (2020) discuss that corporate bond mutual funds liquidate their cash- and cash-like securities first and, therefore, experience no significant price pressure for their corporate bonds. In this light, research on the impact of crises on green bonds within investment funds becomes increasingly important, as it can contribute to the understanding of how these innovative financial instruments can serve as catalysts for sustainability while enduring crises.

This paper searches the effect of asset fire sales in distressed mutual funds on green bonds. Data for this research is obtained from the following databases: Morningstar, Centre for Research in Security Prices (CRSP), Bloomberg, Mergent Fixed-Income Securities Database (FISD), Trade Reporting and Compliance Engine (TRACE), and Refinitiv Eikon. Using a novel data set of US open-end corporate bond mutual funds, this study shows that green bonds outperform non-green bonds before but underperform after fire sale events. To the extent of the author's knowledge, no research has been done on this topic yet. Therefore, this paper will contribute to the existing research on sustainability and green debt stability.

The remainder of this paper is structured as follows. Section 2 introduces the relevant literature and hypotheses development. Section 3 outlines the data. After that, the methodology is discussed in section 4. In section 5, the results are tabulated and discussed. Subsequently, section 6 discusses areas for future research and possible limitations. Lastly, section 7 concludes the paper.

2 Literature Review

2.1 Mutual Funds

Prior research on mutual funds contributes to a better comprehension of their role within the financial system. However, their involvement in asset fire sales and bond price impact remains debatable.

2.1.1 Role of Mutual Funds in Financial System

Mutual funds are increasingly popular among retail investors. The total global net assets of mutual funds registered in the United States amounted to approximately 27 trillion US dollars in 2021, compared to around 5.53 trillion US dollars in 1998 (Lee, 2022). In addition, a study by the De Nederlandsche Bank (DNB) shows that mutual funds and pension funds have a high demand for green bonds, contrary to insurance corporations and households (Boermans, 2023). Mutual funds play an essential part in the economy as they enable retail investors to easily invest in a diverse range of asset classes and offer diversification, professional management, liquidity, and transparency (Gormus et al., 2018). We define two classes of funds: actively managed funds and passively managed funds. The first involves portfolio managers who select and manage the fund's assets, trying to outperform the benchmark index. On the contrary, the latter aims to replicate the performance of a specific benchmark index by diversifying its portfolio of assets that is similar to the composition of the benchmark index (Pástor & Vorsatz, 2020).

Treynor and Mazuy (1966) investigated whether mutual funds outguess the market by looking at fund volatility relative to market volatility. In considering fund performance, two aspects play a key role, namely market timing and portfolio selection. In general, fund managers select securities with a strong risk-reward ratio. Moreover, fund managers strive to predict future price movements by adjusting risk in the portfolio selection (Champagne et al., 2018). However, Galloppo (2021) summarizes that the returns of index funds are often higher than the returns of actively managed funds. In the context of asset fire sales, actively managed funds are challenged by liquidity and the need to fulfill redemption requests. Thus, the investment decisions of active managers can significantly impact security prices (Zhang, 2010).

On the contrary, passively managed funds seek to match the market index with portfolio diversification, not frequently trading. To illustrate, Sushko and Turner (2018) find that active mutual funds exhibit persistent outflows in recent stress periods, whereas passive mutual fund flows were fairly stable. Therefore, this study focuses only on actively managed funds to research the effect of asset fire sales on green bonds.

2.1.2 Mutual Funds and Asset Fire Sales

In this study, the underlying factors contributing to financial fragility in mutual funds are examined first. Extensive research by Chen et al. (2021) and Goldstein and Hotchkiss (2017) has underscored the critical role played by liquidity mismatches. This imbalance is characterized by funds holding illiquid assets while simultaneously promising their investors high levels of liquidity. Institutional investors, e.g., mutual funds, that grant these withdrawal rights to their investors are susceptible to runs (see, e.g., Bernard & Welch, 2004). Manconi et al. (2012) discuss such an asset fire sale in their event study of the beginning of the Great Financial Crisis (GFC), where the sale was driven by funds that held many securitized assets.

During times of a liquidity shock that forces the selling of security for a large group of investors, combined with high transaction costs, Duffie et al. (2007) argue that an extended period in which prices deviate from fundamental values can follow. The speed at which prices recover depends largely on counterparty search costs and related market liquidity. In illiquid environments, price recovery may take considerable time as market participants wait for sufficient counterparties. Coval and Stafford (2007) discuss that simultaneous distress sales of multiple funds facing severe outflows can exert significant downward pressure on the fund's securities, defined as an asset fire sale. In other settings, researchers find price pressure due to sell-offs by insurance companies following credit downgrades (see Ellul et al., 2011).

On the contrary, Ambrose et al. (2013) discuss that corporate bond downgrades and subsequent sell-offs do not significantly affect bond prices if corporate fundamentals take the information on credit ratings into account. These findings contradict the notion of a large body of literature showing flow-induced price pressure in equity holdings, notably Coval and Stafford (2007). One explanation for the diverting conclusions between the bond market and equity market literature is that corporate bond funds do not respond to investor redemption requests by liquidating corporate bonds dollar-for-dollar, as equity funds would do (Choi et al., 2020). Instead, corporate bond funds use their cash buffers or trade securities in other liquid asset classes before trading corporate bonds. This mechanism is supported by Chernenko and Sunderam (2016), who argue that corporate bond mutual funds perform liquidity transformation for investors, which comes from the selective trading by funds of liquid assets. Besides, fund trading can be based on valuations, reducing holdings that funds expect to generate a lower return from. The previous reasoning would suggest that CBMF managers actively avoid fire sales not only at the asset allocation level but also at the security selection level, just as hedge funds do not engage in fire sales (Boyson et al., 2010).

2.2 Green Bonds

Previous research in the domain of green bonds has given insights into the risk characteristics and the associated premium, providing a better understanding of the financial implications of these environmentally-focused investments.

2.2.1 Green Bonds and their Risk-Return Profile

Previous studies examined the risk profile of green bonds in comparison to their conventional counterparts (see, e.g., Zerbib, 2019; Yang & Zhou, 2017). Notably, the prevailing body of literature suggests that green bonds share risk characteristics similar to traditional bonds. While the escalating risk of 'carbon bubbles' challenges the profitability of 'brown' investments (Glomsröd & Wei, 2018), it does not necessarily imply that green investments consistently outperform. The credit metrics, default rates, and credit spreads of green bonds have frequently been found to be on par with, if not slightly better than, those of non-green bonds (Zerbib, 2019). However, research has found that when green bond issuance is announced, the stock market index reacts positively, as more liquidity and trust can be shown in the financial market after this issuance (Tang & Zhang, 2020). Moreover, this positive effect can also be attributed to issuance that has influenced the firm's financial performance (Flammer, 2020). Furthermore, Glomsrod and Wei (2018) argue that green finance leads to shifts in investments toward industries generating more value.

A green bond premium, the so-called 'greenium', refers to the potential outperformance or financial advantage associated with green bonds, remains a subject of interest and debate (Cortellini & Panetta, 2021). Earlier literature primarily explored whether green bonds carry a premium or, conversely, a penalty in terms of returns (Liaw, 2020; MacAskill et al., 2021). Despite varying methodologies and data sources, most studies have yielded similar results: the presence of a green bond premium is elusive. For example, Febi et al. (2018) found a negative relation between credit spreads and green bonds compared to their non-green counterparts within the UK. However, their evidence yields controversial results. Moreover, Wang et al. (2020) support the claim of the existence of the 'greenium' by researching the effect of green bonds on credit spreads in China. On the contrary, Hachenberg and Schiereck (2018) found that green bonds, on average, are priced tighter than conventional bonds for investment-grade bonds. Similarly, Hyun et al. (2019) found no robust and significant yield premium or discount on average.

Turning to the risk-return profiles of socially responsible investing (SRI) funds, Gil-Bazo et al. (2009) argue that US SRI funds have better before- and after-fee performances than non-SRI funds. On the other hand, Ibunkle and Steffen (2015) discuss that initially, green funds underperformed but improved their performance over time, eventually matching that of conventional bonds.

The lack of consistent evidence supporting a green bond premium in favor or against can be explained by several factors. First, the risk profiles of green bonds and their traditional peers are remarkably similar (Yang & Zhou, 2017). Second, Hillebrand and Thier (2023) discuss that investors' motives for choosing green bonds often extend beyond financial gain; motives could also arise from the investor's ethical convictions. This mix of financial and non-financial motivations results in complex investor behavior that does not conform to traditional financial theories (Derwall et al., 2005). Finally, market inefficiencies, such as limited liquidity in the green bond market and the absence of standardized pricing mechanisms, can contribute to irregular pricing dynamics (Deschryver & Mariz, 2020).

2.2.2 Green Bonds in Portfolio Mix

For decades, there has been a prevailing assumption on portfolio optimization theory by Markowitz (1952), which refers to the thought that committing to a limited set of stocks involves a trade-off with standard risk-reward optimization. Advocates of this perspective posit that SRI is motivated by beliefs and personal motivations, which yield non-financial rewards (Hillebrand & Thier, 2023). However, among others, Statman (2000) shows that SRI investors are equally motivated by gaining from financial investments as their conventional peers.

Moreover, some studies have shown that green bonds can benefit diversification by exhibiting lower correlations with traditional financial assets. Naeem et al. (2021) studied the impact of COVID-19 on the dynamic connectedness of green bonds with various substantial financial assets. They suggested that there exists a heterogeneous relationship between financial assets and green bonds. Furthermore, it is found that medium and long-term investors may use green bond investments as a hedge against downside risks (Arif et al., 2022).

Broadstock and Cheng (2019) argue that the financial market's volatility, economic policy uncertainty, and increasing oil and energy prices significantly impacted green bonds. Some scholars found an inverse relationship between oil prices and green energy stocks (Sadorsky, 2012), while others could not find a significant correlation between renewable energy prices and oil (e.g., Reboredo et al., 2020).

The relation among different assets seems to be stronger in the short run than in the long run (Naeem et al., 2021). One could argue that the speculative behavior of active investors drives the correlation between green bonds and other assets. In addition, the increased connectedness reflects the increasing demand for this new asset (Reboredo et al., 2020). Being interested in good portfolio diversification, investors gradually accept green bonds as good alternatives to conventional bonds (Tu et al., 2020).

2.3 Hypotheses Development

Previous studies have already identified a relationship between distressed mutual funds and liquidity (see Choi et al., 2020; Coval & Stafford, 2007). While it is a customary practice for fund managers to prioritize the sale of their most liquid assets initially, the subsequent divestment of various types of corporate bonds remains a less clear and debated area (see, e.g., Chernenko & Sundaram, 2016; Choi et al., 2020; Boyson et al., 2010). In addition, several scholars show a relationship between distressed financial periods and green bonds (Broadstock & Cheng, 2019; Naeem et al., 2021). Based on the previous literature, I derive my hypotheses.

First, fund managers prefer immediate liquidity, prioritizing it over the retention of assets perceived as carrying lower risk during an asset fire sale (Dow & Han, 2017). In this study, where green and non-green bonds share similar characteristics, the emphasis shifts toward preserving assets deemed safer within the fund. Naeem et al. (2021) find that green bonds can serve as a hedge for other assets. The hedging effect arises from the fact that the issuing firm demonstrates a commitment to the future by investing in sustainability and resilience to climate change (Manring & Moore, 2006). Therefore, distressed diversified mutual funds are less likely to prioritize the sale of green bonds over non-green bonds during an asset fire sale. Instead, they are inclined to employ green bonds as a risk hedge, which results in no significant surge in trading volume for these bonds compared to non-green bonds.

H1. Mutual funds are more likely to sell non-green bonds than green bonds during an asset fire sale.

Secondly, to further deepen the relationship between asset fire sales and green bonds, this study examines the price impact following an asset fire sale. Some scholars suggest that green bonds can serve as a hedge, protecting the fund against downside risk in uncertain economic conditions, as observed during the COVID-19 pandemic (see, e.g., Arif et al., 2022; Dong et al., 2023). Moreover, some studies indicate that this connection between green bonds and financial performance is more pronounced in the short and medium term compared to the long term, given that asset fire sales typically represent short-term shocks. Hence, it is expected that, owing to their sustainability focus, green bonds will demonstrate relatively stronger performance during a financial crisis when compared to non-green bonds within the portfolios of corporate bond mutual funds.

H2. Green bonds within portfolios of CBMFs will outperform their peers during an asset fire sale.

3 Data

This section describes the data used in the study, including the data source, sample construction, main variable construction, and descriptive statistics of the variables.

3.1 Data source and sample construction

The sample for this study consists of US open-end active corporate bond mutual funds from 2013 Q1 to 2023 Q1. This period was chosen as green bonds started to gain momentum after 2013 in the United States. Additionally, this period includes COVID-19, which seems interesting as this potentially triggered asset fire sales.

