# "Buy the Rumor, Sell the News":

# Liquidity Provision by Bond Funds Following Corporate News Events*

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### Abstract

Using a comprehensive database of corporate news, we examine how bond mutual funds trade on the sentiment of news releases. We find that bond funds trade against the direction of news sentiment (e.g., selling after good news about a firm). The results are more pronounced in bonds that lie within a fund’s investment objective sector, and in bonds with high turnover and low information asymmetry, and in credit-rating news and news with positive sentiment. Funds that most frequently trade against news sentiment produce a higher alpha, and a source of such alpha is bond price reversals post news events. Fixed income mutual funds, dealers, and insurance companies complement each other in news trading, with mutual funds trading against news largely in the absence of dealers. Our study indicates that bond mutual funds represent a significant liquidity provider, upon corporate news events, in the market for corporate bonds.

## 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, relative to periods without news, institutional investors trade stocks heavily around corporate news announcements, and that their trading is skewed significantly towards selling on negative news. In this paper, we examine how fixed income mutual funds trade around corporate news. We believe that this market is especially interesting to study, given the much lower liquidity and higher search frictions in fixed income relative to stock market; that is, news events may quickly move either the demand or the supply curve for a bond in the face of inelastic prices, thus creating a temporary gap between bond suppliers and demanders.

Similar to the growth of U.S. corporate bonds as an asset class, fixed-income mutual funds have witnessed phenomenal growth over the past two decades. As one of the major financing channels for U.S. corporations, corporate debt sees a total amount of outstanding growth from \$4.5 trillion in 2000 to \$15.3 trillion in 2020.[2] A large fraction of corporate bonds are held by managed funds (Massa, Yasuda, and Zhang, 2013). For example, the total assets under management (AUM) of taxable bond mutual funds have increased to \$4.3 trillion in 2020 (compared with \$807 billion in 2002), and \$2.7 trillion of the total AUM in taxable bond funds is invested in corporate bonds.[3] Fixed income mutual funds hold 17.6% of outstanding corporate bonds, making them the second largest institutional owners of these bonds, second only to insurance companies.[4] Despite non-trivial costs in trading corporate bonds (e.g., Bessembinder, Maxwell, and Venkataraman, 2006), the turnover of fixed income mutual funds is, in fact, not particularly low. For instance, the median

[1] See, for example, https://www.thebalance.com/what-does-buy-the-rumor-sell-the-news-mean-1344971.
[2] Data from FRED of the Federal Reserve Bank, St. Louis.
[3] The former number is from the Investment Company Institute 2021 Fact Book, and the latter from FRED.
[4] At the end of 2020, insurance companies companies (including life and property-casualty) hold 27.5% of corporate bonds, followed by fixed income funds' 17.6% (data from FRED).

turnover ratio is 79.5% in 2020 for all funds classified as U.S. Fund Corporate Bonds by Morningstar.[5]

Coupled with the growth in the fixed income fund industry is a growth in firm-specific news. In the Factiva news database, the number of firm-specific news articles supplied by "Top Sources," such as Dow Jones, Reuters, and the Wall Street Journal (who collectively supply most of the news streamed to trading terminals, such as Bloomberg), 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 and traditional "soft" information such as NRSRO credit ratings and analyst reports, it is plausible that fixed income fund trading is at least partly driven by corporate news releases, given that corporate news is a major venue of public qualitative information (other major venues of soft public information being SEC filings, firm conference calls, and social media posts). After all, in contrast to credit and analyst reports that are typically post-news disclosed (and hence, potentially contain stale information), news is timely.

Anecdotal evidence suggests that funds may opportunistically trade on news. Appendix A depicts an event line of Autodesk releasing a series of positive news in the period of October to December, 2019, while the fund Dimensional Fund Advisors Intermediate-Term Extended Quality Portfolio takes the chance to unwind its long position of the Autodesk bond expiring in 2025. 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, overall, characterized as "sell on positive news," consistent with the provision of liquidity to other market participants. We match over 8 million firm-specific news articles for 4,323 NYSE/Nasdaq firms with the monthly trading data for 664 fixed income funds, as measured using portfolio holdings sourced from the survivor-bias-free Morningstar database. Measuring the tone of the news by counting, in each news article, the occurrences of negative and

[5] Among these funds, the turnover ratio is 72% for Vanguard Intermediate-Term Corporate Bond Index Fund, which has $46 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%.

positive words using the Loughran and McDonald (2011) financial dictionary, we find that news tone is associated with a strong bond return on the same day as the news (but not on the day prior to news), and the price impact continues into the next trading day. Reflecting the growth of the industry and the substantial increase in outstanding public debt securities, funds, overall, are net buyers of bonds. The net-buy amount, however, is significantly more (less) when the corporate news is more negative (positive) in tone. For the average bond fund in our sample, the difference in an individual bond position change between the top and bottom deciles of news tone is $319,000; in comparison, the average unconditional monthly position change in a bond per fund is $158,000. That mutual funds net-buy less (more) in good (bad) news implies trading against the direction of the news, consistent with "sell on news." We dub this phenomenon as "trade against news."

We identify a number of heterogeneities in funds' trade-against-news activities across fund, issue and news types. For fund types, we group fixed income funds to corporate concentrated funds and broad fixed income funds, of which the former has a larger exposure to corporate bond. We find that corporate concentrated funds are more sensitive to corporate news; among which, funds specializing in corporate bond (high-yield) investments trade more on news sentiments of investment-grade (high-yield) bonds. In other words, fund trading on news is consistent with their objectives. We also estimate fund types by their historical turnover ratio in corporate bonds and find that the news trading effect concentrates in higher turnover funds, which are commonly viewed as shorter-term investors (e.g., 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, and that their news trading is consistent with their trading style.

For issue heterogeneity, we find the trading effect of news is more pronounced in bonds with longer durations (as shocks to these bonds have greater impacts on bond prices), bonds with better liquidity, and in issuers that are larger in size and smaller in return volatility (both of which indicate a lower level of information asymmetry, see, e.g., Krishnaswami and Subramaniam, 1999, and Dittmar, 2000). Funds thus exploit opportunities of bigger price impacts while trading on instruments that are more liquid and exhibit a smaller degree of information asymmetry—potentially because these bond issues are "easier" to trade with but with a greater profit potential.

We also examine news heterogeneity. We find that news related to firms' credit ratings carries a strong weight in bond trading: when credit rating news is released, it supersedes non-credit rating news in funds' trading decisions, and the significance of credit rating news is not entirely driven by credit rating change events. In addition, we examine the negative (positive) leg of news tone by, respectively, counting just the negative (positive) words in the news. Here, we find that the trading against news effect is much more pronounced on the positive side of news, consistent with the traditional "sell on news" wisdom that hinges on news positivity.

We hypothesize that the potential motivation for funds to trade against news is to provide liquidity as a means to generate alpha. We first show that the news trading effect is more pronounced if the fund already has a larger existing position of the bond, and if the aggregate institutional ownership of the bond is larger. In addition, we provide complementary evidence on trading activities by bond dealers and insurance companies, whose daily trades are available through, respectively, the Trade Reporting and Compliance Engine (TRACE) and the National Association of Insurance Commissioners (NAIC). We find that i) similar to fixed income funds, dealers trade against news, but the difference is that dealers trade more against negative news shocks than positive news shocks (as compared to funds' largely trading against positive news), and ii) insurance companies mostly trade in the direction of negative news shocks. The trading behaviors of dealers and insurance companies are consistent with the view that dealers in general are considered as liquidity providers in the corporate bond market (e.g., Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Choi, Shachar, and Shin, 2019), while insurance companies are likely liquidity demanders (e.g., Becker and Ivashina, 2015). Importantly, mutual funds serve a valuable complementary role in providing liquidity when dealers are less able to do so. One possibility is that when positive news of a bond hits the market resulting in a surge in customer demand for the bond, dealers (who tend not to hold excessive inventories due to capital constraints) would resort to inventories held by mutual funds to satisfy the demand—this also leads to an equilibrium where funds provide more liquidity when their inventories of the bond is higher.

