"Buy the Rumor, Sell the News":

Liquidity Provision by Bond Funds Following Corporate News Events[*]

Alan Guoming Huang
University of Waterloo

Russ Wermers
University of Maryland

Jinming Xue
Southern Methodist University

November 2023

[*]The authors gratefully acknowledge helpful comments from Huaizhi Chen, Yong Chen, Jaewon Choi, David Feldman, Adam Harper, Elvis Jarnecic, Chotibhak (Pab) Jotikasthira, Mathias Kronlund, Erik Mayer, Stanislava (Stas) Nikolova, Yoshio Nozawa, Lubos Pastor, Manju Puri, Konark Saxena, Ishita Sen, Jiaxun Song, Zheng Sun, Peter Swan, Kumar Venkataraman, Chen Wang, Jason Wei, David Xiaoyu Xu, Feng Zhang, and seminar and conference participants at Southern Methodist University, Chinese University of Hong Kong-Shenzhen, Fordham University, University of New South Wales, University of Nebraska-Lincoln, the 34th Asian Finance Association annual meeting, 2022 China International Conference in Finance, 2022 China International Risk Forum, 2023 Southwestern Finance Association Annual Meeting, 2023 Eastern Finance Association Annual Meeting, 2023 Midwest Finance Association Conference, 2023 Financial Intermediation Research Society conference, 2023 European Finance Association Annual Meeting (poster session), and 2023 Northern Finance Association Annual Meeting.

Huang is at the University of Waterloo, email: aghuang@uwaterloo.ca; Wermers is at the University of Maryland, email: wermers@umd.edu; and Xue is at Southern Methodist University, email: jinmingx@smu.edu.

All errors are ours.

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Abstract

Using a comprehensive database of corporate news, we find that bond funds trade against the direction of news sentiment. The trading against news phenomenon is concentrated in funds selling on positive news and in the post-financial crisis period when dealer liquidity provision is constrained. Funds in so doing exhibit higher alphas, and a potential source of such alphas is bond price reversals post news events. Our findings highlight that bond mutual funds represent a significant liquidity provider in the corporate bond market and play a complementary role to dealers in corporate news events.

JEL classification: G12, G14, G23, G39

Key words: Fixed income mutual funds, Corporate bonds, Institutional trading, Public news, Textual analysis

1. Introduction

"Buy the rumor, sell the news," a trading strategy to buy a security on rumors, and sell it when the (good) news breaks out, has long appeared in the popular press. Practitioners go as far as claiming that it "happens in most financial markets" among professional traders, including equity, foreign exchange, and more recently, cryptocurrency markets.[1] Perhaps due to data limitations, academic support for this long-held trading "axiom" is largely absent. With the availability of large news and institutional trading datasets, Huang, Tan, and Wermers (2020) document that institutional investors trade stocks heavily around corporate news announcements and their trading is skewed significantly towards selling on negative news. This paper explores the trading behaviors of fixed income mutual funds in response to corporate news events. The corporate bond market stands in contrast to the equity market due to its inherently lower information sensitivity but higher trading cost. Corporate bonds predominantly trade over-the-counter (OTC) through dealer networks, characterized by pronounced search frictions and limited liquidity. Consequently, news events can swiftly influence the demand or supply dynamics, especially due to price inelasticities of bonds. This often results in transient imbalances between the availability of bonds and investor demand.

Over the past two decades, U.S. corporate bond market and fixed-income mutual funds have both seen remarkable growth. Corporate debt, a primary financing channel for U.S. corporations, expanded its outstanding amount from $4.5 trillion in 2000 to $15.3 trillion in 2020 (data from FRED of the Federal Reserve Bank, St. Louis). A significant portion of these corporate bonds is held by managed funds (Massa, Yasuda, and Zhang, 2013). The total assets under management (AUM) of taxable bond mutual funds increased to $4.3 trillion in 2020, up from $807 billion in 2002 (data from the Investment Company Institute 2021 Fact Book). Bond funds hold 17.6% of outstanding corporate bonds, positioning them as the second largest institutional owners, only next to insurance companies.[2] Interestingly, despite the non-trivial trading costs, bond funds do not trade infrequently. For instance, funds categorized as U.S. Fund Corporate Bonds by Morningstar reported a median turnover ratio of 79.5% in 2020.[3] The role of mutual funds in

[1] See, for example, https://www.thebalance.com/what-does-buy-the-rumor-sell-the-news-mean-1344971.

[2] At the end of 2020, insurance companies (including life and property-casualty) hold 27.5% of corporate bonds, followed by fixed income funds' 17.6% (data from FRED).

[3] Morningstar's turnover is defined as the lesser of a fund's aggregate purchase and sale, divided by its AUM. Among these funds, the turnover ratio is 72% for Vanguard Intermediate-Term Corporate Bond Index Fund, which has $46

providing liquidity, with aims of reducing trading costs and generating superior returns, has been increasingly recognized in the recent literature.[4]

Alongside the growth in the fixed income fund industry, there has been a significant surge in firm-specific news. In the Factiva news database, the volume of firm-specific news articles supplied by the "Top Sources," such as Dow Jones, Reuters, and the Wall Street Journal, has quadrupled from 167,000 in 2000 to 723,000 in 2020. While bond traders likely rely on "hard" information such as firm earnings and credit rating scores, it is plausible that fixed income fund trading is at least partly driven by corporate news releases. After all, corporate news serves as a major venue of qualitative public information, complementing other venues of soft public information like analyst reports, SEC filings, firm conference calls, and social media posts. Notably, news stands out for its timeliness, especially when compared with credit ratings and analyst reports, which are often disclosed post-news and might carry outdated information.

Anecdotal evidence suggests that funds may opportunistically trade on news. Appendix A depicts an event line of Autodesk releasing a series of positive news from October to December 2019. Concurrently, a fund managed by Dimensional Fund Advisors unwinded its long position in an Autodesk bond. The questions that we address in our paper are: do fixed income funds trade on news, and, if so, does their trading exhibit a pattern that is consistent with "sell on news"? And, in doing so, do fixed-income mutual funds act to supply liquidity to other types of fixed-income pools of capital (e.g., insurance companies) when a news event quickly shifts the supply or demand of bonds of a particular issuer?

We find evidence that answers both questions: fixed income funds trade quickly on news, and their trading patterns can be characterized as "sell on positive news," consistent with providing liquidity to other market participants. We match over eight million firm-specific news articles for 4,323 NYSE/Nasdaq firms with the monthly position changes for 664 fixed income funds sourced from the survivor-bias-free Morningstar database. Measuring news tone using the Loughran and McDonald (2011) financial dictionary, we find that news tone is associated with a strong bond return on the news release day (but not on the day prior to news), and this effect persists into the

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billion AUM with 95% invested in corporate bonds. In contrast, PIMCO Investment Grade Credit Bond Fund, with $19 billion AUM and 75% of AUM in corporate bonds, reports a turnover ratio of 213%.

[4] See, for example, Friewald, Jankowitsch, and Subrahmanyam (2012), Bao, O'Hara, and Zhou (2018), and Dick-Nielsen and Rossi (2019), Ottonello, Rizzo and Zambrana (2023), and Mariassunta, Jotikasthira, Rapp, and Waibel (2023). Liquidity provision in the equity market has also been well documented; see, for example, Da, Gao, and Jagannathan (2011), and Christoffersen, Keim, Musto, and Rzeznik (2022).

subsequent trading days. Given the notable growth in the fund industry, funds predominantly are net bond buyers. The net-buy amount, however, is significantly more (less) when the corporate news is more negative (positive) in tone. The trend of mutual funds purchasing (selling) more bonds during negative (positive) news episodes denotes trading in opposition to news direction—a behavior we term as "trade against news."

We uncover a number of heterogeneities in funds' trade-against-news activities across fund, bond and news types. In terms of fund types, our analysis reveals that, compared to funds investing in broad fixed income instruments such as Treasuries, mortgage-backed securities (MBS), and corporate bonds, corporate concentrated funds are more responsive to corporate news, and that the effect of news trading is more pronounced in funds with higher turnover rates (i.e., funds that are often described as shorter-term investors (Yan and Zhang, 2009). The concentration of the news trading effect in these fund types points to a finding that funds engaging in such trades may enjoy a relative advantage in understanding the segments of bonds they primarily trade, plausibly due to skills in deciphering the nuances of news contents. In terms of bond issue heterogeneity, we find a more procounced effect of trading against news in bonds with higher durations, in bonds with better liquidity, and in issuers with lower information asymmetry (proxied by return volatility and firm size)—all potentially because these bonds are "easier" to trade with but with a greater profit potential. Lastly, in terms of news heterogeneity, we find that the trading against news effect is more pronounced on the positive side of news (as opposed to the negative side), consistent with the traditional "sell on news" wisdom that hinges on news positivity.

We hypothesize that a potential motivation for funds to trade against news is to provide liquidity as a means to generate returns. While corporate bond dealers are generally considered as liquidity providers (e.g., Choi, Shachar, and Shin, 2019), mutual funds serve a valuable complementary role in providing liquidity (e.g., Anand, Jotikasthira, and Venkataraman, 2021), especially when dealers are less able or willing to hold a large inventory of bonds to satisfy liquidity demand. In examining news-trading pre- and post-the 2008 Global Financial Crisis, we find evidence consistent with such a conjecture. Dealer inventory costs rise significantly during and post the crisis, as the period witnesses either rising liquidity costs or a series of regulations such as the Dodd-Frank Act, the Volcker Rule, and the Basel Accords on bank-affiliated dealers that impose more stringent capital requirements and constrain their market-making activities. As a result, there is a noticeable decline in dealers' capital commitment post the crisis (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018); in fulfilling their market-making roles, dealers solicit liquidity provision by other parties by profit sharing via, for example, better spreads (Choi, Huh, and Shin, 2023). We find that mutual funds' trading against news, and in particular, their selling on positive news, takes place only post (and during) the crisis but not before the crisis. This evidence is consistent with dealers demonstrating a higher propensity to share profits with fixed-income mutual funds that provide liquidity.

Relatedly, we provide complementary evidence on trading activities by bond dealers and insurance companies. Similar to fixed income funds, dealers trade against news, but they trade more against negative news shocks than positive news shocks (as compared to funds' largely trading against positive news). In contrast, insurance companies mostly trade in the direction of news. The trading behaviors of dealers and insurance companies are consistent with the view that dealers in general are considered as liquidity providers, while customers such as insurance companies are likely liquidity demanders (e.g., Wang, Zhang, and Zhang, 2020; O'Hara and Zhou 2021).

We find that another potential profit source for funds trading against news is bond price reversal subsequent to news. While the bond price reaction remains largely muted two days after the news breakout, we find that the price slowly reverses, and the reversal becomes significant in about three weeks' time.[5] Therefore, our evidence suggests a short-term overreaction to news in bond prices, only to be (partially) corrected in subsequent weeks. This pattern of return reversal suggests a profitable opportunity: trading against the direction of news to take advantage of potential price corrections. For example, "sell on news" funds tend to sell bonds with higher prices (and therefore bonds with lower alphas), leading to a higher fund-level alpha. This approach is markedly different from a "reaching-for-yield" trading strategy, where funds disproportionately buy bonds that offer higher yields but lower alphas (Choi and Kronlund, 2018; Chen and Choi, 2023).

Consistently, we find that trading against news generates fund alpha. To gauge a fund's tendency to trade against news trading, we aggregate its prior news-trading of individual bonds as its news trading style. Funds with a higher level of "trade against news" style generate larger alphas in subsequent months. When decomposing fund style into a "sell against good news" and a "buy

[5] This average reversal time aligns with the four-to-five-week average half-life of the dealer inventory cycle, as documented by Schultz (2017).

against bad news" style, the former generates higher alphas more than the latter. Moreover, trading against news leads to plausibly unobserved short-term gains that constitute part of a fund's "return gap" alluded to in Kacperczyk, Sialm, and Zheng (2008), i.e., the difference between the fund's reported return and the return generated from the portfolio that it previously reported. Consistent with this premise, we find that funds with a higher level of "trading against news" style, in particular those with a "sell against good news" style, often exhibit larger return gaps. Thus, the "sell on news" wisdom appears to have a grounding in fixed-income funds underscoring fund profitability.

To the best of our knowledge, our paper is among the first to directly study how fixed income funds trade on corporate news. The response of institutional investors to information shocks has long been of interest in the literature. Traditional market microstructure theory models institutional investors as a type of informed investors and thus may be able to trade ahead of public news due to possession of inside information (e.g., Kyle, 1985; Glosten and Milgrom, 1985). The recent data availability of large-scale corporate news allows the literature to test this microstructure foundation from the angle of institutional investors' response to news shocks. Although evidence of whether institutions trade ahead of news is not conclusive, two findings emerge from the equity side of trading: that institutional investors respond quickly to news and that they trade along (instead of against) the direction of news (e.g., Engelberg, Reed, and Ringgenberg, 2012; Hendershott, Livdan, and Schürhoff, 2015; Huang, Tan, and Wermers, 2020). Evidence regarding institutional trading on news in the fixed income market remains limited. Balduzzi, Elton, and Green (2001) and Green (2004) study dealer trading activities in the Treasury market following macroeconomic news announcements. Jiang and Sun (2015) investigate the trading volume and liquidity of corporate bonds around both macroeconomic and firm-specific news; related to our paper, these authors show that firm-specific news arrivals entail larger trading turnover and lower bid-ask spreads and, therefore, the arrival of news "encourages liquidity trades." A number of papers examine bond price reactions around corporate earnings announcements.[6] Current literature, however, remains largely muted on how institutional investors trade on corporate news. Our paper fills this void. Given the importance of fixed income funds as one of the most important types of

[6] Hotchkiss and Ronen (2002) find that corporate bond prices react quickly to earnings news, while Gebhardt, Hvidkjaer, and Swaminathan (2005), Jostova, Nikolova, Philipov, and Stahel (2013), and Nozawa, Qiu, and Xiong (2023) report evidence for bond price drift post earnings announcements.

corporate bond institutional investors, our paper complements the equity side of the studies on institutional trading on news information shocks.

We find that fixed income funds trade against news, and that one mechanism for such trading in generating alpha is price reversals. Our paper is among the first to study corporate bond price reactions to news. The immediate price reaction is consistent with that found in the equity market literature (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008), and the subsequent price reversal post news events also finds grounds in the literature. Theoretically, Brunnermeier (2005) models an informed agent who trades against the public news because of the expected price overshoot, consistent with our empirical findings. Price overreaction to news is also documented in a number of studies.[7] Our findings of bond price reversal to news are also consistent with Bali, Subrahmanyam, and Wen (2021), who report both short- and long-term price reversals in the corporate bond market.

We contribute to the literature documenting that liquidity provision is not just served by dealers but also by fixed income funds (e.g., Choi, Shachar, and Shin, 2019; Anand, Jotikasthira, and Venkataraman, 2021). In the OTC market, broker dealers match the potential sellers and buyers and collect bid-ask spreads (Duffie, Gârleanu, and Pedersen, 2005). In terms of liquidity provision for corporate bonds, the role of broker dealers and other institutional investors remains an important topic for both academics and regulators. Institutional peculiarities of the corporate bond market complicate the process of search and inventory management. Given the rise of stringent regulation (Bessembinder et al., 2018), bank affiliated dealers are less inclined to hold inventories.[8] Dealer would offer better-than-normal quotes to "solicit" liquidity providers when they are less able to provide liquidity themselves (e.g., Harris, 2015; Choi, Huh, and Shin, 2023); for example, Mariassunta, Jotikasthira, Rapp, and Waibel (2023) show that bond mutual funds engaged in more liquidity provision trades after the introduction of leverage ratio constrains on

[7] For example, Tetlock (2011) and Fedyk and Hodson (2023) document that the stock market overreacts to "stale" news (repeated news); and Gilbert, Kogan, Lochstoer, and Ozyildirim (2012) show that U.S. stock and Treasury futures prices overshoot sharply on recurring, stale macroeconomic series of the U.S. Index of Leading Economic Indicators. Hendershott, Kozhan, and Raman (2020) document that corporate bond short sellers trade against price pressure.

[8] Goldstein and Hotchkiss (2020) and Choi, Huh, and Shin (2023) show that dealers exhibit the tendency to offset transactions within the same day, rather than committing overnight capitals; thus, it is likely that either the customer buyer or the customer seller provides liquidity to the other in these offsetting transactions.

bank affiliated dealers. By leveraging these improved quotes alongside post news bond price corrections, fixed income funds may significantly contribute to liquidity provision.[9]

2. News and Fixed-Income Fund Samples

2.1 Samples

We retrieve 22,987,096 corporate news articles for all firms listed on NYSE (including NYSE American) and Nasdaq between January 1, 2002, and December 10, 2020, from the "Top Sources" news outlets in the Factiva database on Dow Jones' Data, News & Analytics (DNA) Platform. The DNA Platform provides three firm identifiers to tag the news with: companies that the news article is deemed to have a high relevance with ("high-relevance companies"), companies mentioned in the article, and companies deemed to be relevant to the article (for instance, the parent company of the mentioned subsidiary). We filter through these firm identifiers and remove news articles that contain fewer than 50 words, are not related to any company (likely macro or general news), or have a high relevance with over five companies (likely industry news or market commentary). We arrive at 8,351,674 news articles assigned to 4,323 firms on Compustat. The sample covers more than 100 news sources, with Dow Jones supplying 50.3% of the news, followed by Reuters News's 11.2% and Business Wire's 8.2%. Appendix B discusses the data filtering procedure in detail.

