“Buy the Rumor, Sell the News”:
Liquidity Provision by Bond Funds Following Corporate News Events

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 low information asymmetry and bonds with positive-sentiment news. Funds that most frequently trade against news sentiment produce a higher alpha, and a source of such alpha is bond price reversals subsequent to such news. Fixed income mutual funds, dealers, and insurance companies complement each other in news trading, with insurance companies trading with the news, while dealers, similar to mutual funds, trading against the news. 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 transparency and liquidity in bond markets, relative to stock markets; 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—which is largely held by managed funds (Massa, Yasuda, and Zhang, 2013)—the total amount of outstanding corporate bonds has grown from $4.5 trillion in 2000 to $15.3 trillion in 2020.[2] 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 are 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 (Bessembinder, Maxwell, and Venkataraman, 2006), the turnover of fixed income mutual funds is, in fact, not particularly low. For instance, the median turnover ratio is 79.5% in 2020 for all funds classified as U.S. Fund Corporate Bonds by Morningstar.[5]

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[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).
[5] Among these funds, the turnover ratio is 72% for Vanguard Intermediate-Term Corporate Bond Index Fund, which has $46 billion asset under management (AUM) with 95% invested in corporate bonds. In contrast, PIMCO Investment

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 supply most of the news streamed to trading terminals, such as Bloomberg), has quadrupled from 167K in 2000 to 723K in 2020. While bond traders likely rely on traditional information sets, such as NRSRO credit ratings and analyst reports, it is plausible that fixed income fund turnover is at least partly driven by corporate news releases, given the growth of the fixed income fund industry and the news supply. After all, in contrast to credit and analyst reports that are typically post-news disclosed (and hence, potentially contain stale information), news is timely. 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 of these 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 positive words using the Loughran and McDonald (2011) financial dictionary, we find that mutual funds' monthly change in their position of a bond is related to the tone of the firm news during that month, but not during the subsequent month. 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 $319K; in comparison, the average unconditional monthly position change in a bond per fund is $158K. That mutual funds net-buy less (more) in good (bad) news implies trading against

Grade Credit Bond Fund, with $19 billion AUM and 75% of AUM in corporate bonds, reports a turnover ratio of 213%.

the direction of the news, consistent with "sell on news," where the motivation appears to be to sell a security on good news. We dub this phenomenon as "trade against news."

We identify a number of cross-sectional heterogeneities in funds' trade-against-news activities. Among the five corporate bond fund categories defined by Morningstar,[6] we find that the effect is significant in Corporate Bond funds when investing in investment grade bonds (as compared to when investing in junk bonds), and in High Yield Bond funds when investing in junk bonds (as compared to when investing in investment-grade bonds). This concentration of the trade against news effect is consistent with fund objectives, and points to a finding that funds engaging in such trades may enjoy a relative advantage in understanding the bonds they primarily trade (for instance, the creditworthiness of the issuers, as well as the impact of news on liquidity). We also find that the trading against news effect is more significant in bonds issued by large-size issuers and by issuers with smaller return volatility (Krishnaswami and Subramaniam, 1999; Dittmar, 2000), both of which indicate a lower level of information asymmetry. Lastly, 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. Overall, these cross-sectional heterogeneities suggest that funds trade against news in bonds that their primary investment objectives lie in, and in bonds that are "easier" trade with, such as bonds with low information asymmetry and good news.

That funds trade against news in such bonds leads us to hypothesize that the potential motivation for funds to do so is to provide liquidity as a means to generate alpha. While direct evidence for funds' liquidity provision is difficult to measure with the availability of only monthly reporting of mutual fund trades, we examine two market participants—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). In the corporate bond market, dealers, in general, are considered as liquidity providers (e.g., Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Choi, Shachar, and Shin, 2019), while insurance companies are likely to trade for reasons other than liquidity provision (e.g.,

[6] Morningstar categorizes corporate bond funds into the following five categories based on the composition of a fund's bond portfolio: 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.

Becker and Ivashina, 2015). We find that i) similar to fixed income funds, dealers trade against news, but the difference is that dealers trade against both positive and negative news shocks (as compared to funds' largely trading against positive news), and ii) contrary to fixed income funds, insurance companies mostly trade in the direction of negative news shocks, and only weakly with positive news shocks. The news trading by both dealers and insurance companies takes place only on or after news releases (but not before). Institutions, therefore, react speedily to news in the fixed income market, a finding that echoes the news reactions in the equity market (Huang, Tan, and Wermers, 2020). The evidence suggests that trading on the negativity and positivity sides of news among fixed income mutual funds, dealers, and insurance companies complement each other, with insurance companies trading with the news, while fixed income mutual funds and dealers trading against the news. The consistency of news trading behavior between dealers and mutual funds indicates that mutual funds follow dealers in providing liquidity to the market, whose counterparties include insurance companies.

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. In the short run, we find that more negative news is associated with a strong, negative bond return on the same day as the news, and the price impact continues into the next trading day. This association is consistent with the literature of price reactions to news in the equity market (e.g., Tetlock, Saar-Tsechansky, and Macskassy, 2008). While the price reaction remains largely muted subsequently, we find that it slowly reverses, and the reversal becomes significant in three weeks' time. Therefore, our evidence indicates that there is a short-term overreaction to news in bond prices, only to be partially corrected in subsequent weeks. This pattern of return reversal provides a potential explanation for mutual fund alpha: one way to profit from such corrections is to strategically trade against the direction of news.

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. Theoretically, Brunnermeier (2005) models an informed agent who trades against the public news because she expects the price to 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.

We interpret fixed income funds' trading against news as a way of liquidity provision. Similar in spirit, 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. 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.[7] Goldstein and Hotchkiss (2019) and Choi and Huh (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 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). Hence, some fund managers may find liquidity provision and thus "trade against news" a means to enhance fund performance.

2. News and Fixed-Income Fund 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 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 that are deemed to be relevant to the article (for instance, the parent

[7] 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).

company of the mentioned subsidiary). We filter through these firm identifiers to remove news articles that contain fewer than 50 words, are not related to any company (likely macro or general news), and have a high relevance with over five companies (likely industry news or market commentary). We arrive at 8,351,674 news articles assigned to 4,323 firms on Compustat. The sample covers more than 100 news sources, with Dow Jones supplying 50.3% of the news, followed by Reuters News's 11.2% and Business Wire's 8.2%. Appendix 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 match the firm-specific news sample to corporate bond trading by fixed income mutual funds. Holdings information for fixed income funds is obtained from survivor-bias-free 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 categories: 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 holdings information to Morningstar at the monthly frequency. 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 in total 859 funds (that is, 77%) for the considered five fund categories in Morningstar.[9] 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.

[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.

[Insert Table I about here.]