In further analysis, we demonstrate that trading by funds against news generates alpha. To capture a fund's trading style on the tendency of trading against news, we aggregate its news-trading of individual bonds over the preceding 9, 12, and 15 months, respectively, and examine whether funds with a higher tendency to trade against news exhibit higher future-period alphas. We find that fixed income funds, on average, generate negative alpha, while funds that trade "more" against news produce less negative, or even positive alphas during subsequent months. When decomposing funds' trading against news style into a "sell against good news" and a "buy against bad news" style, "sell against good news" funds tend to generate larger alphas. Thus, the "sell on news" wisdom appears to have a grounding in fixed-income mutual funds.

A potential source of alpha is price reversal subsequent to news, which is consistent with liquidity provision. While the price reaction remains largely muted after the first two days of news breakout, we find that the price slowly reverses, and the reversal becomes significant in three weeks' time. 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 provides an additional explanation for mutual fund alpha: in addition to profiting from serving the roles of broker-dealer functionalities in liquidity provision (e.g., collecting bid-ask spreads), another way is to strategically trade against the direction of news to take advantage of potential price corrections.

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 from institutional trading on news from the fixed income side of the market is much limited. Balduzzi, Elton, and Green (2001) and Green (2004) study dealer trading activities in the Treasury market following macroeconomic news announcements and find that prices respond to news quickly. Jiang and Sun (2015) investigate the TRACE trading volume and liquidity of corporate bonds around both macroeconomic and firm-specific news; related to this 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; namely, 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(2021) report evidence for bond price drift post earnings announcements. Current literature, however, remains largely muted on how corporate bond 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 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 et al., 2008), and the subsequent price reversal post news events also finds grounds in a number of studies. 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 the literature. For example, Tetlock (2011) and Fedyk and Hodson (2021) 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. Our findings of bond price reversal to news is also consistent with Bali, Subrahmanyam, and Wen (2021), who report both short- and long-term price reversals in the corporate bond market.

We interpret fixed income funds' trading against news as a way of liquidity provision. In the over-the-counter corporate bond market, broker dealers match the potential sellers and buyers and collect economically significant transaction costs (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.[6] Institutional peculiarities of the corporate bond market complicate the process of search and inventory management. Given the rise of stringent capital requirements to banks (Bessembinder et al., 2018), bank affiliated broker dealers are less inclined to hold inventories and tend to function as "brokers" only to match potential customer buyers and sellers. Indeed, Goldstein and Hotchkiss (2019) and Choi and Huh

[6] See, for example, Friewald, Jankowitsch, and Subrahmanyam (2012), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Bao, O'Hara, and Zhou (2018), and Dick-Nielsen and Rossi (2019).

(2019) 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. Broker-dealers would offer better-than-normal quotes to "solicit" liquidity providers when they are less able to provide liquidity themselves, essentially sharing market-making profits (e.g., Harris, 2015; Choi and Huh, 2019). Longer-term buy-side institutions therefore can play an important role in liquidity provision as they do not necessarily incur the inventory cost (Anand, Jotikasthira, and Venkataraman, 2021). Some fund managers may hence find liquidity provision and thus "trade against news" a means to enhance fund performance.[7] Similar in spirit to our paper, Choi, Shachar, and Shin (2019) show that dealers provide liquidity by "trading against" increasing price differentials between corporate bonds and credit default swaps. We contribute to the literature that liquidity provision is not just served by broker dealers.

## 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,

[7] We recognize that it is possible that mutual funds in aggregate could still be liquidity demanders. For example, Bretscher et al. (2021) study institutional investors' demand elasticity of corporate bonds using the demand system approach of Koijen and Yogo (2019). They show that mutual funds on average demand more liquid bonds (as proxied by bid-ask spread); and they interpret the results as mutual funds are liquidity demanders.

followed by Reuters News's 11.2% and Business Wire's 8.2%. Appendix A 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.[8] 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 B 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 available date) 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: U.S. fund corporate bond, U.S. fund high yield bond, U.S. fund intermediate core bond, U.S. fund intermediate core-plus bond, and U.S. fund long-term bond. Funds in Morningstar may provide quarterly or monthly holdings information. To evaluate the holding changes surrounding news events in a timely manner, we restrict our sample to funds that provide monthly holdings information to Morningstar. 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.[9] The average and median assets-under-management (AUM) of monthly reporters are close to those of the entire 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

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

[9] 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.

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 also invest in fixed income securities other than corporate bonds; we hence remove fund-months with less than 10% holdings 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, 2019; Bai, Bali, and Wen, 2021).

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. Dollar change is the change in par value, multiplied by the average price (in the percentage of the par) reported by all fixed income mutual funds. $\Delta w$ reflects a fund's holding change in a given bond, relative to the fund's all corporate bond holdings during the reporting month.[10]

Panel B of Table I provides the summary statistics of the key variables for our primary sample. The average of $\Delta w$ is 0.0062%. The average fund total net assets in our sample are $19.8 billion with $5.92 billion invested in corporate bonds; the mean $\Delta w$ translates into a dollar net-buy amount of $365 thousands.[11] This is consistent with the phenomenal growth of the fixed income fund sector during the past two decades. The median of $\Delta w$ is zero since funds, in general, are non-high-frequency traders. The average of *Neg_net* is slightly positive (0.0039), suggesting that the average news tone is somewhat negative. A median bond in our sample has a credit rating of BBB+ and 7.6 years remaining to maturity.

*2.2 Matching the news sample to the fund holding sample*

To examine the impact of news on bond trading, we align the month-*t* news with the same month $\Delta w$. This alignment is built on the two assumptions i) that institutions react speedily to but do not predict news and ii) that 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

[10] In untabulated results, we also use the dollar change in trading and our findings are robust.
[11] Fund total net assets in the primary sample has a higher mean than the mean of AUM reported in Panel A since larger funds disproportionately have more trades in the primary (regression) sample.

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. 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 evidence.

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 $t$.[12] 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.[13] 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 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

[12] 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.
[13] 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.

negatively related to bond returns on days [-1], [0], [1], and [2, 5]; that is, these results suggest that bond returns react not only 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 successions. In a multiple-day news event, current price may be driven by previous day news; but if the previous-day news is repeated (even partially) in later days, it would give rise to an artifact that current price may predict later-day news that biases regression results. For example, in a persistent two-day news sequel, day [1] price may be related to news of both days [1] and [2]. The latter association would imply predictive price reaction to news, even if the price reaction is stimulated only by day [1] news. 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.[14] 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 days [-5, -2].

Panel B of Table II repeats 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 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

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

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 $\Delta w$. 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.

## 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. Table III provides the results. In the Table, we sort our sample into deciles by *Neg_net* and examine the mean value of $\Delta w$ for each *Neg_net* decile. We find that the mean value of $\Delta w$ is almost monotonically increasing in the decile rank. The mean of $\Delta w$ for the top decile is 0.82 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 $\Delta w$ difference between deciles 6 to 10 and deciles 1 to 5 ("D6:10 to D1:5 difference") is also large and significantly positive at 0.27 bps. While the mean value of our issue-level $\Delta w$'s seems low, noting that $\Delta w$ is measured relative to the fund's entire corporate bond holdings, such differences are economically significant. For instance, a $\Delta w$ 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) thousands for a single bond. In comparison, we note that the unconditional average value of an absolute position change is a smaller amount of $158 thousands in our sample. These results provide the first evidence that fixed income mutual funds exhibit a tendency to trade against the direction of news. That is, contrary to the evidence that equity funds trade along the direction of news (Huang, Tan, and Wermers, 2020), fixed-income funds seem to sell (buy) more of the bond if the issuer experiences more positive (negative) news in the month.