Following the literature (e.g., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Huang, Tan, and Wermers, 2020), we calculate the tone of the news by counting in each news article the occurrences of negative and positive words from Loughran and McDonald (2011). Consistent with these studies, our primary sentiment measure is the net negative tone (*Neg_net*), defined as the number of negative-word occurrences minus positive-word occurrences divided by the total number of words.[10] We also consider the two components of *Neg_net*: *Neg* (*Pos*), the ratio of negative (positive) word count to the total number of words in the news article. Appendix C provides the definitions of the variables used in this paper.

We obtain holdings information for fixed income funds from the survivor-bias-free database of Morningstar Historical Month-End Holdings Full History from 2002 (the earliest

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[9] Our primary focus is on the cross-sectional liquidity provision for bonds influenced by news sentiments. While this is our emphasis, we recognize that it is possible that mutual funds in aggregate could still be liquidity demanders, for example, Bretscher, Schmid, Sen, and Sharma (2022).

[10] We remove stop words from the corpus when counting the total number of words.

available year) to 2020. We focus on the changes in corporate bond holdings for funds under the five Morningstar fund categories that tend to hold corporate bonds: i) U.S. fund corporate bond (which primarily invests in investment grade corporate bonds), ii) U.S. fund high yield bond (which focuses on high-yield corporate bonds), iii) U.S. fund intermediate core bond (which invests in investment-grade U.S. fixed-income issues, including government, corporate, and securitized debt), iv) U.S. fund intermediate core-plus bond (similar to intermediate core bond funds but with greater investment flexibility), and v) U.S. fund long-term bond (which invests in long-term government, corporate, and securitized debt).

Funds in Morningstar may provide quarterly or monthly holdings information. Given the frequent occurrences of firm-specific news, we restrict our sample to funds that provide monthly holdings data, so that we can evaluate holding changes surrounding news events in a timely manner. In Panel A of Table I, we provide fund summary statistics. Our sample contains 664 unique fixed income funds that report monthly holdings, out of a total of 859 funds (77%) for the considered five fund categories in Morningstar.[11] The mean and median AUM for funds that report monthly closely align with the respective values for the broader Morningstar sample. Over the sample period of 19 years, the monthly reporting funds in total make $858 billion worth of trades on 8,355 bonds issued by 822 firms.

[Insert Table I about here.]

In subsequent regressions, we control for two fund characteristics, fund age and expense ratio. Morningstar provides the inception date of each fund share class, and we use the earliest share class to compute the fund age. Expense ratio is from the CRSP survivor-bias-free mutual fund database. We map CRSP and Morningstar databases following Pástor, Stambaugh, and Taylor (2015). Funds under these categories may invest in fixed income securities other than corporate bonds, such as Treasuries and Agency securities; we hence exclude fund-months with less than 10% holdings of AUM in corporate bonds. Following the literature, we also remove trades on bonds with a remaining maturity of less than one year (e.g., Bai, Bali, and Wen, 2021).

2.2 Bond Returns around News and Matching news to fund holdings

To examine the impact of news on bond trading, we align the month-t news with the same month Δw. This alignment is built on two assumptions: i) institutions react promptly to news

[11] Untabulated, the fraction of funds reporting monthly holdings increases over time, for instance, from 46% (in total out of 484 funds) in 2005 to 60% (in total out of 465 funds) in 2019.

without preemptively anticipating it, and ii) institutions do not reverse their position in a given bond within the month. Assumption ii) is plausible due to the significant transaction costs and search friction in the corporate bond market (Bessembinder, Maxwell, and Venkataraman, 2006; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007). As to assumption i), research in equity markets (among others, Huang, Tan, and Wermers, 2020) uses high-frequency institutional trading data and finds that institutions trade speedily on news; in particular, mutual funds trade stocks on the news release day but neither before nor after.[12] While the lack of high-frequency data constrains us from providing direct evidence of speedy reactions of fixed income funds to corporate news, available daily returns would provide indirect support for assumption i).

We construct daily bond returns using bond transactions from TRACE and coupon information from the Mergent Fixed Income Securities Database (FISD). Following the TRACE data cleaning procedures in Dick-Nielsen (2014) and the definitions of bond returns such as in Jostova, Nikolova, Philipov, and Stahel (2013), we define:

$$r_{j,t} = \frac{\left(P_{j,t}+AI_{j,t}+Coupon_{j,t}\right)-\left(P_{j,t-1}+AI_{j,t-1}\right)}{\left(P_{j,t-1}+AI_{j,t-1}\right)},$$

where $r_{j,t}$ is bond j's day-t return, $P_{j,t}$ is the bond's volume-weighted average price using all of the bond's trades at day t, $AI_{j,t}$ is the accrued interest at day t, and $Coupon_{j,t}$ is the coupon(s) paid, if any, on day t.[13] Consistent with the event study literature (e.g., Kothari and Warner, 2007; Hendershott, Livdan, and Schürhoff, 2015), we form excess daily returns by subtracting the same-day return on the market (proxied by the Bloomberg Barclays US Aggregate Total Return Index) from a bond's daily return.

We align news and TRACE trades by trading day.[14] To examine the daily news-return relation, we first average *Neg_net* for all firm-specific news on each trading day to arrive at a daily *Neg_net* value following Huang, Tan, and Wermers (2020). Panel A of Table II regresses daily

[12] In Table A1 in the Internet Appendix, we provide robust evidence to support these two assumptions. Specifically, we show that news tone measures do not predict lead month Δw and our main results in Table III are robust to news tone measures that use only news in the last ten days of a calendar month ("month end").

[13] In calculating daily bond returns, we use all trades, including dealer to customer and interdealer trades, of the bond within the day to reflect the fact that bond trading tends to be sporadic. Our results remain qualitatively the same if we use instead the last trading price of the day, or if we use only inter-dealer trades.

[14] In aligning news and trading, we group all after-market news and news released over non-trading days such as weekends and holidays to the next trading day. Hence, news day-0 trading corresponds to news released after the market close of the previous trading day until the market close of the current trading day. Addressing the fact that news released during trading hours may impact only a portion of the daily trades, our results remain qualitatively the same if we remove all such news.

bond excess returns from day [-1] to day [10] on daily *Neg_net*, along with control variables of bond characteristics (remaining maturity, credit rating) and issuer characteristics (firm market capitalization, idiosyncratic return volatility, long-term debt ratio, and interest coverage ratio), and bond and date fixed effects. All control variables are measured prior to the given month to avoid look-ahead biases. Using all news days, Models (1)-(5) show that *Neg_net* is significantly and negatively related to bond returns on days [-1], [0], [1], and [2, 5]; that is, these results suggest that bond returns react mostly speedily to news, but also ahead of news.

[Insert Table II about here.]

Using all news days, however, may entail look-ahead biases as related news tends to occur in rapid succession. In a multiple-day news event, the current price might be influenced by the news from the previous day. However, if aspects of the previous day's news are reiterated in subsequent days, it creates an illusion that the current price can anticipate news from a later day, thereby biasing the regression outcomes.[15] To mitigate this problem, we follow Huang, Tan, and Wermers (2020) and group firm-days that experience consecutive-day (i.e., non-stopping) news arrivals into a single "news cluster" and restrict our analysis to only the first day of each news cluster.[16] In Models (6)-(10) of Panel A, the results show that out of days [-1, 10], *Neg_net* is instead only significantly related to bond excess return on days [0] and [1]. The magnitude of coefficient estimates increases from day [0] to day [1], suggesting that the return impact of *Neg_net* is the strongest on day [1]. Thus, more negative news is associated with a decrease in bond price on the same day of the news, and the price impact continues into the next trading day. Untabulated, we can also report that returns are not related to news on days [-5, -2].

Panels B and C of Table II repeat the exercises of Panel A for, respectively, *Neg* and *Pos*. The results are similar. Using the initial news days only in news clusters, *Neg* is significantly related to returns on only day [1]; and *Pos* is significantly related to returns on days [0] and [2, 5], a somewhat stronger association than that of *Neg*. Neither *Neg* nor *Pos* has a significant relation with returns on day [-1] in news clusters, again suggesting that the market does not predict news. Overall, Table II suggests that market participants do not trade ahead of news; instead, they react

[15] For instance, within a consecutive two-day news sequence, the news on days [1] and [2] might be interconnected (potentially echoing the same content but from different sources). This subsequent association could suggest a predictive price response of day [1] to the news on day [2], even if the day [1] price adjustment is solely driven by the news from day [1].

[16] By definition, a firm day without adjacent-day news arrivals is treated as a cluster itself.

speedily to news without much delay, consistent with the findings on the news impact in the equity market.

Given that Table II implies that fixed income fund managers are likely to react speedily to news, in-the-month news would translate into holding changes at month end. Reflecting this, we condense daily news tone to the monthly frequency for each bond-month by averaging the daily firm-specific *Neg_net* by month, and match the month-*t* news with the same month Δw. After these procedures, our final news-matched fund holdings sample comprises 3,251,699 fund-bond-months, and trades by 626 distinct funds of 8,266 bonds issued by 820 firms.

We measure fund trading of individual bonds by $\Delta w_{i,j,t}$, defined as fund i's dollar change in holding of bond j from month t-1 to month t, scaled by the fund's month-t beginning total net assets in corporate bonds.[17] Dollar change in bond j is the change in par value, multiplied by the average price (in the percentage of the par) of bond j reported by all fixed income mutual funds. Panel B of Table I provides the summary statistics of the key variables for our final (regression) sample. The average fund total net assets in our sample are $19.8 billion with $5.92 billion invested in corporate bonds.[18] The average of Δw is 0.006%, which translates into a dollar net-buy amount of $365 thousand. This is consistent with the phenomenal growth of the fixed income fund sector during the past two decades. The median of Δw is zero since funds, in general, are non-high-frequency traders. The average of *Neg_net* is slightly positive (0.004), suggesting that the average news tone is somewhat negative. A median bond in our sample has a credit rating of BBB+ (investment grade) and 7.6 years remaining to maturity.

3. Evidence for Funds Trading Against News

3.1 Univariate sorting

In this section, we examine funds' trading on news. We begin by examining bond trading based on univariate sorting of news tone. Figure 1 provides the results. We sort our sample into deciles by *Neg_net* and examine the mean value of Δw for each *Neg_net* decile. We find that the mean value of Δw is almost monotonically increasing in the decile rank. The mean of Δw for the

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[17] We normalize the dollar amount using the fund's corporate bond holdings to account for the fact that some fixed income funds allocate only a fraction of their assets to corporate bonds. In Table A2 in the Internet Appendix, we also use the dollar change in trading and our findings are robust.

[18] Fund total net assets in the regression sample has a higher mean than the mean of AUM reported in Panel A since larger funds disproportionately have more trades in the regression sample.

top decile is 0.82 basis points (bps), almost three times of 0.29 bps for the bottom decile, amounting to a 0.53 bps difference between deciles 10 and 1. In addition, the Δw difference between deciles 6 to 10 and deciles 1 to 5 is also large and significantly positive at 0.27 bps.

[Insert Figure 1 about here.]

While the mean value of our issue-level Δw's seems low, noting that Δw is measured relative to the fund's entire corporate bond holdings, such differences are economically significant. For instance, a Δw of 0.53 bps (0.27 bps) for a fund holding \$6 billion of corporate bonds (the average corporate bond holdings of a fund in our sample) implies a trade of \$319 (\$162) thousand for a single bond. In comparison, we note that the unconditional average value of an absolute position change is \$158 thousand in our sample, smaller than these Δw differences. These results provide the first evidence that fixed income mutual funds exhibit a propensity to trade against the direction of news. Specifically, while equity funds trade along the direction of news (Huang, Tan, and Wermers, 2020), fixed-income funds tend to sell (buy) more of the bond if the issuer experiences more positive (negative) news in the month.

3.2 Regression analysis

We now regress Δw on *Neg_net* with multivariate control variables of bond, issuer, and fund characteristics, as well as bond fixed effects and fund type-month fixed effects. Table III presents the regression results. Model (1), which includes only the fixed effects, and Model (2), which includes the full set of the control variables, both show that *Neg_net* is positively and significantly related to Δw, suggesting that funds tend to buy more or sell less when the issuer is under more negative news, consistent with the univariate results presented in Figure 1.

[Insert Table III about here.]

We use Model (2) as a benchmark to calculate the economic significance of news tone. The economic significance of *Neg_net* on Δw, measured by multiplying the standard deviation of *Neg_net* and its coefficient estimate, is 0.037 bps. Given that the average fund corporate bond holdings in the sample is \$6 billion, this economic significance translates into a dollar value of \$23 thousand. That is, the economic significance of *Neg_net* on Δw corresponds to roughly one-seventh of the mean absolute dollar trading amount (of \$158 thousand).

Subsequently, we explore whether the news tone influences managers' decisions on whether to trade a bond. We create a variable, $Increase_{i,j,t}$, that assumes a value of 1 if the manager purchases a bond ($\Delta w_{i,j,t}$>0), 0 if there is no trade ($\Delta w_{i,j,t} = 0$), or -1 if the manager sells

($\Delta w_{i,j,t} < 0$). Models (3) and (4) show that *Neg_net* is positively and significantly related to *Increase*. Further, Models (5) and (6) continue to find positive and significant coefficient estimates for *Neg_net* when we constrain the sample to non-zero Δw, that is, the sample where funds make directional changes in positions. Model (6) has a much larger *Neg_net* coefficient estimate than Model (2): one standard deviation change in *Neg_net* implies a much larger dollar value of $64,980 for an average fund for the non-zero Δw sample. In sum, these regression results indicate that funds are more likely to net-sell (net-buy) a bond when its news is more positive (negative), confirming the trading against news findings in Figure 1.

3.3 Fund heterogeneity

In this section, we examine the differences of news trading across fund types. Funds within the five Morningstar categories of our sample adhere to different investment mandates and invest distinct portions of the assets in corporate bonds. Based on the potential performance sensitivity of fund managers to corporate news, we consider these five categories into two groups: corporate concentrated funds and broad fixed income funds. Corporate concentrated funds include U.S. fund corporate bond and U.S. fund high yield bond—these are funds specializing in corporate securities. We group the other three categories (U.S. fund intermediate core bond, U.S. fund intermediate core-plus bond, and U.S. fund long-term bond) as broad fixed income funds, as these funds target broader fixed income securities—they typically invest around 30% of their assets in corporate bonds and the rest in other investment-grade fixed-income issues, including government securities and securitized debt. As the required skillset for fund managers is likely to be aligned with the fund's focus, we expect that corporate concentrated funds are more sensitive to corporate news.

Table IV repeats our main analysis for corporate concentrated funds (Models (1) and (2)) and broad fixed income funds (Models (3)). We find that *Neg_net* is positively related to Δw for all fund types, while the effect is much stronger in corporate concentrated funds. The coefficient estimate of *Neg_net* for corporate concentrated funds is about four times that for broad fixed income funds.[19] The evidence hence supports a higher sensitivity of corporate concentrated funds to news.

[Insert Table IV about here.]

[19] In untabulated tests, the difference in the coefficient estimates between the two models is statistically significant. Δw is computed over the total assets in corporate bonds held by a fund. Consequently, the effect is not attributable to broad fixed income funds holding fewer corporate bonds overall.

This finding is consistent with the preferred habitat theory in bond investing. Under the theory, bond market is segmented by maturity, and investors have preferences over particular maturities. More generally, investors exhibit habitat behavior over "segments" other than maturity; for example, Chen, Huang, Sun, Yao, and Yu (2020) find that different insurance companies have a preference over bond liquidity, and this preference is tied to their investment horizons and funding constraints. That news trading is aligned with the fund objective is a manifestation of habitat trading behavior—that is, trading takes place in the investor's preferred habitat (where the investor presumably has the most skills).

In addition to Morningstar fund types, we also estimate fund type based on the fund's past turnover. Fund turnover is often viewed as an "activeness" measure. For instance, Yan and Zhang (2009) classify institutions into short- and long-term investors based on their reported Form 13(f) equity portfolio turnover rates and document that short-term investors play a larger role rather than long-term institutions in driving the positive relation between institutional ownership and future stock returns. In the bond market, Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008) use fund turnover and show that bonds held by higher turnover funds are more liquid. Yan and Zhang (2009) calculate a portfolio "churn rate" for each institution based on the lesser of its aggregate purchase and sale each quarter; Morningstar also adopts this definition for fund turnover. We similarly calculate a monthly churn rate for each fund as the lesser of the aggregate dollar purchase and dollar sales of corporate bonds within the month, divided by the mean of its month-beginning and month-end total holdings in corporate bonds. We then use the rolling average churn rate over the past 12, 9, or 15 months as the fund's portfolio turnover.

