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Retail bond investors and credit ratings☆

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ABSTRACT

Using comprehensive data on U.S. corporate bond trades since 2002, we find evidence that retail bond investors overrely on untimely credit ratings to their financial detriment. Specifically, they appear to select bonds by first screening on a credit rating and then sorting by yield, buying the highest-yielding bonds within each rating level. Because yields lead credit rating changes, selecting on yield-within-rating means that retail investors systematically trade in the opposite direction of changing fundamentals, buy in advance of credit downgrades and defaults, and materially underperform a diversified portfolio. Our study provides new evidence of ill-informed retail trading in a market that is thought to be relatively sophisticated, corroborates regulators' concerns about investor overreliance on credit ratings, and contributes to the academic literature on the roles and consequences of credit ratings in debt markets.

> "… IT WOULD BE RECKLESS AND INAPPROPRIATE FOR RETAIL INVESTORS TO USE MOODY'S CREDIT RATINGS, ASSESSMENTS, OTHER OPINIONS OR PUBLICATIONS WHEN MAKING AN INVESTMENT DECISION."
>
> — Moody's Global Disclaimer, 2021

1. Introduction

Credit rating agencies (CRAs) influence debt markets around the world. While credit ratings are slow to change in response to market conditions and fundamentals (e.g., Baghai et al., 2014; Bonsall et al., 2017; Cheng and Neamtiu, 2009; Beaver et al., 2006; Kaplan and Urwitz, 1979), they remain a convenient measure of risk for use in regulations and contracting. For some

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investors, ratings are likely also a tempting, low-cost source of information for bond trading decisions, despite clear warnings from CRAs that their ratings do not provide investment advice. Reliance on ratings in trading decisions may be particularly acute for retail investors, who have fewer resources for credit analysis and are less likely to understand ratings' shortcomings. This paper investigates retail investors' reliance on credit ratings in their bond trading.

We investigate aggregate retail trading using the monthly buy-sell imbalances of retail-sized trades in the U.S. corporate bond secondary market. Because bond markets are fragmented and transaction costs decrease with size, transaction size remains a reliable and widely accepted proxy for identifying retail trades (O'Hara and Zhou, 2021; Bessembinder et al., 2020). We follow the literature in using a threshold $100,000 to identify retail transactions.[1] Our sample spans 2002 through 2019 and includes 1.7 million bond-month observations.

Our initial analyses investigate whether retail investors use credit ratings to inform their trading. Cornaggia et al. (2018) explain that, unlike some institutions, retail investors have no regulatory reasons to use ratings in their trading. However, they may choose to do so.

On the one hand, ratings are known to lag observable fundamentals and prices and can be biased, due to CRAs' incentive conflicts, so retail investors have good reasons to ignore ratings.[2] Moreover, while Cornaggia et al. (2018) find that retail investors use credit ratings to inform municipal bond trades, they also find that usage decreases with the strength of the issuer's information environment. Substantially more information is available about corporate issuers than municipalities (e.g., Cheng, 2021), so retail investors plausibly put little weight on corporate bond ratings.

On the other hand, the corporate bond market is vast and independent credit analysis is costly, so retail investors plausibly use credit ratings as a starting point for selecting bonds. For example, an investor seeking low-risk bonds plausibly find it efficient to screen on rating levels, even though such a screen generates both types 1 and 2 errors with regard to true credit risk. This sort of two-step procedure for limiting options is widely documented in the consumer choice literature (e.g., Bordalo et al., 2013b; Hauser and Wernerfelt, 1990), and, as of the date of this writing, the largest U.S. retail bond brokers' trading platforms all allow for screening on credit ratings.[3]

Our analyses indicate that retail investors do rely heavily on credit ratings in their trading. Panels (a) and (b) of Fig. 1 document a general downward trend in retail buy-sell imbalances ("BSI") across broad rating categories and a large discontinuity across the investment-grade cutoff. A regression discontinuity test confirms the BSI break across the investment-grade cutoff, and regression analyses find sharp declines in demand of up to 14.40%, as bonds are downgraded across major rating-level thresholds (BBB to BB, etc.). In sum, our tests indicate that retail investors use rating levels at least as a starting point for making trading decisions and generally prefer safer-rated bonds.

We next investigate the remaining variation in retail investors' trading decisions and offer two likely explanations. The first is that retail investors use ratings as a starting point for fundamentals-based credit analysis. Even though CRAs do regularly update their ratings, research shows that accounting information and security prices contain information about credit risk that is incremental to and more timely than credit ratings (e.g., Ogneva et al., 2019; Hilscher and Wilson, 2017; Correia et al., 2012; Beaver, 1966), and that institutions trade on this information (e.g., Even-Tov and Ozel, 2021; Lee et al., 2018). If retail investors use fundamental information to select bonds, in a regression of BSI on ratings and controls, fundamental information should be incrementally significant in expected directions.

The second possibility is that retail investors find fundamental analysis to be too costly, so they resort to simple heuristics when choosing bonds. One plausible heuristic is to assume that the bonds within a rating level are homogeneous, in which case retail investors likely aim to maximize future returns by buying (selling) bonds with the highest (lowest) yields. While such a strategy would ignore that bond yields impound fundamentals more quickly than do ratings, the strategy is plausible at least two reasons. First, yield is likely the most salient information immediately available when selecting a bond, and investors are known to overweight salient information (e.g., Bordalo et al., 2013a; Liao et al., 2021; Frydman and Wang, 2020). Second, selecting on price-related information can be optimal for other financial products (e.g., choosing the highest-yielding savings account or lowest-rate mortgage), so it is easy to imagine that a retail investor could assume a strategy applies to bonds. Anecdotally, the largest retail bond trading platforms are set up to facilitate sorting on yield-within-ratings (see Section 2) and, as Warren Buffet has said: "Reaching for yield is really stupid. But it is very human …" (Belvedere, 2020).[4]