[Insert Table III about here.]

In Table III, we also examine $\Delta w$ separately for each leg of the news tone. We rank the bond holdings sample by either *Neg* or *Pos*. While the monotonicity is less conspicuous for either *Neg* or *Pos*, we note that the general trading patterns against news hold for both legs in the univariate sorting. Specifically, the difference in $\Delta w$ between deciles 10 and 1 is significantly positive (negative) for *Neg* (*Pos*), and so is the D6:10 to D1:5 difference in $\Delta w$. Sample wise, the trading-against-news pattern seems to be stronger in *Pos* than in *Neg*, in that the magnitude of D6:10 to D1:5 difference is larger in *Pos* (negative 0.23 bps) than in *Neg* (0.17 bps).

### *3.2 Regression analysis*

We now regress $\Delta w$ 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 IV 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 $\Delta w$, 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 Table III.

[Insert Table IV about here.]

We use Model (2) as the benchmark for calculating the economic significance of the news tone. Measured by the multiplication of a variable's standard deviation and its coefficient estimate, the economic significance of *Neg_net* on $\Delta w$ is 0.037 bps. Given that the average fund corporate bond holdings in the sample is \$6.02 billion, this economic significance translates into a dollar value of \$23thousands. Given the mean absolute dollar value of a holding change for an individual bond is \$158thousands, the economic significance of *Neg_net* on $\Delta w$ is equivalent to one seventh of the absolute dollar trading amount.

To examine the manager's decision to trade a bond or not at all, we create a variable, $Increase_{i,j,t}$, that takes the value of, respectively, -1, 0, or 1 for $\Delta w_{i,j,t}$ less than, equal to, or greater than zero. 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 $\Delta w$, 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 $\Delta w$ 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 Table IV.

### *3.3 Fund heterogeneity*

In this section, we examine the differences of news trading across fund types. Morningstar breaks corporate fixed income funds into five categories: i) U.S. fund corporate bond (who primarily invests in investment grade corporate bonds), ii) U.S. fund high yield bond (who primarily invests in high-yield corporate bonds and bank loans), iii) U.S. fund intermediate core bond (who invests primarily 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 (who primarily invests in long-term government, corporate, and securitized debt). Based on the potential sensitivity of fund managers to corporate news, we combine 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 as broad fixed income funds, as these funds target broader fixed income securities—they typically invest 20-30% 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 V repeats our main analysis for corporate concentrated funds and broad fixed income funds. We find that *Neg_net* is positively related to $\Delta w$ for both fund types, and the effect is much stronger in corporate concentrated funds (Models (1) and (2) of Table V). The coefficient estimate of *Neg_net* for corporate concentrated funds is about four times of that for broad fixed income funds (in untabulated tests, the difference in the coefficient estimates between the two models is statistically significant). The evidence hence supports a higher sensitivity of corporate concentrated funds to news.

[Insert Table V about here.]

Given the higher tendency of corporate concentrated funds to trade against news, we further examine the potential sources of this trading behavior. We align investment focus with portfolio choice within corporate concentrated funds (that include investment-grade-focused U.S. fund corporate bond and U.S. fund high yield bond). In Models (3) and (4), when we use only investment-grade bonds, we find that between U.S. fund corporate bond and U.S. fund high yield bond the effect of *Neg_net* on $\Delta w$ is only significant for the former. Similarly, in Models (5) and

(6), when we use only high yield bonds, we find that a significant effect of *Neg_net* on $\Delta w$ exists only for U.S. fund high yield bond but not for U.S. fund corporate bond. In other words, the concentration of the *Neg_net* effect is consistent with the fund objectives—funds specializing in corporate bond (high-yield) investments are more likely to focus on news of investment-grade (high-yield) bonds.

The findings above are 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 et al. (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 et al. (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 VI 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 probably better at providing liquidity, and they do so when called for by market events such as news.

[Insert Table VI 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).[15] Other things being equal, shocks to a bond will have greater impacts on bond price if the duration of the bond is longer. Thus, if funds trade on news, they would tend to trade in longer duration bonds for larger profit opportunities.

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

[Insert Table VII about here.]

That the trading effect of news is more pronounced in longer-duration bonds is also consistent with funds providing liquidity to the market. Using the regulatory version of TRACE, Han et al. (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

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

*Neg_net* with a high bond-turnover dummy. Model (3) of Table VII shows that the interaction term is significantly positive, indicating that the trading effect of news is also more pronounced in bonds with better liquidity.

In Table VII, we lastly examine whether the effect is driven by information asymmetry of the bond issuers. We break bond issuers by two information asymmetry measures: firm size and idiosyncratic return volatility. Larger firms or firms with smaller idiosyncratic volatility tend to have a lower degree of information asymmetry (e.g., Krishnaswami and Subramaniam, 1999; Dittmar, 2000). We create a dummy variable for firms with a larger size or smaller idiosyncratic volatility, and interact the dummy variable with *Neg_net*. Models (4) and (5) of Table VII show that the interaction term is significantly positive, suggesting that the trading against news effect is concentrated in bonds with less information asymmetry. If we view trading against news as an activity that funds provide liquidity to the market (we subsequently argue that this is one motivation for funds to trade against news), Models (3)-(5) indicate that funds are more comfortable providing liquidity for bonds with better liquidity and less uncertainties—potentially because these bond issues are "easier" to trade with.

*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.[16] News related to firms' credit ratings, therefore, should carry a strong weight if, as previously discussed, 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, which reflects the news sentiment about the bond issuer's credit rating movements. In about one-third of bond months, there exists credit rating-related news. Model (1) of Table VIII shows that *Neg_net* of credit rating news is still negatively and

[16] For example, this "Bond Basics" article 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.

significantly related to $\Delta w$. This significance takes place with the existence of credit ratings, suggesting that news information about credit ratings carries incremental value. Notably, during credit rating news months, Model (2) shows that when *Neg_net* of credit rating news and *Neg_net* of all other news are placed side by side, the former subsumes the latter.

[Insert Table VIII about here.]

The relative 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 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 (3) of Table VIII 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."

The significance of credit rating news is not driven only by credit rating change events. In Model (4), we exclude bond-months with credit rating change events by keeping a sample with credit rating news but without credit rating changes. We continue to observe that *Neg_net* remains significantly positive on $\Delta w$. In sum, Table VIII 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 does *Pos* (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008). In Table IX, we separately examine the effect of the positive and negative legs of *Neg_net* on $\Delta w$. Models (1) and (2) show that *Neg* is not significantly related to $\Delta w$ or *Increase*, but *Pos* is significantly and negatively related to $\Delta w$ or *Increase*; that is, the trading against news phenomenon is concentrated in tone positivity of the news rather than tone negativity. Compared to Table IV, the coefficient estimate of *Pos* on $\Delta w$ 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. This contrasts with the "buy the dip" phenomenon observed in the equity market, as documented by (Bonini, Shohfi, and Simaan, 2022).

[Insert Table IX about here.]