Information on mutual fund quarterly holdings is retrieved from the Morningstar Direct database, and fund returns and characteristics are obtained from the CRSP Survivorship-Bias-Free US Mutual Fund Database. Survivorship bias occurs when a performance analysis only focuses on the surviving entities (e.g., mutual funds), resulting in an overestimation. Following Brown et al. (2014), this study includes non-surviving funds (liquidated or merged) to overcome this bias. The Morningstar Direct Database serves as a comprehensive financial database that is broadly used for portfolio analysis and investment research. CRSP offers a database with historical information on mutual fund characteristics and performance. It is important to note that data is only available at the share class level of a fund, encompassing specific types of shares, such as class A and class B shares of the fund. This level of granularity allows researchers to analyze the performance and characteristics of each share class separately. Nevertheless, for the scope of this research, which emphasizes broader trends at the fund level, this level of detail is unnecessary. Consequently, share-class-level observations are converted into fund-level observations, whereby share-class data is aggregated and weighted by the net asset values (NAV) of each fund.

Following the methodology of Choi et al. (2020), the mutual funds in the sample are classified as corporate bond funds based on the Lipper objective code A, BBB, HY, SII, SID, and IID or the CRSP objective codes starting with IC. Notably, index funds, exchange-traded funds, and exchange-traded notes are omitted from the sample, aligning with the focus on actively managed funds as discussed in Section 2.1.1. Further, inclusion criteria require funds to have a minimum total net assets of 1 million US dollars, similar to Elton et al. (2003), who discuss that historical data of smaller funds is likely inaccurate. Besides, mutual funds need to have at least one year of holdings data and ten distinct holdings at some point in time to ensure sufficient diversification within the portfolio of the fund (Evans & Archer, 1968). Additionally, $0.5 < \frac{TNA_{j,t}}{TNA_{j,t-1}} < 3$ should hold for fund j in month t. Funds with extreme changes in total net assets (TNA) are eliminated to avoid potential data errors. Lastly, to be classified as a corporate bond mutual fund, funds must have invested at least 20% of their total assets in corporate bonds in the previous quarter (Choi et al., 2020). After applying these criteria, the final sample comprises 673 active corporate bond funds, including 308 funds holding at least one green bond.

Corporate bond pricing data is obtained from the WRDS Bond Database, a source for US corporate bond research. This database combines bond transaction data from TRACE with data for issue and issuer characteristics from the FISD database. The novel database of WRDS aims to provide researchers with a comprehensive dataset for corporate bond trades from July 2002. TRACE provides pricing information, the total traded amount in the market, and other transaction information. Terms and conditions information, including coupons, ratings, maturity, and amounts outstanding, is sourced from FISD. In addition, information on Treasury bonds is obtained from the CRSP US Treasury Database. Data comprises price observations for US Treasury bills, notes, and bonds since 1925. Moreover, to identify and analyze green bonds, the Eikon financial data platform provided by Refinitiv is utilized. Eikon employs a classification system aligned with the Green Bond Principles (Refinitiv Eikon, 2021).

For the analysis at the bond level, convertible bonds, foreign currency bonds, and bonds with a maturity of less than one year are excluded. First, convertible bonds have unique characteristics as they can be converted into a predetermined number of shares of the issuing company's common stock. The conversion feature introduces additional complexities and dynamics that may significantly affect their pricing and trading behavior (Batten, 2018). Secondly, Chernov et al. (2020) discuss that foreign currency bonds involve exchange rate risks, which can introduce additional sources of volatility and variability in their yields. Thirdly, bonds with a short maturity tend to exhibit different characteristics and trading dynamics than longer-term bonds. Additionally, their short-term nature may result in limited availability of data and less meaningful analysis over shorter periods (Goldstein & Namin, 2023). The resulting bond-level sample comprises 256,495 bond-quarter observations from 2013 Q1 to 2022 Q3.[1] Integration with Refinitiv Eikon data expands the sample to identify 126 green bonds held by the sample mutual funds from 2013 Q1 to 2022 Q3.

3.2 Main variable construction

The main objective of this paper is to research the impact of a crisis, especially an asset fire sale, on the liquidity and pricing of green bonds. Coval and Stafford (2007) discuss that mutual funds having substantial outflows find themselves in a position where they must sell off some of their holdings to meet redemption requests. Moreover, alternative options, such as using excess cash reserves or financing via extra borrowing, are considered difficult in practice (Manconi et al., 2012). Further, Almazán et al. (2004) discuss that short-selling other securities is often not feasible due to regulatory constraints. Specifically, the US Investment Company Act of 1940 restricts mutual funds' ability to engage in short selling and margin trading of securities. Therefore, to identify the liquidity-motivated trading behavior of funds, I first follow Coval and Stafford (2007) and calculate contemporaneous monthly mutual fund flows:

$$FundFlow_{j,t} = \frac{TNA_{j,t} - TNA_{(j,t-1)} * (1+r_{j,t})}{TNA_{j,t-1}}, \tag{1}$$

Where $TNA_{j,t}$ is the total net assets for fund j at the end of month t, and $r_{j,t}$ is monthly returns for fund j over month t. Further, to match with the quarterly holding data, quarterly flows are defined as the sum of monthly flows during a quarter.

Secondly, to measure the price effect of asset fire sales on the performance of green bonds, the change in yield spread is used. Goldstein and Namin (2023) argue that using the change in yield spread provides a standardized and comprehensive way to assess the relative price movements of different bonds. The main reason is that you can control for any term spread difference between bonds of a given issuer. In the sample, the last available yield within five days at the end of the month is winsorized at 1% to eliminate potential errors in recorded yields (Bessembinder et al., 2009). After calculating the credit spread, Treasury yields are subtracted

[1] Bond pricing data ranges from 2013Q1 till 2022Q3 due to limits in data availability from the WRDS Bond Returns database.

from the monthly yield using linear interpolation of closest maturity yields at the same recording date (Hagan & West, 2006). Appendix A describes all variables included in this study.

3.3 Descriptive statistics

Descriptive statistics for dependent and independent variables in this study are stated in Table 1, Panel A for fund-level variables, and Panel B for bond-level variables. In Panel A, on average, the sample funds have 63% of corporate bond holdings for 2013-2022. Noteworthy, 308 funds have invested in green bonds, of which the mean investment is about 0.76% of their total net assets, with a maximum investment of 75.27%. The US Mutual Funds investment in green bonds seems quite low compared to European Mutual Funds, where, on average, they invest 3.7% (Boermans, 2023). However, the global average ratio to total outstanding bonds is 1.5% for green bonds (Han & Li, 2022). Surprisingly, the funds have a mean monthly TNA of 1,992 million dollars and a quarterly flow of 0.21% of TNA. From 2013 through 2022, this low quarterly fund flow percentage could be partially explained by uncertain financial periods due to COVID-19 restrictions (International Monetary Fund, 2020). Zahera and Bansal (2018) argue that during uncertain economic times, investors may hold back from making large fund allocations. In Panel B, the average yield spread is 400 percentage points (or 0.04), and the median monthly return equals 0.02%. The average age of the corporate bonds is 4.64 years. Interestingly, the bid-ask spread has a mean of 0.44%.

Table 1. Summary Statistics

This table provides an overview of the summary statistics for the sample funds and bonds. The sample contains active US open-end corporate bond mutual funds available in the Morningstar Direct and CRSP databases. Panel A provides summary statistics for individual funds with quarter-level observations. *TNA* is the total net assets at the end of the quarter in millions of US dollars, and *Quarterly Flow* is the net capital flow to a fund during a quarter. *Equity Ratio and Corp Bond Ratio* are ratios of dollar amounts of equity and corporate bonds, respectively, to total net assets at the end of a quarter. Additionally, the *Green Corp Bond Ratio* is the proportion of green bonds to non-green bonds held within a mutual fund at the end of a quarter; *Expense Ratio* are total expenses relatively to total net assets; *Green Fund* is an indicator variable and denotes 1 for each fund that holds at least 1 green bond during a quarter.

In Panel B, summary statistics are given for individual corporate bonds at quarter observations. *Yield Spread* represents the yield spread of a bond at the end of the quarter; *Return* is the monthly bond return; *Age* is the age of a bond in years; *Rating* is the credit rating of a bond in integers for which 10 is assigned to AAA rating, 9 to AA, 8 to A, and so on; *Amount Outstanding* is the US dollar amount of bonds outstanding in millions of dollars; *Bid-ask Spread* is the average weighted bid-ask spread; *Green Issuer* is a dummy variable and equals 1 if the firms issued at least one green bond. All variable definitions are in Appendix A. The sample period runs from 2013Q1 through 2023 Q1. The sample period for the bond-level variables runs from 2013Q1 to 2022Q3 due to data availability of the TRACE database.

Variables	N	Mean	SD	25%	50%	75%
Panel A: Fund-Quarter Level						
Quarterly Flow Ratio	22,362	0.21	7.52	-0.04	-0.01	0.02
Fund Turnover Ratio	14,338	1.10	1.68	0.40	0.63	1.18
TNA (millions of dollars)	22,362	1,991.71	5,862.33	91.80	335	1,239.80
Fund Return (percent, monthly)	22,362	-0.19	2.80	-0.56	0.05	0.61
Equity Ratio (percent)	22,362	0.97	3.14	0.00	0.01	0.71
Corp Bond Ratio (percent)	22,362	62.75	24.06	40.35	60.12	87.86
Green Corp Bonds Ratio (percent)	22,362	0.76	2.86	0.00	0.13	0.57
Expense Ratio (percent)	22,362	0.47	0.43	0.00	0.50	0.77
Green Fund	22,362	0.78	0.41	1.00	1.00	1.00
Panel B: Bond-Quarter Level						
Yield Spread (monthly)	254,380	0.04	0.04	0.02	0.03	0.05
Bond Return (percent, monthly)	221,633	-0.27	3.94	-0.94	0.02	0.84
Time to maturity (years)	256,495	10.41	9.83	3.72	6.63	15.01
Age (years)	256,495	4.64	4.78	1.00	3.00	6.00
Rating	256,495	7.16	1.16	7.00	7.00	8.00
Amount Outstanding (USD mln)	256,495	762.70	666.39	350.00	505.69	100.00
Bid-Ask Spread (percent)	241,694	0.44	0.58	0.17	0.30	0.53
Green Issuer	256,495	0.11	0.31	0.00	0.00	0.00

4 Methodology

4.1 Identification Strategy

This study investigates the effect of an asset fire sale on green bonds, especially the price impact of green bonds relative to non-green bonds. Price impact can be analyzed by comparing the intrinsic values of bonds with their actual market prices. However, complexity arises as the intrinsic value of a bond is hard to determine. A decline in bond price can result from an asset fire sale or be the reflection of new adverse information regarding the intrinsic value of the bond (Shleifer & Vishny, 2011).

To provide valuable insights, this study seeks to disentangle the effects of liquidity-driven sales from information-driven sales. Two key assumptions must hold. Firstly, fire sales and fund redemptions are not connected to the intrinsic value of the holdings (Choi et al., 2020). Secondly, the decisions of fund managers about which assets to sell are independent of the actual value of those assets (Coval & Stafford, 2007).

Berk and Green (2004) discuss that only a simultaneous sell-off by many funds could have a significant impact on the security. Consequently, aggregate bond flows can be used to indicate investor sentiment (Lamont & Frazzini, 2007). Building on this, other scholars include pre-crisis exposure to financial assets as exogenous shocks to fund flows during the crisis (Hau & Lai, 2013; Manconi et al., 2012). Choi et al. (2020) argue that ideally, the study compares bonds with their peers from the same issuer, all of which share exposure to the same fundamental risks. In that way, even if fund flows or fund managers' decisions are linked to a bond's intrinsic value, such a linkage should similarly affect the bond's peers.

Noteworthy, the unique characteristics of green bonds lie in the intended use of proceeds, emphasizing environmentally responsible projects (Flammer, 2020). Therefore, being 'green' is exogenous to an asset fire sale examined in this study.

To mitigate potential endogeneity issues, this study aggregates mutual funds flows at the bond level per quarter, as suggested by Lamont and Frazzini (2007). In addition, a difference-in-difference regression is conducted, as suggested by Choi et al. (2020). Green bonds are compared with non-green same-issuer bonds held by the same fund during a potential fire sale.