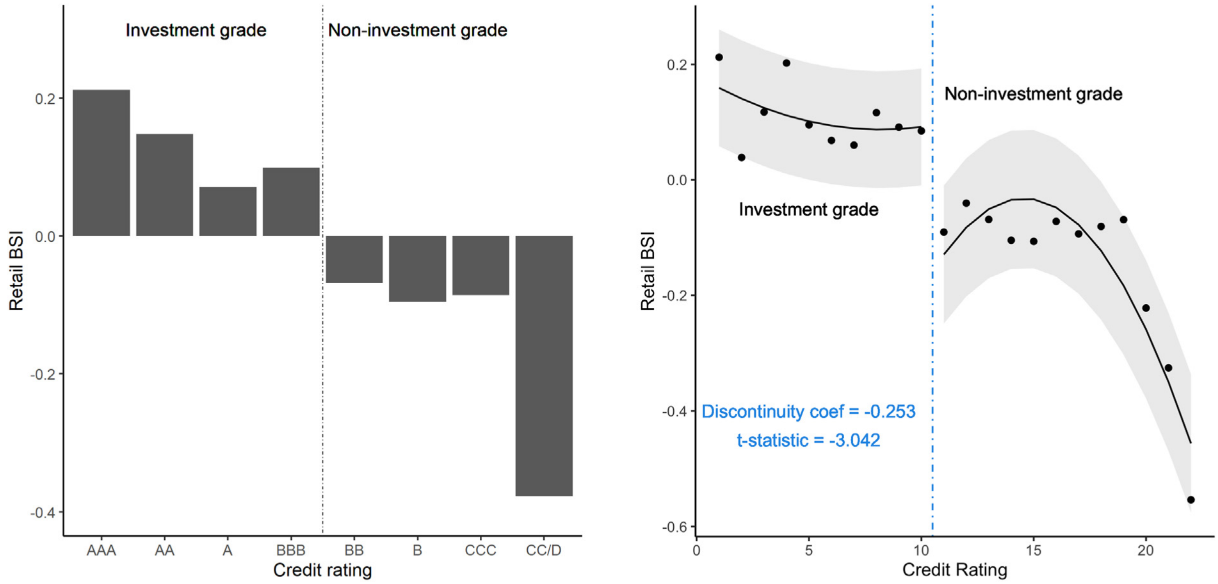
Our analyses are most consistent with the second possibility: in aggregate, retail investors appear to rely on credit ratings as a sufficient statistic for risk and then buy (sell) the highest- (lowest-) yielding bonds within each rating level. These analyses are based on monthly sorts of bonds into quintiles of yield within each rating level, while also conditioning on

[1] Section 3.2 further discusses why transaction size is a valid proxy for investor type. Even so, our identification of retail trades is imperfect and likely captures some trades by small institutions. Small, and presumably less sophisticated, institutions plausibly follow similarly under-informed trading patterns as retail investors.

[2] The literature on slow and biased corporate credit ratings is deep. As a few examples, see Bonsall et al. (2018, 2017, 2015); Beatty et al. (2019); Basu and Naughton (2020); Dimitrov et al. (2015); Jiang et al. (2012); Cheng and Neamtiu (2009); deHaan (2017); White (2010, 2013); Kedia et al. (2017); Beaver et al. (2006); Kraft (2015). Stable ratings that do not respond to short-term changes in risk can be desirable for the main purpose of ratings, which is their use in contracting and regulation. Rating stability, however, is undesirable for investing, which is likely why the CRAs warn that ratings are not investment advice.

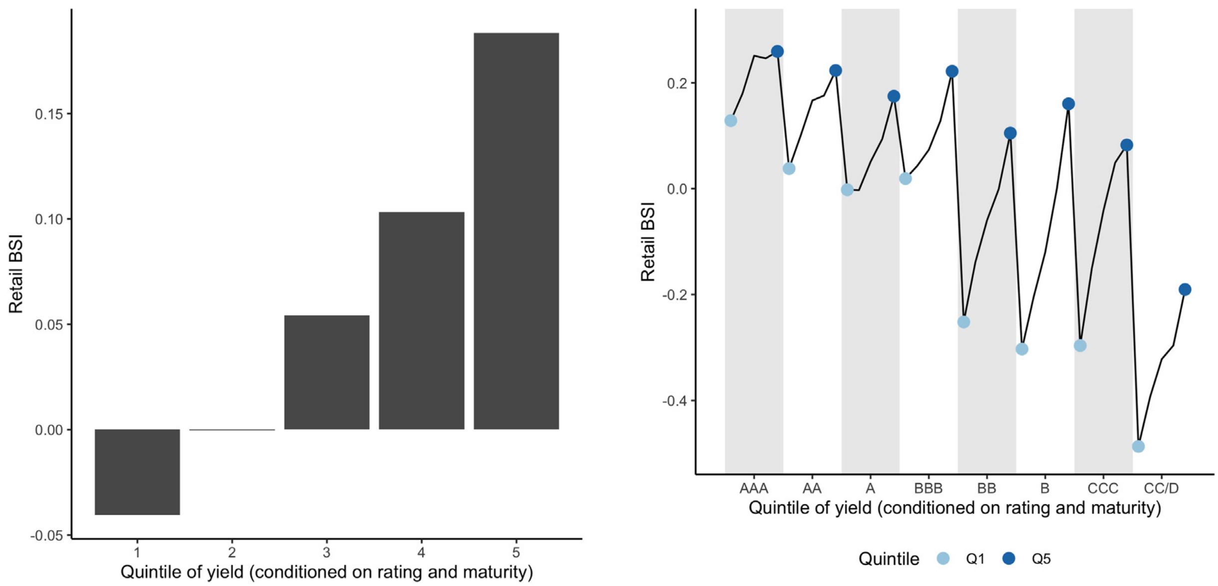
[3] See Section 2 for further discussion of brokers' search tools. As additional anecdotal evidence, the CRAs acknowledge that retail investors likely screen on ratings, despite warnings not to (Standard & Poor's Rating Service, 2014), and the SEC has recently noted that retail investors' reliance on credit ratings is a potential area of focus in coming years (e.g., SEC, 2019, 2020).

[4] The tendency for investors to fixate on yields is well known among practitioners (e.g., Flanagan, 2021; LeMener, 2016).