Table V shows that the trading against news effect is stronger for higher turnover funds. We interact *Neg_net* with a dummy indicating whether the fund has high turnover in the past. We find that for the full sample, the interaction term is significantly positive for fund turnover measured over the past 12, 9, and 15 months (Models (1)-(3)). Furthermore, the interaction term is also significantly positive for, respectively, corporate concentrated funds and broad fixed income funds. While the main effect of *Neg_net* remains significant most of the time, the magnitude of the coefficient estimate of the interaction term is much larger than that of *Neg_net*. These results suggest that the trading against news effect is much stronger for higher turnover funds, consistent with the notion that high turnover funds tend to be short-term investors and are more inclined to trade when opportunities arise. In other words, high turnover funds are plausibly better at providing liquidity, and they do so when called for by market events such as news.

[Insert Table V about here.]

3.4 Issue and issuer heterogeneity

We next examine issue and issuer heterogeneity in the trading against news effect. We first examine bond duration. Duration management, or the so-called "duration targeting," is a widely adopted strategy to balance risk and return during portfolio management (e.g., Langetieg, Leibowitz, and Kogelman, 1990).[20] Other things being equal, shocks to a bond will exert a more pronounced impact on its price when the bond has a longer duration. Consequently, if funds engage in news-driven trading, they would typically gravitate towards longer-duration bonds to exploit larger profit opportunities.

We use the Macaulay duration and the remaining maturity, respectively, to measure a bond's duration and regress Δw on the interaction between *Neg_net* and a high-duration dummy. Models (1) and (2) of Table VI show that the interaction term is significantly positive, and the interaction term subsumes the significance of *Neg_net* on Δw. These results confirm that the trading against news effect is indeed more pronounced in longer-duration bonds.

[Insert Table VI about here.]

That the trading effect of news is more pronounced in longer-duration bonds is consistent with funds providing liquidity to the market. Using the regulatory version of TRACE, Han, Huang, Kalimipalli, and Wang (2022) provide evidence that corporate bonds with longer maturity experience lower dealer round-trip bid-ask spreads and larger trading volume. Directly dichotomizing bonds by bond liquidity would provide liquidity provision evidence. To this end, we measure a bond's turnover by its previous six-month trading volume (divided by its par amount outstanding) and interact *Neg_net* with a high bond-turnover dummy. Model (3) of Table VI shows that the interaction term is significantly positive, indicating that the trading effect of news is more pronounced in bonds with better liquidity.

In Table VI, we lastly examine whether the effect is driven by information asymmetry of the bond issuers. We break bond issuers by two information asymmetry measures: idiosyncratic return volatility and firm size. Firms with smaller idiosyncratic volatility or larger firms or tend to

[20] In duration targeting strategies, the portfolio manager attempts to maintain a relatively constant portfolio duration through periodic rebalancing.

have a lower degree of information asymmetry (e.g., Krishnaswami and Subramaniam, 1999; Dittmar, 2000). We create a dummy variable for firms with a smaller idiosyncratic volatility or larger size, and interact the dummy variable with *Neg_net*. Models (4) and (5) of Table VI show that the interaction term is significantly positive, suggesting that the trading against news effect is concentrated in bonds with less information asymmetry. Should trading against news be viewed as an activity through which funds provide liquidity to the market (a motivation we will subsequently argue for), Models (3)-(5) indicate that funds are more comfortable providing liquidity for bonds with better liquidity and less uncertainties—potentially because it is less restrictive to trade these bonds as they are more transparent and incur smaller transaction costs.

3.5 News heterogeneity

Lastly, we explore news heterogeneity in bond trading. Credit rating is widely perceived as the most important bond-specific factor in bond pricing.[21] News related to firms' credit ratings, therefore, should carry a stronger weight than other news when funds trade against news.

Depending on the nature of the news article, Factiva provides a list of "subject codes" (i.e., topics) and classifies a news article into one or more topics. From our sample of news, we retrieve all news that is assigned with the subject code of "Corporate Credit Ratings," for which Factiva explains that articles under this subject code are about "ratings assigned to corporate debt instruments by credit rating agencies." Using only these credit rating-related news articles, we re-calculate each firm's *Neg_net* measure; this recalculated measure reflects the news sentiment about the bond issuer's credit rating movements. About one-third of bond-months have credit rating-related news. Model (1) of Table VII shows that *Neg_net* of credit rating news remains negatively and significantly related to Δw. This significance takes place with the existence of credit ratings, suggesting that news information about credit ratings carries incremental value.

[Insert Table VII about here.]

The importance of credit rating news is further corroborated by actual credit rating changes. Credit rating news is not necessarily accompanied by actual credit rating changes. In fact, in the credit rating news bond-months, only about a quarter is accompanied by credit rating upgrades or downgrades by (one or more of) the three major rating agencies (Moody's, Standard & Poor's, and

[21] For example, this "Bond Basics" article (link) by PIMCO (one of the largest fixed income asset managers) lists the following three factors influencing bond pricing: market conditions, credit ratings, and bond age, with credit rating treated as the most important bond-specific factor.

Fitch) based on the credit rating change data from FISD. We code credit rating change to take the value of one (negative one) if the bond is upgraded (downgraded) in the month, and zero otherwise. Model (2) of Table VII shows that while *Neg_net* remains significantly positive, the interaction term between *Neg_net* and credit rating change is also significantly positive, suggesting that trading against news is more pronounced in upgrades than in downgrades. In subsequent sections, we also show that trading against news is more pronounced in good news—that is, funds tend more to "sell on good news" than to "buy on bad news."

Rating agencies often attach an outlook to a company—namely, negative watch or positive watch—signifying a potential future change in ratings. In model (3) of Table VII, we further investigate funds' trading against news for bonds under credit watch. We similarly code a "Credit rating watch" variable that takes the value of one (negative one) if the bond is under positive (negative) watch by any of the three major rating agencies in the month, and zero otherwise. The interaction term between *Neg_net* and credit rating watch is positive and statistically significant, on top of the interaction term between *Neg_net* and credit rating change. The result indicates that the impact of *Neg_net* is more pronounced when a bond is under positive watch, further corroborating the "sell on good news" part of the trading against news pattern. In sum, Table VII shows that credit rating news plays an important role in funds' trading on news.

Another facet of news heterogeneity that we examine is the negative and positive sides of the news. In the equity market, *Neg* has a stronger relation to stock returns than *Pos* does (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008). In Table VIII, we separately examine the effect of the positive and negative legs of *Neg_net* on Δw. Models (1) and (2) show that *Neg* is not significantly related to Δw or *Increase*, but *Pos* in Models (3) and (4) is significantly and negatively related to Δw or *Increase*; that is, the trading against news phenomenon is predominantly concentrated in tone positivity of the news rather than tone negativity. Compared to Table III, the coefficient estimate of *Pos* on Δw is about four times that of *Neg_net*; and given that the standard deviation of *Pos* (0.0112) is about the same as that of *Neg_net* (0.0108), this implies that the economic significance of *Pos* is about four times as that of *Neg_net*. Thus, liquidity provision of fixed income funds seems to concentrate on news positivity. In other words, "sell on (good) news" is more prominent than "buy on (bad) news" in the trading of fixed-income funds. The evidence resonates with the results of Figure 1, where Δw is almost monotonically increasing in *Neg_net* from Deciles 1 to 5 (when news is positive) and then the increase tapers off from Deciles 6 to 10 (when news is positive). Overall, selling on news by fixed income funds contrasts with the "buy the dip" phenomenon observed in the equity market, as documented by (Bonini, Shohfi, and Simaan, 2022).

[Insert Table VIII about here.]

4. Potential Motivations for Fund Trading Against News

In this section, we explore the potential motivations for funds trading against news. Our primary hypothesis is that these funds adopt such a strategy to provide liquidity. To support this argument, we present several pieces of evidence. We first present the evidence that funds provide liquidity when dealers face higher capital constraints post the recent financial crisis. We then investigate trading behaviors of institutions other than mutual funds and underscore that bond dealers—often perceived as liquidity providers—likewise trade against news. We find that bond prices exhibit price reversals following the news release. Such price reversals plausibly result in funds that trade against news yield higher risk-adjusted returns.

4.1 Trading against news during and post the global financial crisis

As essential liquidity providers in the corporate bond market, broker-dealers bridge the gap caused by the asynchronous arrival of buyers and sellers. Yet, the costs of maintaining such inventories have risen considerably since the 2008 global financial crisis. As a result, there's been a noticeable decline in dealers' capital commitment (Bessembinder et al., 2018) and a concurrent rise in customer liquidity provision (Choi, Huh, and Shin, 2023). The increased costs associated with inventory holdings deter dealers from retaining excessive amounts of bonds. We expect that this dynamic is particularly pronounced for positive news compared to negative news. In the case of negative news, dealers hold cash and purchase bonds upon the realization of a negative firm specific shock. In order to meet buy demand in case of positive news, dealers have to build up inventories across a broad spectrum of bonds beforehand since they cannot forecast news (e.g., An, 2022); however, they are now capital-constrained from doing so. Consequently, dealers demonstrate a higher propensity to share profits with fixed-income mutual funds providing liquidity from funds' inventories in the wake of positive firm news.

To investigate this mechanism, we analyze the trading patterns of fixed income funds in response to news events across distinct subsamples, as presented in Table IX. To discern variations in dealers' willingness to hold inventories, following Bessembinder et al. (2018) we categorize our sample into four periods: January 2002 to June 2007 (pre-crisis), July 2007 to April 2009 (crisis), May 2009 to March 2014 (post-crisis), and April 2014 to December 2020 (post-Volker Rule). This classification reflects the events that impacted corporate bond liquidity.

[Insert Table IX about here.]

During the pre-crisis period, dealers faced fewer capital constraints, as indicated by the narrower bid-ask spreads in inventory transactions (see, e.g., Figure 3 in Choi, Huh, and Shin, 2023). Contrary to our primary findings in Table III, Model (1) of Table IX shows a coefficient of -0.194 for *Neg_net*, which is statistically significant. Models (2) and (3) of Table IX further indicate that the effect is more pronounced for negative sentiment, as evidenced by a statistically significant coefficient of -0.241 for *Neg*, as compared to *Pos*, which have an insignificant coefficient of 0.061. These results imply that, on average, fixed income mutual funds trade in line with news sentiment, particularly news negativity, and refrain from providing liquidity. This pre-crisis trading pattern aligns with the trading behaviors observed in equity mutual funds, as noted by Huang, Tan, and Wermers (2020).

In the three subsequent subsamples, dealers encountered capital constraints due to a variety of factors. From July 2007 to April 2009, the financial crisis brought about a widespread deterioration of liquidity in the corporate bond market (Dick-Nielsen, Feldhutter, and Lando, 2012; Friewald, Jankowitsch, and Subrahmanyam, 2012). In the post-crisis period from May 2009 to March 2014, the industry saw the implementation of Basel 2.5 and Basel III. These regulations ushered in more stringent capital requirements for bank-affiliated dealers. Lastly, between April 2014 and December 2020, bond dealers' market-making activities were further influenced by the Volcker Rule. While the Volcker Rule was designed to curb bank-affiliated dealers from engaging in risky proprietary trading, it unintentionally dissuaded them from maintaining inventories for market-making purposes, as discussed by Duffie (2012) and Schultz (2017).

Analyzing the crisis period, Models (4)–(6) display coefficients for *Neg_net*, *Neg*, and *Pos* as 0.098, 0.032, and -0.280, respectively. Of these, the coefficients for *Neg_net* and *Pos* are statistically significant, while that for *Neg* is not. These results are consistent with those in Table III, indicating that mutual funds trade against news. Further analyses into the post-crisis and post-Volcker Rule samples with Models (7)–(12), the results consistently highlight that fixed income mutual funds generally trade against news too. This tendency is particularly evident with positive news, with the exception of Model (8) that suggests dealers also trade against negative news.

Collectively, these findings are in line with our primary observations from Tables III and VIII. They underscore the pattern that trading against news events becomes more prevalent once dealers face higher capital constraints.

4.2 Trading by bond dealers and insurance companies

We examine the trading behaviors of other market participants to further shed light on the news trading pattern by fixed income funds. Specifically, we focus on two key players in the market: bond dealers and insurance companies. Corporate bond dealers are generally regarded as liquidity providers.[22] In contrast, insurance companies often trade for other reasons and thus demand for liquidity.[23] If trading against news by funds—that is, fund managers sell the bond when the bond experiences good news—is viewed as providing liquidity to the market, we should observe that liquidity providers such as dealers would similarly trade against news, while potential liquidity demanders such insurance companies would trade along the direction of news.

Unlike mutual fund holdings data, which, to our knowledge, is available at its most granular on a monthly basis, transaction data for bond dealers from TRACE and for insurance companies from NAIC include execution date. This granularity enables a more detailed examination of the trading behaviors of these institutions following news events. We follow the literature and use aggregate institutional net buy for institutional trading (e.g., Huang, Tan, Wermers, 2020). We aggregate TRACE daily dealer-customer transactions for each bond and construct dealer net buy. For a bond on a given execution date, dealer net-buy is calculated as the difference between the aggregate par value of all dealer purchases from customers and all dealer sales to customers, normalized by the bond's amount outstanding.[24] Similarly, we calculate a bond's insurance company net buy as the bond's normalized NAIC aggregate daily buys minus its sells.

Models (1)-(4) in Panel A of Table X examine dealer net buy on news by regressing dealer net buy of days [0] to [10] on *Neg_net*. The results highlight that *Neg_net* is significantly and positively associated with dealer net buy on days [0], [1], and days [2, 5]; and the relation between *Neg_net* and dealer net buy is insignificant for days [6, 10]. Importantly, dealers are most

[22] See, for example, Bessembinder et al. (2018) and Choi, Shachar, and Shin (2019).

[23] For instance, the literature has documented that insurance companies prefer higher rated but also higher yield bonds (Becker and Ivashina, 2015), and, due to regulatory constraints on credit ratings, their holdings are subject to fire sales pressure (Ellul, Jotikasthira, and Lundblad, 2011). These trading motivations are unlikely to be tied to liquidity provision.

[24] Following Adrian, Boyarchenko, and Shachar (2017) and Choi, Huh, and Shin (2023), we exclude affiliated transactions in which dealers transfer bonds to their non-FINRA affiliates for bookkeeping purposes.

responsive to news on day [0], with diminishing sensitivity as time progresses.[25] In Panels B and C of Table X, Models (1)-(4) provide evidence for dealer net buy on *Pos* and *Neg*, respectively. We note that dealers react to *Neg* (buy on bad news) on days [0], [1], and days [2, 5] and react to *Pos* (sell on good news) on days [1] and weakly so on days [2, 5]. These results indicate that dealers in aggregate tend to trade against news. Consistent with the notion that dealers make the market and provide liquidity to customers when news induces demand for selling and asset price is under pressure,[26] our findings suggest that dealers engage more in "buy on bad news" than in "sell on good news" —a trading pattern opposite to mutual funds, who lean towards the latter. In other words, mutual funds serve a useful complementary role in providing liquidity when dealers are less active in doing so. One potential explanation is due to decreased dealer capital commitment for market making (e.g., Bessembinder et al., 2018). In particular, Volker rule prevents dealers from proprietary trading, and, in response, dealers exhibit rapid inventory turnover and avoid maintaining large inventories in particular bonds (Bao, O'Hara, and Zhou, 2018). When positive news hits the market and results in a surge in customer demand for the bond, dealers, reluctant to short-sell, might resort to the inventories held by mutual funds to satisfy the demand.

[Insert Table X about here.]

Models (5)-(8) in Panel A of Table X provide the results of insurance company net buy in relation to *Neg_net*. In contrast to our findings for fixed income mutual funds and bond dealers, the coefficients of *Neg_net* on insurance company net buy are significantly negative for days [0] to [10]. Insurance companies thus trade along the news direction, and this trade direction significantly lasts into subsequent weeks. These results offer support that insurance companies are potential counterparties to dealers and fixed income funds in news events. Models (5)-(8) of Panels B and C examine insurance company net buy on *Pos* and *Neg*, respectively. The effect of *Pos* is mild on insurance company net buy and is significant on day [1], while the coefficients of *Neg* are much more significant for days [0], [2, 5], and [6, 10]. The asymmetric trading behavior in *Pos* and *Neg* by insurance companies suggests that the *Neg_net* effect is largely due to the negative side of news. As insurance companies are known to be risk averse and tend to avoid negative

[25] Dealer net-buy is measured cumulatively over the given time horizon; hence over days [2, 5], the average daily sensitivity of dealer net-buy to news is about one quarter of that on day [0].

[26] See, for example, Kyle (1985), Duffie, Gârleanu, and Pedersen (2005), and Goldstein and Hotchkiss (2020).

events and issues (e.g., Cao, Li, Wermers, Zhan, and Zhou, 2023), the results suggest that insurance companies tend to dispose of their positions in cases of negative news shocks.