4.2 Asset Fire Sale Measure

Building on the work of Choi et al. (2020), fire-sale assets are defined as assets in which a substantial portion of trading is attributable to mutual funds facing large capital outflows. To construct this measure, first of all, funds are sorted cross-sectionally based on quarterly flows and picked as 'distressed funds' if they are in the bottom decile. Sorting is needed because, in the bottom decile, funds are subject to the largest redemptions and, therefore, encounter the most pressure to sell off their holdings. Subsequently, it is calculated how much-distressed funds sell, in aggregate, of a corporate bond holding in a given quarter divided by the average market trading volume of the specific bond i in prior quarters. The historical average market trading volume serves as a benchmark to evaluate deviations in current trading volumes. If mutual fund trading significantly diverges from the broader market activity, it potentially signifies the occurrence of an asset fire sale. Specifically, for bond i of fund j at quarter t, selling pressure due to liquidity-driven sales is defined as:

$$SellPress1_{i,j,t} = \frac{\sum_{f=1}^{F}[\max(-\Delta Holdings_{ijft}, 0)]}{Average\ Volume_{i,t-12:t-6}}, \tag{2}$$

where, $f \in \{flow_{f,t} < Percentile(10^{th})\}$.

In addition, Coval and Stafford (2007) argue that in cases of heavy selling pressure, if another fund is willing to purchase the asset, there should be no substantial downward pressure on the asset's price. Now, flow-induced purchases are labeled as increases in bonds owned by funds experiencing severe inflows and thus sorted funds in the upper decile of quarterly flows. Therefore, the second sell-off exposure measure for bond i of fund j in quarter t is:

$$SellPress2_{i,j,t} = \frac{\sum_{k=1}^{K}[\max(0, \Delta Holdings_{ijft})] - \sum_{f=1}^{F}[\max(-\Delta Holdings_{ijft}, 0)]}{Average\ Volume_{i,t-12:t-6}}, \tag{3}$$

where, $k \in \{flow_{k,t} > Percentile(90^{th})\}$ and $f \in \{flow_{f,t} < Percentile(10^{th})\}$.

In order to be sure that the denominator is not driving the results, I scale the measure by amount outstanding rather than the average trading volume over prior quarters. Scaling by the quantity of bond's outstanding assesses whether trading volume is proportionate to the bond's overall market liquidity. Following, the third sell-off exposure measure:

$$SellPress3_{i,j,t} = \frac{\sum_{k}[\max(\Delta Holding_{i,j,k,t}, 0)] - \sum_{f}^{F}[\max(-\Delta Holding_{i,j,f,t}, 0)]}{Amount\ Outstanding_{i,t-1}}, \tag{4}$$

where, $k \in \{flow_{k,t} > Percentile(90^{th})\}$ and $f \in \{flow_{f,t} < Percentile(10^{th})\}$.

Finally, $Asset\ Fire\ Sale_{i,t}$ a dummy variable is created. Taking the value of one for bonds that are in the top 10th percentile based on the $SellPress1$ measure, and bottom 10th percentile for $SellPress2$ and $SellPress3$, and otherwise zero. Hence, a potential fund fire sale is signified by a binary variable denoted $Fund\ Fire\ Sale_{j,t}$. It takes the value of one if any of the bond holdings are undergoing a fire sale in that specific quarter. Important to note is that a fire sale is not restricted to occur only once within a mutual fund in the sample period. However, repeating fire sales are restricted in the four consecutive quarters. Additionally, they are not allowed in 2013Q1 and 2022Q3, because pre-estimation, and post-estimation effects, respectively, cannot be calculated (Desphande et al., 2019).[2]

[2] Extending the observation period to e.g., 6 consecutive quarters would lead to a substantial data loss.

4.3 Mutual fund-level investigation on trading behavior

4.3.1 Regression model

The main objective of this paper is to research the effect of asset fire sales on green bonds. First of all, to investigate the trading behavior of corporate bond fund managers in response to redemptions concerning green bonds and their non-green counterparts, I follow the approach of Ellul et al. (2011). The focus is to uncover how funds adjust their trading activities between green and non-green bonds, taking into account different levels of market liquidity in response to investor liquidity needs. Therefore, I regress the negative amount of fund trade in corporate green bonds and corporate non-green bonds separately on quarterly fund flows (Choi et al., 2020):

$$FundTrade_{j,t} = \alpha + \beta \cdot FundFlow_{j,t} + X_j + \gamma_j + \delta_t + \varepsilon_{j,t} \text{ ,} \tag{5}$$

where, $FundTrade_{j,t} = \left(\frac{AmountHold_{j,t}}{AmountHold_{j,t-1}}\right) - 1$, is the aggregate trading volume of fund j as a proportion of its holding at the end of quarter t in corporate green bonds or corporate non-green bonds. X_j is a vector for all control variables. And γ_j approaches fund fixed effects to control for fund-specific characteristics that might influence the relation, such as fund strategy or fund culture (Cuthbertson et al., 2016). In addition, quarter fixed effects (δ_t) are included to control for heterogeneity from differences in the timing of observations of fund trading (Dyakov & Verbeek, 2013).

4.3.2 Control Variables

Previous studies in the literature primarily focused on equity mutual funds and explored various non-performance-related determinants of fund flows, which are also likely to hold significance for corporate bond funds (see, e.g., Manconi et al., 2012; Mitchell et al., 2007). Therefore, I draw on existing literature to specify X_j as in Equation (5). which includes controls for the following.

First of all, Yan (2008) discusses that larger funds in terms of TNA tend to receive relatively smaller percentages of fund flows. Thus, fund size is included in the model.[3] In addition, past fund flows often correlate with fund performance. Positive flows may be driven by strong performance, while negative flows could result from underperformance. A fund's past performance can affect its ability to invest in green bonds and its investors' willingness to invest (Cuthbertson et al., 2016). Moreover, a higher equity ratio can signify greater exposure to stock market fluctuations and may be characterized by significant stock price declines during a fire sale crisis. Therefore, mutual funds with high equity ratios may respond by reducing their stock holdings to mitigate further losses and encompass bond holdings (Moyer et al., 2003). Additionally, fund returns can have a lagged impact on other variables. For example, positive

[3] It is important to note that the variable is highly skewed. According to Adkins & Hill (2008), the logarithm of a variable can be taken to improve normality if the variable is highly skewed.

returns in the past may attract more investors or lead to changes in the fund's strategy (Amihud & Goyenko, 2012). Including returns as a control can account for this lagged impact. Furthermore, the average maturity of a fund's holdings is added to control for interest rate risk, potential returns, income generation, and alignment with the investors' risk preferences and market expectations (International Monetary Fund, 2022). On top of that, Sirri and Tufano (1998) find a negative relation between fund flows and total fund expenses (amortized front-end-load fees and operating expenses). Thus, the expense ratio is included as a control variable in the regression.

4.4 Bond-level investigation on price impact

4.4.1 Stacked Difference-in-Differences

To further deepen the relationship between asset fire sales and green bonds, the price impact of green bonds following a fund fire sale is analyzed. I use the change in the yield spread as a proxy for price impact. This study employs a robust stacked difference-in-differences (DiD) model. The treatment group consists of green bonds held by a fund under fire sale (as defined in Section 4.2). Accordingly, the control group exists of non-green bonds with similar characteristics held by the same fund during a fire sale.

The control group is constructed by matching treated bonds based on the following criteria: (1) bonds must be issued by the same firm to account for firm-specific effects and to tackle potential endogeneity as discussed in Section 4.1.; (2) bonds have the same seniority, option features, and credit rating to ensure comparability; (3) the difference in time-to-maturity between treated and control bonds is restricted to be less than one year. Furthermore, the bonds are held by the same fund j at time t one quarter prior to an asset fire sale (Choi et al., 2020).

In this study, mutual funds experience asset fire sales at different times in the sample ranging from 2013 Q3 to 2022 Q2. Meaning that treatment for a green bond across funds varies across asset fire sale quarters. Moreover, treatment switches within groups as fire sales are restricted to once per five quarters (two quarters before and after). The dynamic treatment periods and dynamic treatment status introduces complexity to the traditional DiD design (Baker et al., 2021; Callaway & Sant'Anna, 2020).

In their work on the staggered rollout of treatments, Sun and Abraham (2021) propose the estimation of group-specific dynamic effects and the calculation of group-specific estimates. However, this approach poses challenges related to the parallel trend assumption due to the dynamic nature of the treatment status. In this dynamic setting, the counterfactual scenario may involve units switching between treated and untreated funds, making it challenging to establish the underlying trends. Strict exogeneity, as described by Kahn-Lang and Lang (2019), is achieved only when the structural error term in a dynamic regression model is uncorrelated with the treatment variable.

Cengiz et al. (2019) incorporate an idea introduced by Goodman-Bacon (2019), which highlights that identical trends are not necessary; variance-weighted common trends suffice. A noteworthy aspect of their approach is the application of the same weights used in the Variance-weighted Average Treatment Effect on the Treated (VATT) to address non-parallel-trend biases. In this context, time-varying treatment effects, even when consistent across units, can lead to significant cross-group heterogeneity. This occurrence would be due to varying post-treatment windows and the role of earlier-treated groups as controls, potentially introducing bias.

To mitigate this bias, Cengiz et al. (2019) address the issues discussed by Goodman-Bacon (2019) by employing a data stacking technique. Within this framework, each stack comprises treatment and control groups linked to a specific 'event'. An essential criterion is that only non-treated bonds that within the sample stack window are allowed to be controls. Therefore, a stacked event study approach is an analytical method designed to assess the causal impact of a treatment or intervention when the timing of the treatment varies across different units or groups (Cunningham, 2021).

In the model, I follow the methodology as outlined in Cunningham (2021), and as implemented in Cengiz et al. (2019). First, 250 separate datasets (or stacks) are created associated with a fund fire sale. Each comprises bond-quarter observations from a specific 'cohort' of green bonds that experienced a fund fire sale in the same quarter and fund and non-green bonds as a control group. These 250 estimates are then stacked together, and a linear regression with multiple-level fixed effects is executed. Multiple-level fixed effects are used to control for unobservable heterogeneity that stays constant within an economic unit (Correia, 2016). Fixed effects include bond by stack fixed effects, issuer by stack fixed effects, and standard errors are clustered on bond level (Bertrand, 2002; Cengiz et al., 2019). Leads and lags are included in the regression to consider the effects of the treatment over a range of periods before and after the treatment event (Miller et al., 2019).

Overall, this gives the following regression model:

$$\Delta YieldSpread_{i,t} = \alpha + \beta * Green_i + \sum_{n=-2}^{1} \gamma_n Q(n)_{i,j,t} + \sum_{n=-2}^{1} \theta_n Q(n)_{i,j,t} \cdot Green_i + \vartheta_m + \varepsilon_{i,t} \quad (6)$$

where $\Delta YieldSpread_{i,t}$ is the change in yield spread of bond i in quarter t, to control for any term spread difference between bonds of specific issuers (Manconi et al., 2012). $Green_i$ is a dummy variable indicating that it is a green bond defined by the Green Bond Principles, however, this effect is subsumed by introducing bond fixed effects. $Q(n)_{i,t}$ is an indicator variable for indicating the n^{th} quarter from a fund fire sale quarter for bond i in fund j in quarter t. Issuer fixed effects (ϑ_m) for issuer m are introduced to control for issuer-specific information. Finally, heterogeneity within funds and time is accounted for by creating different stacks on asset fire sale events within a specific fund and quarter.

4.4.2 Parallel trend assumption

When conducting a traditional difference-in-differences analysis, it is crucial to assess the validity of the control group. Namely, suppose there are non-zero mean or median differences in matching variables. In that case, it suggests that systematic disparities between the treatment and control groups potentially violate the assumption of parallel trends (Goodman-Bacon, 2019). Namely, the parallel trend assumption assumes that treatment and control groups follow similar trends without treatment (Adkins & Hill, 2008).

Table 2 shows summary statistics for the treatment, control, and non-treatment groups for the last quarter before a fire-sale event. The treatment group consists of 165 green bonds issued by 90 firms that experience one or multiple fund fire sales in 274 different. Accordingly, the control group exists of 1,584 non-green bonds issued by the same firms. The non-treatment group includes all other bonds from different issuers or in funds that never experienced an asset fire sale, compromising 14,407 bonds.

Results for the mean and median tests, tabulated in Table 2, indicate that the treated and control groups share many key characteristics. Only the mean difference in rating is statistically significant, however not substantial in magnitude. For example, the average difference in security level is 0.12 (equal to 5.25 – 5.13), which is unlikely to challenge the identification strategy. The same yields for the time to maturity, where the median difference is -0.44 (12.38-11.94). Nonetheless, to ensure robustness, the difference in the median for time to maturity and mean in security level is approached by controlling for those variables in the difference-in-difference regression as a control.

While non-parallel trends can challenge the validity of conventional difference-in-differences models, a stacked difference-in-differences model offers an effective solution to this issue. As discussed in Section 4.3, this model creates a separate DiD analysis for each treatment event. By isolating these events, a stacked DiD can accommodate variations in trends and treatment effects. Consequently, the difference in median or mean values between green and non-green bonds is incorporated into the model, mitigating the risk of potential bias.