(a) BSI by ratings (b) BSI by ratings: Regression discontinuity

Fig. 1. Retail buy-sell imbalances (BSI) across credit rating levels. Panel (a) plots the issue value-weighted BSI of retail investors by broad credit rating categories. The vertical dashed line separates the investment grade and non-investment grade ratings. Panel (b) plots the average value-weighted BSI by notched credit ratings, which range from 1 to 22, and examines whether there is a discontinuity at the investment grade/non-investment grade (IG/NIG) cutoff. Quadratic controls, as functions of the credit ratings distance to the cutoff, are fitted to both sides of the cutoff. The shaded areas are 95% confidence intervals. The estimated drop off BSI at the cutoff is 25.28% of the sample standard deviation ($t = -3.042$). For presentation purposes, in both Panels, BSI has been standardized to have mean zero and a standard deviation of one.



(a) Average BSI by yield quintile (b) BSI by both yield quintile and rating level

Fig. 2. Retail buy-sell imbalances (BSI) across yield quintiles and credit rating levels. Panel (a) plots the issue value-weighted retail BSI for each quintile of yield, sorted within broad credit rating levels and within quintiles of maturity (i.e, variable $Y|RM_t$). Panel (b) further plots BSI by $Y|RM_t$ for each broad credit rating level, and the light and dark blue dots mark the first and last $Y|RM_t$ quintiles. The shaded and non-shaded areas demarcate different rating levels. For presentation purposes, in both Panels, BSI has been standardized to have mean zero and a standard deviation of one. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

remaining maturity. Despite our previous finding that retail investors generally prefer safer bonds overall, Panel (a) of Fig. 2 shows that BSI increases across yield quintiles within each rating level, consistent with retail investors preferring the *riskier* bonds. Looking both within and across rating levels, Panel (b) of Fig. 2 reveals a sharp seesaw pattern in BSI, which shows that retail investors tend to buy bonds in the highest quintile of yield within each rating level relative to both 1) the lower quintiles of yield within the same rating level and 2) the lowest quintile of yield within the subsequently lower credit rating level. These patterns are highly significant in regressions including controls, year-month fixed effects, and bond fixed effects. These results are highly consistent with retail investors following a two-step search process of first screening on certain rating levels and then sorting on yields.

We also find that retail investors systematically trade in the *opposite* direction of fundamental news, which is an expected repercussion of trading on yield-within-rating. Specifically, we examine four fundamental signals related to bond credit risk: the firm's recent earnings surprise, its Piotroski (2000) F-Score, recent changes in the issuer's CDS, and trailing stock returns. All four are positively associated with improving credit risk and firm prospects. However, despite retail investors' general preference for safer bonds, we find that they trade contrary to all four signals, after conditioning on credit rating. The likely explanation is not that retail investors observe the signals and choose a contrarian strategy, but rather that all four signals are impounded in yields more quickly than in credit ratings. Thus the highest yielding bonds within each rating level are those that have recent declines in fundamentals.

The second part of our study investigates the wealth consequences of retail investors' trading. Because yields tend to lead rating changes, we expect the highest-yielding bonds within each rating to be more likely downgraded in the near future, and vice versa. Indeed, we find that retail investor BSI is positively associated with future rating downgrades and negatively associated with upgrades. In economic terms, a one-standard-deviation increase in BSI is associated with a 0.199% higher (0.153% lower) chance of being downgraded (upgraded) in the following month, which is meaningful, given baseline downgrade (upgrade) probabilities of 1.637%(1.080%). We also find that retail BSI is positively associated with future defaults over the bond's remaining life. Finding that retail buying predicts downgrades and defaults indicates that retail investors' portfolios underperform, even over long horizons (e.g., Choi and Kronlund, 2018; Becker and Ivashina, 2015).

Following studies of retail equity trades (e.g., Boehmer et al., 2021) and institutional bond trades (e.g., Choi and Kronlund, 2018; Becker and Ivashina, 2015), we more directly explore the performance of retail investors' bond trades using portfolio tests and Fama-MacBeth regressions. Portfolio tests find a difference in one-month-ahead alpha of −51.4 bps between the bonds that retail investors are most heavily buying versus selling, which is economically meaningful underperformance in relation to the sample average monthly bond return of 60.5 bps. Fama-Macbeth regressions conditioning on bond and issuer characteristics indicate that retail investors' one-month-ahead underperformance remains significantly negative through at least two years, with no evidence of return reversals. These findings are again consistent with retail investors significantly underperforming, relative to a broadly diversified strategy, even over relatively long horizons.

We perform several additional analyses to better understand retail investors' underperformance. First, we further partition transaction sizes to explore the role of investor sophistication. We find consistently stronger results for smaller trades that are likely from less sophisticated retail investors (i.e., trades under $50, 000), and we find that institutional investors (i.e., trades over $100, 000) collectively display the opposite behaviors of retail investors. Second, because our returns prediction tests indicate that bond prices are imperfectly efficient, we examine whether retail investors underperform to a lesser degree when they trade in more efficiently priced bonds. As expected, value-weighted portfolio tests show smaller but still economically meaningful underperformance of 38.3 bps per month, and we find that underperformance is attenuated for more efficiently priced bonds. Finally, we confirm that retail investors could meaningfully improve their performance by following simple alternative investment strategies, including simply holding bond index funds. In dollar terms, we estimate that retail investors could have collectively saved over $1 billion during just the last year of our sample by opting for index funds.

Overall we conclude that retail investors appear to overrely on untimely credit ratings to inform bond trades, to their financial detriment. Sorting on yield-within-rating indicates that retail investors treat credit ratings as a sufficient statistic for credit risk, disregard fundamental information, and fail to appreciate that abnormally high bond yields likely reflect abnormally high risk. That said, we take seriously the possibility that our findings could be confounded by measurement error in identifying retail trades, correlated omitted variables, or alternative incentives for trading on yield-within-rating. We include robustness tests to reduce concerns about the most likely alternative explanations, including the possible effects of time-varying liquidity, but still caveat that our results should be interpreted with some caution.

Our paper's first contribution is to the literature on retail investors. Research generally finds that retail equity investors under-use accounting information and lose money relative to a diversified portfolio (Barber and Odean, 2013; Blankespoor et al., 2020). We provide novel evidence that ill-informed trading extends to retail bond market investors, where the overall level of sophistication is thought to be higher than in equity markets.[5] More importantly, we find that retail bond investors not only appear to neglect fundamental information but, by overrelying on ratings, systematically trade in the opposite direction of fundamental news. To date, very few papers in either the equity or bond markets have identified what causes investors to systematically trade contrary to fundamental news (e.g., Blankespoor et al., 2020).