Table X, combined with our main results on mutual fund trading, depicts the trading behaviors of three major market participants in the corporate bond market. We show the tendency of mutual funds to trade against positive news shocks, insurance companies to trade mainly along negative news shocks but modestly along positive news shocks, and dealers to trade against both positive and negative new shocks. The evidence overall suggests that trading on the negativity and positivity sides of news among fixed income funds, dealers, and insurance companies complement each other.

Although mutual funds collectively represent a significant presence in the corporate bond market, they account for approximately 20% of the outstanding corporate bonds. Dictated by the fact that there are other market participants for which trading information is largely unavailable, for example, registered investment advisors, hedge funds, and wealthy individuals, we recognize that trading activities on news tones by fixed income funds and dealers as a whole do not completely offset those by insurance companies.

4.3 Bond price reversal subsequent to news

In this section, we demonstrate the reversal of bond prices following news events as a potential motivation for fund trading. While we recognize that, by filling in the roles of dealers in providing liquidity, funds may profit from improved quotes from dealers, we are constrained by data availability to test such a motivation. Post news price reactions provide instead an indirect method for us to examine the potential sources of alpha for funds. Specifically, if there exists a price reversal after news, trading against news can be profitable (as compared to the fund benchmark). In equity markets, the extant literature has documented price reversal to news (e.g., Tetlock, 2011; Gilbert, Kogan, Lochstoer, and Ozyildirim, 2012; Fedyk and Hodson, 2023). In the fixed income market, Bali, Subrahmanyam, and Wen (2021) show that there exist both a short-term (one-month) and a long-term (three- to five-year) price reversal.

We provide evidence of post-news bond price reversal in Table XI, where we regress bond excess return on *Neg_net* for each of the trading days over days [11, 20] post news. While the coefficient estimate remains negative (but insignificant) in days [11, 12], it starts to turn positive on day [13], and becomes significantly positive for days [18, 19]. If we group trading days by week, we observe that the coefficient estimate of *Neg_net* is insignificant over days [11, 15] but significantly positive over days [16, 20]. This finding is consistent with the post-news equity price reversal literature discussed above.

[Insert Table XI about here.]

The remainder of Table XI offers further evidence for *Neg* and *Pos*, respectively, and finds a similar pattern: there is evidence of statistically significant return reversion for both *Neg* and *Pos* around days [17, 19]. The coefficient estimate of *Pos* is all negative from day [15] to day [20]. On the weekly basis, we observe statistically significant price reversal on week 4 (days [16, 20]) for *Pos* but not for *Neg*. This asymmetric behavior in return reversal on *Pos* is consistent with our earlier findings that trading against news by mutual funds is only significant in *Pos* and that selling against positive news could potentially generate alphas. Overall, the pattern of immediate returns observed earlier in Table II and return reversal identified in Table XI suggests that there is a short-term overreaction to news in bond prices, which is partially corrected in about three weeks. For fund managers, one way to profit from such correction is to strategically trade against the direction of the news.[27] Price reversal therefore constitutes a potential explanation for fund trading against news.

4.4 Alpha for individual funds

As discussed above, funds may provide liquidity by trading against news and take advantage of the price reversal to earn abnormal returns. We now investigate directly whether funds that trade against news outperform their peers by earning an alpha (abnormal return). We measure fund alpha using a five-factor model (e.g., Choi and Kronlund, 2018). The five factors include an aggregate stock market factor, an aggregate bond market factor, a default spread, a term spread, and an option spread adjusting for prepayment risks.[28] Following Anand, Jotikasthira, and Venkataraman (2021), we estimate the factor loadings using the previous 18-month observations,

[27] Funds do not have to repurchase the "sold-on-news" bond following the completion of a price reversal. Maintaining the exact holdings to those of their benchmarks is costly.

[28] The construction of the factors is as follows. The stock market factor is the return of the CRSP value weighted index in excess of risk free rate. The aggregate bond market factor is the excess return of Bloomberg Barclays US aggregate Bond Index (LBUSTRUU). The default spread is the return of a long-short portfolio buying Bloomberg Barclays US Corporate High Yield Index (LF98TRUU) and shorting Bloomberg Barclays Intermediate US Government/Credit Bond Index (LF97TRUU). The term spread is the return of a long-short portfolio buying Bloomberg Barclays US Treasury: Long Index (LUTLTRUU) and shorting Bloomberg Barclays US Treasury: 1-3 Year Index (LT01TRUU). Finally, the option spread is the return of a long-short portfolio buying Bloomberg Barclays GNMA Total Return Index Value Unhedged USD (LGNMTRUU) and shorting Bloomberg Barclays Intermediate US Government/Credit TRIndex (LF97TRUU).

and compute the fund alpha using the current month fund return adjusted by the current month factor returns and the corresponding estimated factor loadings.[29]

To capture the tendency of trading against news, we construct an indicator variable if the fund is trading against news on a bond, denoted as $Against_{i,j,t}$, a dummy variable that equals one if $\Delta w_{i,j,\mathrm{t}} \times Neg\_net_{j,\mathrm{t}} > 0$ and zero otherwise; that is, $Against_{i,j,t} = 1$ if fund i net-buys (net-sells) bond j when the bond's *Neg_net* value is positive (negative) in month *t*. We then aggregate $Against_{i,j,t}$ to a fund-level variable weighted by the trading magnitude of each bond:

$$TradeAgainstNews_{i,t} = \frac{1}{L}\sum_{l=1}^{L}\left\{\frac{1}{\sum_j\left|\Delta w_{i,j,t-l}\right|}\sum_j\left|\Delta w_{i,j,t-l}\right| \times Against_{i,j,t}\right\}.$$

That is, *TradeAgainstNews* aggregates $Against_{i,j,t}$ to the fund i level at time *t*, weighted by $\left|\Delta w_{i,j,t-l}\right|$. We calculate the rolling average over the past L months, in order to measure a fund's long-term trading pattern against news.

In Table XII, we rank mutual funds by *TradeAgainstNews*, with $L = 12$, and evaluate fund performance. We sort mutual funds into ten groups on *TradeAgainstNews* at month [-1] end. The average value of *TradeAgainstNews* for these sorted funds ranges from 0.324 to 0.759; that is, during our sample, a typical fund in Decile 1 (Decile 10) conducts 32.4% (75.9%) of its trades against the news tone. The average *TradeAgainstNews* across the ten deciles is 54% (as compared to 46% of trades in the direction of the news), consistent with our main finding that mutual funds tend to trade against news. Table XII shows the one- and three-month-ahead alphas for the decile mutual fund portfolios. For the one-month-ahead alpha, the difference in the average alpha of Decile 10 funds versus Decile 1 funds is 2.36 bps, which is both statistically and economically significant—this performance difference translates into an annualized alpha of 28.32 bps. For context, the unconditional mean of annualized fund alpha for all of the funds in the sample is -22.08 bps.[30] While fixed income funds on average generate negative alpha, the evidence shows that funds that trade "more" against news produce less negative or even positive alpha.

[Insert Table XII about here.]

[29] We require a fund to have the full 18 months of past returns for each fund-month-alpha observation. When a fund consists of multiple share classes, we keep the share class with the lowest expense ratio.
[30] The negative alpha of the overall fixed income funds arises (at least partly) because the benchmark indexes are free of transaction costs and fund expense fees.

The remainder of Table XII shows that the differences in alpha among decile portfolios persist in longer holding horizons at the three-month-ahead horizon. The magnitude of the alpha performance difference grows with the holding horizon. For example, the cumulative quarterly alpha difference between Decile 10 and Deciles 1 is 4.46 bps, about two times of its monthly counterpart. Overall, Table XII provides univariate evidence that trading against news generates alpha.

We provide multivariate evidence for fund alpha in Table XIII, where we regress each fund's alpha on *TradeAgainstNews*, along with the control variables of fund age, expense ratio, and size. We also include Morningstar fund category fixed effects and month fixed effects to absorb unobservable variations across fund types and market conditions over time. Models (1) and (2) of Table XIII examine the impact of *TradeAgainstNews* on the subsequent one- and three-month-ahead fund alphas (with $L = 12$). Consistent with the evidence from portfolio sorting, we find that *TradeAgainstNews* is positively associated with future fund alpha. Focusing on Model (2), an increase from a fund with $TradeAgainstNews = 0.5$ (that is, a fund trades against or along the news with equal probability) to a fund with $TradeAgainstNews = 0.76$ (the average *TradeAgainstNews* value for the Decile 10 funds in Table XII) would result in an improvement of 17.5 bps in annualized alpha ((0.76-0.5)×5.60×12). Model (2) shows that *TradeAgainstNews* is associated with a similar magnitude of improvement for three-month fund alphas.

[Insert Table XIII about here.]

We further examine the trading direction from which funds generate alphas. By trading against news, funds could generate alphas from buying on bad news, selling on positive news, or both. We decompose *TradeAgainstNews* into the buy and sell arms, by defining the following two news trading variables for a given fund *i*:

$$BuyAgainstNews_{i,t} = \frac{1}{L}\sum_{l=1}^{L}\left\{\frac{1}{\sum_j\left|\Delta w_{i,j,t-l}\right|}\sum_j\left|\Delta w_{i,j,t-l}\right| \times Against_{i,j,t}\right\} \text{ for all } \Delta w_{i,j,t-l} > 0$$

$$SellAgainstNews_{i,t} = \frac{1}{L}\sum_{l=1}^{L}\left\{\frac{1}{\sum_j\left|\Delta w_{i,j,t-l}\right|}\sum_j\left|\Delta w_{i,j,t-l}\right| \times Against_{i,j,t}\right\} \text{ for all } \Delta w_{i,j,t-l} < 0$$

That is, *BuyAgainstNews* (*SellAgainstNews*) is the equivalent of *TradeAgainstNews*, but only uses buy (sell) trades, capturing the fraction of trades that the fund buys on bad news (sells on good news).

Models (3) to (6) of Table XIII presents the results. While *BuyAgainstNews* is insignificantly associated with future fund alpha, we find that *SellAgainstNews* contributes to future fund alphas. The relation between *SellAgainstNews* and fund alpha is statistically and economically significant; for instance, *SellAgainstNews* and the one-month-ahead alpha is associated at a magnitude of coefficient estimate of 9.06, which is 1.6 times of that for *TradeAgainstNews*. These results thus suggest that funds with a trading style of "sell against good news" tend to generate alpha more than funds that "buy against bad news."

In Models (7) to (12) of Table XIII, we demonstrate that our findings are robust to an extended window of $L = 18$ in calculating *TradeAgainstNews* and the associated buy and sell legs. Overall, the finding that fund selling against news generates alphas is consistent with our earlier results that funds' trading against news is concentrated in news positivity.

4.4 Return gap for individual funds

In the previous section, we show that trading against news generates alpha, which is fund's reported returns for investors after risk adjustments. Yet a fund's reported return can be different from return generated from the portfolio that it previously reported, due to unobservable actions of the fund. The difference between these two returns is dubbed "return gap" of a fund (see, e.g., Kacperczyk, Sialm, and Zheng, 2008; Cici and Gibson, 2012). As discussed in Kacperczyk, Sialm, and Zheng (2008), the return gap is positively (inversely) related to the hidden benefits such as short-term trading benefits (costs such as transaction costs) of a fund, and hence directly measures the added value of the fund.

As previously discussed, bond prices, in the wake of positive news, exhibit reversals relatively swiftly, averaging around three weeks. Liquidity provision through news selling can constitute part of these unobserved benefits. Specifically, short-term trading in corporate bonds after a fund's most recent holdings report could be a major source of the return gap, as such trading profit and loss will be reflected in future reported returns but not in the return of the hypothetical portfolio based on previous month-end portfolio holdings (e.g., Cici and Gibson, 2012). Trading against news therefore will drive the unobservable actions, contributing to return gaps.

Recognizing that fixed-income funds in our sample maintain portfolios of fixed income securities beyond just corporate bonds and the data limitation that the exact holding periods of bonds are unknown, we compute the return gap for a specific fund i at month t as follows (e.g., Kacperczyk, Sialm, and Zheng, 2008; Cici and Gibson, 2012):

$$return\ gap_{i,t} = ret_{i,t} - \sum w_{i,t-1}^{k} ret_{t}^{k} - w_{i,t-1}^{Corp} ret_{t}^{Corp,Holdings} + expense\ ratio_{i,t},$$

where ret is the fund's reported return, $w_{i,t-1}^{k}$ ($w_{i,t-1}^{Corp}$) represents the portion of total net assets invested in non-corporate bond asset class k (corporate bonds) at the end of month *t-1* (i.e., beginning of month *t*), and ret_t^k is the month-*t* benchmark return asset class k. $ret_t^{Corp,Holdings}$ is the value-weighted portfolio return, based on the corporate bonds held by the fund at the beginning of the month. We consider four major non-corporate bond asset classes, which in addition to corporate bonds account for almost 100% of total net assets for our sample of fixed income funds: government bonds, Mortgage-Backed Securities (MBS), Asset-Backed Securities (ABS), and cash.[31] If interim trading due to news trading in corporate bonds enhances fund performance, such a strategy would result in a higher $ret_{i,t}$ but wouldn't affect other components. Consequently, trading against news would lead to a larger return gap.

Table XIV presents the evidence that funds trading against news consistently exhibit a higher return gap. In Models (1) and (2), we observe that *TradeAgainstNews* has a statistically significant positive correlation with the return gap, both one and three months ahead. Further exploration in Models (3) to (6) and (9) to (12) reveals that this positive association primarily stems from *SellAgainstNews* rather than *BuyAgainstNews*. This aligns with findings from Table XII, where *SellAgainstNews* is the major driver in fund alpha, which could potentially be driven by short term trading profits and fund return gaps. In sum, the results in Table XIV suggest that trading against news contributes to unobserved short-term gains embodied in return gap—another manifestation that trading against news is profitable at the fund level.

[Insert Table XIV about here.]

5. Conclusion

In the past two decades, corporate debt financing has more than tripled, and fixed income mutual funds have seen their assets under management grow more than five times. Fixed income funds now hold about one fifth of the total outstanding corporate bonds, making them the second largest institutional owners of corporate debt (only after insurance companies). Yet little is known

[31] We focus on a select sample of funds for which aggregate weights in government bonds, MBS, ABS, and corporate bonds are available from CRSP, with data typically starting in 2011. The corresponding benchmark total return indexes are from Bloomberg: Bloomberg US Treasury Total Return Index, Bloomberg US Mortgage Back Securities (MBS) Index, and Bloomberg US Agg ABS Total Return Value Unhedged USD. We assume the weight in cash is the residual, calculated as one minus the combined weights in Treasury, MBS, ABS, and corporate bonds.

on how fixed income funds trade on information shocks. This paper examines how fixed income funds trade on corporate news.

Combining a comprehensive database of corporate news releases from Factiva and a survivor bias-free fixed income mutual fund holdings dataset from Morningstar, we find that funds trade contrary to the direction of the news, consistent with the traditional wisdom of "sell on news" implying that investors sell a security when good news breaks out. The trading against news pattern is more pronounced in fixed income funds with a specialization in corporate bonds, in bonds with long duration, high liquidity and low information asymmetry, and in bonds experiencing good news. These cross-sectional heterogeneities suggest that funds trade against news in their expertise areas and in bonds that are less restrictive to trade with but with a greater profit potential.

Fixed income funds' trading against news is a manifestation of liquidity provision. Our findings echo the recent literature that broker-dealers retreat on dealer functionalities to function more as pure brokers to match potential customer buyers and sellers (Bessembinder et al., 2018; Choi and Huh, 2023; Goldstein and Hotchkiss, 2019). When broker-dealers are less able to provide liquidity, they tend to offer better-than-normal quotes to entice other customers to fill in the role (e.g., Harris, 2015; Choi and Huh, 2023). In our case, we find that mutual funds' trading against news takes place only post (and during) the crisis but not before the crisis—consistent with the former is characterized by a series of events and rules that constrain dealers' market-making abilities.

We provide evidence that funds with a style of trading against news enjoy a higher alpha. Similar to equities prices overreacting to news (e.g., Tetlock, 2011; Fedyk and Hodson, 2021), there is a bond price reversal subsequent to news. This price reversal, coupled with plausible profit from improved quotes, leads to alpha generation for funds trading against news. We find that funds that exihibit a "trade against news" style enjoys a higher alpha in subsequent months. In addition, funds trading on news can form part of the unobserved short-term "return gap" (the difference between the fund's reported return and the return generated from the portfolio that it previously reported). Trading against news is consistently related to such return gaps.

Overall, our paper sheds light on how fixed income institutional investors respond to corporate information shocks. At odds with the equity side of the study on institutional trading on news shocks, we find that fixed income funds trade against the news direction. Our findings point to the complexity of the price discovery process—that even sophisticated investors may process the same piece of underlying information differently in market segments with different binding conditions.