In subsequent regressions, we control for two fund characteristics, fund age and expense ratio. Morningstar provides inception dates of each fund share class, and we use the earliest share class to compute the fund age. Expense ratio and relative percentage in corporate bond for mutual funds come from 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. Δw reflects a fund's change in a given bond holding during the month, relative to the fund's all corporate bond holdings during the reporting month.[10] We next match the news during the month to Δw. Specifically, we construct news tones for each bond-month by first averaging *Neg_net* for all firm-specific news on each trading day to arrive at a daily *Neg_net*, and then averaging the daily *Neg_net* by month. After these procedures, our final news-matched fund holdings sample comprises 3,251,699 fund-bond-months, and trades by 626 distinct funds, and 8,266 bonds issued by 820 firms.

Research in equity markets (among others, Huang, Tan, and Wermers, 2020) uses high-frequency institutional trading data and finds that institutions trade speedily on news; in particular, mutual funds trade stocks on the news release day but neither before nor after. Absent high-frequency trading data for fixed-income funds, an extrapolation on such equity market finding would imply mapping our monthly Δw to in-the-month news—that is, similar to their equity fund colleagues, fixed income fund managers tend to react speedily to news, and hence in-the-month news would translate into holding changes at month end.

[10] We also use the dollar change in trading (log-transformed), and our findings are robust (see Internet Appendix).

One assumption is that portfolio managers are not likely to revert their trading within the month. This is plausible due to the significant transaction cost in the corporate bond market (Bessembinder, Maxwell, and Venkataraman, 2006; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007). Further, we note that such a mapping does not rule out fixed income funds trading ahead of news; however, in Section 4.1 we provide evidence that news impacts bond prices only on and after the news day, making such a conjecture less likely. We also provide evidence that the current month news is not related to Δw next month (see Internet Appendix).

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

[Insert Table II about here.]

Table II provides the univariate evidence of funds' trading on news. We sort our sample into deciles by *Neg_net* and examine the mean value of Δw for each *Neg_net* decile. We find that the mean value of Δw is almost monotonically increasing in the decile rank. The mean of Δw for the top decile is 0.82 bps, almost three times that of 0.29 bps for the bottom decile, translating into a 0.53bps difference between deciles 10 and 1. In addition, the Δw 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 Δw's seems low, such differences are economically significant. For instance, a Δw of 0.53 bps (0.27 bps) for a fund holding \$6 billion of corporate bonds (the average corporate bond holdings of a fund in our sample) implies a trade of \$319K (\$162K) for a single bond. In comparison, we note that the average value of an absolute position change is \$158K 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 buy (sell) more of the bond if the issuer experiences more negative (positive) news in the month.

In Table II, we also examine Δw 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. Specifically, the difference in Δw between deciles 10 and 1 is significantly positive (negative) for *Neg* (*Pos*), and so is the D6:10 to D1:5 difference in Δw. 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. Evidence for Funds Trading Against News

We now formally provide empirical evidence for funds trading against news. We regress Δw on *Neg_net*, along with the set of control variables, defined in Appendix B, of bond characteristics (remaining maturity, credit rating, and past bond return), issuer characteristics (firm market capitalization, idiosyncratic return volatility, long-term debt ratio, and interest coverage ratio), and fund characteristics (fund age and expense ratio). All control variables are measured prior to the given month to avoid look-ahead bias. We control for bond fixed effects and fund type-month fixed effects.

Table III presents the regression results. Models (1) and (2) show that *Neg_net* is positively and significantly related to Δw, suggesting that funds tend to buy more or sell less when the issuer is under more negative news, consistent with the univariate results presented in Table II.

The economic significance of *Neg_net* on Δw in Model (2) is 0.037 bps, measured by the multiplication of a variable's standard deviation and its coefficient estimate.[11] We note that Δw is measured relative to the fund's entire corporate bond holdings. Given that the average fund corporate bond holdings in the sample is \$6.02 billion, this economic significance translates into a dollar value of \$23K. As a benchmark, we note that the mean absolute dollar value of a holding change for an individual bond is \$156K; therefore, the economic significance of *Neg_net* on Δw

[11] 0.037 bps is derived as the standard deviation of *Neg_net* of 0.0108 (%) times the coefficient estimate of Δw of 0.0344, divided by 100.

is equivalent to one seventh of the absolute dollar trading amount. If we focus on the subsample that funds make trades (that is, $\Delta w \neq 0$), one standard deviation change in *Neg_net* implies instead a much larger dollar value of $64,980 for an average fund.

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) find similar results when we constrain the sample to non-zero Δw, that is, the sample where funds make directional changes in positions. In sum, these regression results indicate that funds are more likely to net-buy a bond when the news is more negative, confirming the trading against news findings in Table II.

[Insert Table III about here.]

Morningstar breaks fixed income funds into five categories: U.S. fund corporate bond (who primarily invests in investment grade corporate bonds), U.S. fund high yield bond (who primarily invests in high-yield corporate bonds and bank loans), U.S. fund intermediate core bond (who invests primarily in investment-grade U.S. fixed-income issues, including government, corporate, and securitized debt), U.S. fund intermediate core-plus bond (similar to intermediate core bond funds but with greater investment flexibility), and U.S. fund long-term bond. Table IV repeats our main analysis for each of these fund categories. We find that although *Neg_net* is positively related to Δw for all these fund types, the effect is significant in Corporate Bond funds and High Yield Bond funds (Panel A of Table IV). In Panels B and C of Table IV, we further break the trading of these funds into trading of investment grade bonds and non-investment grade bonds, and find that for Corporate Bond funds the effect of *Neg_net* on Δw is largely in investment grade bonds, and for High Yield Bond funds, the effect in non-investment grade bonds. The concentration of the *Neg_net* effect is consistent with the fund objectives; that is, funds specialized in corporate bond investments are more likely to focus on news sentiments, thus exploiting price movements due to news shocks. In contrast, intermediate core and core-plus bond funds do not respond much to *Neg_net* and trade along the news tone in non-investment grade bonds, which are not their primary investment focus.

[Insert Table IV about here.]

We next examine whether the trading against news effect is driven by information asymmetry of the bond issuers. To this end, 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*. Table V presents the results. In all of the models presented, the interaction term is significantly positive, and by and large, the interaction term subsumes the significance of *Neg_net* on Δw. These results suggest that the trading against news effect is concentrated in bonds with less information asymmetry. Suppose 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). These results then indicate that funds are more comfortable providing liquidity for bonds issued by firms of larger size and less idiosyncratic volatility—potentially because these bond issues are likely to exhibit better liquidity and are thus "easier" to trade with.

[Insert Table V about here.]

Finally, in Table VI, we examine the effect for the positive and negative legs of *Neg_net* on Δw. Models (1) and (2) show that *Neg* is not significantly related to Δw or *Increase*, but *Pos* is significantly and negatively related to Δw or *Increase*; that is, the trading against news phenomenon is concentrated in tone positivity of the news rather than tone negativity. Compared to Table III, the coefficient estimate of *Pos* on Δw is about four times that of *Neg_net*; 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*. In our multiple conversations with fixed income fund managers at a major U.S. asset manager,[12] we attest that fixed income funds tend not to trade against negative news. Thus, liquidity provision of fixed income funds seems to concentrate on news positivity.