Table 2. Summary Statistics: treated, matched control group, and non-treated bonds

This table provides the results of difference tests on means and medians across the treated, control, and non-treated bonds at the end of the last quarter before a fire-sale quarter. The treated group (*Treated*) comprises green bonds, exposed to a fund fire sale, and the control group (*Control*) exists of non-green bonds that are exposed to the same fund fire sale. Section 4.4.1. describes matching criteria. The group of non-treated bonds (Non-treated) are composed of all other bonds held by corporate bond mutual funds in the sample that have never been exposed to fire sales. I provide statistics for bond-level characteristics and test statistics of mean and median differences. The mean test is a two-sample t-test, and the median test is a Pearson's chi-squared test. Absolute values of t- and χ^2- statistics from the mean and median tests, respectively. N is the number of bond-quarter observations. The variable descriptions are in Appendix A. The values in parentheses are p-values. The sample period for the treatment runs from 2013 Q2 through 2023 Q2.

	Summary Statistics			Test of Difference			
				Treated vs Non-Treated		Treated versus Control	
Variable	Treat mean [median]	Non-treat mean [median]	Control mean [median]	Mean $\lvert t \rvert$ (p-value)	Median χ^2 (p-value)	Mean $\lvert t \rvert$ (p-value)	Median χ^2 (p-value)
TTM (years)	12.38	10.40	11.94	6.73	158.37	1.13	28.18
	[9.00]	[7.00]	[8.00]	(0.00)	(0.00)	(0.13)	(0.00)
Rating	7.56	7.15	7.78	12.37	171.80	10.51	76.81
	[8.00]	[7.00]	[8.00]	(0.00)	(0.00)	(1.00)	(0.84)
Bond type	1.06	1.07	1.19	1.67	2.57	11.78	137.07
	[1.00]	[1.00]	[1.00]	(0.95)	(0.11)	(1.00)	(0.95)
Security	5.25	5.01	5.13	20.27	803.58	8.53	75.04
	[5.00]	[5.00]	[5.00]	(0.00)	(0.11)	(0.00)	(0.11)
N	1,552	254,943	24,437				

5 Results

The following section outlines the results of the different regressions.

5.1 Trading Behavior on Mutual Fund-Level

As defined in Section 4.2., I use quarterly fund flow as a proxy for a fund's liquidity needs. This model is estimated using a linear regression model for panel data with quarter-fixed effects and standard errors clustered around each fund (Podnobik et al., 2009). The sample includes all mutual funds holding at least one green bond in the pre-crisis period, belonging to the merged data set over the period 2013 Q1 until 2022 Q9.

Before turning to the results of Hypothesis 1, I examine the trading behavior of mutual funds regarding green bonds and non-green bonds, respectively, on fund flows in the pre-crisis period. Some researchers, like Deschryver and Mariz (2020), have observed that green bonds may have limited liquidity compared to non-green bonds. However, there are other factors, such as expectations of better financial performance (as suggested in Hartzmark & Sussmann, 2019) or reduced risk (Kruger, 2015), that might exert a more significant positive influence on how these bonds are held in a fund's portfolio. Considering the mixed results in prior research, I expect that, within mutual funds, there is no correlation between liquidity requirements in typical market conditions and their pre-crisis allocations to green and non-green bonds.

Table 3, in Columns 1 and 2, shows the estimation results for the regression of a fund's negative trade on fund flows, as specified in Equation (5). The aim is to assess whether investors with higher liquidity requirements tend to divest more corporate green bonds than non-green bonds. The results indicate an insignificant relation between the mutual fund's liquidity needs and the trading outflow for both types of bonds.

Among the control variables, it is noteworthy that funds with a higher return have a lower probability of selling both kinds of bonds. One possible explanation is that funds with higher returns demonstrate greater resilience in the face of liquidity demands and may opt to divest from other holdings before corporate bonds (Nanda et al., 2000). Additionally, the results show a negative relation between the selling of both bonds and the expense ratio. Ivković and Weisbenner (2009) explain that especially investors with high expense ratios pay attention to investment costs related to redemptions. Therefore, high expense ratios might lead to a mitigation in the outflow of corporate bonds. Moreover, a higher equity ratio does not significantly affect green bond redemption. On the contrary, it has a positive relation with the outflow of non-green bonds. This observation may be attributed to the fact that pure bond funds are often associated with fund families that prioritize fixed-income securities. Therefore, increasing equity holdings could signify a shift in investment focus.

Columns 3 and 4 display the outcomes of Equation (5) during an asset fire sale, while columns 5 and 6 depict the results during the post-quarter following an asset fire sale. Hypothesis 1 proposes that funds with greater liquidity requirements will sell a larger volume of corporate non-green bonds, respectively, to green bonds.

As seen in Columns 3 and 4, the significant coefficient on outflows β is -0.003 and-0.005 for green and non-green corporate bonds, respectively. This finding suggests that in distressed periods, more corporate bonds, both green and non-green, are sold. For a one-unit decrease in fund flow, there are 0.5% more corporate bonds sold and 0.3% of non-green bonds. Thus, this validates Hypothesis 1.

Moreover, Columns 5 and 6 tabulate the regression estimates of Equation (5) in the quarter following an asset fire sale. Interestingly, the outflow for corporate non-green bonds increases significantly to -0.127. At the same time, the outflow for corporate green bonds remains similar to the crisis period (β = -0.003). This outcome supports the notion that when fund managers require liquidity, their preference is to sell non-green bonds rather than green bonds. Fatica and Panzica (2021) found similar results for the COVID-19 pandemic. An alternative explanation could be the limited liquidity of green bonds, potentially leading to higher redemption costs. This higher cost may make fund managers more hesitant to sell green bonds (Kahn & Wagner, 2010).

Overall, the results reported in Table 3 show that (i) mutual funds engage in trading activities for corporate bonds which are seemingly uncorrelated with the fund's liquidity needs prior to a crisis, and (ii) when faced with an asset fire sale, mutual funds initially liquidate roughly equal percentages of both types of corporate bonds. However, post-crisis, they tend to increase their trading activity of non-green corporate bonds while the amounts of corporate green bonds they sell remain relatively stable.

Table 3. Liquidity-Sensitive Trading at Mutual Fund-Level

This table reports the estimations of the following regression model:

$$FundTrade_{j,t} = \alpha + \beta \cdot FundFlow_{j,t} + X_j + \gamma_j + \delta_t + \varepsilon_{j,t} \quad , \tag{5}$$

where $FundTrade_{j,t} = \left(\frac{AmountHold_{j,t}}{AmountHold_{j,t-1}}\right) - 1$, is the aggregate trading volume of fund j as a proportion of its holding at the end of quarter t in corporate green bonds or corporate non-green bonds. And $FundFlow_{j,t}$ is the quarterly flow of a fund as specified in Equation (1). X_j is a vector for all control variables. γ_j and δ_t denote fixed effects for funds and time, respectively. Robust standard errors are clustered at the fund level (Petersen, 2009). Appendix A gives all variable definitions. The sample includes all mutual funds belonging to the merged sample set during 2013 Q1 – 2022 Q3. Robust standard errors are in parentheses and appear below coefficients. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Asset Fire Sale (T = -1)		Asset Fire Sale (T = 0)		Asset Fire Sale (T = 1)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Green	Non-Green	Green	Non-Green	Green	Non-Green
Quarterly Flow	-0.0022**	-0.0035	-0.0027**	-0.0053*	-0.0024**	-.0049
	(0.0009)	(0.0024)	(0.0011)	(0.0032)	(0.001)	(0.003)
Fund Size	-0.0074*	-0.0143***	-0.0072*	-0.0192***		-0.0157***
	(0.0043)	(0.003)	(0.0043)	(0.0035)		(0.0035)
Fund Return	0.0162	-1.0917***	-0.0622	-0.3000**	-0.0766	-0.3158**
	(0.0637)	(0.0579)	(0.0502)	(0.1334)	(0.0542)	(0.1422)
Equity Ratio	-0.0035*	0.0025**	-0.0033	0.0037***	-0.0018	0.0049***
	(0.002)	(0.0012)	(0.0022)	(0.0014)	(0.0022)	(0.0015)
Expense Ratio	-7.5268***	-2.2368*	-6.8891***	-6.0511***	-6.079***	-5.3902***
	(2.0113)	(1.1486)	(1.5803)	(1.2279)	(1.5285)	(1.289)
TTM	0.0015	0.0002	0.0013	0.0007	0.0016	0.0003
	(0.0013)	(0.0007)	(0.0012)	(0.0007)	(0.0014)	(0.0007)
Constant	0.1026***	1.0101***	0.1024***	1.5389***	0.0491***	1.582***
	(0.0327)	(0.1589)	(0.0301)	(0.219)	(0.0164)	(0.2269)
Observations	9,585	9,585	10,189	10,189	9,885	9,885
R-squared	0.0259	0.0907	0.0268	0.0569	0.0223	0.0606
Adj R^2	0.0252	0.09	0.0261	0.0563	0.0217	0.0599
F-stat	9.6747	66.6089	11.4881	20.9129	10.9826	19.3264

5.1.1. Robustness Check

To further add to the previous analysis and test the robustness of the model, I use an alternative proxy for a fund's liquidity needs, namely the fund's turnover ratio. Manconi et al. (2012) discuss that investors with significant liquidity requirements will exert pressure on mutual funds to offer increased liquidity. This is based on the idea of Chen et al. (2010), who discuss that short-term investors with high redemption needs mostly invest in funds with high portfolio turnover ratios. Jin et al. (2020) explain this behavior by considering investor's tax considerations. Buying and selling frequently can lead to capital gains within a short period. Therefore, these taxable capital gains can result in undesirable higher tax liabilities for long-term investors. As a result, this fund will participate in trading driven by changes in fund flows and motivated by liquidity needs. In this research, I use the CRSP mutual fund's turnover ratio as a proxy for the fund's turnover.

The results, available in Appendix B, indicate no statistically significant impact of a mutual fund's liquidity needs on the trading of both green and non-green bonds. This confounding result highlights the complex nature of the relationship between these bond categories and the liquidity-trading behavior of mutual funds. It is worth noting that the adjusted R-squared in Column 3 of Table 3 is quite low (0.0268), signaling limited predictive power. This shared attribute of low adjusted R-squared values across these regressions suggests that the insignificant relationship observed may be because quarterly outflows offer a more direct indication of investors' liquidity requirements. In contrast, the turnover ratio may not capture these dynamics as effectively.

5.2 Price impact on green bonds after an asset fire sale in that fund

The previous sections show that distressed mutual funds tend to liquidate both green and non-green corporate bonds during an asset fire sale; however, in the quarters past an asset fire sale, their preference shifts towards selling non-green corporate bonds over green ones. Now, I examine whether corporate green bonds, held by investors with substantial exposure to asst fire sales, undergo a price impact relative to their non-green counterparts. As discussed in Section 4.4, the change in yield spread is employed to indicate the price impact resulting from a fund asset fire sale on bonds.

Table 4 displays the regression results for Equation 6, where difference measures of asset fire sales ($SellPress1$, $SellPress2$, and $SellPress3$) are used. Before delving into the examination of Hypothesis 2, it is important to ensure that these proxies behave as anticipated. Therefore, their pre-trends in the change in yield spread of green bonds relative to non-green bonds are analyzed.

Previous research, such as Zerbib (2019), has often found that the credit spread of green bonds is comparable to, if not slightly better than, those of non-green bonds. Consistent with this, the results reveal a coefficient of -0.0128 for the change in credit spread of green bonds relative to their non-green counterparts two quarters prior to an asset fire sale. This result suggests that the change in yield spread of green bonds is 128 basis points lower than that of non-green bonds. For the quarter prior to a fire sale, the effect is similar, only smaller (-0.0048). When a bond's yield spread is lower, it indicates a lower perceived risk and, consequently, a lower expected return. In turn, this leads to an increase in bond prices.

This finding aligns with the work of other researchers, such as Dong et al. (2023), who have explored green bonds and their ability to hedge against stock market risks, particularly in the context of carbon market risk. Regardless of various geopolitical, economic, and climate policy risks, investors favor green bonds due to their environmentally friendly characteristics, which enable them to hedge against extreme risks, or "tail risks".

Recall that Hypothesis 2 states that as green bonds are used as a hedge against downside risk (Naeem et al., 2021), and the connectedness between green bonds and other assets is largest in the short-term, an asset fire sale would lead to a smaller change in yield spread than for non-green bonds.