## 4. Potential Motives for Fund Liquidity Provision

In this section, we examine potential motives for funds to trade against news. We argue that funds trade against news to provide liquidity. We provide a number of pieces of evidence. We show that trading against news is tied to the fund's inventory level of the bond; as well, we provide complementary evidence on trading activities by institutions other than mutual funds (bond dealers and insurance companies). We demonstrate that funds' trading against news generates alpha, and that a potential source of this alpha is bond price reversal subsequent to news.

### *4.1 Inventory level and trading against news*

A trader's capability to provide liquidity in selling is directly tied to her long position. While short selling exists, it is less persuasive in the fixed income market than in the equity market (e.g., Hendershott, Kozhan, and Raman, 2020). Furthermore, fixed income funds are usually not allowed to sell short by mandate. We thus expect that the news trading effect is more pronounced if the fund already has a larger existing position of the bond. Unwinding a large position on good news also gives the fund an opportunity to lock in profit and rebalance its portfolio.

We rank a fund's dollar holdings of bonds every month, and use a dummy variable "High inventory" that equals to one for a given bond if the fund holds an above-median amount of the bond in the previous month. Model (1) of Table X shows that the coefficient estimate of the interaction term of *Neg_net* × High inventory is significantly positive in relation to $\Delta w$; moreover, the coefficient estimate of *Neg_net* itself is reversed to be significantly negative. The magnitude of the coefficient estimate of the interaction term is four times of that of *Neg_net*. These results suggest that funds trade against news only when they have a high inventory of the bond; otherwise, they would tend to trade in the direction of news, consistent with the findings in the equity market (e.g., Huang, Tan, and Wermers, 2020). In other words, funds only provide liquidity when they are more able to—and such provision of liquidity in our case of news arrivals echoes opportunistic trading too.

[Insert Table X about here.]

Models (2) and (3) of Table X repeat the analysis of Model (1) for *Neg* and *Pos*, respectively. Consistent with Table IX, funds do not trade on *Neg*, nor is their decision to trading on *Neg* affected by their inventory level of the bond. In contrast, funds' selling on news positivity is dominantly driven by their inventory level, in that the estimate of the interaction term of *Pos* × High inventory is significantly negative and that the estimate *Pos* is reversed to be positive—a pattern highly consistent with Model (1).

Our results so far focus on individual funds' trading. These results may be disproportionately driven by a subset of funds making a large number of trades on a particular bond. To address this possibility, we calculate the overall institutional trading as the sum of signed trading volume of the given bond at the given month by all funds, divided by the bond's par amount outstanding; in other words, aggregate fund level $\Delta w$ measures the trading imbalance by all funds. Models (4), (6) and (8) continue to show that a significantly positive coefficient estimate for *Neg_net*, an insignificant estimate for *Neg*, and a significantly negative estimate for *Pos*. Thus, the findings in Tables IV and IX hold at the aggregate institutional level.

More importantly, we show that the fund inventory results in Models (1)-(3) of Table X continue to hold at the aggregate fund level. We calculate institutional ownership of a bond as the total par amount held by all funds divided by the outstanding par amount. Without abuse of notation, "High inventory" is now a dummy variable that takes the value of one if the bond's previous-month institutional ownership is above the median value of all bonds in the month. Models (5), (7), and (9) show that the interaction terms of news tone with High inventory have the same sign and significance as those in Models (1)-(3). Thus, funds as a whole sell on news when their overall position of the bond is high.

*4.2 Trading by bond dealers and insurance companies*

In this section, we examine the trading behaviors of other market participants to further shed light on the news trading pattern by fixed income funds. We consider two types of other market participants: bond dealers and insurance companies. In contrast to mutual fund holding data, whose finest reporting interval is monthly in the databases that we know of, transaction data for bond dealers from TRACE and insurance companies from NAIC contain the execution date. Hence, we can examine the granular trading activities of bond dealers and insurance companies on news.

In the corporate bond market, dealers are considered liquidity providers in general (for instance, Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Choi, Shachar, and Shin, 2019), while customers such as insurance companies are likely to trade for reasons other than liquidity provision.[17] If trading against news by fund managers—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.

We aggregate daily position changes in the dealer sector for each bond and construct dealer net buy. For any bond on a given execution date, we compute the variable *dealer net-buy* as the difference in the aggregate par value between all dealer buy from customers and all dealer sell to customers, scaled by the bond's outstanding par amount.[18]

Models (1)-(4) of Panel A of Table XI examine dealer net buy on news by regressing dealer net buy of days [0] to [10] on *Neg_net*. The results show that *Neg_net* is significantly and positively associated with dealer net buy on days [0], [1], and days [2, 5] as a whole; and the relation between *Neg_net* and dealer net buy is insignificant for days [6, 10]. That is, dealers trade against news on the daily level until day [5]. Magnitude wise, dealers are most sensitive to the news on day [0]; and their sensitivity is attenuated further along the news event.[19] In Models (1)-(4) of Panel B of Table XI, we provide evidence for dealer net buy on *Pos* and *Neg*, respectively, and find 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 idea that dealers make the market and

[17] For instance, the literature has documented that insurance companies prefer higher rated 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); both of these trading motivations are unlikely to be tied to liquidity provision.
[18] Following Adrian, Boyarchenko, and Shachar (2017) and Choi and Huh (2019), we exclude affiliated transactions in which dealers transfer bonds to their non-FINRA affiliates for bookkeeping purposes.
[19] 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 one quarter of the coefficient estimate of *Neg_net*.

provide liquidity to customers when news induces demand for selling and asset price is under pressure (Kyle, 1985; Duffie, Gârleanu, and Pedersen, 2005; Goldstein and Hotchkiss, 2019). Further, our findings suggest that dealers engage more in "buy on bad news" than in "sell on good news," contrasting mutual funds' concentrated trading of 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 that due to capital constraints dealers do not tend to hold excessive inventory in a particular bond. When positive news of the bond hits the market resulting in a surge in customer demand for the bond, dealers unwilling to short-sell the bond would resort to the inventory held by mutual funds to satisfy the demand.

[Insert Table XI about here.]

We similarly examine daily net buy of insurance companies on news. Insurance company net buy is the aggregate amount of daily buy minus sell of a bond by all insurance companies, using the NAIC individual insurance companies' transactions data. Models (5)-(8) in Panel A of Table XI 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 in Panel A of Table XI 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 Panel B 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] only; in contrast, 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 events and issues, the results suggest that insurance companies tend to dispose of the position in cases of negative news shocks.

Table XI, combined with our main results on mutual fund trading, depicts the trading behavior 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 weakly along positive news shocks, and dealers to trade against both positive and negative new shocks. 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. We have limited evidence that when mutual funds sell on news, their counterparties can be other funds that are low in inventory (Table X), or insurance companies. The evidence overall, however, suggests that trading on the negativity and positivity sides of news among fixed income funds, dealers, and insurance companies complement each other, with insurance companies trading along the news while fixed income funds and dealers in aggregate trading against the news.

*4.3 Alpha for individual funds*

Funds are ultimately profit-driven. While functionally, funds may provide liquidity by trading against news, funds must be able to earn non-negative abnormal returns for against-news trades to be sustainable. In this section, we investigate 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.[20] Following Anand, Jotikasthira, and Venkataraman (2018), we estimate the factor loadings using the previous 18-month observations, and compute the fund alpha using the current month fund return adjusted by the current month factors and the corresponding estimated factor loadings.[21]

To capture the tendency of trading against news, we construct an indicator variable if the fund is trading against news of an issue, denoted as $Against_{i,j,t}$, which is equal to 1 if $\Delta w_{i,j,\mathrm{t}} \times Neg\_net_{j,\mathrm{t}} > 0$ and 0 otherwise; that is, $Against_{i,j,t} = 1$ if fund $i$ net-buys (net-sells)

[20] The construction of the factors is as follows. The stock market factor is the return of the contemporaneous 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).