[Insert Table VI about here.]

Our results earlier focus on funds' trading of individual bonds. These results may be disproportionately driven by a subset of firms issuing a large number of bonds, or analogously, by

[12] Two co-authors of this paper maintain a long-term consulting relationship with the asset manager on fixed income trading.

a subset of funds making a large number of trades on a particular bond. To investigate these possibilities, we first aggregate Δw to the bond issuer level. Within our sample, an issuer on average issues 10.17 bonds, while each fund on average holds 2.71 bonds from the same issuer. For each fund, we derive the issuer-level Δw as the sum of Δw by each issuer. Models (1) to (3) of Table VII present the regression of issuer-level Δw on news sentiment. We observe that *Neg_net* remains significantly and positively related to issuer-level Δw, with the coefficient of estimate for *Neg* being insignificant and that for *Pos* being significantly positive. Hence, at the issuer level, we continue to find support that funds trade against the news and that the effect is concentrated in news positivity.

[Insert Table VII about here.]

Next, we aggregate Δw to the aggregate fund level, and present the results in Models (4) to (6) of Table VII. We compute the aggregate fund level Δw 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 Δw measures the trading imbalance by all funds. Models (4) to (6) continue to show that a significantly positive coefficient of estimate for *Neg_net*, an insignificant estimate for *Neg*, and a significantly negative estimate for *Pos*. Thus, our findings hold at the aggregate institutional level.

4. Potential Mechanisms

In this section, we examine potential mechanisms 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 provide complementary evidence on trading activities by institutions other than mutual funds, that is, 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 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 in days surrounding news events.

In the corporate bond market, dealers are considered as 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.[13] 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 align news and trades of dealers and insurance companies by trading day.[14] The daily alignment of news and trading activities provides a powerful test for the above hypothesis. 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.[15]

Panel A of Table VIII examines dealer net buy surrounding news by regressing on *Neg_net* dealer net buy of each individual day during days [-1, 2] and each five-day interval during days [1, 20].[16] Panel A of Table VIII shows that *Neg_net* is significantly and positively associated with dealer net buy on days [0], [1], [2], and days [1,5] as a whole; the relation between *Neg_net* and dealer net buy is insignificant for all other cases. The impact of news tone on dealer trading is short-lived and becomes insignificant after days [6,10]. In Panel B of Table VIII, we provide

[13] 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.

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

[15] 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.

[16] Huang, Tan, and Wermers (2020) form "news clusters" and show that related news tends to occur in rapid successions. In Model (1), we follow these authors by grouping firm-days that experience consecutive news arrivals into a single cluster, and we subsequently restrict our analysis to only the first day of each news cluster. In a "predictive trading" setting such as day [-1] trading on day [0] news, doing so ameliorates potential look-ahead biases introduced in successive but related news in the same cluster.

evidence for dealer net buy on *Pos* and *Neg*, respectively, and find that dealers react to both *Pos* and *Neg* on days [1, 5]. These results indicate that dealers in aggregate tend to buy bonds with less positive or more negative news, consistent with the idea that dealers make the market and 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). That dealers trade against the news aligns with fixed income mutual funds' trading behaviors, suggesting hat fixed income mutual funds also participate in liquidity provision in news events.

[Insert Table VIII about here.]

We similarly define daily net buy activities of insurance companies around 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. Table IX provides 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 on *Neg_net* on insurance company net buy are significantly negative in Panel A of Table IX, for days [0], [1], and day durations [1, 5] until [16, 20]. The results indicate that insurance companies trade along the news direction and that this trade direction significantly lasts into subsequent weeks. There are two potential reasons for this trading pattern. First, as previously discussed, insurance companies are potential counterparties to dealers and fixed income funds. Second, insurance companies are known to be risk averse and tend to avoid negative events and issues.

[Insert Table IX about here.]

To support the second reason above, Panel B of Table IX examines 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]; in contrast, the coefficients for *Neg* continue to be statistically significant (in the range of -0.21 and -0.19) for all four five-day subperiods for days [1, 20]. 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, consistent with insurance companies avoiding negative news shocks.

Table VIII and Table IX, combined with our main results on mutual fund trading, depict 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. 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 trading against the news.

4.2 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 via the abnormal return measure of alpha.

We measure fund alpha using a five-factor model (for instance, 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.[17] 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.[18]

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)

[17] 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).

[18] 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 exploit the rolling average over the past *L* months, in order to measure the long-term trading pattern of a fund against news.

In Table X, we rank mutual funds by *TradeAgainstNews* and evaluate fund performance. We set $L = 12$ and 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, while the remaining 67.6% (24.1%) of its trades are in the same direction of 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.

[Insert Table X about here.]

The remainder of Table X reports fund alpha conditioning on *TradeAgainstNews*. For the one-month ahead alpha (alpha in month 0), 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. The month-0 alpha difference between Deciles 6 to 10 and Deciles 1 to 5 is also large and significantly positive at 1.51 bps. In contrast, the unconditional mean of fund alpha for all of the funds in the sample is only -1.84 bps per month. 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.

The last two columns of Table X provide quarterly (months [0, 2]) and semi-annual (months [0, 5]) alpha for the decile portfolios. 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 months [0, 2] alpha difference between Deciles 6 to10 and Deciles 1 to 5 is 3.45 bps, about three times its monthly counterpart. Furthermore, we observe that the increase in alpha concentrates in higher *TradeAgainstNews* funds (Deciles 7 to 10). Overall, Table X provides univariate evidence that fund alpha increases with a fund's tendency to trade against news.

We provide multivariate evidence for fund alpha in Table XI, 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 XI utilize *TradeAgainstNews* computed over the past twelve months ($L = 12$) and study the impact 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, the fund trades against or along the news with equal probability) to a fund with $TradeAgainstNews = 0.76$ (the average $TradeAgainstNews$ value for the Decile 10 funds in Table X) results 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. In Models (4) to (9) in Table XI, we exploit $TradeAgainstNews$ estimated over different windows ($L = 9$ and 15, respectively) and find similar results.

[Insert Table XI 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).

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 with a *t*-statistic of 4.57 and a coefficient estimate of 9.06 (1.6 times of the coefficient estimate for *TradeAgainstNews*). The evidence thus suggests that funds with a trading style of "sell against good news" tend to generate alpha more than funds that "buy against bad news." Overall, this evidence is consistent with our findings in Table VI and Table VII that funds tend to trade on news positivity, which is likely to be associated with price reversals. Hence, "sell on news" seems to be a trading pattern adopted by fixed-income funds.

[Insert Table XII about here.]

4.3 Daily bond returns around news

In this subsection, we analyze daily bond returns surrounding corporate news. We present two findings: i), bond prices respond swiftly to news following but not before news announcements; and ii) such a price response is likely to be reversed in about three weeks. The former finding supports our main analysis that links monthly averaged news tones to funds' trading summarized in the month-end, while the latter finding points to a potential source for the fund alpha documented in the previous section.