Appendix

A. Example of trading against news

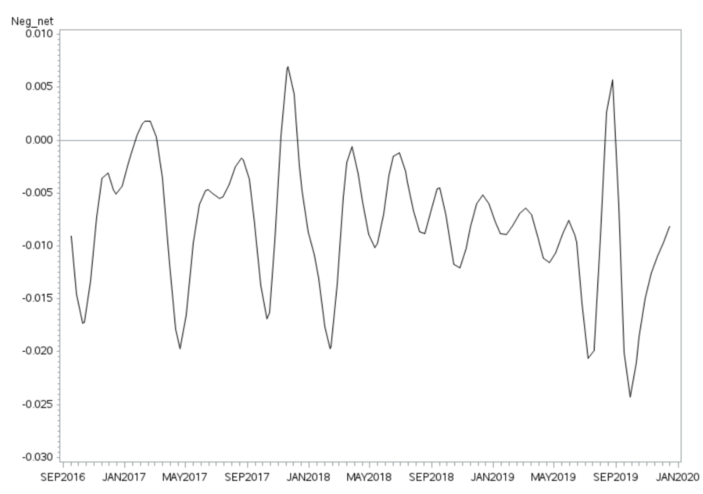
DFA intermediate-term extended quality portfolio (DFTEX) is a mutual fund actively managed by Dimensional Fund Advisors. The example below depicts the trading of DFTEX on a bond expiring in 2025 issued by Autodesk, Inc., an American multinational software corporation. The fund established a $6,017,000 par amount position in August 2016, kept the position for three years, and completely unwound its positions in the last quarter of 2019 (see the table below). The figure below shows the monthly mean value of *Neg_net* for Autodesk between September 2016 and December 2019. We observe that during the fund's holding period, Autodesk coincidentally experienced the most positive news in the fourth quarter of 2019.

Autodesk News

News Date	Title
10/9/2019	...Autodesk Unveils Robust New Features for BIM 360
10/24/2019	Autodesk-Five Years of Impact: Using Design to Make a Better World
12/16/2019	President Obama, ...What We Saw at Greenbuild…
12/19/2019	Denodo Announces Winners of Second Annual Data Innovation Award…

Position in 052769AD8 (issuer: AUTODESK INC; exp: 2025) by
DFA Intermediate-Term Extended Quality Portfolio (DFTEX)

Date	Number of Shares	Share Change	Unit Price
8/31/2016	6,017,000	6,017,000	105.88
8/31/2019	6,017,000	-	108.86
9/30/2019	6,017,000	-	108.25
10/31/2019	4,017,000	(2,000,000)	109.54
11/30/2019	4,017,000	-	108.97
12/31/2019	-	(4,017,000)	109.04



Autodesk News Sentiment of *Neg_net*

B. News Filtering and Firm Assignment

We retrieve 22,987,096 corporate news articles for all firms listed on NYSE (including NYSE American) and Nasdaq between January 1, 2002, and December 10, 2020, from the Top Sources in the Factiva database on Dow Jones' Data, News & Analytics (DNA) Platform. We remove news articles that contain fewer than 50 words (e.g., Tetlock et al., 2008). We use the firm identifiers provided by DNA to assign a news article to a given firm in the following procedure. The DNA Platform provides three firm identifiers to tag the news with: companies that the news article is deemed to have a high relevance with ("high-relevance companies"), companies mentioned in the article ("companied mentioned"), and companies that are deemed to be relevant to the article ordered by the degree of relevance ("companies related"). The three identifiers are not always present and consistent, but each news article is tagged to at least one firm in at least one of three identifiers to begin with. If only one firm is in "high-relevance companies," we assign the article to the firm. If there are multiple firms in "high-relevance companies" for the news, we remove the news if the news is also tagged to more than five "companied mentioned" or "companies related," as these news articles tend to be general news such as industry news or market commentaries; for the surviving news, if a firm appears in the top-three "companies related" and also appears in "companied mentioned," the news is assigned to all of the "high-relevance companies." Lastly, for news without any "high-relevance companies," we keep only news that has three or fewer "companied mentioned" and at least one firm in "companies related," and assign the news to only the top two "companies related" if these firms also appear in "companied mentioned." We manually read a subsample of 1,000 news articles and find our assignment accurate. Although a news article can potentially be assigned to multiple firms, 97.4% of the news articles filtered as above are assigned to just one firm. In total, the news covers 4,323 Compustat firms that are listed on NYSE and Nasdaq. The following table reports the news articles from 2002 to 2020 to align with our Morningstar fixed income mutual fund data. The sample contains 8,351,674 firm-specific news stories with more than 100 news sources. Dow Jones supplies half of the news (50.3%), followed by Reuters News's 11.2%, Business Wire's 8.2%, and major US newspapers' 7.3% (such as New York Times).

Year	All news sources	Dow Jones	Reuters News	Business Wire	Major US Newspapers	Associated Press	Others
2002	163,109	38,725	38,213	23,943	17,230	23,778	21,220
2003	163,974	36,171	36,106	25,935	19,550	25,678	20,534
2004	190,454	47,521	43,624	26,259	21,523	26,267	25,260
2005	205,025	56,933	38,533	30,454	20,773	31,227	27,105
2006	229,380	71,131	36,570	30,720	20,622	37,448	32,889
2007	223,782	60,828	33,426	30,542	16,547	44,380	38,059
2008	288,051	130,384	29,508	31,336	14,151	37,031	45,641
2009	357,384	212,099	28,830	28,804	13,558	32,343	41,750
2010	433,598	289,299	26,635	29,440	15,335	28,398	44,491
2011	459,560	325,865	21,038	30,491	13,823	22,061	46,282
2012	540,248	410,962	19,114	32,112	14,893	16,600	46,567
2013	599,667	401,517	26,477	39,312	26,472	28,679	77,210
2014	504,908	276,026	39,419	41,580	34,896	18,443	94,544
2015	546,293	269,506	47,280	41,981	51,088	15,777	120,661
2016	663,118	312,537	75,953	46,366	71,362	15,574	141,326
2017	660,125	304,856	84,869	46,045	69,723	14,526	140,106
2018	685,623	298,593	84,094	46,937	62,869	13,547	179,583
2019	714,417	322,823	109,464	48,794	54,398	11,702	167,236
2020	722,958	334,916	113,084	50,230	47,361	14,816	162,551
Total	8,351,674	4,200,692	932,237	681,281	606,174	458,275	1,473,015
Percent		50.3%	11.2%	8.2%	7.3%	5.5%	17.6%

C. Variable Definitions

Variable	Definition
Δw	A fund's change in holding of a given bond during the month, divided by the fund's total corporate bond holdings at the beginning of the month.
Neg_net	The fraction of total negative word count net of total positive word count relative to the total number of words in a news article. The word list is from Loughran and McDonald (2011).
Neg (*Pos*)	The fraction of total negative (positive) word counts relative to the total number of words in a news article. The word list is from Loughran and McDonald (2011).
Maturity	A bond issue's remaining maturity (in years) at the time of trading.
Credit rating	A bond issue's credit rating at the time of trading ranging from 1 to 16. AAA = 1, AA+ =2, … BBB- = 10, …, C = 15, and DDD and below = 16.
alpha [t-3, t-1]	A bond's cumulative alpha in months [t-3, t-1]. Bond monthly returns are from WRDS monthly bond returns calculated from TRACE. To arrive at monthly alpha, we adjust the bond return with the bond's previous-month beta using a single index model, where beta is estimated over the past 3-year window with Bloomberg Barclays US Aggregate Total Return Index serving as the market return and one-month Treasury bill rate as the riskfree rate.
Firm size	The logarithm of market capitalization of the issuing firm at the end of the previous month.
Idio. volatility	The issuing firm's standard deviation of idiosyncratic return volatility of the daily stock returns of the previous month in a Fama-French four-factor model of market, size, book to market, and momentum.
LT debt ratio	Ratio of long-term debt to total book value of assets of the issuing firm at the end of previous quarter.
Interest coverage	Ration of interest expense to EBIT of the issuing firm at the end of the previous quarter.
Fund age	The difference in years between the first offering date of the oldest share class and the beginning of the month.
Fund expense ratio	The lowest expense ratio among all share classes at the beginning of the month.
Fund size	The total net asset, summing for all share classes, at the beginning of the month.
Fund turnover	Fund turnover is calculated as the lesser of the aggregate dollar purchase and dollar sales of corporate bonds within the month, divided by the mean of its month-beginning and month-end total holdings in corporate bonds.
Excess bond return [0]	A bond's excess return over the market return (proxied by Bloomberg Barclays US Aggregate Total Return Index) on day [0] relative to the news event day. Other horizons examined are individual days [-1], [1], and [11]-[20], and cumulative day horizons [2, 5], [6, 10], [11, 15], and [16, 20]. All days are trading days.
TradeAgainstNews	The probability of a fund to trade against news in the previous 12 months. We, *i*) measure the fund's trading against news of an issue in a given month (with an indicator equal to one if the fund buys (sells) a bond when the bond's *Neg_net* is positive (negative)); *ii*) aggregate these indicator values weighted by absolute Δw; and *iii*) average the monthly aggregate over the previous months.
BuyAgainstNews	The equivalent of *TradeAgainstNews*, but use only buy trades ($\Delta w > 0$).
SellAgainstNews	The equivalent of *TradeAgainstNews*, but use only sell trades ($\Delta w < 0$).
Dealers (insurance companies) *Net buy*	The aggregate amount of daily buy minus sell of a bond by dealers using all customer-dealer transactions on TRACE (or by insurance companies using NAIC trades), scaled by the bond's outstanding par amount.

References

Adrian, T., N. Boyarchenko, and O. Shachar. 2017. Dealer Balance Sheets and Bond Liquidity Provision. *Journal of Monetary Economics* 89, 92–109.

An, Y., 2022. Competing with inventory in dealership markets. Available at SSRN 3284836.

Anand, A., C. Jotikasthira, and K. Venkataraman. 2021. Mutual Fund Trading Style and Bond Market Fragility. *Review of Financial Studies* 34, 2993–3044.

Bai, J., T. G. Bali, and Q. Wen. 2021. Is There a Risk-Return Tradeoff in the Corporate Bond Market? Time-Series and Cross-Sectional Evidence. *Journal of Financial Economics* 142, 1017–37.

Balduzzi, P., E. J. Elton, and T. C. Green. 2001. Economic News and Bond Prices: Evidence from the U.S. Treasury Market. *Journal of Financial and Quantitative Analysis* 36, 523–43.

Bali, T. G., A. Subrahmanyam, and Q. Wen. 2021. Long-Term Reversals in the Corporate Bond Market. *Journal of Financial Economics* 139, 656–77.

Bao, J., M. O'Hara, and X. Zhou. 2018. The Volcker Rule and Corporate Bond Market Making in Times of Stress. *Journal of Financial Economics* 130, 95–113.

Becker, B., and V. Ivashina. 2015. Reaching for Yield in the Bond Market. *Journal of Finance* 70, 1863–1902.

Bessembinder, H., S. Jacobsen, W. Maxwell, and K. Venkataraman. 2018. Capital Commitment and Illiquidity in Corporate Bonds. *Journal of Finance* 73, 1615–61.

Bessembinder, H., W. Maxwell, and K. Venkataraman. 2006. Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds. *Journal of Financial Economics* 82, 251–88.

Bonini, S., T. Shohfi, and M. Simaan. 2023. Buy the Dip? Available at SSRN 3835376.

Bretscher, L., L. Schmid, I. Sen, and V. Sharma. 2022. Institutional Corporate Bond Pricing. Available at SSRN 3756280 .

Brunnermeier, M. K. 2005. Information Leakage and Market Efficiency. *Review of Financial Studies* 18, 417–57.

Cao, J, G. Li, R. Wermers, X. Zhan, and L. Zhou. 2023. Do Insurers Listen to Earnings Conference Calls? Evidence from the Corporate Bond Market.

Chen, Q., and J. Choi. 2023. Reaching for Yield and the Cross Section of Bond Returns. *Management Science* forthcoming.

Chen, X., J. Z. Huang, Z. Sun, T. Yao, and T. Yu. 2020. Liquidity Premium in the Eye of the Beholder: An Analysis of the Clientele Effect in the Corporate Bond Market. *Management Science* 66, 932–57.

Choi, J., Y. Huh, and S. Shin. 2023. Customer Liquidity Provision: Implications for Corporate Bond Transaction Costs. *Management Science* 0.

Choi, J., and M. Kronlund. 2018. Reaching for Yield in Corporate Bond Mutual Funds. *Review of Financial Studies* 31, 1930–65.

Choi, J., O. Shachar, and S. S. Shin. 2019. Dealer Liquidity Provision and the Breakdown of the Law of One Price: Evidence from the CDS–Bond Basis. *Management Science* 65, 4100–4122.

Christoffersen, S. K., D. B. Keim, D. K. Musto, and A. Rzeznik. 2022. Passive-Aggressive Trading: The Supply and Demand of Liquidity by Mutual Funds. *Review of Finance* 26, 1145–77.

Cici, G. and S. Gibson. 2012. The Performance of Corporate Bond Mutual Funds: Evidence Based on Security-Level Holdings. *Journal of Financial and Quantitative Analysis* 47, 159–178.

Da, Z., P. Gao, and R. Jagannathan. 2011. Impatient Trading, Liquidity Provision, and Stock Selection by Mutual Funds. *Review of Financial Studies* 24, 675–720.

Dick-Nielsen, J. 2014. How to Clean Enhanced TRACE Data. Available at SSRN 2337908.

Dick-Nielsen, J., P. Feldhütter, and D. Lando. 2012. Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis. *Journal of Financial Economics*, 103, 471–492.

Dick-Nielsen, J., and M. Rossi. 2019. The Cost of Immediacy for Corporate Bonds. *Review of Financial Studies* 32, 1–41.

Dittmar, A. K. 2000. Why Do Firms Repurchase Stock? *Journal of Business* 73, 331–55.

Duffie, D., 2012. Market Making Under the Proposed Volcker Rule. Available at SSRN 1990472.

Duffie, D., N. Gârleanu, and L. Pedersen. 2005. Over-the-Counter Markets. *Econometrica* 73, 1815–47.

Edwards, A. K., L. E. Harris, and M. S. Piwowar. 2007. Corporate Bond Market Transaction Costs and Transparency. *Journal of Finance* 62, 1421–51.

Ellul, A., C. Jotikasthira, and C. T. Lundblad. 2011. Regulatory Pressure and Fire Sales in the Corporate Bond Market. *Journal of Financial Economics* 101, 596–620.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg. 2012. How Are Shorts Informed?: Short Sellers, News, and Information Processing. *Journal of Financial Economics* 105, 260–78.

Fedyk, A., and J. Hodson. 2023. When Can the Market Identify Old News? *Journal of Financial Economics* 149, 92–113.

Friewald, N., R. Jankowitsch, and M. Subrahmanyam. 2012. Illiquidity or Credit Deterioration: A Study of Liquidity in the US Corporate Bond Market during Financial Crises. *Journal of Financial Economics* 105, 18–36.

Gebhardt, W. R., S. Hvidkjaer, and B. Swaminathan. 2005. Stock and Bond Market Interaction: Does Momentum Spill Over? *Journal of Financial Economics* 75, 651–90.

Gilbert, T., S. Kogan, L. Lochstoer, and A. Ozyildirim. 2012. Investor Inattention and the Market Impact of Summary Statistics. *Management Science* 58, 336–50.

Glosten, L. R., and P. R. Milgrom. 1985. Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics* 14, 71–100.

Goldstein, M., and E. Hotchkiss. 2020. Providing Liquidity in an Illiquid Market: Dealer Behavior in US Corporate Bonds. *Journal of Financial Economics* 135, 16–40.

Goldstein, M., E. Hotchkiss, and E. Sirri. 2007. Transparency and Liquidity: A Controlled Experiment on Corporate Bonds. *Review of Financial Studies* 20, 235–73.

Green, T. C. 2004. Economic News and the Impact of Trading on Bond Prices. *Journal of Finance* 59, 1201–33.

Han, S., A. G. Huang, M. Kalimipalli, and K. Wang. 2022. Information and Liquidity of Over-the-Counter Securities: Evidence from Public Registration of Rule 144A Bonds. *Journal of Financial Markets* 59, 100655.

Harris, L. 2015. Transaction Costs, Trade Throughs, and Riskless Principal Trading in Corporate Bond Markets. Available at SSRN 2661801.

Hendershott, T., R. Kozhan, and V. Raman. 2020. Short Selling and Price Discovery in Corporate Bonds. *Journal of Financial and Quantitative Analysis* 55, 77–115.

Hendershott, T., D. Livdan, and N. Schürhoff. 2015. Are Institutions Informed about News? *Journal of Financial Economics* 117, 249–87.

Hotchkiss, E. S., and T. Ronen. 2002. The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis. *Review of Financial Studies* 15, 1325–54.

Huang, A. G., H. Tan, and R. Wermers. 2020. Institutional Trading around Corporate News: Evidence from Textual Analysis. *Review of Financial Studies* 33, 4627–75.

Jiang, H., and Z. Sun. 2015. News and Corporate Bond Liquidity. Available at SSRN 2437975.

Jostova, G., S. Nikolova, A. Philipov, and C. W. Stahel. 2013. Momentum in Corporate Bond Returns. *Review of Financial Studies* 26, 1649–93.

Kacperczyk, M., C. Sialm, and L. Zheng. 2008. Unobserved actions of mutual funds. *Review of Financial Studies* 21, 2379–2416.