[21] 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.

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 the long-term trading pattern of a fund against news. We set $L = 12$ (past one year), but can report that our results are robust to $L$ of 9 and 15.

In Figure 1, we rank mutual funds by *TradeAgainstNews* and evaluate fund performance. We sort mutual funds into ten groups on *TradeAgainstNews* at the end of month [-1]. 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. Figure 1 shows the one-month-ahead, quarterly and semi-annual alphas for the decile 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. In contrast, the unconditional mean of fund alpha for all of the funds in the sample is only -1.84 bps per month.[22] 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 Figure 1 about here.]

For the quarterly and semi-annual alphas, we find that the differences in alpha among decile portfolios persist in longer holding horizons, consistent with the monthly alpha sorting results. The magnitude of the alpha performance difference grows along with the holding horizon. For example, the cumulative quarterly alpha difference between Decile 10 and Deciles 1 is 4.46 bps, about two

[22] The negative alpha of the overall fixed income funds arises (at least partly) because the construction of fixed income indexes usually does not take transaction costs into account.

times of its monthly counterpart. Overall, Figure 1 provides univariate evidence that trading against news generates alpha.

We provide multivariate evidence for fund alpha in Table XII, 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 variations across time. Models (1) to (3) of Table XII examines the impact of *TradeAgainstNews* on the subsequent one-, three-, and six-month fund alphas. Consistent with the evidence from portfolio sorting, we find that *TradeAgainstNews* is positively associated with future fund alpha. 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 Figure 1) would result in an improvement of 17.5 bps in annualized alpha ((0.76-0.5)×5.60×12). *TradeAgainstNews* is associated with a similar magnitude of improvement for three, and six-month fund alphas.

[Insert Table XII about here.]

We further examine the trading side 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*:

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

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

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 (4) to (9) of Table XII 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 that is 1.6 times of the coefficient estimate 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." Overall, the finding that fund selling against news generates alphas is consistent with our earlier results that funds' trading against news is concentrated on news positivity.

*4.4 Bond price reversal subsequent to news*

Lastly, we show that a potential source of alpha is bond price reversal subsequent to news. While we recognize that by filling in the roles of dealers in providing liquidity funds may profit from dealer functionalities such as bid-ask spread, we are constrained by data availability to test such a hypothesis. Medium-term price reactions post news provides another outlet for us to examine the potential sources of alpha. Specifically, if there exists a price reversal after news, trading against news can be profitable. In equity markets, the literature has documented price reversal to news (e.g., Tetlock, 2011; Gilbert et al., 2012; Fedyk and Hodson, 2021). 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 XIII, 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 XIII about here.]

The remainder of Table XIII offers further evidence for *Neg* and *Pos*, respectively, and finds 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 generates alpha. Overall, the pattern of immediate returns observed earlier in Table II and return reversal identified in Table XIII 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. Price reversal therefore constitutes a potential explanation for fund trading against news.

## 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 on how fixed income funds trade on information shocks. This contrasts with the findings on institutional trading of equities, where the recent literature documents that institutional investors respond quickly to news and that they trade along the direction of news (e.g., Engelberg, Reed, and Ringgenberg, 2012; Hendershott, Livdan, and Schürhoff, 2015; Huang, Tan, and Wermers, 2020). The equity-side of findings provides important support to the market microstructure theory foundation that institutional investors, as a type of informed investors, possess superior information processing ability.

Combining a comprehensive database of corporate news releases from Factiva and survivor bias-free fixed income mutual fund holdings data from Morningstar, we examine how fixed income funds trade on corporate news. 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 bonds where the funds' investment objectives lie in (for instance, Corporate Bond funds invest in investment grade bonds), in bonds with long duration, high liquidity and low information asymmetry (for instance, issuers are large in size or low in return volatility), and in bonds experiencing credit-rating and 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.

Fixed income funds' trading against news is a manifestation of liquidity provision. We compare the trading behaviors of the largest institutional owners of corporate bonds—insurance companies—and broker-dealers who act as middlemen in the OTC bond trading market. We find that dealers also trade against news, while insurance companies trade along the direction of news. Intriguingly, dealers trade more against negative news shocks than positive news shocks, whereas funds mostly sell against positive news. In addition, fund trading on news is more pronounced if the fund already holds a larger inventory in the bond. These 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, 2019; 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, 2019). Mutual funds emerge as a potential choice for such purposes; for example, mutual fund managers earn alpha from liquidity provision and therefore are incentivized (e.g., Anand, Jotikasthira, and Venkataraman, 2018). Overall, our findings point to funds filling in the void left by dealers in liquidity provision in events such as news shocks.

We provide evidence that funds with a style of trading against news enjoy a higher alpha. Apart from potential profit from liquidity provision, another potential source of alpha is price reversal subsequent to news. While in the short run, news negativity is negatively related to bond returns, the price reaction slowly reverses, and the reversal becomes significant on average in three weeks, consistent with equities' over-reaction to stale corporate news in Tetlock (2011) and Fedyk and Hodson (2021). Fixed income funds may, therefore, strategically trade against the direction of news to capture this price reversal for their alpha generation.

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

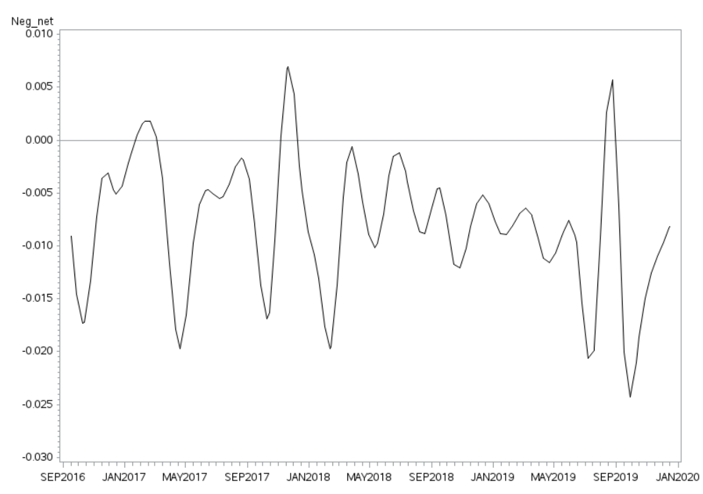
### A. Example of trading against news

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 |
|---|---|
| $\Delta w$ | 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. |
| Fund inventory (of a given bond) | Fund inventory is market value of a bond from Morningstar fixed income mutual fund holding database. |
| *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 $\Delta w$; 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. |

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## Table I Summary statistics of funds and trades

Panel A presents the number of funds in the Morningstar database 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 B for variable definitions.