[5] In this regard, we build on the work of Wei (2018), who finds that retail corporate bond investors exhibit behavioral biases in their trading. Cornaggia et al. (2022) also find that municipal bond retail investors are inattentive to information affecting equity and CDS markets and only respond once credit ratings are downgraded. Few other studies examine retail bond investors, which contrasts starkly with the large literature on retail equity investors.

Second, our study contributes to the literature on the role of credit ratings in debt markets. Our findings indicate that retail bond investors do not appreciate that ratings are slow to respond to changes in risk, and overrely on them to their detriment.[6] These findings corroborate concerns expressed by regulators about retail investors overrelying on credit ratings (SEC, 2019, 2020), and provide empirical evidence to support extant theories in which an unsophisticated clientele is assumed to naively rely on credit ratings (e.g., Bolton et al., 2012; Skreta and Veldkamp, 2009; Stango and Zinman, 2009).

Finally, we contribute to the literature on "reaching for income" among investors, in which investors aim to maximize expected returns subject to constraints. Studies find that institutions with rating-based incentives attempt to maximize yield, conditional on rating levels. For example, insurance companies select higher-yielding bonds while complying with rating-based capital requirements, and mutual funds select high-yielding bonds to beat rating-based benchmarks (e.g., Becker and Ivashina, 2015; Choi and Kronlund, 2018; Iannotta et al., 2019). We find that retail investors sort on yield-within-rating in the absence of institutional incentives, which indicates that their reaching for income has different causes and so is distinct from what has been studied in prior literature.

2. Institutional details

Retail investors are important participants in bond markets, holding approximately 75% of all municipal and 28% of all corporate bonds (SEC, 2013). While many of these holdings are indirect (e.g., through mutual funds), retail investors also regularly trade in individual bonds. For example, in the last year of our sample, retail investors' trades comprised 73% of all transactions and totaled over $150 billion. Given the prominence of fixed income securities in many retail investors' retirement savings, these bond trades have potentially significant implications for consumers' financial well-being.

Retail investors typically trade corporate bonds over-the-counter through brokers (Bessembinder et al., 2020). Because brokers typically use their own accounts to take the other side of retail-size trades, retail investors trade against comparatively sophisticated institutions. Brokers broadly fall into two categories: low-cost broker-dealers (e.g., TD Ameritrade) and full-service brokers (e.g., Wells Fargo Advisors). Retail bond investors using low-cost brokers typically make their own portfolio decisions, while full-service brokers often provide access to financial advisors.[7]

Regardless of the type of broker, retail bond investors are likely more sophisticated than retail equity investors on average and likely have different objectives. This is mainly driven by several institutional features of the bond market. First, because bond payoffs have capped upsides, bond investors are unlikely to seek the lottery-like extreme payoffs sought by some retail equity investors (e.g., Kumar, 2009; Conrad et al., 2014). Second, corporate bonds typically have large minimum purchases, at least $1,000, so direct investment in bonds is limited to larger (and likely more experienced) retail investors. Third, bonds have less price volatility and higher transaction costs than equities, which likely deters retail investors who trade to capture daily price swings.

The vast number and variety of outstanding fixed-income securities necessitate tools for searching and selection. Figure C-1 presents an example search tool for Charles Schwab, which is among the largest retail bond brokers. Panel (a) presents the introductory bond buying screen and shows that Schwab offered over 36,000 unique securities on the date of our visit. Panel (b) shows that Schwab's search tool provides four categories of screening criteria: security type, maturity, credit rating, and basic features such as callability. Panel (c) presents the results from our example search, which is by default sorted on maturity and then yield. Clicking on a bond's name provides additional information about the security, which in many cases includes an analyst research report (e.g., from Moody's).

Figure C-1 shows that Schwab's search tool operates much like we expect retail investors to shop for bonds, by sorting on yield after filtering on rating and desired maturity. Additional examples, presented in Figure IA-1 of the Internet Appendix, confirm that the search tools of other major retail bond brokers also facilitate screening on rating level and sorting by yield.[8] Conversations with practitioners indicate that similar search platforms are used by retail financial advisors, although likely with more nuanced functionality. While some investors and advisors have access to additional resources for selecting bonds, many retail investors and advisors plausibly expect that the cost of further research exceeds the benefit, in which case their searches plausibly conclude with a sorted list like that in Panel (c) of Figure C-1.

The process for selling bonds differs because investors choose from among the bonds they own, rather than the full universe. Still, trading platforms likely allow investors to screen and sort their bonds to determine which to sell.

[6] In this regard, our study extends the work of Cornaggia et al. (2018), who find that retail investors use ratings when selecting municipal bonds and that rating usage declines for bonds with stronger information environments. We build on Cornaggia et al. (2018) by: 1) documenting that retail investors use ratings in the corporate bond market, where the information environment is stronger, so investors plausibly do not need ratings; 2) investigating how retail investors select bonds after conditioning on credit ratings; and 3) investigating the consequences of retail investors' trading decisions.

[7] Like many studies that use anonymous trade data to analyze retail investors in equity markets (e.g., Lee, 1992; Kumar, 2009; Boehmer et al., 2021) and bond markets (e.g., Cornaggia et al., 2018; Green et al., 2007a), we do not differentiate between trading decisions that are made solely by retail investors versus those influenced by advisors. We instead treat advisors as extensions of the retail investors themselves. Retail financial advisors are typically not bond analysts and are likely susceptible to the same ill-informed trading decisions and biases as their clients (e.g., Linnainmaa et al., 2021; Mullainathan et al., 2012). We further discuss the role of financial advisors in Section 7.3.

[8] Specifically, we checked the search tools for TD Ameritrade, Interactive Brokers, E-Trade, and Fidelity, which are widely reported as the largest U.S. retail bond brokers. Canada's largest wealth manager, CIBC, has a similar search tool. A caveat is that we cannot observe the search tools' historical functionality.