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):

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

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*.[19] Consistent with the event study literature (e.g., Kothari and Warner, 2007;

[19] 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.

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.

Panel A of Table XIII regresses bond excess returns over various horizons on *Neg_net*. Models (1) to (4) examine individual days over days [-1, 2], relative to news event day 0. We first investigate whether market participants expect and trade on the information contained in news before the news event. If market participants are able to predict news and trade ahead, we would expect that day [-1] returns to be negatively associated with *Neg_net*. Model (1) shows otherwise that *Neg_net* is insignificantly related to bond excess return on day [-1], suggesting that market participants do not trade ahead of news. Untabulated, we can also report that returns are not related to days [-5, -2].

[Insert Table XIII about here.]

The relation between *Neg_net* and return becomes significantly negative on day [0] (Model (2)) and this relation continues into day [1] (Model (3)). That is, 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. In Model (4), the negative relation between *Neg_net* and daily bond returns turns weaker and statistically insignificant on day [2]. Further, the magnitude of coefficient estimates decreases from day [0] to day [2], suggesting that the return impact of *Neg_net* is the strongest on day [0]. Overall, Models (1)-(4) are highly consistent with the findings on the news impact in the equity market in Huang, Tan, and Wermers (2020), who show that equity funds respond quickly—on day [0] only—to but do not trade ahead of news.

Turning to the longer-term effect of news, Models (5) to (8) investigate the relation between *Neg_net* and returns for each five day period among days [1, 20]. Consistent with our daily analysis, *Neg_net* is negatively associated with cumulative excess returns for days [1, 5]. There is no significant association between the two for either days [6, 10] or days [11, 15]. Interestingly, we find a significantly positive relationship between *Neg_net* and cumulative returns for days [16, 20], approximately three weeks after the news event. The magnitude of reversal in days [16, 20] (as reflected in the coefficient estimate) is about half of that in days [1, 5]. This pattern of return reversal provides a potential explanation for mutual fund managers to trade against the news. That is, the evidence suggests that there is a short-term overreaction to news in bond prices, which is partially corrected in about three weeks. One way to profit from such correction is to strategically trade against the direction of news.

Panel B of Table XIII offers further evidence for negative tone *(Neg)* and positive tone *(Pos)*, respectively. While bond prices respond significantly to both *Neg* and *Pos* shortly after news events in similar magnitudes (the coefficients for *Neg* and *Pos* in days [1, 5] are, respectively, -0.34 and 0.33), we find that the strong and statistically significant reversal exists only on *Pos* (the coefficients for *Neg* and *Pos* in days [16, 20] are, respectively, -0.06 and -0.36). This asymmetric behavior in return reversal on *Pos* is consistent with our findings in Table VI that trading against news by mutual funds is only significant in *Pos*.

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 grown 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 low information asymmetry (for instance, issuers are large in size or low in return volatility), and in bonds experiencing good news. These cross-sectional heterogeneities suggest that funds trade against news in their expertise areas and in bonds that are less restrictive to trade with.

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. Similarly, across the three, news trading takes place only on or after news releases (but not before). The consistency of news trading behavior between dealers and mutual funds indicates that mutual funds may follow dealers in providing liquidity to counterparties such as insurance companies. 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). We provide evidence that funds with a style of trading against news enjoy a higher alpha. A 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. 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%

B. Variable Definitions

Variable	Definition
Δw	A fund's change in holding of a given bond during the month, divided by the fund's total corporate bond holdings at the beginning of the month.
Neg_net	The fraction of total negative word count net of total positive word count relative to the total number of words in a news article. The word list is from Loughran and McDonald (2011).
Neg (*Pos*)	The fraction of total negative (positive) word counts relative to the total number of words in a news article. The word list is from Loughran and McDonald (2011).
Maturity	A bond issue's remaining maturity (in years) at the time of trading.
Credit rating	A bond issue's credit rating at the time of trading ranging from 1 to 16. AAA = 1, AA+ =2, … BBB- = 10, …, C = 15, and DDD and below = 16.
alpha [*t*-3, *t*-1]	A bond's cumulative alpha in months [*t*-3, *t*-1]. Bond monthly returns are from WRDS monthly bond returns calculated from TRACE. To arrive at monthly alpha, we adjust the bond return with the bond's previous-month beta using a single index model, where beta is estimated over the past 3-year window with Bloomberg Barclays US Aggregate Total Return Index serving as the market return and one-month Treasury bill rate as the riskfree rate.
Firm size	The logarithm of market capitalization of the issuing firm at the end of the previous month.
Idio. volatility	The issuing firm's standard deviation of idiosyncratic return volatility of the daily stock returns of the previous month in a Fama-French four-factor model of market, size, book to market, and momentum.
LT debt ratio	Ratio of long-term debt to total book value of assets of the issuing firm at the end of previous quarter.
Interest coverage	Ration of interest expense to EBIT of the issuing firm at the end of the previous quarter.
Fund age	The difference in years between the first offering date of the oldest share class and the beginning of the month.
Fund expense ratio	The lowest expense ratio among all share classes at the beginning of the month.
Fund size	The total net asset, summing for all share classes, at the beginning of the month.
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 [2], and cumulative day horizons [1, 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 months (12, 9, 15, respectively). We, *i*) measure the fund's trading against news of an issue in a given month (with an indicator equal to one if the fund buys (sells) a bond when the bond's *Neg_net* is positive (negative)); *ii*) aggregate these indicator values weighted by absolute Δw; and *iii*) average the monthly aggregate over the previous months.
BuyAgainstNews	The equivalent of *TradeAgainstNews*, but use only buy trades ($\Delta w > 0$).
SellAgainstNews	The equivalent of *TradeAgainstNews*, but use only sell trades ($\Delta w < 0$).
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 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	Long-Term Bond
# of funds (Morningstar)	859	54	273	357	143	32
# of funds (Monthly reporters)	664	38	198	283	120	25
# of trades	589,366	62,357	100,352	251,971	126,854	47,832
Trading volume ($million)	857,899	116,527	176,019	317,555	207,100	40,697
# of bonds traded	8,355	5,529	2,525	7,478	7,055	2,552
# of firms traded	822	651	610	723	773	465

Panel B: Summary statistics of main variables

	N	Mean	Std	Median	Minimum	Maximum
Δw	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	3,369,477	5,915	13,229	710	0	70,214
Excess bond return, day [-1] relative to news	2,659,351	0.0099	0.7336	0.0075	-3.0956	3.1299
Excess bond return, day [0] relative to news	3,018,501	0.0143	0.7655	0.0092	-3.0956	3.1299
Excess bond return, day [1] relative to news	3,024,105	0.0136	0.7659	0.0088	-3.0956	3.1299
Excess bond return, day [2] relative to news	2,668,349	0.0101	0.7295	0.0082	-3.0956	3.1299

Table II Univariate sorting between mutual fund trading and news tone

This table shows the mean values (Mean) and the standard deviation (Std) of monthly mutual fund holdings change (Δw) in decile portfolios ranked by *Neg_net*, *Neg*, and *Pos*, respectively. Δw is a fund's change (in percentage) in holding of a given bond during the month, relative to the fund's all corporate bond holdings. Decile 10 – 1 provides the difference of the means between Decile 1 and Decile 10; similarly, Deciles 6:10 - 1:5 provides the difference of the means between the average of Deciles 1:5 and the average of Deciles 6:10. Reported in parentheses are *t*-statistics. *p<.1; **p<.05; ***p<.01.