**Panel A: Summary statistics of Morningstar fixed income mutual funds**

| | | Fund category | | | | |
|---|---|---|---|---|---|---|
| | Full sample | Corporate Bond | High Yield Bond | Int. Core Bond | Int. Core-Plus Bond | Long-Term Bond |
| # of institutions (Morningstar) | 859 | 54 | 273 | 357 | 143 | 32 |
| Average (median) AUM (Morningstar) | 2,130.9 (332.3) | 1,270.9 (362.3) | 1,102.9 (316.0) | 2,680.8 (247.8) | 3,051.8 (561.1) | 1,522.6 (214.0) |
| # of institutions (Monthly reporters) | 664 | 38 | 198 | 283 | 120 | 25 |
| Average (median) AUM (Monthly reporters) | 1,994.6 (329.8) | 1,164.8 (383.1) | 934.8 (304.3) | 2,901.6 (247.8) | 2,354.6 (565.9) | 1,214.2 (152.2) |
| # of trades | 589,366 | 62,357 | 100,352 | 251,971 | 126,854 | 47,832 |
| Trading volume ($million) | 857,898.60 | 116,526.95 | 176,019.43 | 317,555.28 | 207,099.98 | 40,696.96 |
| # 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 |
|---|---|---|---|---|---|---|
| $\Delta w$ | 3,251,699 | 0.0062 | 0.1079 | 0.0000 | -0.4644 | 0.7031 |
| *Neg_net* | 3,276,681 | 0.0039 | 0.0109 | 0.0029 | -0.0227 | 0.0390 |
| *Pos* | 3,276,681 | 0.0113 | 0.0058 | 0.0109 | 0.0000 | 0.0298 |
| *Neg* | 3,276,681 | 0.0151 | 0.0095 | 0.0142 | 0.0000 | 0.0470 |
| Maturity | 3,276,681 | 11.251 | 9.316 | 7.625 | 1.000 | 38.956 |
| 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 | 10.151 | 1.660 | 10.233 | 5.657 | 13.573 |
| 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 | 67.345 |
| Fund age | 3,116,213 | 15.899 | 10.715 | 13.921 | 0.589 | 44.773 |
| Fund expense ratio | 2,999,623 | 0.004 | 0.003 | 0.004 | 0.000 | 0.011 |
| Fund total net asset (in millions) | 3,190,504 | 19,757 | 48,538 | 1,644 | 0 | 269,025 |
| Fund total net asset in corporate bonds (in millions) | 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 Panel B, 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) |
| Constant | -0.154** | -0.037 | -0.070 | -0.132 | -0.124 | -0.227** | 0.037 | 0.045 | -0.009 | 0.082 |
| | (-2.10) | (-0.51) | (-1.08) | (-0.69) | (-0.52) | (-2.44) | (0.40) | (0.50) | (-0.06) | (0.43) |
| 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 |

**Panel B: Returns on *Pos and 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) |
| *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 Univariate sorting of mutual fund trading by news tone

This table shows the mean value (Mean) and the standard deviation (Std) of monthly mutual fund holdings change ($\Delta w$) in decile portfolios ranked by *Neg_net*, *Neg*, and *Pos*, respectively. $\Delta w$ 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. 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. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | Mutual fund holdings change ($\Delta w$) | | | | | |
|---|---|---|---|---|---|---|
| Ranking variable | *Neg_net* | | *Neg* | | *Pos* | |
| Decile | Mean | Std | Mean | Std | Mean | Std |
| 1 | 0.0029 | 0.0933 | 0.0025 | 0.0905 | 0.0058 | 0.1044 |
| 2 | 0.0038 | 0.0960 | 0.0047 | 0.0996 | 0.0075 | 0.1136 |
| 3 | 0.0050 | 0.0989 | 0.0070 | 0.1058 | 0.0081 | 0.1168 |
| 4 | 0.0052 | 0.1004 | 0.0065 | 0.1034 | 0.0078 | 0.1154 |
| 5 | 0.0072 | 0.1055 | 0.0060 | 0.1035 | 0.0074 | 0.1131 |
| 6 | 0.0072 | 0.1073 | 0.0069 | 0.1058 | 0.0069 | 0.1104 |
| 7 | 0.0069 | 0.1095 | 0.0064 | 0.1093 | 0.0048 | 0.1030 |
| 8 | 0.0075 | 0.1152 | 0.0067 | 0.1121 | 0.0049 | 0.1040 |
| 9 | 0.0078 | 0.1202 | 0.0066 | 0.1165 | 0.0048 | 0.1009 |
| 10 | 0.0082 | 0.1276 | 0.0085 | 0.1282 | 0.0037 | 0.0953 |
| Decile 10 - 1 | 0.0053*** | | 0.0059*** | | -0.0022*** | |
| | (9.14) | | (9.38) | | (-6.60) | |
| Deciles 6:10 - 1:5 | 0.0027*** | | 0.0017*** | | -0.0023*** | |
| | (9.64) | | (6.79) | | (-10.10) | |

## Table IV Mutual fund trading on news tone

This table regresses $\Delta w$ (mutual fund holdings change) and *Increase* (which takes the value of, respectively, -1, 0, or 1 for $\Delta w$ less than, equal to, or greater than zero) on the news tone measure of *Neg_net*. See Appendix B for variable definitions. Models (5) and (6) constrain the sample to non-zero $\Delta w$'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) |
|---|---|---|---|---|---|---|
| | $\Delta w$ | $\Delta w$ | *Increase* | *Increase* | $\Delta w$ (traded only) | $\Delta w$ (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) |
| Constant | 0.0060*** | -0.0262*** | 0.0233*** | -0.0392 | 0.0365*** | -0.1507*** |
| | (20.74) | (-4.07) | (3.98) | (-1.40) | (17.00) | (-3.49) |
| 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 V Mutual fund news trading: Heterogeneity in fund categories and bond ratings**

This table regresses mutual fund holdings change ($\Delta w$) on the news tone measure of *Neg_net* using partitioned samples by Morningstar fund categories and bond investment grades. Model (1) investigates corporate concentrated mutual funds, which include US fund corporate bond and US fund high yield bond. Model (2) studies funds targeting broad fixed indexes, which include US fund intermediate core bond, US fund intermediate core-plus bond, and US fund long-term bond. Models (3)-(6) partition the corporate concentrated mutual funds by granular fund categories of US fund corporate bond and US fund high yield bond and further by bond credit ratings (investment grade and junk). 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: $\Delta w$ | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | Within Corporate concentrated funds | | | |
| | | | Using only investment grade bonds | | Using only junk bonds | |
| Funds | Corporate concentrated | Broad fixed income | Corporate | High yield | Corporate | High yield |
| *Neg_net* | 0.0723*** | 0.0175* | 0.0825** | 0.0105 | 0.1373 | 0.0522* |
| | (3.34) | (1.69) | (2.22) | (0.07) | (1.16) | (1.97) |
| Maturity | 0.0020* | 0.0008* | 0.0045** | -0.0001 | -0.0391* | 0.0049*** |
| | (1.73) | (1.92) | (2.11) | (-0.04) | (-2.00) | (4.56) |
| Credit rating | 0.0050*** | 0.0019*** | 0.0025** | -0.0196*** | 0.0092 | 0.0080*** |
| | (5.26) | (5.94) | (2.10) | (-3.54) | (1.56) | (6.56) |
| alpha [*t*-3, *t*-1] | -0.0250*** | 0.0210*** | 0.0350* | -0.1454** | -0.0060 | -0.0293*** |
| | (-3.33) | (4.32) | (1.79) | (-2.47) | (-0.12) | (-3.90) |
| Firm size | -0.0003 | 0.0011*** | -0.0019 | -0.0249*** | 0.0109 | 0.0009 |
| | (-0.39) | (2.78) | (-1.02) | (-3.16) | (1.68) | (0.92) |
| Idio. volatility | 0.4077*** | -0.0305 | -0.0939 | 0.8937 | -0.4024 | 0.4570*** |
| | (6.00) | (-0.85) | (-0.58) | (1.51) | (-1.46) | (5.74) |
| LT debt ratio | -0.0351*** | -0.0436*** | -0.0635*** | 0.0357 | 0.0036 | -0.0341*** |
| | (-6.75) | (-7.92) | (-3.57) | (0.81) | (0.11) | (-6.16) |
| Interest coverage | 0.0005*** | 0.0002*** | 0.0005*** | 0.0009** | 0.0003 | 0.0008*** |
| | (4.68) | (7.02) | (2.92) | (2.37) | (0.68) | (6.28) |
| Fund age | -0.0003*** | -0.0001*** | -0.0003*** | -0.0003 | -0.0003* | -0.0004*** |
| | (-5.28) | (-3.50) | (-3.67) | (-1.47) | (-1.85) | (-4.65) |
| Fund expense ratio | 0.4803 | 0.3644** | 0.5154 | 1.1175 | 1.4924 | 0.2186 |
| | (1.16) | (2.03) | (0.81) | (0.92) | (1.42) | (0.43) |
| Constant | -0.0532*** | -0.0198*** | -0.0247 | 0.3924*** | 0.1155 | -0.1198*** |
| | (-3.33) | (-2.87) | (-0.86) | (3.71) | (0.75) | (-6.39) |
| Issue FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Fund type - month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 558,732 | 1,839,139 | 166,366 | 15,167 | 14,719 | 362,336 |
| Adj R-squared | 0.0194 | 0.0297 | 0.0214 | 0.0877 | 0.0409 | 0.0207 |