3. Methodology and data

3.1. Sample construction

Our data is constructed from several sources. To begin, we obtain the WRDS Bond Returns database from Wharton Research Data Services (WRDS), which provides cleaned monthly corporate bond returns sourced from TRACE. This data also includes bond characteristics from the Mergent FISD database, such as default date, issuance size, and monthly bond ratings. Time-varying bond characteristics, such as ratings and maturity, are continuously updated in the WRDS Bond Returns database to represent the bond's current value in that bond-month. All bond-months must have at least one trade to be included in the sample, which mitigates concerns about completely illiquid bonds. Our initial sample includes 1,727,049 bond-months and 79,717 bonds over the period from August 2002 through September 2019.[9]

Data used to calculate bond-month buy-sell imbalances ("BSI") are sourced from Enhanced TRACE, which includes information on all U.S. corporate bond transactions. We follow Dick-Nielsen (2014) to correct trade errors and cancellations in TRACE. We construct BSI using the steps outlined in Section 3.2. Our sample with BSI data includes 1,689,502 bond-month observations and 79,704 bonds.

Several of our analyses require supplementary data. We obtain firm-level fundamental data from Compustat using the firms' most recent quarterly and annual financial statements as of each bond-month. We obtain five-year senior unsecured CDS spread data from Markit. Stock returns data are from CRSP. These supplementary data are not available for all observations. We also obtain data on bond and equity factors from Amit Goyal's website and WRDS, respectively.[10]

Appendix A defines all of the variables in subsequent analyses. We conduct all analyses on the full sample of bond-month 1,689,502 observations, subject to data availability.

3.2. Measuring investor size and demand

We follow the standard practice of using trade size as a proxy for investor type, with trades of $100,000 or less attributed to retail investors.[11] Bond trading occurs in relatively opaque over-the-counter markets, where algorithmic trading — and thus trade splitting — remains scarce (e.g., O'Hara and Zhou, 2021). Institutional traders also have little incentive to break up their trades, as transaction costs are substantially higher for smaller trades than large ones, even in recent years (e.g., Bessembinder et al., 2020). While the specific identities of small traders are unobservable, trades below $100,000 are widely attributed to retail investors.[12]

We measure aggregate retail investor trading using buy-sell imbalances (BSI). Studies have used BSI to examine the aggregate trading of institutional investors (e.g., Lee and Zhu, 2022; Ben-David et al., 2013), retail investors (e.g., Kumar and Lee, 2006), and informed traders or insiders (e.g., Bushee et al., 2023; Bernile et al., 2016). Like prior studies, we define the retail BSI of bond *i* in month *t* to be:

$$BSI_{i,t}^{Retail} = \frac{TDVB_{i,t}^{Retail} - TDVS_{i,t}^{Retail}}{TDVB_{i,t}^{Retail} + TDVS_{i,t}^{Retail}}.$$

where $TDVB_t^{Retail}$ and $TDVS_t^{Retail}$ are the total dollar volume of all customer buys and sells among retail investors for bond *i* in month *t*, respectively.[13] In instances where there are no retail trades of a bond in a given month, we assign a value of zero (i.e., there is an equal number of buys and sells). A given month's bond-level BSI_t^{Retail} measures the extent to which aggregated retail investors are net buyers ($BSI_t^{Retail} > 0$) or sellers ($BSI_t^{Retail} < 0$) of a given bond.

3.3. Descriptives

Table 1 presents summary statistics for our main variables. Mean and median values for BSI are −0.204% and 0.000%, respectively, indicating that average retail BSI is roughly neutral. The BSI standard deviation is 61.528%, consistent with

[9] These data are discussed in detail at https://tinyurl.com/y27xb6jn. We drop the first month of the WRDS Bond Returns sample due to incomplete data. The WRDS Bond Returns database is increasingly used in research (e.g., Boons et al., 2023; Li, 2022; Guernsey et al., 2022).

[10] All bond factors are calculated following Welch and Goyal (2008).

[11] For examples, see O'Hara and Zhou (2021); Cuny et al. (2021); Larcker and Watts (2020); Bessembinder et al. (2018); Cuny (2018); Feldhütter (2012); Bessembinder et al. (2009); Green et al. (2007b); Edwards et al. (2007). Practitioners and regulators also widely attribute trades of $100,000 or less to retail investors. For example, a 2015 FINRA notice states: "FINRA has observed that a significant number of retail-sized transactions (100 bonds or less or bonds with a face value of $100,000 or less) …".

[12] O'Hara and Zhou (2021) note that electronic trading is growing in corporate bond markets, so it is unclear whether transaction size will remain an effective identifier of investor type going forward. Untabulated robustness tests find that all of our main results hold in a sample ending in 2007, long before algorithmic trading gained popularity. Sensitivity analyses in Section 6.1 use a cutoff of $50,000 to identify retail investors, which Goldstein et al. (2007) note is extremely conservative, and find generally stronger results.

[13] TRACE trades explicitly identify whether the customer is buying from or selling to dealers. Below we discuss robustness tests using alternative specifications for retail investor demand.

Table 1
Descriptive statistics.

	Mean	StDev	$StDev^{Resid.}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	Obs.
Dependent variables							
BSI_t^{Retail} (%)	−0.204	61.528	53.296	−39.623	0.000	43.624	1,689,502
$Downgrade_t^{1mo.}$ (%)	1.637	12.691	12.271	0.000	0.000	0.000	1,393,409
$Upgrade_t^{1mo.}$ (%)	1.084	10.356	10.177	0.000	0.000	0.000	1,393,409
$Default_t^{Maturity}$ (%)	2.153	14.513	0.000	0.000	0.000	0.000	1,689,502
Ret_{t+1} (%)	0.605	4.609	4.257	−0.406	0.384	1.562	1,451,455
Bond and trading characteristics							
$Maturity_t$ (Yrs.)	7.792	8.122	0.335	2.150	4.870	9.170	1,681,959
Bond size	5.171	1.955	0.000	4.828	5.704	6.397	1,689,502
$Rating_t$	8.515	3.549	0.981	6.000	8.000	10.000	1,425,386
$Yield_t$ (%)	5.146	4.243	2.354	2.962	4.455	6.007	1,384,542
$Volume_t$	15.289	2.661	1.465	13.346	15.830	17.346	1,689,502
$BA\text{-}Spread_t$ (%)	0.601	0.688	0.514	0.180	0.380	0.750	1,404,423
Issuer characteristics							
$F\text{-}Score_t$	4.899	1.507	1.192	4.000	5.000	6.000	1,450,665
SUE_t (%)	0.020	4.594	4.296	−0.428	0.136	0.622	1,422,821
ΔCDS_t (bps)	2.131	104.319	86.605	−16.090	−1.167	11.547	605,867
$Ret6M_t$ (%)	4.640	21.644	16.301	−6.807	4.841	15.998	1,447,788