	Mutual fund holdings change (Δw)					
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 III Mutual fund trading on news tone

This table regresses Δ*w* (mutual fund holdings change) and *Increase* (which takes the value of, respectively, -1, 0, or 1 for Δ*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 Δ*w*'s, that is, the sample where funds make directional changes in positions. Reported in parentheses are *t*-statistics, cluster-adjusted at fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ*w*	Δ*w*	*Increase*	*Increase*	Δ*w* (traded only)	Δ*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 IV   Mutual fund news trading: Heterogeneity in fund categories and bond ratings

This table regresses mutual fund holdings change (Δw) on the news tone measure of *Neg_net* using partitioned samples by Morningstar fund categories (Panel A) and bond investment grades (Panels B and C). Presented are regression results with the same specification of Model (2) in Table III (the control variables are included in the regressions but not reported). All regressions include month fixed effects and individual bond fixed effects. Reported in parentheses are *t*-statistics, cluster-adjusted at fund level. *p<.1; **p<.05; ***p<.01.

Panel A: All bonds by Morningstar fund categories

	US Fund Corporate Bond	US Fund High Yield Bond	US Fund Intermediate Core Bond	US Fund Intermediate Core-Plus Bond	US Fund Long-Term Bond
	Δw	Δw	Δw	Δw	Δw
Neg_net	0.0812*	0.0643**	0.0133	0.0197	0.0069
	(2.00)	(2.42)	(1.08)	(0.84)	(0.48)
Observations	181,113	377,530	1,201,693	490,418	146,853

Panel B: Using only investment-grade bonds

	US Fund Corporate Bond	US Fund High Yield Bond	US Fund Intermediate Core Bond	US Fund Intermediate Core-Plus Bond	US Fund Long-Term Bond
	Δw	Δw	Δw	Δw	Δw
Neg_net	0.0825**	0.0105	0.0151	0.0473*	0.0121
	(2.22)	(0.07)	(1.27)	(1.79)	(0.77)
Observations	166,366	15,167	1,152,215	379,524	143,629

Panel C: Using only non-investment grade bonds

	US Fund Corporate Bond	US Fund High Yield Bond	US Fund Intermediate Core Bond	US Fund Intermediate Core-Plus Bond	US Fund Long-Term Bond
	Δw	Δw	Δw	Δw	Δw
Neg_net	0.1373	0.0522*	-0.1018	-0.0738**	0.0089
	(1.16)	(1.97)	(-1.58)	(-1.99)	(0.05)
Observations	14,719	362,336	49,412	110,881	3,200

Table V Mutual fund news trading: Information asymmetry in issuers

This table regresses fund holdings change (Δw) on *Neg_net*, an *InfoDummy* that equals one if the issuer firm size is greater than the sample median or if the issuer's idiosyncratic volatility is smaller than the sample median, and the interaction of these two variables. Reported in parentheses are *t*-statistics, cluster-adjusted at fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	InfoDummy = 1 for		*InfoDummy* = 1 for		*InfoDummy* = 1 for	
	Large firm size	Small idio. volatility	Large firm size	Small idio. volatility	Large firm size	Small idio. volatility
	Δw	Δw	*Increase*	*Increase*	(traded only)	(traded only)
Neg_net	0.0132	0.0323**	0.0565	0.0775	-0.0653	0.0170
	(1.05)	(2.49)	(1.20)	(1.58)	(-0.82)	(0.23)
InfoDummy × *Neg_net*	0.0828***	0.0285*	0.1905***	0.1227*	0.4927***	0.2779***
	(4.23)	(1.78)	(3.12)	(1.83)	(4.03)	(2.68)
InfoDummy	0.0010**	0.0007**	0.0034**	0.0034***	0.0037	0.0018
	(2.50)	(2.54)	(1.99)	(2.65)	(1.32)	(1.09)
Maturity	0.0036***	0.0036***	0.0120***	0.0120***	0.0192***	0.0191***
	(12.63)	(12.60)	(8.02)	(7.99)	(10.19)	(10.16)
Credit rating	0.0021***	0.0021***	0.0148***	0.0149***	0.0163***	0.0163***
	(6.48)	(6.49)	(11.50)	(11.52)	(7.08)	(7.08)
alpha [*t*-3, *t*-1]	0.0000	-0.0005	0.0319	0.0294	-0.0151	-0.0164
	(0.01)	(-0.10)	(1.26)	(1.16)	(-0.62)	(-0.67)
Firm size	0.0001	0.0004	-0.0030	-0.0019	-0.0007	0.0007
	(0.16)	(1.00)	(-1.61)	(-1.10)	(-0.28)	(0.28)
Idio. volatility	0.2203***	0.2544***	0.5963***	0.7541***	0.8695***	0.9751***
	(5.38)	(5.46)	(3.05)	(3.45)	(3.98)	(3.99)
LT debt ratio	-0.0368***	-0.0370***	-0.1408***	-0.1418***	-0.1516***	-0.1531***
	(-9.36)	(-9.36)	(-16.63)	(-16.72)	(-8.52)	(-8.55)
Interest coverage	0.0003***	0.0003***	0.0007***	0.0007***	0.0009***	0.0009***
	(7.21)	(7.24)	(8.27)	(8.33)	(5.61)	(5.65)
Fund age	-0.0002***	-0.0002***	-0.0006	-0.0006	-0.0012***	-0.0012***
	(-5.00)	(-5.00)	(-1.00)	(-1.00)	(-5.43)	(-5.43)
Fund expense ratio	0.4039**	0.4034**	-10.4699***	-10.4720***	0.9930	0.9900
	(2.35)	(2.34)	(-3.79)	(-3.79)	(0.91)	(0.91)
Constant	-0.0475***	-0.0511***	-0.1335***	-0.1466***	-0.2927***	-0.3063***
	(-8.56)	(-9.02)	(-3.67)	(-4.00)	(-7.99)	(-8.12)
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,398,071	2,398,071	2,415,136	2,415,136	392,930	392,930
Adj R-squared	0.0211	0.0211	0.0287	0.0287	0.0678	0.0677