Turning to the results in Columns 2 – 6, it shows that being green relative to being non-green will lead to a deterioration in a change in the yield spread during an asset fire sale. Therefore, we observe a negative price impact. In the two quarters following an asset fire sale, this effect stays the same but diminishes in time. In the quarter after an asset fire sale, this effect is a change in +75 basis points, whereas, in two quarters following the event, the effect is already +18 percent points.

These results do not support Hypothesis 2. Interestingly, Deschryver and Mariz (2020) came up with an explanation that due to limited liquidity in the green bond market and the absence of standardized pricing mechanisms, irregular pricing dynamics can arise. Moreover, Naeem et al. (2021) find, comparing results, that green bonds can play a role as a hedge for some assets while being a contagion amplifier in times of crisis. This could be explained by the fact that green bonds are more subject to volatility (Pham, 2016). Liu (2022) discusses that hedging strategies involving green bonds do not help under extreme market conditions such as COVID-19. The stage of development of the green bond market matters. As a relatively young market, it may be more prone to volatility as it matures and stabilizes. Fluctuations in interest rates can significantly impact bond prices. When interest rates rise, bond prices tend to fall, and vice versa. Green bonds are not immune to these interest rate movements, and their prices can become more volatile (Kahn & Wagner, 2010).

In summary, the regression outcomes presented in Equation (6) suggest that green bonds exhibit a potential for outperformance compared to their non-green counterparts during non-crisis periods. However, as an asset fire sale commences, this positive effect swiftly diminishes, and green bonds begin to underperform. Importantly, this pattern is confirmed by the asset fire sales identified through the alternative selling pressure measures in Columns 2 and 3, thereby validating the findings from Column 1.

Table 4. Price Impact on Bonds Following an Asset Fire Sale

This table tabulates the estimation results of the following regression model:

$$\Delta YieldSpread_{i,t} = \alpha + \beta * Green_i + \sum_{n=-2}^{1} \gamma_n Q(n)_{i,j,t} + \sum_{n=-2}^{1} \theta_n Q(n)_{i,j,t} \cdot Green_i + \vartheta_m + \varepsilon_{i,t} \quad (6)$$

where $\Delta YieldSpread_{i,t}$ is the change in yield spread of bond i in quarter t. $Green_i$ is a dummy variable indicating that it is a green bond defined by the Green Bond Principles, however, this effect is subsumed by introducing bond fixed effects. $Q(n)_{i,t}$ is an indicator variable for indicating the n^{th} quarter from a fund fire sale quarter for bond i in fund j in quarter t. Issuer fixed effects (ϑ_m) for issuer m are introduced to control for issuer-specific information. Finally, heterogeneity within funds and time is accounted via creating different stacks on asset fire sale events within a specific fund and quarter. Appendix A gives all variable definitions. Standard errors are clustered at bond-level. The sample includes all mutual funds from the sample set from 2013Q1 – 2022Q3. Robust standard errors are in parentheses and appear below coefficients. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	SellPress 1	SellPress 2	SellPress 3
	(1)	(2)	(3)
Asset Fire Sale [T = -2]	-0.0128***	-0.0127***	-0.0127***
	(0.0009)	(0.0009)	(0.0009)
Asset Fire Sale [T = -1]	-0.0048***	-0.0044***	-0.0050***
	(0.0003)	(0.0003)	(0.0003)
Asset Fire Sale [T = 0]	0.0075***	0.0067***	0.0082***
	(0.0009)	(0.0009)	(0.0009)
Asset Fire Sale [T = 1]	0.0034***	0.0035***	0.0027***
	(0.0003)	(0.0003)	(0.0003)
Asset Fire Sale [T = 2]	0.0018***	0.0022***	0.0015***
	(0.0003)	(0.0003)	(0.0003)
Rating	-0.0018***	-0.0018***	-0.0018***
	(0.0007)	(0.0007)	(0.0007)
Bond	0.0001	0.0001	0.0001
	(0.0014)	(0.0014)	(0.0014)
Security	-0.0022***	-0.0022***	-0.0022***
	(0.0003)	(0.0003)	(0.0003)
TTM	0.0007***	0.0007***	0.0007***
	(0.0000)	(0.0000)	(0.0000)
Constant	0.0469***	0.0469***	0.0469***
	(0.0046)	(0.0046)	(0.0046)
Observations	8,722,073	8,721,908	8,957,670
R-squared	0.4723	0.4723	0.4723
Adj R^2	0.4723	0.4723	0.4723
F-stat	210.9294	209.2092	207.1621

5.2.1 Robustness checks

To further add to the previous analysis, several robustness tests are executed to validate the results.

First of all, $SellPress1$, $SellPress2$, and $SellPress3$ are created to capture the outflows experienced by distressed funds (as defined in Section 4.2). These distressed funds are initially identified by sorting the sample cross-sectionally based on their fund flows. These selling pressure measures are subsequently employed to detect instances of asset fire sales. To ensure that results are not contingent on the initial sorting of the sample dataset, a validation approach is undertaken, as recommended by Choi et al. (2020). In this alternative approach, identifying distressed funds involves a dual sorting process. First, the sorting is carried out based on the Lipper Objective Code, which assigns specific investment objectives to each mutual fund. Subsequently, the mutual funds are sorted based on their fund flows in each class of Lipper Objective code. The results are in Appendix C and confirm the robustness of the findings in Table 4.

Secondly, to ensure that the findings are not solely driven by the dependent variable, which is the change in yield spread, an additional variable, return, is introduced. While the interpolation-based construction of yield spread has been well-regarded in previous research (see Section 3.2), it is good to research whether the return variable yields similar results. Following Choi et al. (2020), the bond return variable is used as a proxy for assessing price impact. The model can be found in Appendix D. The results demonstrate that the effects of an asset fire sale on the price impact of green bonds compared to non-green bonds maintain a consistent pattern in the regression. Thus, this serves as a validation of the results presented in Table 4.

Thirdly, to further check the stacked difference-in-difference model (specified in Equation 6), a stacked triple differences model is run to check robustness. Unlike the latter, the triple difference estimator doesn't necessitate the assumption of two parallel trends for causal interpretation. However, it can be computed as the difference between two difference-in-differences estimators, as discussed by Olden and Møen (2022). Additionally, the triple difference model has the advantage of providing an estimate of spillover effects, which is the effect of green bonds on non-green bonds during an asset fire sale. Important to note is that while this paper does not specifically focus on investigating spillover effects, scholars have identified the presence of such effects in the context of green bond issues (Berck & Villas-Boas, 2016). In Appendix E, two separate difference-in-differences (on green and non-green bonds) are conducted. Subsequently, the difference is calculated. Findings support the outcomes of Table 4.

6 Discussion

While this study provides valuable insights for future research, it must be noted that it is subject to several limitations.

One limitation of this study is the relatively modest representation of green bonds within the dataset, potentially introducing bias into the results. The identification of green bonds relied on data from Refinitiv Eikon and Bloomberg, while detailed holding information was drawn from Morningstar Direct and CRSP databases. The study was only able to link bonds that possessed an ISIN or CUSIP code across these databases. Although additional green bonds were identified by converting CUSIP8 to CUSIP9, the dataset's size remained constrained. The focus on US corporate green bonds further exacerbates this limitation. To illustrate, in 2016, about 2% of municipal US bonds were green, whereas only about 0.3% of US corporate bond issues had a green status (Baker et al., 2018). Consequently, the calculated average of 0.59% of green bond holding in mutual funds (see Section 3.3) might not be fully representative. Future research might be interested in the green bond mechanism in the Eurozone, as green bonds comprised 3.7% of bond portfolios by the end of 2022, exceeding the current international average of 1.5% (Boermans, 2023).

Important to note is that this research operates under the assumption of exogeneity. Specifically, I assume that fire sales and fund redemptions are not linked to the fundamental value of holdings (Choi et al., 2020). Additionally, decisions made by fund managers are assumed to be independent of the actual value of those assets (Coval & Stafford, 2007). Section 4.1. outlines the identification strategy to mitigate potential bias. Yet, if the assumption is violated due to a correlation between the fundamental value of green bonds and the fund managers' decision to sell, it could introduce bias into our results and potentially exaggerate the impact of asset fire sales. This situation might occur if sales are indeed linked to the fundamental characteristics of green bonds.

In addition, the only limitation of the stacked difference-in-differences model lies in its potential exclusion of policy events that may be either too recent (2022Q3) or too early (2013Q1) to be studied within this framework (Cengiz et al., 2021). This limitation is particularly of interest due to the research focus on investigating the impact of a fire sale at the fund level and its subsequent effect on the green bonds held. In doing so, I eliminate more fire sale events than when analyzing fire sales at the bond level. However, it's worth noting that insufficient data on green bonds was available to conduct a detailed analysis at the bond level. Future research could delve into the individual effects on bonds, exploring differences between the impact on a conventional bond under a fire sale and that on a green bond under a fire sale, adding to the results in this paper.

Lastly, future research could explore the spillover effects of green bonds on their non-green counterparts and vice versa. Previous studies have indicated that the announcement of green bond issuance positively reflects on the stock market index, enhancing liquidity and trust in the financial market (Tang & Zang, 2020). If a positive spillover effect from green bonds to other assets exists, the effect of including green bonds in the portfolio may be understated. Conversely, negative spillover effects have been observed from shocks in the conventional bond market to the green bond market (Reboredo, 2018). In the context of this study, where green bonds outperform in normal times and face potential amplification of contagion during crises (as found in Naeem et al., 2021), further research into spillover effects could yield valuable insights.

7 Conclusion

The need to finance sustainable development globally highlights the importance of understanding the factors influencing green investment decisions. In the face of the ongoing uncertainties within financial markets, such as the COVID-19 pandemic, energy crisis, and current inflation, investors find themselves looking for alternative investment opportunities. At the same time, governments worldwide implement economic policies aimed at stimulating the economy. However, concerns arise whether the energy transition remains a priority. Therefore, assessing the possible hedging potential of green financial assets is particularly interesting.

This research provides a novel contribution to understanding the dynamics of distressed mutual funds during asset fire sales and their impact on green bonds. The study analyzes a dataset of bond transactions within mutual funds spanning from 2013Q1 till 2023Q1. The findings suggest that mutual funds exhibit a propensity to hold onto their green bonds, which is similarly found by other scholars (Fatica & Panzica, 2021). Instead, they prioritize divesting non-green corporate bonds in the quarters following such an asset fire sale event. Additionally, evidence shows that green bonds exhibit an ambiguous relationship relative to their non-green counterparts using an identification methodology unique to the corporate bond market (Choi et al., 2021). In the quarters leading up to an asset fire sale, green bonds outperform their non-green peers. However, once an asset fire sale occurs, this outperformance swiftly erodes to underperformance. This phenomenon can be explained by the notion that green bonds are more heavily influenced by speculative investors and, consequently, display greater price volatility (see, e.g., Reboredo et al., 2020; Pham, 2016).

These findings shed light on the unique behavior of active corporate bond mutual funds in portfolio management, particularly in the context of environmental and socially responsible investment decisions. While green bonds are an appealing option for diversification, they have displayed vulnerability to severe external shocks, as evident from significant fluctuations following asset fire sales. Regarding policy implications, strengthening the green bond market can be achieved through government-backed issuance and support of these bonds, which could enhance market stability (Kahn & Wagner, 2010). Now, governments get the possibility to support green invests by allocating their resources and can align with their commitments, such as in the Paris Agreement (Ning et al., 2022).