This table reports descriptive statistics on the monthly bond observations used throughout this study. These include the sample mean, standard deviation, and residual standard deviation after controlling for bond and year-month fixed effects.

substantial variation in retail investor demand. The residual standard deviation, after being orthoganlized to bond and date fixed effects (which are used in several of our analyses), is similar (deHaan, 2021).

The WRDS Bond Returns data sources credit ratings from Mergent FISD from the three major CRAs, converted to a numeric scale of 1 for AAA through 22 for D. Throughout the paper, we use the term “broad ratings” to refer to the seven major credit rating levels, AAA, AA, etc. “Notched ratings” refer to the subgroups AA+, AA, AA-, etc. The average notched rating in our sample is 8.515, which equates to between a BBB+ and BBB.

Several of our analyses investigate returns to retail investors' trades, so it is useful to have a sense of retail investors' typical holding periods. An estimate can be calculated from retail investors’ total annual trading volume as a fraction of their total bond holdings. Average annual gross retail trading volume is $94.1 billion and $150.7 billion in the full sample and last year of our sample, respectively. Retail holdings are not directly observable in trading data, but, using the method of He et al. (2022), a conservative estimate is $128.4 billion and $206.5 billion for the corresponding sample periods.[14] Estimated portfolio turnover is therefore $94.1/128.4 \approx 73\%$ per year, for an average holding period of $1/73\% = 1.36$ years. Using just the last year produces an estimated holding period of 1.41 years. These estimates indicate that the representative retail bond investor in our sample trades fairly frequently.

4. Determinants of retail investor trading

4.1. Retail investors’ use of credit ratings

We begin by examining the relationship between retail investor demand and credit ratings. Research has discussed institutional reasons why credit ratings matter for many institutional investors’ trading decisions. For example, banks and insurance companies must use credit ratings when determining their portfolio allocations (e.g., Becker and Ivashina, 2015; White, 2013, 2010), and mutual funds use credit ratings for benchmarking (e.g., Chen et al., 2021).

It is unclear whether retail investors use credit ratings as a primary input to corporate bond trading decisions. Retail investors are unaffected by regulations that require the use of ratings, and the major CRAs stress that their ratings should not be considered investment advice. Moreover, research finds that credit ratings are slow to respond to market conditions and fundamentals, undermining their value for investing purposes. However, credit analysis is costly, and retail investors are likely capacity-constrained, so retail investors might find credit ratings to be a low-cost signal, despite the known weaknesses.[15]

Panel (a) of Fig. 1 plots the average monthly retail BSI by each broad rating level. BSI generally declines as ratings worsen, indicating that retail investors prefer safer bonds. BSI becomes negative for non-investment grade ratings (i.e., selling exceeds buying for ratings below BBB-) and declines sharply for bonds approaching default (CC/D rating). These patterns suggest that

[14] See Appendix B.1 for detailed calculations. Using the last year of our sample is more accurate because the He et al. (2022) method requires estimated beginning-of-period holdings, which is most accurate for bonds issued since TRACE coverage started 2002. 96.6% of the bonds in the last year of our sample were issued since the beginning of TRACE, indicating that, by the end of the sample, our estimate should be very accurate.

[15] While Cornaggia et al. (2018) find that retail investors rely on credit ratings in the context of municipal bonds, they show this reliance decreases in the presence of stronger information environments, as is the case among corporate bond issuers.

retail investors use ratings to inform their trades, but investors may also trade on other information that correlates with ratings.

As a first test of whether retail investors trade on credit ratings as opposed to other correlated information, Panel (b) of Fig. 1 tests the discontinuity in BSI around the investment-grade threshold from Panel (a). Assuming that correlated bond fundamentals do not change discontinuously between BBB- and BB+, observing a statistically significant drop in BSI across the investment-grade threshold would be consistent with retail investors trading on credit ratings themselves. Panel (b) indeed finds a 25.28% standard deviation drop in BSI across the threshold, statistically significant at 1% ($t = -3.042$).

We next use an OLS regression to test for differences in BSI across rating levels:

$$BSI_{i,t}^{Retail} = \sum_{r=AAA/AA}^{\text{CCC and below}} \beta_r \cdot Rating\ Level_{r,i,t} + Controls_{i,t} + Fixed\ Effects_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $Rating\ Level_t$ is either an indicator for any investment grade credit rating or is a set of indicators for each round credit rating level r for bond i at the end of month t. When using the set of indicators, we combine AAA and AA into one group because AAA bonds comprise just 1.30% of the sample. The seventh (i.e., worst) rating group, CCC and below, is then omitted as the baseline group. $Controls_t$ includes the natural logarithm of bond issuance size (*Bond size*) and remaining time-to-maturity ($Maturity_t$). Year-month fixed effects control for common temporal trends and macroeconomic conditions. Bond fixed effects restrict our estimates to only using within-bond variation and therefore eliminate time-invariant bond characteristics, such as payment frequency, covenants, or call features. Standard errors are clustered by bond and year-month.

Table 2 presents results of estimating model (1). Results in columns (1) and (4) include controls without fixed effects. In column (1), the coefficient on the indicator for investment grade ratings (IG_t) is positive and highly statistically significant, again indicating that retail investors prefer safer securities. Similarly, in column (4), the coefficients for AAA/AA_t, A_t, and BBB_t are all positive and highly significant. The control variable estimates indicate that investors prefer larger bond issues (i.e., likely from larger firms) that are closer to maturity.