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

This table regresses Δw (mutual fund holdings change) and *Increase* (which takes the value of, respectively, -1, 0, or 1 for Δw less than, equal to, or greater than zero) on *Neg* or *Pos*. In Models (5) to (6), we augment our baseline model in Table III by interacting *Neg_net* with *Badnews*, a dummy variable that equals 1 if *Neg_net* is above the sample median and 0 else. Reported in parentheses are *t*-statistics, cluster-adjusted at the fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δw	*Increase*	Δw	*Increase*	Δw	*Increase*
Neg	-0.0087	-0.0281				
	(-0.87)	(-0.76)				
Pos			-0.1435***	-0.5042***		
			(-6.29)	(-7.09)		
Neg_net					0.3607***	1.4011***
					(8.30)	(11.78)
*Badnews * Neg_net*					-0.4600***	-1.8005***
					(-8.41)	(-11.87)
Maturity	0.0011***	0.0015	0.0011***	0.0016	0.0010***	0.0008
	(2.77)	(0.90)	(2.80)	(0.93)	(2.69)	(0.50)
Credit rating	0.0025***	0.0154***	0.0025***	0.0154***	0.0027***	0.0170***
	(7.31)	(11.63)	(7.32)	(11.68)	(7.99)	(12.52)
alpha [t-3, t-1]	0.0032	0.0419	0.0033	0.0422	0.0021	0.0238
	(0.75)	(1.62)	(0.77)	(1.63)	(0.46)	(0.94)
Firm size	0.0006*	-0.0008	0.0006	-0.0009	0.0007*	0.0009
	(1.68)	(-0.53)	(1.64)	(-0.58)	(1.72)	(0.46)
Idio. volatility	0.1470***	0.2133	0.1459***	0.2097	0.1533***	0.3001*
	(4.31)	(1.19)	(4.28)	(1.17)	(4.25)	(1.68)
LT debt ratio	-0.0392***	-0.1420***	-0.0393***	-0.1421***	-0.0376***	-0.1311***
	(-9.92)	(-17.34)	(-9.92)	(-17.34)	(-9.57)	(-15.35)
Interest coverage	0.0003***	0.0007***	0.0003***	0.0007***	0.0003***	0.0006***
	(7.59)	(8.93)	(7.59)	(8.93)	(7.28)	(8.01)
Fund age	-0.0002***	-0.0005	-0.0002***	-0.0005	-0.0002***	-0.0007
	(-5.03)	(-0.92)	(-5.03)	(-0.92)	(-4.92)	(-1.09)
Fund expense ratio	0.400**	-10.020***	0.400**	-10.020***	0.341**	-11.443***
	(2.27)	(-3.53)	(2.27)	(-3.53)	(2.07)	(-4.38)
Constant	-0.0251***	-0.0355	-0.0237***	-0.0306	-0.0255***	-0.0482
	(-3.90)	(-1.27)	(-3.67)	(-1.11)	(-3.98)	(-1.57)
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund type - month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,398,071	2,415,136	2,398,071	2,415,136	2,398,072	2,415,138
Adj R-squared	0.0211	0.0287	0.0211	0.0288	0.0211	0.0225

Table VII   Mutual fund news trading: Issuer level and aggregate fund level

This table regresses issuer level and aggregate fund level holdings change (Δw) on news tone measures: *Neg_net*, *Pos*, and *Neg*. To derive issuer level Δw, we sum Δw by each issuer within each fund. For aggregate fund level Δw, we sum the signed trading volume of the given bond at the given month by all funds, divided by the bond's par amount outstanding. Reported in parentheses are *t*-statistics, cluster-adjusted at the fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Issuer level			Aggregate fund level		
	Δw	Δw	Δw	Δw	Δw	Δw
Neg_net	0.0700***			0.2501**		
	(4.51)			(2.58)		
Neg		-0.0017			0.0335	
		(-0.10)			(0.29)	
Pos			-0.2375***			-0.8066***
			(-8.00)			(-4.42)
Maturity				0.0020	0.0019	0.0020
				(0.87)	(0.84)	(0.85)
Credit rating				0.0234***	0.0232***	0.0234***
				(10.41)	(10.32)	(10.38)
alpha [*t*-3, *t*-1]				-0.0126	-0.0139	-0.0140
				(-0.34)	(-0.37)	(-0.38)
Firm size	0.0019***	0.0019***	0.0018***	0.0051	0.0047	0.0045
	(4.56)	(4.48)	(4.35)	(1.13)	(1.05)	(1.02)
Idio. volatility	0.4040***	0.4179***	0.4165***	1.3842***	1.4215***	1.4154***
	(8.15)	(8.45)	(8.41)	(3.71)	(3.81)	(3.79)
LT debt ratio	-0.0329***	-0.0329***	-0.0331***	-0.2499***	-0.2495***	-0.2498***
	(-11.59)	(-11.59)	(-11.64)	(-9.28)	(-9.27)	(-9.28)
Interest coverage	0.0004***	0.0004***	0.0004***	0.0014***	0.0014***	0.0014***
	(11.64)	(11.68)	(11.64)	(5.70)	(5.71)	(5.68)
Fund age	-0.0003***	-0.0003***	-0.0003***			
	(-6.92)	(-6.92)	(-6.92)			
Fund expense ratio	0.3736	0.3732	0.3735			
	(1.53)	(1.53)	(1.53)			
Constant	-0.0052	-0.0049	-0.0016	-0.1897***	-0.1842***	-0.1739***
	(-1.18)	(-1.10)	(-0.37)	(-3.27)	(-3.17)	(-2.99)
Issuer FE	Yes	Yes	Yes			
Fund type - month FE	Yes	Yes	Yes			
Issue FE				Yes	Yes	Yes
Month FE				Yes	Yes	Yes
Observations	1,296,878	1,296,878	1,296,878	329,955	329,955	329,955
Adj R-squared	0.0220	0.0220	0.0220	0.0296	0.0296	0.0296

Table VIII Dealer net-buy around news

Panel A regresses the daily dealer 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 construct the dealer net buy. For day [-1], we remove news days that are accompanied by news arrivals in the previous two days to reduce the confounding effect of previous news (Huang, Tan, and Wermers, 2020). 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. Reported in parentheses are *t*-statistics, cluster-adjusted at the issuer and the date level. *p<.1; **p<.05; ***p<.01.