## Table VI 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 IV, 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: $\Delta w$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (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 VII Mutual fund news trading: issue and issuer heterogeneity

This table regresses fund holdings change ($\Delta w$) 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 the issuer and the date level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent variable: $\Delta w$ | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | *Dummy* = 1 for | | | | |
| | Long duration | Long maturity | 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) |
| Constant | -0.0244*** | -0.0245*** | -0.0389*** | -0.0511*** | -0.0475*** |
| | (-3.82) | (-3.83) | (-5.73) | (-9.02) | (-8.56) |
| 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 VIII Mutual fund trading on credit rating news

This table regresses $\Delta w$ (mutual fund holdings change) on *Neg_net* calculated using credit rating news only and other non-credit rating news, respectively. *Credit rating change* takes the value of 1 if the bond is upgraded in the month, −1 if downgraded, and 0 otherwise. Models (1) - (3) include all bond-months that have credit rating news. Model (4) excludes bond-months with credit rating changes from Model (1). 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: $\Delta w$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All | All | All | *Credit rating change* = 0 |
| *Neg_net* (credit rating news) | 0.0329*** | 0.0332*** | 0.0370*** | 0.0214** |
| | (3.96) | (3.90) | (4.38) | (2.17) |
| *Neg_net* (other news) | | 0.0050 | | |
| | | (0.30) | | |
| *Credit rating change* | | | -0.0000 | |
| | | | (-0.01) | |
| *Neg_net* (credit rating news) | | | 0.2523*** | |
| × *Credit rating change* | | | (7.43) | |
| Maturity | 0.0025*** | 0.0025*** | 0.0025*** | 0.0031*** |
| | (3.73) | (3.68) | (3.78) | (3.70) |
| Credit rating | 0.0050*** | 0.0050*** | 0.0047*** | 0.0055*** |
| | (7.69) | (7.64) | (7.43) | (7.68) |
| alpha [*t-3*, *t-1*] | 0.0225*** | 0.0227*** | 0.0169** | 0.0182* |
| | (2.83) | (2.87) | (2.17) | (1.89) |
| Firm size | -0.0045*** | -0.0045*** | -0.0051*** | -0.0093*** |
| | (-4.37) | (-4.42) | (-4.77) | (-6.29) |
| Idio. volatility | -0.2331*** | -0.2314*** | -0.1963*** | -0.4277*** |
| | (-3.55) | (-3.56) | (-3.04) | (-5.26) |
| LT debt ratio | -0.1169*** | -0.1168*** | -0.1173*** | -0.1571*** |
| | (-9.52) | (-9.50) | (-9.52) | (-9.52) |
| Interest coverage | 0.0003*** | 0.0003*** | 0.0003*** | 0.0002*** |
| | (5.47) | (5.47) | (5.43) | (3.08) |
| Fund age | -0.0001** | -0.0001** | -0.0001** | -0.0001* |
| | (-2.29) | (-2.30) | (-2.29) | (-1.65) |
| Fund expense ratio | 2.4422*** | 2.4490*** | 2.4413*** | 3.4696*** |
| | (6.83) | (6.84) | (6.83) | (7.45) |
| Constant | 0.0160 | 0.0177 | 0.0245* | 0.0730*** |
| | (1.19) | (1.30) | (1.76) | (3.84) |
| Issue FE | Yes | Yes | Yes | Yes |
| Fund type - month FE | Yes | Yes | Yes | Yes |
| Observations | 845,722 | 843,389 | 845,722 | 617,028 |
| Adj R-squared | 0.0643 | 0.0646 | 0.0645 | 0.0927 |

## Table IX  Mutual fund news trading: Negative and positive legs of news

This table regresses $\Delta w$ (mutual fund holdings change) and *Increase* (which takes the value of, respectively, -1, 0, or 1 for $\Delta w$ 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) |
|---|---|---|---|---|
| | $\Delta w$ | *Increase* | $\Delta w$ | *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) |
| Constant | -0.0251*** | -0.0355 | -0.0237*** | -0.0306 |
| | (-3.90) | (-1.27) | (-3.67) | (-1.11) |
| 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 X Mutual fund news trading and inventory level**

This table examines fund news trading conditional on the fund's bond inventory level at the beginning of the month. Models (1) – (3) examine the individual fund sample, where *High inventory* (individual fund level) is a dummy equal to one if the previous-month market value of the bond is above the median with fund-month. The *t*-statistics are reported in parentheses, cluster-adjusted at the fund level. Models (4) – (9) investigate aggregated fund new trading. For aggregate fund level, $\Delta w$ is the sum of the signed trading volume of the given bond at the given month by all funds, divided by the bond's par amount. We calculate the institutional ownership of a bond as the total par amount held by all funds divided by the outstanding par amount. *High inventory* (aggregate fund level) is a dummy variable that takes the value of one if the bond's previous-month institutional ownership is above the median value of all bonds in the month. Following the specification in Model (2) of Table IV, the control variables are included in all regressions but not reported. The *t*-statistics are reported in parentheses, cluster-adjusted at the bond level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent variable: $\Delta w$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Individual fund level analysis | | | Aggregate fund level analysis | | | | | |
| *Neg_net* | -0.0296** | | | 0.3253*** | -0.0437 | | | | |
| | (-2.56) | | | (2.85) | (-0.44) | | | | |
| *Neg_net × High inventory* | 0.1312*** | | | | 0.7034*** | | | | |
| | (6.73) | | | | (3.56) | | | | |
| *Neg* | | -0.0173 | | | | 0.0706 | -0.0964 | | |
| | | (-1.15) | | | | (0.52) | (-0.81) | | |
| *Neg × High inventory* | | 0.0168 | | | | | 0.3140 | | |
| | | (0.62) | | | | | (1.35) | | |
| *Pos* | | | 0.0431** | | | | | -0.9812*** | -0.0934 |
| | | | (2.18) | | | | | (-4.57) | (-0.52) |
| *Pos × High inventory* | | | -0.4007*** | | | | | | -1.6481*** |
| | | | (-11.62) | | | | | | (-4.54) |
| High inventory | 0.0152*** | 0.0201*** | 0.0154*** | | -0.0073** | | 0.0143*** | | -0.0094* |
| | (10.22) | (11.99) | (10.17) | | (-2.23) | | (2.60) | | (-1.93) |
| 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 | | | | | | |
| Month FE | | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,398,070 | 2,398,070 | 2,398,070 | 329,955 | 329,955 | 329,955 | 329,955 | 329,955 | 329,955 |
| Adj R-squared | 0.0309 | 0.0310 | 0.0308 | 0.0296 | 0.0364 | 0.0297 | 0.0365 | 0.0296 | 0.0362 |