Kothari, S. P., and J. B. Warner. 2007. Econometrics of Event Studies. *Handbook of Empirical Corporate Finance*, 3–36.

Krishnaswami, S., and V. Subramaniam. 1999. Information Asymmetry, Valuation, and the Corporate Spin-Off Decision. *Journal of Financial Economics* 53, 73–112.

Kyle, A. S. 1985. Continuous Auctions and Insider Trading. *Econometrica* 53, 1315–36.

Langetieg, T. C., M. L. Leibowitz, and S. Kogelman. 1990. Duration Targeting and the Management of Multiperiod Returns. *Financial Analysts Journal* 46, 35–45.

Loughran, T., and B. McDonald. 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance* 66, 35–65.

Mahanti, S., A. Nashikkar, M. Subrahmanyam, G. Chacko, and G. Mallik. 2008. Latent Liquidity: A New Measure of Liquidity, with an Application to Corporate Bonds. *Journal of Financial Economics* 88, 272–98.

Mariassunta G., C. Jotikasthira, A. Rapp, and M. Waibel. 2023. Intermediary Balance Sheet Constraints, Bond Mutual Funds' Strategies, and Bond Returns. Available at SSRN 4607843.

Massa, M., A. Yasuda, and L. Zhang. 2013. Supply Uncertainty of the Bond Investor Base and the Leverage of the Firm. *Journal of Financial Economics* 110, 185–214.

Nozawa, Y., Y. Qiu, and Y. Xiong. 2023. Disagreement and Bond PEAD. Available at SSRN 3990000.

O'Hara, M., and X. (Alex) Zhou. 2021. Anatomy of a Liquidity Crisis: Corporate Bonds in the COVID-19 Crisis. *Journal of Financial Economics* 142, 46–68.

Ottonello, G., A. E. Rizzo, and R. Zambrana. 2023. Is Bond Financing Disintermediated? The Role of Bank Trading Networks. Available at SSRN 4287217.

Pástor, Ľ., R. F. Stambaugh, and L. A. Taylor. 2015. Scale and Skill in Active Management. *Journal of Financial Economics* 116, 23–45.

Schultz, P., 2017. Inventory management by corporate bond dealers. Available at SSRN 2966919.

Tetlock, P. C. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance* 62, 1139–68.

Tetlock, P. C. 2011. All the News That's Fit to Reprint: Do Investors React to Stale Information? *Review of Financial Studies* 24, 1481–1512.

Tetlock, P., M. Saar-Tsechansky, and S. Macskassy. 2008. More Than Words: Quantifying Language to Measure Firms' Fundamentals. *Journal of Finance* 63, 1437–67.

Wang, Z. J., H. Zhang, and X. Zhang. 2020. Fire Sales and Impediments to Liquidity Provision in the Corporate Bond Market. *Journal of Financial and Quantitative Analysis* 55, 2613–40.

Yan, X., and Z. Zhang. 2009. Institutional Investors and Equity Returns: Are Short-Term Institutions Better Informed? *Review of Financial Studies* 22, 893–924.

Table I Summary statistics of funds and trades

Panel A presents the number of fixed income funds contained in the Morningstar database (All) and the funds selected in our sample (Monthly reporters), as well as the trading characteristics of monthly reporters. Panel B reports the summary statistics for the variables in the main regressions, with all variables winsorized at the 1st and 99th percentiles. See Appendix C for variable definitions.

Panel A: Summary statistics of Morningstar fixed income mutual funds

		Fund category				
	Full sample	Corporate Bond	High Yield Bond	Core Bond	Core-Plus Bond	Long-Term Bond
# of funds (All)	859	54	273	357	143	32
# of funds (Monthly reporters)	664	38	198	283	120	25
Average AUM (All)	2,131	1,271	1,103	2,681	3,052	1,523
Average AUM (Monthly reporters)	1,995	1,165	935	2,902	2,355	1,214
Median AUM (All)	332	362	316	248	561	214
Median AUM (Monthly reporters)	330	383	304	248	566	152
# of trades	589,366	62,357	100,352	251,971	126,854	47,832
Trading volume ($million)	857,899	116,527	176,019	317,555	207,100	40,697
# of bonds traded	8,355	5,529	2,525	7,478	7,055	2,552
# of firms traded	822	651	610	723	773	465

Panel B: Summary statistics of main variables

	N	Mean	Std Dev	Median	Minimum	Maximum
Δw	3,251,699	0.006	0.108	0.000	-0.464	0.703
Neg_net	3,276,681	0.004	0.011	0.003	-0.023	0.039
Pos	3,276,681	0.011	0.006	0.011	0.000	0.030
Neg	3,276,681	0.015	0.010	0.014	0.000	0.047
Maturity	3,276,681	11.25	9.32	7.62	1.00	38.96
Credit rating	3,275,888	8.110	2.436	8 (BBB+)	1 (AAA)	16 (D & under)
alpha [t-3, t-1]	2,165,153	0.004	0.032	0.003	-0.162	0.161
Firm size	3,078,411	10.15	1.66	10.23	5.66	13.57
Idio. volatility	3,078,457	0.014	0.007	0.012	0.006	0.045
LT debt ratio	3,126,642	0.279	0.154	0.263	0.019	0.729
Interest coverage	2,776,223	9.271	10.014	6.514	-5.782	67.34
Fund age	3,116,213	15.90	10.71	13.92	0.59	44.77
Fund expense ratio	2,999,623	0.004	0.003	0.004	0.000	0.011
Fund TNA ($million)	3,190,504	19,757	48,538	1,644	0	269,025
Fund TNA in corporate bonds ($million)	3,369,477	5,915	13,229	710	0	70,214

Table II Daily bond returns around news

Panel A regresses excess bond returns over various horizons on *Neg_net*. We form excess daily returns by subtracting from a bond's daily return the same-day return on the market, proxied by the Bloomberg Barclays US Aggregate Total Return Index. In Panels B and C, we follow the same specifications in Panel A but substitute *Pos* or *Neg* for *Neg_net* (the control variables are included in the regressions but not reported). For the "All news" sample, we use all news days; and for the "Initial news only in news clusters" sample, we keep only the first news day in a "news cluster" (days with consecutive, non-stopping news arrivals) to reduce the confounding effect of previous news (Huang, Tan, and Wermers, 2020). All regressions include date fixed effects and individual bond fixed effects. The *t*-statistics are reported in parentheses, cluster-adjusted at the issuer and the date level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Returns on *Neg_net*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All news					Initial news only in news clusters				
Excess return on day(s)	-1	0	1	[2, 5]	[6, 10]	-1	0	1	[2, 5]	[6, 10]
Neg_net	-0.180***	-0.212***	-0.206***	-0.137**	0.018	-0.063	-0.108*	-0.243***	-0.079	0.125
	(-4.15)	(-4.78)	(-5.09)	(-2.06)	(0.27)	(-0.82)	(-1.72)	(-3.30)	(-0.91)	(0.91)
Maturity	0.024**	0.027***	0.027***	0.060***	0.089***	0.021*	0.031***	0.029**	0.049***	0.074***
	(2.58)	(3.04)	(3.02)	(4.41)	(4.50)	(1.86)	(2.84)	(2.47)	(3.85)	(3.91)
Credit rating	0.007***	0.003*	0.005***	0.015***	0.017***	0.009**	-0.002	0.002	0.009	0.010
	(3.85)	(1.72)	(3.36)	(4.20)	(3.42)	(2.06)	(-0.42)	(0.45)	(1.29)	(1.12)
Firm size	0.001	-0.006	-0.005	-0.019	-0.029	0.007	-0.010	-0.018***	-0.028**	-0.047***
	(0.12)	(-1.04)	(-0.96)	(-1.13)	(-1.39)	(0.93)	(-1.34)	(-2.63)	(-2.14)	(-2.97)
Idio. volatility	2.654***	2.351***	2.554***	7.293***	8.982***	3.137***	1.959***	3.309***	7.796***	9.924***
	(5.43)	(4.96)	(5.50)	(6.64)	(6.39)	(4.08)	(3.22)	(4.88)	(6.24)	(6.23)
LT debt ratio	0.074***	0.047**	0.057***	0.100**	0.156***	0.038	0.018	0.092***	0.096*	0.177**
	(3.56)	(2.18)	(2.60)	(2.39)	(3.11)	(0.97)	(0.62)	(2.68)	(1.84)	(2.54)
Interest coverage	-0.000	0.000	-0.000	-0.000	-0.001**	-0.000	0.000**	-0.000	0.000	-0.000
	(-1.36)	(0.21)	(-1.50)	(-1.61)	(-2.08)	(-1.31)	(2.08)	(-0.17)	(0.44)	(-0.89)
Observations	2,038,934	2,337,591	2,342,040	2,872,110	2,559,016	490,765	590,242	591,431	773,092	661,035
Adj R-squared	0.005	0.005	0.005	0.017	0.025	0.007	0.007	0.007	0.014	0.024

Table II, cont'd

Panel B: Returns on *Neg*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All news					Initial news only in news clusters				
Excess return on day(s)	-1	0	1	[2, 5]	[6, 10]	-1	0	1	[2, 5]	[6, 10]
Neg	-0.184***	-0.187***	-0.272***	-0.088	0.002	-0.043	-0.013	-0.286***	0.057	0.155
	(-3.39)	(-3.80)	(-5.74)	(-1.03)	(0.02)	(-0.46)	(-0.16)	(-3.10)	(0.47)	(0.95)

Panel C: Returns on *Pos*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All news					Initial news only in news clusters				
Excess return on day(s)	-1	0	1	[2, 5]	[6, 10]	-1	0	1	[2, 5]	[6, 10]
Pos	0.173**	0.276***	0.070	0.245**	-0.068	0.096	0.293**	0.147	0.340**	-0.077
	(2.49)	(3.56)	(1.00)	(2.29)	(-0.54)	(0.81)	(2.45)	(1.27)	(2.35)	(-0.39)

Table III Mutual fund trading on news tone

This table regresses Δw (mutual fund holdings change) and *Increase* (which takes the value of, respectively, -1, 0, or 1 for Δw less than, equal to, or greater than zero) on the news tone measure of *Neg_net*. See Appendix C for variable definitions. Models (5) and (6) constrain the sample to non-zero Δw's, that is, the sample where funds make directional changes in positions. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δw	Δw	*Increase*	*Increase*	Δw (traded only)	Δw (traded only)
Neg_net	0.0396***	0.0344***	0.1275***	0.1156***	0.1270**	0.0993*
	(4.31)	(3.59)	(4.02)	(3.33)	(2.40)	(1.72)
Maturity		0.0011***		0.0016		0.0030
		(2.79)		(0.92)		(1.15)
Credit rating		0.0026***		0.0154***		0.0190***
		(7.36)		(11.69)		(7.67)
alpha [*t-3*, *t-1*]		0.0035		0.0430*		0.0060
		(0.82)		(1.66)		(0.25)
Firm size		0.0007*		-0.0006		0.0033
		(1.86)		(-0.41)		(1.54)
Idio. volatility		0.1408***		0.1925		0.5134***
		(4.13)		(1.08)		(2.65)
LT debt ratio		-0.0393***		-0.1421***		-0.1516***
		(-9.93)		(-17.34)		(-8.89)
Interest coverage		0.0003***		0.0007***		0.0009***
		(7.59)		(8.93)		(6.19)
Fund age		-0.0002***		-0.0005		-0.0012***
		(-5.03)		(-0.92)		(-5.46)
Fund expense ratio		0.4003**		-10.0197***		1.0404
		(2.27)		(-3.53)		(0.92)
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,251,636	2,398,070	3,274,247	2,415,135	538,932	392,914
Adj R-squared	0.027	0.029	0.031	0.035	0.084	0.096

Table IV Mutual fund news trading: Heterogeneity in fund categories

This table regresses mutual fund holdings change (Δw) on the news tone measure of *Neg_net* using partitioned samples by Morningstar fund categories. Model (1) presents the results for all corporate concentrated funds, that is, U.S. fund corporate bond and U.S. fund high yield bond. Models (2) and (3) present the results for U.S. fund corporate bond and U.S. fund high yield bond, respectively. Model (4) studies funds targeting broad fixed indexes, which include U.S. fund intermediate core bond, U.S. fund intermediate core-plus bond, and U.S. fund long-term bond. The *t*-statistics are reported in parentheses, cluster-adjusted at fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Δw				
	(1)	(2)	(3)	(4)
	Corporate concentrated funds			Broad fixed income funds
	All	Corporate	High yield	
Neg_net	0.0723***	0.0812*	0.0643**	0.0175*
	(3.34)	(2.00)	(2.42)	(1.69)
Maturity	0.0020*	0.0039*	0.0010	0.0008*
	(1.73)	(1.71)	(0.72)	(1.92)
Credit rating	0.0050***	0.0036***	0.0051***	0.0019***
	(5.26)	(2.84)	(3.84)	(5.94)
alpha [*t*-3, *t*-1]	-0.0250***	0.0443**	-0.0339***	0.0210***
	(-3.33)	(2.09)	(-4.38)	(4.32)
Firm size	-0.0003	-0.0001	-0.0002	0.0011***
	(-0.39)	(-0.06)	(-0.23)	(2.78)
Idio. volatility	0.4077***	-0.1344	0.4796***	-0.0305
	(6.00)	(-0.89)	(6.31)	(-0.85)
LT debt ratio	-0.0351***	-0.0580***	-0.0303***	-0.0436***
	(-6.75)	(-3.78)	(-5.36)	(-7.92)
Interest coverage	0.0005***	0.0004***	0.0008***	0.0002***
	(4.68)	(2.99)	(6.48)	(7.02)
Fund age	-0.0003***	-0.0002***	-0.0004***	-0.0001***
	(-5.28)	(-3.43)	(-4.65)	(-3.50)
Fund expense ratio	0.4803	0.5729	0.2535	0.3644**
	(1.16)	(0.93)	(0.49)	(2.03)
Issue FE	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes
Observations	558,732	181,113	377,530	1,839,139
Adj R-squared	0.0194	0.0194	0.0219	0.0297

Table V Mutual fund news trading: Heterogeneity in fund turnover

This table examines fund news trading conditional on previous fund turnover. *High turnover fund* is a dummy equal to one if the turnover is above the sample median. The *t*-statistics are reported in parentheses, cluster-adjusted at fund level. Following the specification in Model (2) of Table III, the control variables are included in all regressions but not reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Δw									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Funds		All			Corporate concentrated			Broad fixed income	
Neg_net	0.0227**	0.0220**	0.0185**	0.0259	0.0187	0.0070	0.0176*	0.0189**	0.0168*
	(2.47)	(2.39)	(2.06)	(0.95)	(0.69)	(0.26)	(1.97)	(2.09)	(1.93)
High turnover fund	-0.0016***			-0.0018			-0.0018***		
(over previous 12 months)	(-2.91)			(-1.63)			(-2.66)		
Neg_net × High turnover fund	0.0626***			0.0934**			0.0471**		
(over previous 12 months)	(3.30)			(2.30)			(2.11)		
High turnover fund		-0.0017***			-0.0023**			-0.0017***	
(over previous 9 months)		(-3.20)			(-2.15)			(-2.69)	
Neg_net × High turnover fund		0.0629***			0.1074**			0.0425**	
(over previous 9 months)		(3.34)			(2.56)			(1.97)	
High turnover fund			-0.0017***			-0.0023**			-0.0016**
(over previous 15 months)			(-3.03)			(-2.09)			(-2.46)
Neg_net × High turnover fund			0.0739***			0.1244***			0.0521**
(over previous 15 months)			(3.79)			(2.91)			(2.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,259,165	2,274,355	2,213,565	523,329	527,246	510,907	1,735,610	1,746,881	1,702,421
Adj R-squared	0.0250	0.0250	0.0232	0.0193	0.0197	0.0192	0.0281	0.0280	0.0255