Panel A: Net-buy of dealers on *Neg_net*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Day	-1	0	1	2	[1, 5]	[6, 10]	[11, 15]	[16, 20]
Neg_net	-0.0122	0.0535***	0.0507***	0.0314**	0.1014***	0.0315	0.0431	-0.0181
	(-0.52)	(4.27)	(4.05)	(2.38)	(3.86)	(1.17)	(1.60)	(-0.69)
Maturity	-0.0005	-0.0047***	-0.0024	-0.0035**	-0.0160***	-0.0199***	-0.0205***	-0.0178***
	(-0.16)	(-2.81)	(-1.51)	(-2.13)	(-3.34)	(-4.25)	(-4.35)	(-3.72)
Credit rating	0.0007	0.0001	-0.0000	0.0002	-0.0002	-0.0007	-0.0029*	-0.0036**
	(0.66)	(0.19)	(-0.08)	(0.35)	(-0.13)	(-0.39)	(-1.74)	(-2.18)
Firm size	0.0039*	0.0022**	0.0033***	0.0027**	0.0100***	0.0114***	0.0077**	0.0077**
	(1.86)	(2.05)	(2.64)	(2.03)	(2.66)	(3.01)	(2.03)	(2.13)
Idio. volatility	0.0136	0.1084	0.1074	0.1293	0.2578	0.2314	0.4702*	0.1712
	(0.09)	(1.17)	(1.17)	(1.39)	(0.95)	(0.89)	(1.79)	(0.74)
LT debt ratio	0.0173	0.0141**	0.0077	0.0121**	0.0359*	0.0590***	0.0657***	0.0336*
	(1.49)	(2.37)	(1.32)	(2.01)	(1.93)	(3.26)	(3.78)	(1.94)
Interest coverage	-0.0002***	0.0000	0.0000	-0.0001	-0.0002	-0.0002	-0.0001	-0.0002
	(-3.15)	(0.26)	(0.45)	(-1.37)	(-1.04)	(-0.98)	(-0.83)	(-1.19)
Constant	-0.0514**	-0.0222	-0.0335**	-0.0283*	-0.0822*	-0.0910*	-0.0394	-0.0258
	(-2.09)	(-1.59)	(-2.13)	(-1.75)	(-1.72)	(-1.95)	(-0.84)	(-0.57)
Observations	657,498	2,481,342	2,475,031	2,473,722	3,548,587	3,540,476	3,512,423	3,495,850
Adj R-squared	0.00432	0.00206	0.00178	0.00197	0.00583	0.00612	0.00553	0.00542

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Day	-1	0	1	2	[1, 5]	[6, 10]	[11, 15]	[16, 20]
Pos	-0.0286	-0.0242	-0.0756***	-0.0356	-0.1160**	-0.0176	-0.0505	0.0069
	(-0.74)	(-0.96)	(-3.24)	(-1.36)	(-2.56)	(-0.34)	(-1.06)	(0.16)
Neg	-0.0325	0.0663***	0.0393***	0.0295*	0.0962***	0.0369	0.0423	-0.0199
	(-1.18)	(3.96)	(2.58)	(1.95)	(2.86)	(1.10)	(1.24)	(-0.58)

Table IX Insurance company net-buy around news

Panel A regresses the daily insurance company net-buy over various horizons on *Neg_net*. We aggregate daily trading in the insurance company sector from NAIC for each bond issue and construct the insurance company 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. Reported in parentheses are *t*-statistics, cluster-adjusted at the issuer and the date level. *p<.1; **p<.05; ***p<.01.

Panel A: Net-buy of insurance companies on *Neg_net*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Day	-1	0	1	2	[1, 5]	[6, 10]	[11, 15]	[16, 20]
Neg_net	-0.0086	-0.0507**	-0.0396**	-0.0017	-0.1292**	-0.1683***	-0.1844***	-0.1247***
	(-0.24)	(-2.56)	(-2.37)	(-0.10)	(-2.34)	(-3.50)	(-3.68)	(-2.59)
Maturity	0.0537***	0.0522***	0.0441***	0.0415***	0.1096***	0.1052***	0.1003***	0.1116***
	(8.65)	(8.97)	(8.58)	(8.49)	(4.63)	(4.58)	(4.42)	(4.88)
Credit rating	-0.0048***	0.0001	-0.0008	-0.0005	0.0040	0.0042	0.0080	0.0096
	(-2.68)	(0.05)	(-0.49)	(-0.35)	(0.49)	(0.61)	(1.17)	(1.42)
Firm size	0.0057*	0.0070**	0.0064**	0.0075***	0.0403***	0.0373***	0.0451***	0.0460***
	(1.87)	(2.37)	(2.29)	(2.89)	(3.05)	(2.87)	(3.44)	(3.45)
Idio. volatility	-1.3887***	-1.1899***	-0.9980***	-0.8896***	-5.6084***	-5.8522***	-5.6046***	-5.4909***
	(-5.53)	(-7.40)	(-6.54)	(-6.03)	(-8.11)	(-8.60)	(-8.50)	(-8.45)
LT debt ratio	-0.0575***	-0.0778***	-0.0529***	-0.0522***	-0.2974***	-0.2837***	-0.2569***	-0.2362***
	(-3.58)	(-6.09)	(-4.94)	(-5.15)	(-6.00)	(-6.22)	(-5.69)	(-5.30)
Interest coverage	0.0002	0.0001*	0.0001**	0.0001	0.0006*	0.0004	0.0004	0.0005*
	(1.36)	(1.65)	(2.01)	(1.37)	(1.69)	(1.14)	(1.40)	(1.67)
Constant	-0.0735*	-0.1346***	-0.1236***	-0.1371***	-0.5274***	-0.4947***	-0.6118***	-0.6684***
	(-1.86)	(-3.87)	(-3.67)	(-4.39)	(-3.41)	(-3.25)	(-3.97)	(-4.25)
Observations	51,588	211,333	206,558	203,747	815,390	803,412	793,215	788,729
Adj R-squared	0.0787	0.0760	0.0645	0.0634	0.0871	0.0845	0.0810	0.0814

Panel B: Net-buy of insurance companies on *Pos and Neg*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Day	-1	0	1	2	[1, 5]	[6, 10]	[11, 15]	[16, 20]
Pos	-0.0027	-0.0163	0.0745***	-0.0061	0.0005	0.0699	0.1334*	-0.0101
	(-0.04)	(-0.48)	(2.62)	(-0.21)	(0.01)	(0.86)	(1.84)	(-0.12)
Neg	-0.0103	-0.0790***	-0.0252	-0.0042	-0.1901***	-0.2112***	-0.2140***	-0.1915***
	(-0.23)	(-3.33)	(-1.08)	(-0.22)	(-2.70)	(-3.56)	(-3.36)	(-3.22)

Table X   Fund performance from trading against news: Alpha sorting

This table 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. Decile 10 – 1 provides the difference of the means between Decile 1 and Decile 10; Deciles 6:10 - 1:5 provides the difference of the means between the average of Deciles 1:5 and the average of Deciles 6:10. Reported in parentheses are *t*-statistics.