Columns (2) and (5) add year-month fixed effects and find virtually unchanged results, indicating that our findings are largely unaffected by temporal trends. Coefficients are generally both larger and more statistically significant in columns (3) and (6) with bond fixed effects, indicating that ratings are a more important determinant of BSI within a given bond's life than across bonds. Untabulated tests find the differences in BSI between each pair of adjacent rating levels (e.g., A versus BBB) in column (6) are also statistically significant, and analyses presented in Table IA-1 of the Internet Appendix of changes in BSI around changes in credit ratings produce similar inferences.

Collectively, this section's results indicate that retail investors heavily rely on credit ratings in their trading.

Table 2
Credit ratings and retail bond trading.

	Dependent variable:					
	BSI_t^{Retail}					
	(1)	(2)	(3)	(4)	(5)	(6)
IG_t	7.114***	6.398***	17.002***			
	(7.489)	(6.874)	(19.637)			
AAA/AA_t				4.845***	4.016***	38.154***
				(3.801)	(3.144)	(21.179)
A_t				6.261***	5.895***	32.054***
				(5.411)	(4.994)	(20.036)
BBB_t				9.102***	8.355***	28.924***
				(8.269)	(7.356)	(18.592)
BB_t				0.681	0.446	14.523***
				(0.810)	(0.508)	(11.192)
B_t				−0.052	0.443	8.800***
				(−0.064)	(0.536)	(8.237)
$Maturity_t$	−0.423***	−0.428***	1.347***	−0.430***	−0.435***	1.315***
	(−11.252)	(−11.287)	(4.061)	(−11.552)	(−11.660)	(3.962)
Bond size	5.309***	4.848***		5.226***	4.790***	
	(18.110)	(14.152)		(18.503)	(14.526)	
Month fixed effects	No	Yes	Yes	No	Yes	Yes
Bond fixed effects	No	No	Yes	No	No	Yes
Observations	1,419,114	1,419,114	1,419,114	1,419,114	1,419,114	1,419,114
R^2	0.019	0.034	0.156	0.019	0.035	0.157

This table examines the ratings-based determinants of retail bond trading. The dependent variable in all regressions is the monthly buy-sell imbalance of retail investors, BSI_t^{Retail}, measured in percent. The explanatory variable in columns (1) through (3) is an indicator for investment-grade bonds (IG_t). Columns (4) through (6) replace IG with indicators for each broad credit rating category. Certain models include fixed effects for each year-month and bond, as specified in the lower rows of each column. All variables are further defined in Appendix A. All regressions are estimated using the full sample, subject to data availability. Robust t-statistics, clustered by bond and year-month, are in parentheses. Levels of significance are presented as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

4.2. Retail investors' use of other information

We next investigate the remaining variation in retail investors' bond trading decisions. As mentioned in Section 1, we offer two possibilities for how retail investors proceed in making bond trading decisions. The first is that they use rating levels as a starting point for further credit analysis. If so, in a regression of BSI on ratings and controls, fundamental information should be incrementally significant in the expected directions. The second possibility is that retail investors heuristically assume that the bonds within a rating level are reasonably homogenous and therefore discriminate based on price. In this case, a regression of retail investor BSI on ratings and within-rating yields should find higher demand for higher-yielding bonds.

4.2.1. Selecting based on within-rating yield

To test for trading on yields, we sort bonds on yield within each notched credit rating level and then examine whether BSI increases with yield-within-rating. To accommodate differences in maturities across bonds, which have a largely mechanical relation with yield, we also condition the sorts on maturity. Thus, in each month, we first sort bonds within each rating level into five maturity buckets and then sort each rating-maturity bucket into quintiles of contemporaneous bond yield. The resulting quintile, labeled $Y|RM_t$, is the within-rating quintile of yield after controlling for maturity.

We preview our primary findings in Fig. 2, which plots retail investor BSI on the vertical axis by quintile of $Y|RM_t$ on the horizontal. In Panel (a), we see that retail investor demand appears highly dependent on within-rating yield, with the BSI in the top (i.e., rightmost) yield quintile exceeding the bottom (leftmost) yield quintile by more than 20% of the BSI standard deviation. These findings indicate that retail investors tend to buy (sell) bonds with highest (lowest) yield within each rating level.

Considering both Figs. 1 and 2 together, retail investors appear to prefer bonds with safer credit ratings, but then prefer the riskiest bonds within each rating level. Consistent with these opposing preferences, Panel (b) of Fig. 2 presents a sharp seesaw pattern: BSI increases with $Y|RM_t$ within each rating level but then decreases sharply across rating level thresholds. The effect strengthens with worse credit rating levels, likely because within-rating yields vary to a greater extent within worse rating levels. The effect of selecting on yield is economically large with average differences of over 30%−40% of the sample standard deviation in some rating categories.

We empirically test these relations in Table 3 using the following model:

$$BSI_{i,t}^{Retail} = \beta_1 \cdot Y|RM_{i,t} + \beta_2 \cdot Yield_{i,t}^{\mathrm{Rank}} + Controls_{i,t} + Fixed\ Effects_{i,t} + \varepsilon_{i,t}, \tag{2}$$

Model (2) has a few differences from model (1). The right-side determinant of interest is now $Y|RM_t$. To control for investors' overall yield preferences (i.e., not within-rating yield), we add a control for the bond's quintile of yield measured across all ratings in the same month ($Yield_t^{Rank}$). We continue to control for bond size, maturity, and credit rating level but untabulate their coefficients for brevity.[16]

Column (1) of Panel A of Table 3 excludes fixed effects and finds a highly significant and positive coefficient on $Y|RM_t$, consistent with investors sorting on yield within each rating level. Column (2) replaces the count variable control for credit rating level with indicators for each rating level, which allows for a flexible relation between each rating and $Y|RM_t$ and BSI_t^{Retail}. Column (3) adds year-month fixed effects and (4) adds bond fixed effects. The $Y|RM_t$ coefficient is qualitatively similar in all three columns. The coefficient on $Yield_t^{Rank}$ tends to have the opposite sign of $Y|RM_t$ or is statistically insignificant.