Table VI Mutual fund news trading: Issue and issuer heterogeneity

This table regresses fund holdings change (Δw) on *Neg_net*, a bond characteristic dummy variable, and the interaction of these two variables. The *Dummy* equals one if bond maturity, modified duration, issuer firm size, or bond turnover is greater than the sample median, or if issuer's idiosyncratic volatility is smaller than the sample median. The *t*-statistics are reported in parentheses, cluster-adjusted at fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Δw	(1)	(2)	(3)	(4)	(5)
	Dummy = 1 for				
	Long duration	Long maturity	High bond turnover	Small idio. volatility	Large firm size
Neg_net	0.0043	0.0130	0.0064	0.0323**	0.0132
	(0.36)	(1.12)	(0.61)	(2.49)	(1.05)
Dummy × *Neg_net*	0.0642***	0.0439***	0.0421***	0.0285*	0.0828***
	(4.02)	(2.88)	(2.71)	(1.78)	(4.23)
Dummy	0.0049***	0.0034***	0.0113***	0.0007**	0.0010**
	(6.88)	(4.97)	(9.25)	(2.54)	(2.50)
Maturity	0.0007*	0.0008**	0.0010***	0.0036***	0.0036***
	(1.91)	(2.09)	(2.66)	(12.60)	(12.63)
Credit rating	0.0025***	0.0025***	0.0024***	0.0021***	0.0021***
	(7.33)	(7.23)	(7.02)	(6.49)	(6.48)
alpha [*t*-3, *t*-1]	0.0029	0.0036	0.0018	-0.0005	0.0000
	(0.69)	(0.84)	(0.43)	(-0.10)	(0.01)
Firm size	0.0007*	0.0007*	0.0016***	0.0004	0.0001
	(1.79)	(1.86)	(4.53)	(1.00)	(0.16)
Idio. volatility	0.1527***	0.1476***	0.0725**	0.2544***	0.2203***
	(4.44)	(4.28)	(2.16)	(5.46)	(5.38)
LT debt ratio	-0.0393***	-0.0394***	-0.0363***	-0.0370***	-0.0368***
	(-10.03)	(-10.01)	(-10.12)	(-9.36)	(-9.36)
Interest coverage	0.0003***	0.0003***	0.0002***	0.0003***	0.0003***
	(7.57)	(7.52)	(7.33)	(7.24)	(7.21)
Fund age	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(-5.06)	(-5.06)	(-5.30)	(-5.00)	(-5.00)
Fund expense ratio	0.3966**	0.3970**	0.5460***	0.4034**	0.4039**
	(2.26)	(2.26)	(3.15)	(2.34)	(2.35)
Issue FE	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes
Observations	2,398,070	2,398,070	2,398,070	2,398,071	2,398,071
Adj R-squared	0.0262	0.0262	0.0283	0.0211	0.0211

Table VII Mutual fund trading on credit rating news

This table regresses Δw (mutual fund holdings change) on *Neg_net* calculated using credit rating news only. Credit rating change takes the value of 1 if the bond is upgraded in the month, −1 if downgraded, and 0 otherwise. Credit rating watch takes the value of 1 if the bond is under positive watch in the month, −1 if negative watch, and 0 otherwise. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Δw	(1)	(2)	(3)
Neg_net (credit rating news)	0.0329***	0.0369***	0.0655***
	(4.02)	(4.44)	(6.57)
Credit rating change		-0.0000	0.0004
		(-0.02)	(0.65)
Neg_net (credit rating news)		0.2515***	0.2262***
× Credit rating change		(7.42)	(7.03)
Credit rating watch			0.0050***
			(6.23)
Neg_net (credit rating news)			0.1257***
× Credit rating watch			(5.97)
Maturity	0.0025***	0.0025***	0.0025***
	(3.76)	(3.81)	(3.85)
Credit rating	0.0050***	0.0047***	0.0041***
	(7.71)	(7.46)	(6.63)
alpha [*t-3*, *t-1*]	0.0225***	0.0169**	0.0151**
	(2.85)	(2.19)	(1.99)
Firm size	-0.0044***	-0.0051***	-0.0055***
	(-4.39)	(-4.79)	(-5.04)
Idio. volatility	-0.2323***	-0.1959***	-0.1772***
	(-3.57)	(-3.05)	(-2.78)
LT debt ratio	-0.1164***	-0.1168***	-0.1174***
	(-9.60)	(-9.60)	(-9.65)
Interest coverage	0.0003***	0.0003***	0.0003***
	(5.49)	(5.45)	(5.59)
Fund age	-0.0001**	-0.0001**	-0.0001**
	(-2.35)	(-2.35)	(-2.34)
Fund expense ratio	2.4238***	2.4228***	2.4159***
	(6.79)	(6.79)	(6.77)
Issue FE	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes
Observations	853,010	853,010	853,010
Adj R-squared	0.0644	0.0645	0.0648

Table VIII Mutual fund news trading: Negative and positive legs of news

This table regresses Δw (mutual fund holdings change) and *Increase* (which takes the value of, respectively, -1, 0, or 1 for Δw less than, equal to, or greater than zero) on *Neg* or *Pos*. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Δw	*Increase*	Δw	*Increase*
Neg	-0.0087	-0.0281		
	(-0.87)	(-0.76)		
Pos			-0.1435***	-0.5042***
			(-6.29)	(-7.09)
Maturity	0.0011***	0.0015	0.0011***	0.0016
	(2.77)	(0.90)	(2.80)	(0.93)
Credit rating	0.0025***	0.0154***	0.0025***	0.0154***
	(7.31)	(11.63)	(7.32)	(11.68)
alpha [*t*-3, *t*-1]	0.0032	0.0419	0.0033	0.0422
	(0.75)	(1.62)	(0.77)	(1.63)
Firm size	0.0006*	-0.0008	0.0006	-0.0009
	(1.68)	(-0.53)	(1.64)	(-0.58)
Idio. volatility	0.1470***	0.2133	0.1459***	0.2097
	(4.31)	(1.19)	(4.28)	(1.17)
LT debt ratio	-0.0392***	-0.1420***	-0.0393***	-0.1421***
	(-9.92)	(-17.34)	(-9.92)	(-17.34)
Interest coverage	0.0003***	0.0007***	0.0003***	0.0007***
	(7.59)	(8.93)	(7.59)	(8.93)
Fund age	-0.0002***	-0.0005	-0.0002***	-0.0005
	(-5.03)	(-0.92)	(-5.03)	(-0.92)
Fund expense ratio	0.400**	-10.020***	0.400**	-10.020***
	(2.27)	(-3.53)	(2.27)	(-3.53)
Issue FE	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes
Observations	2,398,071	2,415,136	2,398,071	2,415,136
Adj R-squared	0.0211	0.0287	0.0211	0.0288

Table IX Mutual fund news trading: Subsample results

This table presents the subsample results of regressions in which the dependent variable is Δw (mutual fund holdings change), and the explanatory variable is the news tone measure of *Neg_net, Neg,* or *Pos*. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2002.01 - 2007.06 Pre-crisis			2007.07 - 2009.04 Crisis			2009.05 - 2014.03 Post-crisis			2014.04 - 2020.12 Post-Volker Rule		
Neg_net	-0.194***			0.098**			0.099***			0.053***		
	(-4.73)			(2.04)			(4.57)			(4.64)		
Neg		-0.241***			0.032			0.087***			-0.000	
		(-5.19)			(0.58)			(3.60)			(-0.01)	
Pos			0.061			-0.280***			-0.106***			-0.187***
			(0.72)			(-2.99)			(-2.76)			(-6.06)
Maturity	-0.009	-0.009	-0.009	0.017***	0.017**	0.017***	0.004***	0.004***	0.004***	0.000	0.000	0.000
	(-0.72)	(-0.72)	(-0.71)	(2.61)	(2.59)	(2.63)	(3.82)	(3.83)	(3.83)	(0.64)	(0.60)	(0.66)
Credit rating	0.010***	0.010***	0.010***	0.006**	0.006**	0.006**	0.006***	0.006***	0.006***	0.003***	0.003***	0.003***
	(5.50)	(5.50)	(5.60)	(2.38)	(2.29)	(2.29)	(6.93)	(6.88)	(6.88)	(6.62)	(6.62)	(6.59)
alpha [*t-3*, *t-1*]	0.088***	0.088***	0.091***	-0.032***	-0.032***	-0.032***	-0.009	-0.009	-0.009	-0.003	-0.003	-0.003
	(2.89)	(2.89)	(2.97)	(-2.66)	(-2.66)	(-2.65)	(-1.02)	(-1.04)	(-1.06)	(-0.69)	(-0.79)	(-0.82)
Firm size	-0.004	-0.004	-0.004	0.006**	0.006**	0.005**	-0.004***	-0.004***	-0.004***	-0.000	-0.000	-0.000
	(-1.44)	(-1.51)	(-1.18)	(2.44)	(2.30)	(2.22)	(-3.32)	(-3.33)	(-3.58)	(-0.76)	(-0.88)	(-1.04)
Idio. volatility	0.059	0.065	0.037	0.856***	0.853***	0.834***	0.324***	0.326***	0.331***	0.014	0.021	0.023
	(0.34)	(0.38)	(0.22)	(4.29)	(4.29)	(4.21)	(4.11)	(4.15)	(4.21)	(0.37)	(0.53)	(0.59)
LT debt ratio	-0.103***	-0.104***	-0.104***	-0.186***	-0.186***	-0.188***	-0.080***	-0.080***	-0.080***	-0.031***	-0.031***	-0.031***
	(-8.04)	(-8.06)	(-8.04)	(-8.71)	(-8.72)	(-8.74)	(-10.15)	(-10.15)	(-10.14)	(-7.98)	(-7.97)	(-7.99)
Interest coverage	0.001***	0.001***	0.001***	-0.000	-0.000	-0.000	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(4.09)	(4.07)	(4.03)	(-0.38)	(-0.39)	(-0.37)	(5.31)	(5.31)	(5.33)	(5.99)	(5.98)	(5.97)
Fund age	-0.001***	-0.001***	-0.001***	-0.000*	-0.000*	-0.000*	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.82)	(-3.82)	(-3.84)	(-1.71)	(-1.71)	(-1.71)	(-5.61)	(-5.61)	(-5.61)	(-3.93)	(-3.93)	(-3.93)
Fund expense ratio	-0.231	-0.231	-0.234	0.654	0.654	0.656	0.009	0.009	0.008	0.470**	0.470**	0.470**
	(-0.39)	(-0.39)	(-0.39)	(0.99)	(0.99)	(0.99)	(0.03)	(0.03)	(0.03)	(2.56)	(2.56)	(2.56)
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149,872	149,872	149,872	80,106	80,106	80,106	504,726	504,726	504,726	1,663,270	1,663,270	1,663,270
Adj R-squared	0.0728	0.0728	0.0727	0.0646	0.0646	0.0647	0.0257	0.0257	0.0256	0.0145	0.0145	0.0145

Table X Dealer and insurance company net-buy on news

Panel A regresses the daily dealer and insurance companies net-buy over various horizons on *Neg_net*. We aggregate daily directional position changes in the dealer sector from TRACE for each bond issue and changes in the insurance company sector from NAIC. Then, we construct the dealers (insurance companies) net buy. In Panels B and C, we follow the same specifications in Panel A but substitute *Pos* or *Neg* for *Neg_net* (the control variables are included in the regressions but not reported). All regressions include month fixed effects and individual bond fixed effects. The *t*-statistics are reported in parentheses, cluster-adjusted at the issuer and the date level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Net-buy on *Neg_net*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dealers net-buy on day(s)				Insurance companies net-buy on day(s)			
	0	1	[2, 5]	[6, 10]	0	1	[2, 5]	[6, 10]
Neg_net	0.0535***	0.0507***	0.0693***	0.0315	-0.0507**	-0.0396**	-0.1326**	-0.1683***
	(4.27)	(4.05)	(2.79)	(1.17)	(-2.56)	(-2.37)	(-2.31)	(-3.50)
Maturity	-0.0047***	-0.0024	-0.0138***	-0.0199***	0.0522***	0.0441***	0.1193***	0.1052***
	(-2.81)	(-1.51)	(-3.32)	(-4.25)	(8.97)	(8.58)	(4.91)	(4.58)
Credit rating	0.0001	-0.0000	-0.0003	-0.0007	0.0001	-0.0008	0.0041	0.0042
	(0.19)	(-0.08)	(-0.17)	(-0.39)	(0.05)	(-0.49)	(0.51)	(0.61)
Firm size	0.0022**	0.0033***	0.0082**	0.0114***	0.0070**	0.0064**	0.0429***	0.0373***
	(2.05)	(2.64)	(2.58)	(3.01)	(2.37)	(2.29)	(3.17)	(2.87)
Idio. volatility	0.1084	0.1074	0.1998	0.2314	-1.1899***	-0.9980***	-5.7693***	-5.8522***
	(1.17)	(1.17)	(0.87)	(0.89)	(-7.40)	(-6.54)	(-8.14)	(-8.60)
LT debt ratio	0.0141**	0.0077	0.0301*	0.0590***	-0.0778***	-0.0529***	-0.2990***	-0.2837***
	(2.37)	(1.32)	(1.88)	(3.26)	(-6.09)	(-4.94)	(-5.94)	(-6.22)
Interest coverage	0.0000	0.0000	-0.0002	-0.0002	0.0001*	0.0001**	0.0007*	0.0004
	(0.26)	(0.45)	(-1.20)	(-0.98)	(1.65)	(2.01)	(1.71)	(1.14)
Observations	2,481,342	2,475,031	3,449,519	3,540,476	211,333	206,558	742,573	803,412
Adj R-squared	0.002	0.002	0.005	0.006	0.076	0.065	0.091	0.085

Table X, cont'd

Panel B: Net-buy on *Neg*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dealers net-buy on day(s)				Insurance companies net-buy on day(s)			
	0	1	[2, 5]	[6, 10]	0	1	[2, 5]	[6, 10]
Neg	0.0663***	0.0393***	0.0718**	0.0369	-0.0790***	-0.0252	-0.2038***	-0.2112***
	(3.96)	(2.58)	(2.37)	(1.10)	(-3.33)	(-1.08)	(-2.80)	(-3.56)

Panel C: Net-buy on *Pos*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dealers Net-buy on day(s)				Insurance companies Net-buy on day(s)			
	0	1	[2, 5]	[6, 10]	0	1	[2, 5]	[6, 10]
Pos	-0.0242	-0.0756***	-0.0679	-0.0176	-0.0163	0.0745***	-0.0189	0.0699
	(-0.96)	(-3.24)	(-1.62)	(-0.34)	(-0.48)	(2.62)	(-0.22)	(0.86)

Table XI Evidence of return reversal

This table regresses bond excess returns over various horizons on *Neg_net, Pos, and Neg*. We form excess daily returns by subtracting from a bond's daily return the same-day return on the market, proxied by the Bloomberg Barclays US Aggregate Total Return Index. We follow the same specifications in Table II, but substitute returns 11-20 days after the news day (the control variables are included in the regressions but not reported). All regressions include date fixed effects and individual bond fixed effects. Reported in parentheses are *t*-statistics, cluster-adjusted at the issuer and the date level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Neg_net		*Neg*		*Pos*	
Days after news	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
11	-0.0470	(-1.11)	-0.0427	(-0.80)	0.0622	(0.93)
12	-0.0620	(-1.44)	-0.1129*	(-1.84)	-0.0536	(-0.74)
13	0.0531	(1.19)	0.0321	(0.63)	-0.1022	(-1.44)
14	-0.0073	(-0.21)	0.0087	(0.19)	0.0543	(0.77)
15	0.0327	(0.83)	0.0276	(0.56)	-0.0412	(-0.56)
16	-0.0030	(-0.08)	-0.0060	(-0.14)	-0.0044	(-0.07)
17	0.0351	(0.89)	-0.0115	(-0.25)	-0.1528**	(-2.30)
18	0.0775*	(1.90)	0.0965**	(2.27)	-0.0360	(-0.47)
19	0.0993**	(2.25)	0.0654	(1.21)	-0.1907**	(-2.33)
20	-0.0380	(-0.97)	-0.0903	(-1.64)	-0.0790	(-1.19)
[11,15]	-0.0127	(-0.16)	-0.0500	(-0.44)	-0.0581	(-0.46)
[16,20]	0.1527*	(1.91)	0.0678	(0.72)	-0.3623***	(-2.59)

Table XII   Fund performance from trading against news: Alpha sorting

This table shows the mean values of one-month- and three-month-ahead fund alphas in decile subsamples ranked by *TradeAgainstNews*, which proxies the fund tendency of trading against news over the past 12 months. We measure fund alpha using a model of five factors of stock market return, bond market return, default spread, term spread, and option spread. Decile 10 – 1 provides the difference of the means between Decile 1 and Decile 10; Deciles 6:10 - 1:5 provides the difference of the means between the average of Deciles 1:5 and the average of Deciles 6:10. Reported in parentheses are *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TradeAgainstNews		Fund alpha (bps) in month(s)	
Decile	*TradeAgainstNews*	[0]	[0, 2]
1	0.324	-2.22	-4.06
2	0.431	-2.52	-6.38
3	0.474	-2.29	-9.14
4	0.504	-2.10	-6.26
5	0.528	-3.83	-7.13
6	0.553	-2.26	-6.19
7	0.577	-1.01	-4.05
8	0.607	-1.04	-4.43
9	0.652	-1.26	-1.43
10	0.759	0.14	0.41
Decile 10 - 1	0.435***	2.36*	4.46**
	(175.61)	(1.93)	(2.11)
Deciles 6:10 - 1:5	0.177***	1.51***	3.45***
	(181.33)	(2.92)	(3.78)

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Table XIII Fund performance from trading against news: Fund alpha