TradeAgainstNews		Fund alpha in month(s)		
Decile	*TradeAgainstNews*	[0]	[0, 2]	[0, 5]
1	0.324	-2.22	-4.06	-8.04
2	0.431	-2.52	-6.38	-12.89
3	0.474	-2.29	-9.14	-14.93
4	0.504	-2.10	-6.26	-11.97
5	0.528	-3.83	-7.13	-12.88
6	0.553	-2.26	-6.19	-10.57
7	0.577	-1.01	-4.05	-7.83
8	0.607	-1.04	-4.43	-7.67
9	0.652	-1.26	-1.43	-3.08
10	0.759	0.14	0.41	-0.72
Decile 10 - 1	0.435***	2.36*	4.46**	7.32**
	(175.61)	(1.93)	(2.11)	(2.37)
Deciles 6:10 - 1:5	0.177***	1.51***	3.45***	6.17***
	(181.33)	(2.92)	(3.78)	(4.58)

Table XI Fund performance from trading against news: Regression analysis

This table regresses monthly fund alphas on *TradeAgainstNews*, which proxies the fund tendency of trading against news, over the past 12 months (Model (1)-(3)), the past 9 months (Model (4)-(6)), or the past 15 months (Model (7)-(9)). We measure fund alpha using a model of five factors of stock market return, bond market return, default spread, term spread, and option spread. Reported in parentheses are *t*-statistics, cluster-adjusted at fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	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*						
(over previous 12 months)	(1.92)	(1.94)	(1.85)						
TradeAgainstNews				6.26**	16.45**	23.16**			
(over previous 9 months)				(2.45)	(2.46)	(1.97)			
TradeAgainstNews							5.17*	15.65**	22.58
(over previous 15 months)							(1.69)	(1.99)	(1.63)
Fund age	-0.05	-0.13	-0.22	-0.05	-0.13	-0.22	-0.05	-0.13	-0.22
	(-1.54)	(-1.54)	(-1.34)	(-1.47)	(-1.50)	(-1.34)	(-1.57)	(-1.53)	(-1.34)
Fund expense ratio	-703.7***	-1,817.4***	-3,309.2***	-702.2***	-1,813.8***	-3,305.8***	-708.3***	-1,818.0***	-3,316.1***
	(-3.87)	(-3.73)	(-3.60)	(-3.86)	(-3.72)	(-3.59)	(-3.89)	(-3.73)	(-3.61)
Fund size	0.09	0.14	0.21	0.08	0.15	0.26	0.09	0.13	0.20
	(0.40)	(0.23)	(0.18)	(0.37)	(0.25)	(0.22)	(0.39)	(0.21)	(0.17)
Constant	-0.41	-0.68	-0.70	-0.78	-1.75	-0.45	-0.13	-1.11	0.24
	(-0.17)	(-0.11)	(-0.06)	(-0.33)	(-0.28)	(-0.04)	(-0.05)	(-0.17)	(0.02)
Observations	30,982	31,206	31,553	30,932	31,156	31,502	31,009	31,233	31,580
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	0.178	0.138	0.155	0.177

Table XII   Fund performance from trading against news: Buy and sell legs

This table regresses 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. We measure fund alpha using a model of five factors of stock market return, bond market return, default spread, term spread, and option spread. Reported in parentheses are t-statistics, cluster-adjusted at the fund level. *p<.1; **p<.05; ***p<.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Fund alpha in month(s)			Fund alpha in month(s)		
	[0]	[0, 2]	[0, 5]	[0]	[0, 2]	[0, 5]
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	-0.14	-0.23	-0.06*	-0.15*	-0.24
	(-1.52)	(-1.58)	(-1.43)	(-1.84)	(-1.72)	(-1.47)
Fund expense ratio	-718.2***	-1,827.4***	-3,316.6***	-776.6***	-2,033.9***	-3,623.7***
	(-3.92)	(-3.70)	(-3.56)	(-4.24)	(-4.11)	(-3.88)
Fund size	0.09	0.19	0.34	0.17	0.35	0.48
	(0.38)	(0.31)	(0.29)	(0.76)	(0.57)	(0.42)
Constant	2.13	6.60	12.29	-0.09	0.69	2.26
	(0.88)	(1.01)	(1.00)	(-0.04)	(0.12)	(0.22)
Observations	30,830	31,053	31,399	30,469	30,692	31,024
Fund type FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.139	0.156	0.177	0.142	0.161	0.184

Table XIII Daily returns around news

This table regresses bond excess returns over various horizons on *Neg_net* in Panel A. 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). 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. *p<.1; **p<.05; ***p<.01.

Panel A: Returns on *Neg_net*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess return on day				Excess return on days			
	-1	0	1	2	[1, 5]	[6, 10]	[11, 15]	[16, 20]
Neg_net	-0.0632	-0.2123***	-0.2063***	-0.0421	-0.3346***	0.0176	-0.0127	0.1527*
	(-0.82)	(-4.78)	(-5.09)	(-1.06)	(-3.97)	(0.27)	(-0.16)	(1.91)
Maturity	0.0214*	0.0272***	0.0271***	0.0186**	0.0891***	0.0893***	0.0874***	0.0904***
	(1.86)	(3.04)	(3.02)	(2.04)	(4.66)	(4.50)	(4.41)	(4.45)
Credit rating	0.0090**	0.0027*	0.0050***	0.0069***	0.0207***	0.0173***	0.0093**	0.0092*
	(2.06)	(1.72)	(3.36)	(4.36)	(4.33)	(3.42)	(2.13)	(1.90)
Firm size	0.0068	-0.0064	-0.0052	-0.0040	-0.0243	-0.0289	-0.0548**	-0.0429*
	(0.93)	(-1.04)	(-0.96)	(-0.62)	(-1.11)	(-1.39)	(-2.36)	(-1.93)
Idio. volatility	3.1372***	2.3509***	2.5542***	2.2517***	9.9902***	8.9819***	9.1498***	8.6416***
	(4.08)	(4.96)	(5.50)	(4.64)	(6.98)	(6.39)	(6.24)	(5.72)
LT debt ratio	0.0384	0.0469**	0.0565***	0.0237	0.1616**	0.1561***	0.1519***	0.1658***
	(0.97)	(2.18)	(2.60)	(1.39)	(2.57)	(3.11)	(2.89)	(3.21)
Interest coverage	-0.0003	0.0000	-0.0001	-0.0001*	-0.0005*	-0.0006**	-0.0006**	-0.0004
	(-1.31)	(0.21)	(-1.50)	(-1.95)	(-1.71)	(-2.08)	(-2.40)	(-1.34)
Constant	-0.2275**	-0.0370	-0.0704	-0.0689	-0.2080	-0.1238	0.2146	0.0815
	(-2.44)	(-0.51)	(-1.08)	(-0.86)	(-0.83)	(-0.52)	(0.81)	(0.32)
Observations	490,765	2,337,591	2,342,040	2,046,186	2,642,832	2,559,016	2,547,716	2,540,430
Issue FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.00679	0.00543	0.00515	0.00431	0.0261	0.0248	0.0322	0.0388

Panel B: Returns on *Pos* and *Neg*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excess return on day				Excess return on days			
	-1	0	1	2	[1, 5]	[6, 10]	[11, 15]	[16, 20]
Pos	0.0959	0.2756***	0.0701	0.0952	0.3345**	-0.0678	-0.0581	-0.3623***
	(0.81)	(3.56)	(1.00)	(1.44)	(2.37)	(-0.54)	(-0.46)	(-2.59)
Neg	-0.0426	-0.1874***	-0.2721***	-0.0187	-0.3392***	0.0020	-0.0500	0.0678
	(-0.46)	(-3.80)	(-5.74)	(-0.36)	(-3.11)	(0.02)	(-0.44)	(0.72)