**Table XI 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 Panel B, 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 | | | | Insurance companies | | | |
| | Net-buy on day(s) | | | | 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) |
| Constant | -0.0222 | -0.0335** | -0.0655 | -0.0910* | -0.1346*** | -0.1236*** | -0.5750*** | -0.4947*** |
| | (-1.59) | (-2.13) | (-1.61) | (-1.95) | (-3.87) | (-3.67) | (-3.62) | (-3.25) |
| 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 |

**Panel B: Net-buy on *Pos and Neg***

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Dealers | | | | Insurance companies | | | |
| | Net-buy on day(s) | | | | 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) |
| *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 XII Fund performance from trading against news: Regression analysis

Models (1)-(3) regress monthly fund alphas 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 (4)-(9) 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. 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) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|---|---|
| | Fund alpha in month(s) | | | Fund alpha in month(s) | | | Fund alpha in month(s) | | |
| | [0] | [0, 2] | [0, 5] | [0] | [0, 2] | [0, 5] | [0] | [0, 2] | [0, 5] |
| *TradeAgainstNews* | 5.60* | 14.71* | 24.13* | | | | | | |
| | (1.92) | (1.94) | (1.85) | | | | | | |
| *BuyAgainstNews* | | | | 0.83 | 0.76 | -0.61 | | | |
| | | | | (0.36) | (0.12) | (-0.05) | | | |
| *SellAgainstNews* | | | | | | | 9.06*** | 22.04*** | 34.05*** |
| | | | | | | | (4.57) | (4.13) | (3.66) |
| Fund age | -0.05 | -0.13 | -0.22 | -0.05 | -0.14 | -0.23 | -0.06* | -0.15* | -0.24 |
| | (-1.54) | (-1.54) | (-1.34) | (-1.52) | (-1.58) | (-1.43) | (-1.84) | (-1.72) | (-1.47) |
| Fund expense ratio | -703.7*** | -1,817.4*** | -3,309.2*** | -718.2*** | -1,827.4*** | -3,316.6*** | -776.6*** | -2,033.9*** | -3,623.7*** |
| | (-3.87) | (-3.73) | (-3.60) | (-3.92) | (-3.70) | (-3.56) | (-4.24) | (-4.11) | (-3.88) |
| Fund size | 0.09 | 0.14 | 0.21 | 0.09 | 0.19 | 0.34 | 0.17 | 0.35 | 0.48 |
| | (0.40) | (0.23) | (0.18) | (0.38) | (0.31) | (0.29) | (0.76) | (0.57) | (0.42) |
| Constant | -0.41 | -0.68 | -0.70 | 2.13 | 6.60 | 12.29 | -0.09 | 0.69 | 2.26 |
| | (-0.17) | (-0.11) | (-0.06) | (0.88) | (1.01) | (1.00) | (-0.04) | (0.12) | (0.22) |
| Observations | 30,982 | 31,206 | 31,553 | 30,830 | 31,053 | 31,399 | 30,469 | 30,692 | 31,024 |
| Fund type FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-squared | 0.138 | 0.155 | 0.178 | 0.139 | 0.156 | 0.177 | 0.142 | 0.161 | 0.184 |

## Table XIII 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) |

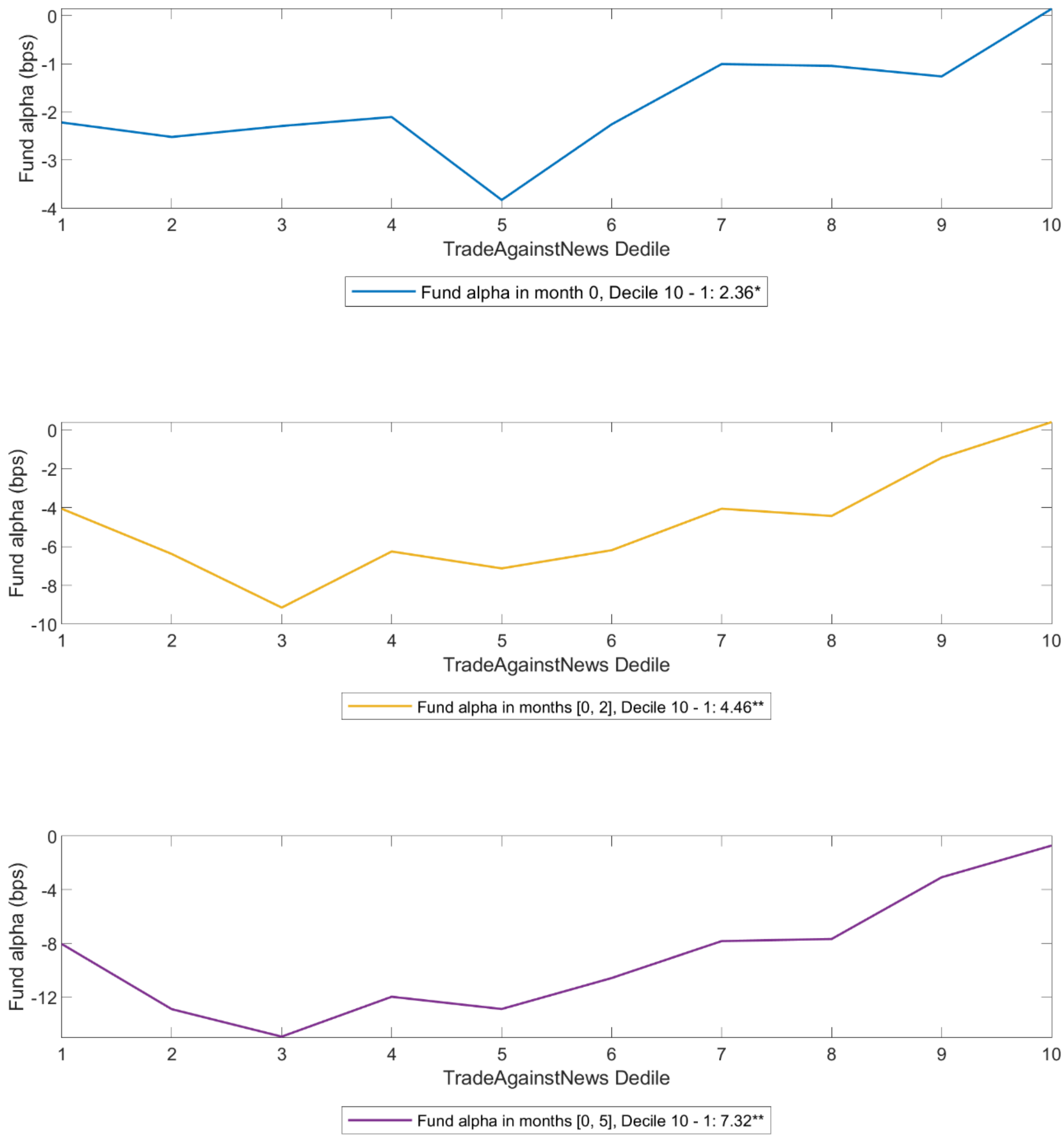


**Figure 1 Alpha sorting of fund performance from trading against news.** This figure shows the mean values of fund alphas in decile subsamples ranked by *TradeAgainstNews*, which proxies the fund tendency of trading against news over the past 12 months. We measure fund alpha using a model of five factors of stock market return, bond market return, default spread, term spread, and option spread. The differences in the means between Decile 1 and Decile 10 are reported in figure legends.