Models (1)-(2) regress monthly fund alpha and cumulative three-month alpha on *TradeAgainstNews*, which proxies the fund tendency of trading against news over the past 12 months. We measure fund alpha using a model of five factors of stock market return, bond market return, default spread, term spread, and option spread. Models (3)-(6) regress monthly fund alphas on two measures for fund tendency of trading against news (the buy and sell legs). *BuyAgainstNews* measures a fund's tendency to buy bonds when the news tone is negative over the past 12 months, while *SellAgainstNews* measures a fund's tendency to sell bonds when the news tone is positive over the past 12 months. Models (7)-(12) repeat the analyses with *TradeAgainstNews, BuyAgainstNews,* and *SellAgainstNews* measured over the past 18 months. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	TradeAgainstNews with *L*=12 months						*TradeAgainstNews* with *L*=18 months					
	Fund alpha (bps) in month(s)						Fund alpha (bps) in month(s)					
	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]
TradeAgainstNews [-L,-1]	5.60*	14.71*					4.41	14.23*				
	(1.92)	(1.94)					(1.35)	(1.72)				
BuyAgainstNews [-L,-1]			0.83	0.76					-2.31	-4.69		
			(0.36)	(0.12)					(-0.87)	(-0.66)		
SellAgainstNews [-L,-1]					9.06***	22.04***					10.07***	25.46***
					(4.57)	(4.13)					(4.19)	(4.01)
Fund age	-0.05	-0.13	-0.05	-0.14	-0.06*	-0.15*	-0.05	-0.13	-0.05	-0.14	-0.06*	-0.15*
	(-1.54)	(-1.54)	(-1.52)	(-1.58)	(-1.84)	(-1.72)	(-1.59)	(-1.53)	(-1.58)	(-1.61)	(-1.87)	(-1.70)
Fund expense ratio	-0.07***	-0.18***	-0.07***	-0.18***	-0.08***	-0.20***	-0.07***	-0.18***	-0.07***	-0.18***	-0.08***	-0.20***
	(-3.87)	(-3.73)	(-3.92)	(-3.70)	(-4.24)	(-4.11)	(-3.90)	(-3.74)	(-3.94)	(-3.72)	(-4.23)	(-4.08)
Fund size	0.09	0.14	0.09	0.19	0.17	0.35	0.09	0.12	0.10	0.21	0.16	0.33
	(0.40)	(0.23)	(0.38)	(0.31)	(0.76)	(0.57)	(0.41)	(0.20)	(0.43)	(0.34)	(0.74)	(0.54)
Observations	30,982	31,206	30,830	31,053	30,469	30,692	31,032	31,256	30,915	31,138	30,626	30,849
Fund type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.138	0.155	0.139	0.156	0.142	0.161	0.138	0.155	0.139	0.155	0.141	0.160

Table XIV Fund performance from trading against news: Fund return gap

Models (1)-(2) regress monthly return gap and cumulative three-month return gap on *TradeAgainstNews*, which proxies the fund tendency of trading against news over the past 12 months. We measure return gap as the difference between the fund's report return (before expense) and the holding based return, following Kacperczyk, Sialm, and Zheng (2008). Models (3)-(6) regress monthly return gaps on two measures for fund tendency of trading against news (the buy and sell legs). *BuyAgainstNews* measures a fund's tendency to buy bonds when the news tone is negative over the past 12 months, while *SellAgainstNews* measures a fund's tendency to sell bonds when the news tone is positive over the past 12 months. Models (7)-(12) repeat the analyses with *TradeAgainstNews, BuyAgainstNews,* and *SellAgainstNews* measured over the past 18 months. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	TradeAgainstNews with *L*=12 months						*TradeAgainstNews* with *L*=18 months					
	Fund return gap (bps) in month(s)						Fund return gap (bps) in month(s)					
	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]	[0]	[0, 2]
TradeAgainstNews [-L,-1]	16.23*	45.69*					20.69**	69.39**				
	(1.71)	(1.66)					(2.03)	(2.21)				
BuyAgainstNews [-L,-1]			4.29	1.09					-0.34	3.44		
			(0.54)	(0.04)					(-0.04)	(0.13)		
SellAgainstNews [-L,-1]					9.28	28.06					15.02**	42.38**
					(1.50)	(1.47)					(2.39)	(2.24)
Fund age	-0.05	0.06	-0.07	0.02	-0.06	0.03	-0.05	0.07	-0.07	0.02	-0.06	0.02
	(-0.79)	(0.29)	(-1.16)	(0.09)	(-0.88)	(0.12)	(-0.79)	(0.35)	(-1.06)	(0.10)	(-0.99)	(0.07)
Fund expense ratio	-0.09**	-0.28*	-0.08*	-0.27*	-0.10**	-0.34**	-0.09**	-0.27*	-0.09**	-0.27*	-0.10**	-0.32**
	(-2.03)	(-1.94)	(-1.88)	(-1.88)	(-2.22)	(-2.34)	(-2.01)	(-1.88)	(-2.02)	(-1.91)	(-2.09)	(-2.16)
Fund size	-0.30	-2.13	-0.20	-1.79	-0.12	-1.95	-0.29	-2.26	-0.16	-1.82	-0.04	-1.75
	(-0.62)	(-1.33)	(-0.43)	(-1.10)	(-0.25)	(-1.21)	(-0.61)	(-1.40)	(-0.33)	(-1.11)	(-0.08)	(-1.09)
Observations	20,580	20,911	20,541	20,867	20,372	20,692	20,602	20,935	20,574	20,904	20,449	20,771
Fund type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.661	0.616	0.662	0.615	0.661	0.615	0.661	0.615	0.661	0.616	0.661	0.614

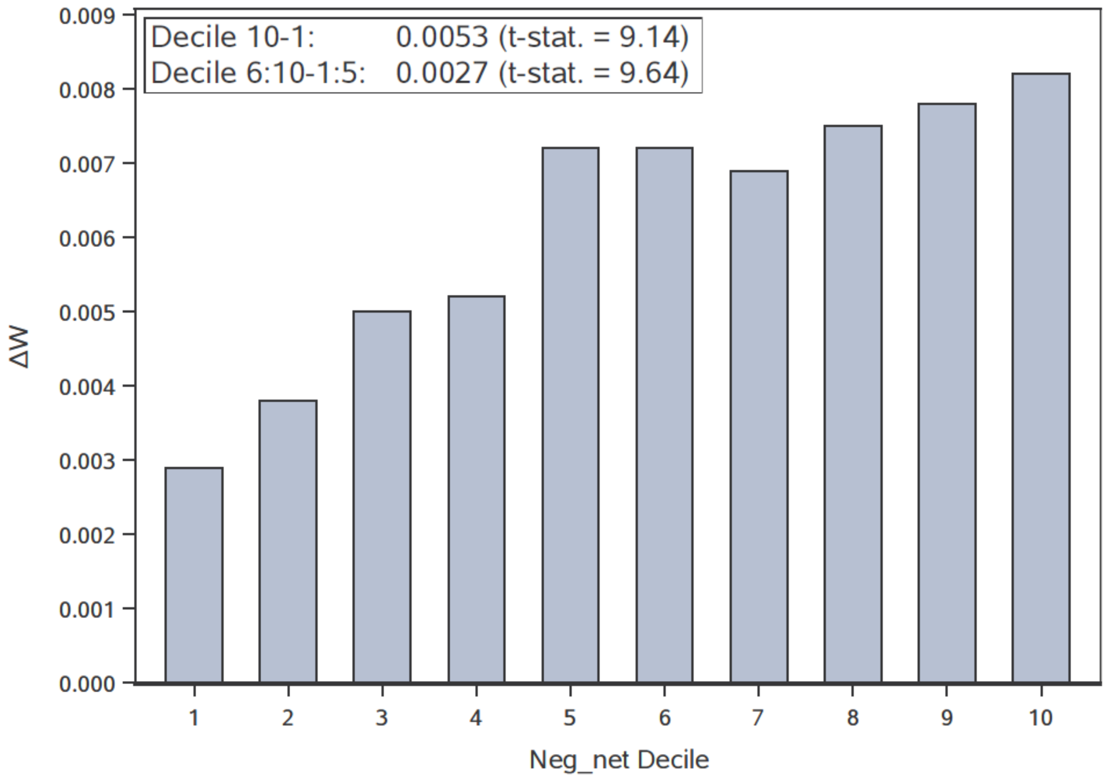

Figure 1 Univariate sorting of mutual fund trading by news tone. This table shows the mean value of monthly mutual fund holdings change (Δw) in decile portfolios ranked by *Neg_net*. Δw is a fund's change (in percentage) in holding of a given bond during the month, relative to the fund's all corporate bond holdings. Presented in the top-left box, Decile 10 - 1 provides the difference in the mean values between Decile 1 and Decile 10; similarly, Deciles 6:10 - 1:5 provides the difference in the means between the average of Deciles 1:5 and the average of Deciles 6:10. The *t*-statistics are reported in parentheses.

Internet Appendix to
"Buy the Rumor, Sell the News: Liquidity Provision by Bond Funds Following Corporate News Events"

This Internet Appendix reports results supplementary to the paper "*Buy the Rumor, Sell the News: Liquidity Provision by Bond Funds Following Corporate News Events*." We present additional results on the relations among institutional trading and news.

I. Robustness on the trade-against news phenomenon

In the main paper, we map monthly Δw to the same-month news. While research suggests that institutional traders respond quickly to news in the equity market (Huang, Tan, and Wermers, 2020), it remains unclear whether corporate bond fund managers would react to corporate news in a timely manner. In models (1)-(3) of Table A1, we examine the impact of news tone on the next month's holdings change. The evidence shows that the holdings change next month is related to neither the current month's *Neg_net*, *Pos*, nor *Neg*; that is, fund managers do not trade on the news tone of the previous month.

[Table A1 about here.]

Another way to test whether fund managers react quickly to news is to use news closer to the month end. To this end, we compute our tone measures based on news that occurs only in the last ten days of each month. If it takes on average a fund manager longer than ten days to react to and trade against news, we would expect that Δw is unrelated to the tone of the last ten days news during the month.[1] Evidence in Models (4)-(6) of Table A1, however, suggests that managers instead trade against the news that occurs in the month end, consistent with our main results.

Our main variable, Δw, utilizes the AUM in corporate bonds for each fund to normalize the dollar value change in fund tradings. One concern is that variations in Δw would be relatively large for smaller funds or funds investing less in corporate bonds, biasing our results towards these funds. To mitigate this concern, we provide further robustness checks using the dollar changes in holdings. Specifically, we construct the variable *Share change* as the logarithm of dollar changes

[1] One potential reason is that market illiquidity may render it difficult to locate a potential counterparty for a good price within a short period of time.

for a fund position, defined as the logarithm of the difference in par value between the month-end and the previous month-end, multiplied by the average price (in percentage of the par) reported by all fixed income mutual funds, and then signed by position chage direction. We find the results with this alternative measure consistent with our findings in the main text (Models (1)-(3) of Table A2).

[Table A2 about here.]

Exploiting our corporate news database, we differ from the literature studying institutional traders' reactions and price drifts post-earnings announcements. To further disentangle the effect of earning announcements, we construct our news tone measures during "non-earnings-news" days, defined as news that is not within [-3, 3] trading days around an earnings announcement. Models (4)-(6) of Table A2 show that earnings announcement news does not drive our main results, as Δw is positively (negatively) related to *Neg_net* (*Pos*), consistent with our main results.

Table A1 Mutual fund news trading: Lead effects and logarithm in shares changes

Models (1) - (3) regresses *lead* Δw (next month mutual fund holdings change) on the news tone measures of *Neg_net*, *Pos*, and *Neg*. Models (4) - (6) regresses Δw (mutual fund holdings change) on an alternative set of news tone measures of *Neg_net*, *Pos*, and *Neg*, that uses only news in the last ten days of a calendar month ("month end"). Reported in parentheses are *t*-statistics, cluster-adjusted at fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	lead Δw	*lead* Δw	*lead* Δw	Δw	Δw	Δw
Neg_net	0.0061					
	(0.91)					
Pos		0.0063				
		(0.54)				
Neg			0.0125			
			(1.59)			
Neg_net (month end)				0.0384***		
				(5.57)		
Pos (month end)					-0.1196***	
					(-7.22)	
Neg (month end)						-0.0012
						(-0.17)
Maturity	-0.0003	-0.0003	-0.0003	0.0010**	0.0010**	0.0010**
	(-1.00)	(-1.01)	(-1.00)	(2.49)	(2.49)	(2.46)
Credit rating	0.0016***	0.0016***	0.0016***	0.0026***	0.0025***	0.0025***
	(6.41)	(6.41)	(6.42)	(7.40)	(7.36)	(7.37)
alpha [*t*-3, *t*-1]	0.0025	0.0025	0.0026	0.0051	0.0048	0.0047
	(0.97)	(0.95)	(0.99)	(1.13)	(1.08)	(1.05)
Firm size	0.0011***	0.0011***	0.0011***	0.0007*	0.0006*	0.0007*
	(3.41)	(3.40)	(3.44)	(1.89)	(1.73)	(1.76)
Idio. volatility	0.1259***	0.1267***	0.1250***	0.1403***	0.1443***	0.1463***
	(4.87)	(4.91)	(4.85)	(4.08)	(4.19)	(4.25)
LT debt ratio	0.0098***	0.0098***	0.0098***	-0.0391***	-0.0391***	-0.0391***
	(5.44)	(5.44)	(5.44)	(-9.58)	(-9.57)	(-9.56)
Interest coverage	-0.0001***	-0.0001***	-0.0001***	0.0003***	0.0003***	0.0003***
	(-3.18)	(-3.18)	(-3.18)	(7.63)	(7.64)	(7.63)
Fund age	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***
	(-3.12)	(-3.12)	(-3.12)	(-4.92)	(-4.92)	(-4.92)
Fund expense ratio	-2.3493***	-2.3493***	-2.3493***	0.4131**	0.4132**	0.4131**
	(-8.68)	(-8.68)	(-8.68)	(2.31)	(2.31)	(2.31)
Constant	-0.0205***	-0.0204***	-0.0208***	-0.0254***	-0.0232***	-0.0247***
	(-3.44)	(-3.45)	(-3.47)	(-3.86)	(-3.53)	(-3.74)
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,231,317	2,231,317	2,231,317	2,222,599	2,222,599	2,222,599
Adj R-squared	0.0287	0.0287	0.0287	0.0270	0.0270	0.0270

Table A2 Mutual fund news trading: Month end effects and non-earnings announcement news

Models (1) - (3) regress *Share change* (contemporaneous logarithm of the shares change in fund holdings), on the news tone measures of *Neg_net*, *Pos*, and *Neg*. Models (4) - (6) regresses Δw (mutual fund holdings change) on an alternative set of news tone measures of *Neg_net*, *Pos*, and *Neg*, that excludes news [-3, 3] trading days around each of the issuer's earning announcement dates ("non-EA"). Reported in parentheses are *t*-statistics, cluster-adjusted at fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Share change	*Share change*	*Share change*	Δw	Δw	Δw
Neg_net	1.6549***					
	(3.70)					
Pos		-7.0501***				
		(-7.85)				
Neg			-0.3491			
			(-0.73)			
Neg_net (non-EA)				0.0238***		
				(2.84)		
Pos (non-EA)					-0.1087***	
					(-6.05)	
Neg (non-EA)						-0.0153
						(-1.57)
Maturity	0.0212	0.0214	0.0207	0.0010***	0.0010***	0.0010***
	(0.98)	(0.98)	(0.96)	(2.61)	(2.62)	(2.59)
Credit rating	0.2034***	0.2032***	0.2021***	0.0026***	0.0026***	0.0025***
	(11.90)	(11.90)	(11.84)	(7.39)	(7.35)	(7.35)
alpha [*t*-3, *t*-1]	0.5216	0.5099	0.5057	0.0027	0.0025	0.0023
	(1.57)	(1.53)	(1.52)	(0.62)	(0.57)	(0.54)
Firm size	-0.0109	-0.0147	-0.0138	0.0007*	0.0007*	0.0007*
	(-0.55)	(-0.75)	(-0.70)	(1.95)	(1.79)	(1.81)
Idio. volatility	2.9512	3.1971	3.2419	0.1453***	0.1473***	0.1502***
	(1.27)	(1.37)	(1.39)	(4.26)	(4.34)	(4.41)
LT debt ratio	-1.9296***	-1.9294***	-1.9276***	-0.0397***	-0.0397***	-0.0396***
	(-18.79)	(-18.80)	(-18.79)	(-9.84)	(-9.83)	(-9.83)
Interest coverage	0.0095***	0.0095***	0.0095***	0.0003***	0.0003***	0.0003***
	(10.22)	(10.23)	(10.23)	(7.59)	(7.59)	(7.59)
Fund age	-0.0048	-0.0048	-0.0048	-0.0002***	-0.0002***	-0.0002***
	(-0.68)	(-0.68)	(-0.68)	(-5.01)	(-5.01)	(-5.01)
Fund expense ratio	-130.5755***	-130.5847***	-130.5842***	0.4032**	0.4031**	0.4030**
	(-3.76)	(-3.76)	(-3.76)	(2.29)	(2.29)	(2.29)
Constant	-0.5253	-0.4040	-0.4740	-0.0258***	-0.0239***	-0.0248***
	(-1.47)	(-1.14)	(-1.33)	(-4.01)	(-3.72)	(-3.87)
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,415,135	2,415,135	2,415,135	2,377,004	2,377,004	2,377,004
Adj R-squared	0.0310	0.0310	0.0310	0.0260	0.0260	0.0259