References

Adkins, L. C., & Hill, R. C. (2008). *Using STATA for principles of econometrics*. http://ci.nii.ac.jp/ncid/BB07841069

Agliardi, E., & Agliardi, R. (2019). Financing environmentally-sustainable projects with green bonds. *Environment and Development Economics*, *24*(6), 608–623. https://doi.org/10.1017/s1355770x19000020

Almazán, A., Brown, K. C., Carlson, M., & Chapman, D. A. (2004). Why constrain your mutual fund manager? *Journal of Financial Economics*, *73*(2), 289–321. https://doi.org/10.1016/j.jfineco.2003.05.007

Ambrose, B. W., Cheng, Y., & King, T. H. D. (2013). The Financial Crisis and Temporary Liquidity Guarantee Program: *Their Impact on Fixed-Income Markets*. *The Journal of Fixed Income*, *23*(2), 5–26. https://doi.org/10.3905/jfi.2013.23.2.005

Amihud, Y., & Goyenko, R. (2012). Mutual Fund's R2 as predictor of performance. *Social Science Research Network*. https://doi.org/10.2139/ssrn.1319786

Arif, M., Naeem, M. A., Farid, S., Nepal, R., & Jamasb, T. (2022). Diversifier or more? Hedge and safe haven properties of green bonds during COVID-19. *Energy Policy*, *168*, 113102. https://doi.org/10.1016/j.enpol.2022.113102

Baker, A. C., Larcker, D. F., & Wang, C. C. Y. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395. https://doi.org/10.1016/j.jfineco.2022.01.004

Baker, M., Bergstresser, D., Serafeim, G., & Wurgler, J. (2018). *Financing the response to climate change: the pricing and ownership of U.S. green bonds*. https://doi.org/10.3386/w25194

Batten, S. (2018). Climate Change and the Macro-Economy: A Critical review. *Social Science Research Network*. https://doi.org/10.2139/ssrn.3104554

Bao, J., Pan, J., & Wang, J. (2011). The illiquidity of corporate bonds. *The Journal of Finance*, *66*(3), 911–946. https://doi.org/10.1111/j.1540-6261.2011.01655.x

Berck, P., & Villas-Boas, S. B. (2015). A note on the triple difference in economic models. *Applied Economics Letters*, *23*(4), 239–242. https://doi.org/10.1080/13504851.2015.1068912

Berk, J. B., & Green, R. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, *112*(6), 1269–1295. https://doi.org/10.1086/424739

Bernardo, A. E., & Welch, I. (2004). Liquidity and financial market runs. *Quarterly Journal of Economics*, *119*(1), 135–158. https://doi.org/10.1162/003355304772839542

Bertrand, M. (2002). *How much should we trust differences-in-differences estimates?*

Bessembinder, H., Jacobsen, S. E., Maxwell, W. F., & Venkataraman, K. (2018). Capital commitment and illiquidity in corporate bonds. *The Journal of Finance*, *73*(4), 1615–1661. https://doi.org/10.1111/jofi.12694

Bessembinder, W., Kahle, K., Maxwell, W., & Xu, D. (2009). New methodology for event studies in bonds. *Review of Financial Studies*, *22*, 42194258

Boermans, M. (2023). Preferred habitat investors in the green bond market. In *De Nederlandsche Bank* (No. 773). De Nederlandsche Bank.

Boyson, N. M., Stahel, C. W., & Stulz, R. M. (2010). Hedge fund contagion and liquidity shocks. *The Journal of Finance*, *65*(5), 1789–1816. https://doi.org/10.1111/j.1540-6261.2010.01594.x

Broadstock, D. C., & Cheng, L. T. W. (2019). Time-varying relation between black and green bond price benchmarks: Macroeconomic determinants for the first decade. *Finance Research Letters*, *29*, 17–22. https://doi.org/10.1016/j.frl.2019.02.006

Brown, N. C., Wei, K. D., & Wermers, R. (2014). Analyst recommendations, mutual fund herding, and overreaction in stock prices. *Management Science*, *60*(1), 1–20. https://doi.org/10.1287/mnsc.2013.1751

Cabezas, H., Diwekar, U., Beck, J., Beloff, B., Bakshi, B. R., Crittenden, J. C., Farley, J., Fernando, H. J. S., French, S. P., Garmestrani, A., Gorman, M. E., Guhathakurta, S., Heberling, M. T., Hopton, M. E., Jeong, H., Jenkins, L. D., Kempener, R., Ke, L., Meyer, A., . . . Xu, M. (2012). Sustainability: Multi-Disciplinary Perspectives. In *BENTHAM SCIENCE PUBLISHERS eBooks*. https://doi.org/10.2174/97816080510381120101

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Canale, R. R., & Mirdala, R. (2019). *Fiscal and monetary policy in the eurozone: Theoretical Concepts and Empirical Evidence*. Emerald Group Publishing.

Cengiz, D., Dubé, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on Low-Wage jobs*. *Quarterly Journal of Economics*, *134*(3), 1405–1454. https://doi.org/10.1093/qje/qjz014

Champagne, C., Karoui, A., & Patel, S. (2018). Portfolio turnover activity and mutual fund performance. *Managerial Finance*, *44*(3), 326–356. https://doi.org/10.1108/mf-01-2017-0003

Chen, W., Chen, Y., & Huang, S. (2021). Liquidity risk and bank performance during financial crises. *Journal of Financial Stability*, *56*, 100906. https://doi.org/10.1016/j.jfs.2021.100906

Chernenko, S., & Sunderam, A. (2016). *Liquidity Transformation in Asset Management: Evidence from the Cash Holdings of Mutual Funds*. https://doi.org/10.3386/w22391

Chernov, M., Dahlquist, M., & Lochstoer, L. A. (2020). *Pricing currency risks*. https://doi.org/10.3386/w28260

Choi, J., Hoseinzade, S., Shin, S. S., & Tehranian, H. (2020). Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics*, *138*(2), 432–457. https://doi.org/10.1016/j.jfineco.2020.05.006

Cortellini, G., & Panetta, I. C. (2021). Green Bond: A Systematic Literature Review for future research Agendas. *Journal of Risk and Financial Management*, *14*(12), 589. https://doi.org/10.3390/jrfm14120589

Correia, S. (2016). Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator. Working Paper

Coval, J. D., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479–512. https://doi.org/10.1016/j.jfineco.2006.09.007

Cunningham, S. (2021). *Causal inference*. Yale University Press.

Cuthbertson, K., Nitzsche, D., & O'Sullivan, N. (2016). A review of behavioural and management effects in mutual fund performance. *International Review of Financial Analysis*, *44*, 162–176. https://doi.org/10.1016/j.irfa.2016.01.016

Deschryver, P., & De Mariz, F. R. (2020). What future for the green bond market? How can policymakers, companies, and investors unlock the potential of the green bond market? *Journal of Risk and Financial Management*, *13*(3), 61. https://doi.org/10.3390/jrfm13030061

Deshpande, M., & Li, Y. (2019). Who is screened out? Application costs and the targeting of disability programs. American Economic Journal: Economic Policy, 11(4), 213–248. https://doi.org/10.1257/pol.20180076

Derwall, J., Guenster, N., Bauer, R., & Koedijk, K. (2005). The Eco-Efficiency Premium puzzle. *Financial Analysts Journal*, *61*(2), 51–63. https://doi.org/10.2469/faj.v61.n2.2716

Dong, X., Xiong, Y., Nie, S., & Yoon, S. (2023). Can bonds hedge stock market risks? Green bonds vs conventional bonds. *Finance Research Letters*, *52*, 103367. https://doi.org/10.1016/j.frl.2022.103367

Dow, J., & Han, J. (2017). The Paradox of financial fire sales: The role of arbitrage capital in determining liquidity. *The Journal of Finance*, *73*(1), 229–274. https://doi.org/10.1111/jofi.12584

Duffie, D., Saita, L., & Ke, W. (2007). Multi-period corporate default prediction with stochastic covariates. *Journal of Financial Economics*, *83*(3), 635–665. https://doi.org/10.1016/j.jfineco.2005.10.011

Dyakov, T., & Verbeek, M. (2013). Front-running of mutual fund fire-sales. *Journal of Banking and Finance*, *37*(12), 4931–4942. https://doi.org/10.1016/j.jbankfin.2013.08.013

Ellul, A., Jotikasthira, C., & Lundblad, C. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, *101*(3), 596–620. https://doi.org/10.1016/j.jfineco.2011.03.020

Elton, E. J., Gruber, M. J., & Blake, C. R. (2003). Incentive fees and mutual funds. *The Journal of Finance*, *58*(2), 779–804. https://doi.org/10.1111/1540-6261.00545

Evans, J. L., & Archer, S. H. (1968). DIVERSIFICATION AND THE REDUCTION OF DISPERSION: AN EMPIRICAL ANALYSIS*. *The Journal of Finance*, *23*(5), 761–767. https://doi.org/10.1111/j.1540-6261.1968.tb00315.x

Fatica, S., & Panzica, R. (2021). Sustainable Investing in Times of Crisis: Evidence from Bond Holdings and the COVID-19 Pandemic. *Social Science Research Network*. https://doi.org/10.2139/ssrn.3991007

Flammer, C. (2020). Green Bonds: Effectiveness and implications for public policy. *Environmental and Energy Policy and the Economy*, *1*, 95–128. https://doi.org/10.1086/706794

Febi, W., Schäfer, D., Stephan, A., Sun, C. (2018). The impact of liquidity risk on the yield spread of green bonds, *Finance Research Letters*, *27*, 53-59. https://doi.org/10.1016/j.frl.2018.02.025.

Feroli, M., Kashyap, A., Schoenholtz, K. L., & Shin, H. S. (2014). Market tantrums and monetary policy. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2409092

Galloppo, G. (2021). Asset allocation strategies for mutual funds. In *Springer eBooks*. https://doi.org/10.1007/978-3-030-76128-8

Gil-Bazo, J., Ruiz-Verdú, P., & Santos, A. a. P. (2009). The performance of socially responsible mutual funds: the role of fees and management companies. *Journal of Business Ethics*, *94*(2), 243–263. https://doi.org/10.1007/s10551-009-0260-4

Glomsröd, S., & Wei, T. (2018). Business as unusual: The implications of fossil divestment and green bonds for financial flows, economic growth and energy market. *Energy for Sustainable Development*, *44*, 1–10. https://doi.org/10.1016/j.esd.2018.02.005

Goldstein, M. A., & Hotchkiss, E. S. (2017). Providing liquidity in an illiquid market: dealer behavior in U.S. corporate bonds. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2977635

Goldstein, M. A., & Namin, E. S. (2023). Corporate bond liquidity and yield spreads: A review. *Research in International Business and Finance*, *65*, 101925. https://doi.org/10.1016/j.ribaf.2023.101925

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Gormus, A., Diltz, J. D., & Soytaş, U. (2018). Energy mutual funds and oil prices. *Managerial Finance*, *44*(3), 374–388. https://doi.org/10.1108/mf-04-2017-0124

Hachenberg, B., & Schiereck, D. (2018). Are green bonds priced differently from conventional bonds? *Journal of Asset Management*, *19*(6), 371–383. https://doi.org/10.1057/s41260-018-0088-5

Hagan, P. S., & West, G. (2006). Interpolation methods for curve construction. *Applied Mathematical Finance*, *13*(2), 89–129. https://doi.org/10.1080/13504860500396032

Han, Y., & Li, J. (2022). Should investors include green bonds in their portfolios? Evidence for the USA and Europe. *International Review of Financial Analysis*, *80*, 101998. https://doi.org/10.1016/j.irfa.2021.101998

Hartzmark, S. M., & Sussman, A. B. (2019). Do investors value sustainability? A natural experiment examining ranking and fund flows. *The Journal of Finance*, *74*(6), 2789–2837. https://doi.org/10.1111/jofi.12841

Hau, H., & Lai, S. (2013). Real effects of stock underpricing. *Journal of Financial Economics*, *108*(2), 392–408. https://doi.org/10.1016/j.jfineco.2012.11.001

Hillebrand, M., & Thier, C. (2023). Who is the Green Investor? Demand for Green Bonds in the Primary Market. Available at SSRN : https://ssrn.com/abstract=4405686 or http://dx.doi.org/10.2139/ssrn.4405686

Hyun, S., Park, D., & Tian, S. (2019). The price of going green: the role of greenness in green bond markets. *Accounting & Finance*, *60*(1), 73–95. https://doi.org/10.1111/acfi.12515

Ibikunle, G., & Steffen, T. (2015). European Green Mutual Fund Performance: A Comparative Analysis with their Conventional and Black Peers. *Journal of Business Ethics*, *145*(2), 337–355. https://doi.org/10.1007/s10551-015-2850-7

ICMA, 2017. Voluntary process guidelines for issuing green bonds. ICMA, Paris.

International Monetary Fund. (2020). A Year Like No Other. In *International Monetary Fund*.

International Monetary Fund. (2022a). Global Financial Stability Report—Navigating the High-Inflation Environment. In *International Monetary Fund*.

International Monetary Fund. (2022b). *Wage-Price spiral risks appear contained despite high inflation*. https://www.imf.org/en/Blogs/Articles/2022/10/05/wage-price-spiral-risks-appear-contained-despite-high-inflation

Ivković, Z., & Weisbenner, S. J. (2007). Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices. *Review of Financial Studies*, *20*(4), 1327–1357. https://doi.org/10.1093/revfin/hhm009

Jin, J., Han, L., Wu, L., & Zeng, H. (2020). The hedging effect of green bonds on carbon market risk. *International Review of Financial Analysis*, *71*, 101509. https://doi.org/10.1016/j.irfa.2020.101509

Kahn, C. M., & Wagner, W. (2010). Sources of liquidity and liquidity shortages. *Social Science Research Network*. https://doi.org/10.2139/ssrn.1570504

Kahn-Lang, A., & Lang, K. (2019). The Promise and Pitfalls of Differences-in-Differences: Reflections on *16 and Pregnant* and Other Applications. *Journal of Business & Economic Statistics*, *38*(3), 613–620. https://doi.org/10.1080/07350015.2018.1546591

Klarin, T. (2018). The Concept of Sustainable Development: From its Beginning to the Contemporary Issues. *Zagreb International Review of Economics and Business*, *21*(1), 67–94. https://doi.org/10.2478/zireb-2018-0005

Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of Financial Economics*, *115*(2), 304–329. https://doi.org/10.1016/j.jfineco.2014.09.008

Lamont, O. A., & Frazzini, A. (2007). *The earnings announcement premium and trading volume*. https://doi.org/10.3386/w13090

Lee, I. (2022, December 16). Record $1.5 Trillion Flow Widest on Record Between Mutual Funds And ETFs. *Bloomberg.com*. https://www.bloomberg.com/news/articles/2022-12-16/record-1-5-trillion-flow-widest-on-record-between-mutual-funds-and-etfs#xj4y7vzkg

Liaw, K. T. (2020). Survey of Green Bond Pricing and Investment Performance. *Journal of Risk and Financial Management*, *13*(9), 193. https://doi.org/10.3390/jrfm13090193

Liu, M. (2022). The driving forces of green bond market volatility and the response of the market to the COVID-19 pandemic. *Economic Analysis and Policy*, *75*, 288–309. https://doi.org/10.1016/j.eap.2022.05.012

Löffler, K.U., Petreski, A. & Stephan, A. Drivers of green bond issuance and new evidence on the "greenium". *Eurasian Econ Rev* 11, 1–24 (2021). https://doi.org/10.1007/s40822-020-00165-y

MacAskill, S., Roca, E., Liu, B., Stewart, R. A., & Sahin, O. (2021). Is there a green premium in the green bond market? Systematic literature review revealing premium determinants. *Journal of Cleaner Production*, *280*, 124491. https://doi.org/10.1016/j.jclepro.2020.124491

Maltais, A., & Nykvist, B. (2020). Understanding the role of green bonds in advancing sustainability. *Journal of Sustainable Finance & Investment*, 1–20. https://doi.org/10.1080/20430795.2020.1724864

Manconi, A., Massa, M., & Yasuda, A. (2012). The role of institutional investors in propagating the crisis of 2007–2008. *Journal of Financial Economics*, *104*(3), 491–518. https://doi.org/10.1016/j.jfineco.2011.05.011

Manring, S. L., & Moore, S. B. (2006). Creating and managing a virtual inter-organizational learning network for greener production: a conceptual model and case study. *Journal of Cleaner Production*, *14*(9–11), 891–899. https://doi.org/10.1016/j.jclepro.2005.11.033

Massa, M., Yasuda, A., & Zhang, L. (2013). Supply uncertainty of the bond investor base and the leverage of the firm. *Journal of Financial Economics*, *110*(1), 185–214. https://doi.org/10.1016/j.jfineco.2013.04.011

Markowitz, H. M. (1952). The utility of wealth. *Journal of Political Economy*, *60*(2), 151–158. https://doi.org/10.1086/257177

Mitchell, M. L., Pedersen, L. H., & Pulvino, T. (2007). Slow moving capital. *The American Economic Review*, *97*(2), 215–220. https://doi.org/10.1257/aer.97.2.215

Moyer, R. C., McGuigan, J. R., & Kretlow, W. J. (2003). Contemporary Financial Management, ed. *United States of America: Thomson*.

Naeem, M. A., Adekoya, O. B., & Oliyide, J. A. (2021). Asymmetric spillovers between green bonds and commodities. *Journal of Cleaner Production*, *314*, 128100. https://doi.org/10.1016/j.jclepro.2021.128100

Nanda, V. (2000). Liquidity, investment ability, and mutual fund structure. *Journal of Financial Economics*, *57*(3), 417–443. https://doi.org/10.1016/s0304-405x(00)00063-5

Ning, Y., Cherian, J., Sial, M. S., Otero, S. Á., Comite, U., & Zia-Ud-Din, M. (2022). Green bond as a new determinant of sustainable green financing, energy efficiency investment, and economic growth: a global perspective. *Environmental Science and Pollution Research*, *30*(22), 61324–61339. https://doi.org/10.1007/s11356-021-18454-7

Olden, A., & Møen, J. (2022). The triple difference estimator. *Econometrics Journal*, *25*(3), 531–553. https://doi.org/10.1093/ectj/utac010

Pasewark, W. R., & Riley, M. E. (2009). It's a Matter of Principle: The Role of Personal Values in Investment Decisions. *Journal of Business Ethics*, *93*(2), 237–253. https://doi.org/10.1007/s10551-009-0218-6

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642–685. https://doi.org/10.1086/374184

Pástor, Ľ., & Vorsatz, M. (2020). Mutual Fund Performance and Flows during the COVID-19 Crisis. *The Review of Asset Pricing Studies*, *10*(4), 791–833. https://doi.org/10.1093/rapstu/raaa015

Pham, L. (2016). Is it risky to go green? A volatility analysis of the green bond market. *Journal of Sustainable Finance & Investment*, *6*(4), 263–291. https://doi.org/10.1080/20430795.2016.1237244

Podobnik, B., Horvatić, D., Petersen, A. M., & Stanley, H. E. (2009). Cross-correlations between volume change and price change. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(52), 22079–22084. https://doi.org/10.1073/pnas.0911983106

Rambachan, A., & Roth, J. (2023). A more credible approach to parallel trends. *The Review of Economic Studies*, *90*(5), 2555–2591. https://doi.org/10.1093/restud/rdad018

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, *74*, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030

Reboredo, J. C., Ugolini, A., & Aiube, F. a. L. (2020). Network connectedness of green bonds and asset classes. *Energy Economics*, *86*, 104629. https://doi.org/10.1016/j.eneco.2019.104629

Refinitiv Eikon. (2021.). ESG Data in Eikon. In *Refinitiv Eikon*.

Roll, R. (1971). Investment Diversification And Bond Maturity. *The Journal of Finance*, *26*(1), 51–66. https://doi.org/10.1111/j.1540-6261.1971.tb00588.x

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, *34*(1), 248–255. https://doi.org/10.1016/j.eneco.2011.03.006

Salvia, A. L., Filho, W. L., Brandli, L. L., & Griebeler, J. S. (2019). Assessing research trends related to Sustainable Development Goals: local and global issues. Journal of Cleaner Production, 208, 841–849. https://doi.org/10.1016/j.jclepro.2018.09.242

Schmidt, L., Timmermann, A., & Wermers, R. (2016). Runs on money market mutual funds. *The American Economic Review*, *106*(9), 2625–2657. https://doi.org/10.1257/aer.20140678

Seo, M., & Barrett, L. F. (2007). Being Emotional During Decision Making—Good or Bad? an Empirical Investigation. *Academy of Management Journal*, *50*(4), 923–940. https://doi.org/10.5465/amj.2007.26279217

Shleifer, A., & Vishny, R. W. (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives*, *25*(1), 29–48. https://doi.org/10.1257/jep.25.1.29

Sirri, E. R., & Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance*, *53*(5), 1589–1622. https://doi.org/10.1111/0022-1082.00066

Statman, M. (2000). Socially Responsible Mutual Funds (corrected). *Financial Analysts Journal*, *56*(3), 30–39. https://doi.org/10.2469/faj.v56.n3.2358

Sushko, V., & Turner, G. (2018). The implications of passive investing for securities markets. *BIS Quarterly Review*. https://EconPapers.repec.org/RePEc:bis:bisqtr:1803j

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Tang, D. Y., & Zhang, Y. (2020). Do shareholders benefit from green bonds? *Journal of Corporate Finance*, *61*, 101427. https://doi.org/10.1016/j.jcorpfin.2018.12.001

Treynor, J. L., & Mazuy, K. K. (1966). Can mutual funds outguess the market? *Harvard Business Review*, *44*, 131–136.

Tu, C. A., Rasoulinezhad, E., & Sarker, T. (2020). Investigating solutions for the development of a green bond market: Evidence from analytic hierarchy process. *Finance Research Letters*, *34*, 101457. https://doi.org/10.1016/j.frl.2020.101457

United Nations. (2019, September 26). *Secretary-General Urges Sustainable Stock Exchanges Initiative to Step-Up Green Bonds, Divest from Fossil Fuels | UN Press*. https://press.un.org/en/2019/sgsm19775.doc.htm

Wang, J., Chen, X., Li, X., Yu, J., & Zhong, R. (2020). The market reaction to green bond issuance: Evidence from China. *Pacific-Basin Finance Journal*, *60*, 101294. https://doi.org/10.1016/j.pacfin.2020.101294

Yan, X. S. (2008). Liquidity, Investment Style, and the Relation between Fund Size and Fund Performance. *Journal of Financial and Quantitative Analysis*, *43*(3), 741–767. https://doi.org/10.1017/s0022109000004270

Yang, Z., & Zhou, Y. (2017). Quantitative easing and volatility spillovers across countries and asset classes. *Management Science*, *63*(2), 333–354. https://doi.org/10.1287/mnsc.2015.2305

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210–251. https://doi.org/10.1108/qrfm-04-2017-0028

Zerbib, O. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking and Finance*, *98*, 39–60. https://doi.org/10.1016/j.jbankfin.2018.10.012

Zhang, P. (2010). Board Information and Strategic Tasks performance. *Corporate Governance: An International Review*, *18*(5), 473–487. https://doi.org/10.1111/j.1467-8683.2010.00816.x

Zhang, H. (2010). Asset fire sales, liquidity provision, and mutual fund performance. *Social Science Research Network*. https://doi.org/10.2139/ssrn.1573330

Zhou, X., & Cui, Y. (2019). Green bonds, corporate performance, and corporate social responsibility. *Sustainability*, *11*(23), 6881. https://doi.org/10.3390/su11236881

Appendix

Appendix A. Variable Construction

This table provides an overview of variable definitions, and simple construction used in this study.

Variable	Definition	Source
Panel A: Fund-Level		
Quarterly Fund Flow	Quarterly fund flows, estimate monthly flows using monthly returns from the CRSP Mutual Fund database: Stafford (2007), and calculate contemporaneous monthly mutual fund flows: $FundFlow_{j,t} = \frac{TNA_{j,t} - TNA_{(j,t-1)} * (1+r_{j,t})}{TNA_{j,t-1}}$, (1) where $TNA_{j,t}$ is the total net assets for fund j at the end of month t, and $r_{j,t}$ is monthly returns for fund j over month t. Further, to match with the quarterly holding data, quarterly flows are defined as the sum of monthly flows during a quarter.	Calculated, data from CRSP Mutual Fund database
Fund Turnover Ratio	Turnover ratio of the mutual fund's portfolio. Defined by CRSP as $\frac{aggregated\ flow}{the\ average\ 12-month\ TNA}$	CRSP Mutual Fund database
TNA	Total net assets of a share class of a fund in millions of US dollars.	CRSP Mutual Fund database
Fund Return	Monthly return of the mutual fund	CRSP Mutual Fund database
Equity Ratio	Percentage amounts of US stock holdings scaled by total net assets at the end of each quarter.	
Corp Bond Ratio	Percentage amounts of US corporate bond holdings scaled by total net assets at the end of each quarter.	Calculated, data from Morningstar Direct and CRSP Mutual Fund database
Green Corp Bonds Ratio	The ratio of green corporate bonds in total corporate bond holding: $\frac{Amount\ Hold_{green}}{Amount\ Hold_{corporatebonds}}$	Calculated, data from CRSP Mutual Fund, and Refinitiv Eikon
Expense Ratio (percent)	Fund's expense ratio in the most recent fiscal year, defined as: $\frac{total\ operating\ expenses}{TNA}$	CRSP Mutual Fund database
Green Fund	Dummy variable, indicating 1 if the mutual fund has once invested in green bonds during the sample period, else is 0.	Calculated, data from CRSP Mutual Fund database and Refinitiv Eikon
Fund Trade	Aggregate trading in green bonds or non-green bonds by a mutual fund in a quarter, by percentage. $FundTrade_{j,t} = \left(\frac{AmountHold_{j,t}}{AmountHold_{j,t-1}}\right) - 1$	Calculated, data from Morningstar Direct and CRSP Mutual Fund database
Amount Hold	The amount in par value of a bond held by a fund at the end of the quarter.	Calculated, data from Morningstar Direct and CRSP Mutual Fund database
Fund Size	Natural logarithm taken of the total net assets of the fund	Calculated, data from CRSP Mutual Fund database

Panel B: Bond- Level		
Yield Spread	Monthly changes in the yield spread. The last available daily yield within five days of the end of the month as month-end yields (Bessembinder et al., 2009). The yield spreads are calculated by subtracting Treasury yields using a linear interpolation of closest maturity yields.	Calculated, data from WRDS Bond Returns, CRSP Treasury database
Bond Return	Monthly return calculated based on the last price at which the bond was traded in a given month, and accrued interest. The last day traded should fall within the last five trading days of the month.	WRDS Bond Returns
Time to Maturity (TTM)	Time to maturity in years	WRDS Bond Returns
Age	The age of a bond in years	Calculated, data from WRDS Bond Returns
Rating	The credit rating of a bond in integers for which 10 is assigned to AAA rating, 9 to AA, 8 to A, 7 to BBB, 6 to BB, 5 to B, 4 to CCC, 3 to CC, 2 to C, 1 to D. 0 if rating is missing.	Converted into integers, data from CRSP Mutual Fund
Amount Outstanding	The amount of the issue remaining outstanding as of the effective date.	Mergent FISD
Bid-Ask Spread	Average trade-weighted bid-ask spread in percentage amounts	WRDS bond returns
Green Issuer	Dummy variable that denotes 1 if the issuer has issued at least one green bond, otherwise 0.	Manually calculated
Bond Type	US corporate bond types: Convertible (1), Debenture (2), Medium Term Note (3), or MTN Zero (4)	Mergent FISD
Security Level	Indicates if the security is a secured (1), senior (2), or subordinated (3) issue of the issuer	Mergent FISD
Bond Trade	Trading in a bond by a mutual fund in a quarter, by percentage. $\text{BondTr}ade_{j,t} = \left(\frac{AmountHold_{i,j,t}}{AmountHold_{i,j,t-1}}\right) - 1$	Calculated, data from Morningstar Direct and CRSP Mutual Fund database
Market trading volume	Total par-value volume traded in a given month	WRDS bond returns

Appendix B. Robustness Check on Liquidity-Sensitive Trading

This table reports the estimations of the following regression model:

$FundTrade_{j,t} = \alpha + \beta \cdot FundTurnover_{j,t} + X_j + \gamma_j + \delta_t + \varepsilon_{j,t}$,

where $FundTrade_{j,t} = \left(\frac{AmountHold_{j,t}}{AmountHold_{j,t-1}}\right) - 1$, is the aggregate trading volume of fund j as a proportion of its holding at the end of quarter t in corporate green bonds or corporate non-green bonds. $FundTurnover_{j,t}$ is the turnover ratio of a fund respectively to TNA. X_j is a vector for all control variables. γ_j and δ_t denote fixed effects for funds and time, respectively. Robust standard errors are clustered at fund-level (Petersen, 2009). Appendix A gives all variable definitions. The sample includes all mutual funds belonging to the merged sample set, over the period 2013 Q1 – 2022 Q3. Robust standard errors are in parentheses and appear below coefficients. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Asset Fire Sale (T = -1)		Asset Fire Sale (T = 0)		Asset Fire Sale (T = 1)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Green	Non-Green	Green	Non-Green	Green	Non-Green
Quarterly Flow	-0.0029	-0.0017	-0.0014	-0.0015	-0.0017	-0.0014
	(0.0034)	(0.0018)	(0.0037)	(0.0027)	(0.0037)	(0.0029)
Fund Size	-0.0076	-0.0132***	-0.0074	-0.0173***	-0.0092*	-0.0142***
	(0.005)	(0.0028)	(0.0052)	(0.0036)	(0.0054)	(0.0037)
Fund Return	0.0751	-1.07***	0.0389	-0.4509	0.0036	-0.4787
	(0.0813)	(0.0673)	(0.0655)	(0.283)	(0.0789)	(0.3055)
Equity Ratio	-0.0041*	0.0032**	-0.0053*	0.0042**	-0.0034	0.0054***
	(0.0024)	(0.0016)	(0.0028)	(0.0019)	(0.0029)	(0.002)
Expense Ratio	-10.8295***	-2.8834*	-13.0328***	-6.0252***	-10.505***	-5.0544***
	(2.5942)	(1.6306)	(3.1089)	(1.9122)	(3.0271)	(1.9322)
Maturity	0.0009	-0.0003	0.0012	-0.0004	0.0016	-0.0008
	(0.0017)	(0.0008)	(0.0015)	(0.0008)	(0.0018)	(0.0009)
Constant	0.1527***	0.8567***	0.1641***	1.2746***	0.153***	1.3243***
	(0.0454)	(0.1623)	(0.0474)	(0.2575)	(0.0492)	(0.2723)
Observations	6,993	6,993	7,365	7,365	7,152	7,152
R-squared	0.0281	0.0793	0.0282	0.0529	0.0252	0.0582
Adj R^2	0.0271	0.0784	0.0273	0.052	0.0242	0.0573
F-stat	9.3073	47.9798	7.5923	14.3393	6.4157	13.3508

Appendix C. Robustness Check on Fund's Sorting

This table tabulates the estimation results of the following regression model:

$$\Delta YieldSpread_{i,t} = \alpha + \beta * Green_i + \sum_{n=-2}^{1} \gamma_n Q(n)_{i,j,t} + \sum_{n=-2}^{1} \theta_n Q(n)_{i,j,t} \cdot Green_i + \vartheta_m + \varepsilon_{i,t} \quad (6)$$

where $\Delta YieldSpread_{i,t}$ is the change in yield spread of bond i in quarter t. $Green_i$ is a dummy variable indicating that it is a green bond defined by the Green Bond Principles, however, this effect is subsumed by introducing bond fixed effects. $Q(n)_{i,t}$ is an indicator variable for indicating the n^{th} quarter from a fund fire sale quarter for bond i in fund j in quarter t. Issuer fixed effects (ϑ_m) for issuer m are introduced to control for issuer-specific information. Finally, heterogeneity within funds and time is accounted via creating different stacks on asset fire sale events within a specific fund and quarter. Appendix A gives all variable definitions. Standard errors are clustered at bond-level. The sample includes all mutual funds from the sample set over the period 2013Q1 – 2022Q3. Robust standard errors are in parentheses and appear below coefficients. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	SellPress 1	SellPress 2	SellPress 3
	(1)	(2)	(3)
Asset Fire Sale [T = -2]	-0.0121***	-0.0123***	-0.0126***
	(0.0008)	(0.0008)	(0.0008)
Asset Fire Sale [T = -1]	-0.0050***	-0.0055***	-0.0062***
	(0.0003)	(0.0003)	(0.0003)
Asset Fire Sale [T = 0]	0.0058***	0.0061***	0.0069***
	(0.0008)	(0.0008)	(0.0008)
Asset Fire Sale [T = 1]	0.0039***	0.0035***	0.0035***
	(0.0003)	(0.0003)	(0.0003)
Asset Fire Sale [T = 2]	0.0025***	0.0031***	0.0032***
	(0.0003)	(0.0003)	(0.0003)
Rating	-0.0018***	-0.0018***	-0.0018***
	(0.0007)	(0.0007)	(0.0007)
Bond	0.0001	0.0001	0.0001
	(0.0014)	(0.0014)	(0.0014)
Security	-0.0022***	-0.0022***	-0.0022***
	(0.0003)	(0.0003)	(0.0003)
TTM	0.0007***	0.0007***	0.0007***
	(0.0000)	(0.0000)	(0.0000)
Constant	0.0469***	0.0469***	0.0469***
	(0.0046)	(0.0046)	(0.0046)
Observations	8,721,908	8,722,108	8,957,897
R-squared	0.4723	0.4723	0.4724
Adj R^2	0.4723	0.4723	0.4724
F-stat	206.8958	217.3884	228.7093

Appendix D. Robustness Check on Price Impact by Using Return

This table tabulates the estimation results of the following regression model:

$$\Delta BondReturn_{i,t} = \alpha + \beta * Green_i + \sum_{n=-2}^{1} \gamma_n Q(n)_{i,j,t} + \sum_{n=-2}^{1} \theta_n Q(n)_{i,j,t} \cdot Green_i + \vartheta_m + \varepsilon_{i,t} \quad (6)$$

where $\Delta BondReturn_{i,t}$ is the change in return of bond i in quarter t. $Green_i$ is a dummy variable indicating that it is a green bond defined by the Green Bond Principles, however, this effect is subsumed by introducing bond fixed effects. $Q(n)_{i,t}$ is an indicator variable for indicating the n^{th} quarter from a fund fire sale quarter for bond i in fund j in quarter t. Issuer fixed effects (ϑ_m) for issuer m are introduced to control for issuer-specific information. Finally, heterogeneity within funds and time is accounted via creating different stacks on asset fire sale events within a specific fund and quarter. Appendix A gives all variable definitions. Standard errors are clustered at bond-level. The sample includes all mutual funds from the sample set over the period 2013Q1 – 2022Q3. Robust standard errors are in parentheses and appear below coefficients. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	SellPress 1	SellPress 2	SellPress 3
	(1)	(2)	(3)
Asset Fire Sale [T = -2]	0.0242***	0.0240***	0.0223***
	(0.0029)	(0.0029)	(0.0030)
Asset Fire Sale [T = -1]	0.0117***	0.0111***	0.0133***
	(0.0016)	(0.0015)	(0.0016)
Asset Fire Sale [T = 0]	-0.0344***	-0.0328***	-0.0355***
	(0.0030)	(0.0029)	(0.0029)
Asset Fire Sale [T = 1]	-0.0041***	-0.0037***	-0.0015
	(0.0012)	(0.0011)	(0.0011)
Asset Fire Sale [T = 2]	0.0006	-0.0010	-0.0003
	(0.0013)	(0.0011)	(0.0011)
Rating	-0.0001	-0.0001	-0.0001
	(0.0011)	(0.0011)	(0.0011)
Bond	0.0004	0.0004	0.0004
	(0.0014)	(0.0014)	(0.0014)
Security	-0.0002	-0.0002	-0.0002
	(0.0004)	(0.0004)	(0.0004)
TTM	-0.0001*	-0.0001*	-0.0001*
	(0.0000)	(0.0000)	(0.0000)
Constant	0.0002	0.0002	0.0002
	(0.0069)	(0.0069)	(0.0069)
Observations	8,041,504	8,041,337	8,258,689
R-squared	0.0208	0.0208	0.0207
Adj R^2	0.0208	0.0208	0.0207
F-stat	23.1968	22.9746	23.0323

Appendix E. Robustness Check on Price Impact by Triple Differences Model

This table tabulates the estimation results of the following regression model:

$$\Delta YieldSpread_{i,t} = \alpha + \beta * Firesale_i + \sum_{n=-2}^{1} \gamma_n Q(n)_{i,j,t} + \sum_{n=-2}^{1} \theta_n Q(n)_{i,j,t} \cdot Firesale_i + \vartheta_m + \varepsilon_{i,t} \quad (6)$$

where $\Delta YieldSpread_{i,t}$ is the change in yield spread of bond i in quarter t. $Firesale_i$ is a dummy variable indicating that a bond is in a fund undergoing an asset fire sale, however, this effect is subsumed by introducing bond fixed effects. $Q(n)_{i,t}$ is an indicator variable for indicating the n^{th} quarter from a fund fire sale quarter for bond i in fund j in quarter t. Issuer fixed effects (ϑ_m) for issuer m are introduced to control for issuer-specific information. Finally, heterogeneity within funds and time is accounted via creating different stacks on asset fire sale events within a specific fund and quarter. Appendix A gives all variable definitions. Standard errors are clustered at bond-level.

In Column 1, the regression model is estimated for only green bonds, and in Column 2 for only non-green corporate bonds. Subsequently, the difference is taking of the regression coefficients in Column 3.

The sample includes all mutual funds from the sample set over the period 2013Q1 – 2022Q3. Robust standard errors are in parentheses and appear below coefficients. The symbols *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Green Bonds	Non-Green Bonds	Difference
	(1)	(2)	(3)
Asset Fire Sale [T = -2]	-0.0130***	-0.0059***	-0.0071
	(0.0008)	(0.0002)	
Asset Fire Sale [T = -1]	-0.0049***	-0.0024***	-0.0025
	(0.0003)	(0.0002)	
Asset Fire Sale [T = 0]	0.0000	0.0098***	0.0098
	(1.0000)	(0.0018)	
Asset Fire Sale [T = 1]	0.0032***	0.0010***	0.0022
	(0.0003)	(0.0001)	
Asset Fire Sale [T = 2]	0.0018***	0.0000***	0.0018
	(0.0002)	(0.0002)	
Rating	-0.0008	-0.0020***	0.0012
	(0.0024)	(0.0007)	
Bond	0.0000	0.0009	-0.0009
	(1.0000)	(0.0014)	
Security	0.0013	-0.0022***	-0.0009
	(0.0024)	(0.0004)	
TTM	0.0005***	0.0007***	-0.0002
	(0.0000)	(0.0000)	
Constant	0.0341	0.0444***	-0.0103
	(0.0215)	(0.0052)	
Observations	15,676	216,569	
R-squared	0.6433	0.5441	
Adj R^2	0.6412	0.5439	
F-stat	93.1433	361.6652	