Panel B provides further granularity by separating $Y|RM_t$ into indicators for each quintile. The regression coefficients trend monotonically across the quintiles and are, in all but one case, highly significant. In terms of economic magnitudes, these estimates suggest that retail investor BSI is approximately 6.271%−10.427% higher for those securities in the highest yield quintile, relative to the lowest.[17]

Overall the results in this section and the previous section are consistent with retail investors following a two-step procedure: 1) they screen on rating categories to narrow the investment universe, and then 2) they choose bonds with higher within-rating yields.

4.2.2. Selecting based on fundamentals

This section investigates the second possibility of how retail investors select bonds: by using ratings as an initial screen followed by fundamentals-based credit analysis. The results in Section 4.2.1 already indicate that this is unlikely to be the case. Specifically, because credit ratings are slow to respond to market conditions and fundamentals, higher-yielding bonds within each rating level are likely to be those with deteriorating fundamentals. By favoring higher-yield bonds within rating levels, retail investors likely trade in precisely the opposite direction of fundamentals.

We empirically examine these relations by estimating a modified version of model (2):

[16] Untabulated control coefficients resemble those in Table 2. We use a quintile ranking of yield so that the coefficient is comparable to $Y|RM_t$, but a specification with a continuous yield measure produces qualitatively unchanged results.

[17] In Table IA-2, we find similar results when using several alternative measures of retail investor trading, including unscaled retail buys minus sells, buys minus sells scaled by issuance size instead of the volume, just buys scaled by volume, and just sells scaled by volume. Thus our inferences do not appear sensitive to the specific functional form of our dependent variable. We also find similar results across various subsamples of bonds.

Table 3
Bond yields and retail bond trading, conditional on credit ratings.

Panel A: Within rating pricing

	Dependent variable: BSI_t^{Retail}			
	(1)	(2)	(3)	(4)
$Y\|RM_t$	2.728***	2.474***	2.552***	1.650***
	(20.557)	(18.835)	(19.248)	(13.355)
$Yield_t^{Rank}$	−1.145***	−0.495	−0.961***	0.471
	(−3.250)	(−1.469)	(−2.885)	(1.635)
Controls	Yes	Yes	Yes	Yes
Rating indicators	No	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,358,537	1,358,537	1,358,537	1,358,537
R^2	0.016	0.019	0.037	0.147

Panel B: Within rating pricing (quantiles)

	Dependent variable: BSI_t^{Retail}			
	(1)	(2)	(3)	(4)
$Y\|RM_t^2$	1.401***	1.126***	1.372***	0.036
	(4.125)	(3.384)	(4.147)	(0.135)
$Y\|RM_t^3$	4.421***	3.964***	4.288***	1.840***
	(10.785)	(9.938)	(10.909)	(5.409)
$Y\|RM_t^4$	7.834***	7.160***	7.516***	4.270***
	(16.940)	(16.008)	(16.935)	(10.899)
$Y\|RM_t^5$	10.427***	9.343***	9.661***	6.271***
	(18.590)	(16.806)	(17.195)	(11.955)
$Yield_t^{Rank}$	−1.129***	−0.472	−0.933***	0.486*
	(−3.212)	(−1.404)	(−2.808)	(1.694)
Controls	Yes	Yes	Yes	Yes
Rating indicators	No	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,358,537	1,358,537	1,358,537	1,358,537
R^2	0.016	0.019	0.037	0.147

This table examines whether retail investors select bonds by sorting on yield-within-rating. Panel A presents regressions of retail BSI on the quintile rank of bond yield conditional on rating and maturity ($Y|RM_t$), and controlling for the quintile rank of yield ($Yield_t^{Rank}$). Untabulated controls include $Rating_t$, *Bond size*, and $Maturity_t$, as defined in Appendix A. Certain models also include indicators for each rating level and fixed effects for each year-month and bond, as specified in the lower rows of each column. Panel B repeats Panel A but replaces $Y|RM_t$ with indicators for each $Y|RM_t$ level. All regressions are estimated using the full sample, subject to data availability. Clustered t-statistics, by bond and year-month, are included in parentheses. Levels of significance are presented as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

$$BSI_{i,t}^{Retail} = \beta_1 \cdot Fundamental\ Signal_{i,t} + Controls_{i,t} + Fixed\ Effects_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where *Fundamental Signal* is one of several fundamental signals for the issuer of bond i using data available at the end of month t. The first is the issuer's most recent standardized earnings surprise, SUE_t. Positive earnings surprises are associated with improving firm financial strength, so informed bond investors should trade in the direction of earnings surprises. The second is the Piotroski $F\text{-}Score_t$ aggregate measure of the trend in the issuer's fundamental strength, which should positively correlate with BSI if investors conduct fundamentals-based analysis. The third is the six-month change in the issuer's CDS spread (ΔCDS_t), which has been found to contain credit risk information not conveyed by equity or bond prices (e.g., Lee et al., 2018; Batta et al., 2016). The fourth is the trailing six-month stock return ($Ret6M_t$). As described by Gebhardt et al. (2005), prices in equities markets impound fundamental news more quickly than do those in bond markets, so positive returns is a useful aggregate statistic for improving fundamentals. Similar to the above, we expect informed bond investors to trade in the same direction of $Ret6M_t$. To facilitate comparisons across regression coefficients and mitigate the effects of outliers, all four measures are sorted into quintile rankings on a monthly basis.[18]

[18] These are just four of any number of fundamental signals about bond value. We chose them because they are relatively easy for retail investors to interpret and are commonly used in the literature as measures of firm fundamental performance. Analyses presented in Table IA-3 of the Internet Appendix find qualitatively unchanged inferences when considering other measures, including changes in common bankruptcy prediction statistics (Altman, 1968; Ohlson, 1980; Campbell et al., 2008). In Table IA-4, we also confirm these measures predict credit rating changes over the subsequent one and six months.

Table 4
Firm performance and retail bond trading, conditional on credit ratings.

Panel A: Standardized unexpected earnings

	Dependent variable: BSI_t^{Retail}			
	(1)	(2)	(3)	(4)
SUE_t	−0.817***	−0.770***	−0.749***	−0.545***
	(−8.735)	(−8.460)	(−9.414)	(−8.018)
Controls	Yes	Yes	Yes	Yes
Rating indicators	No	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,202,198	1,202,198	1,202,198	1,202,198
R^2	0.019	0.023	0.040	0.169

Panel B: F-Score

	Dependent variable: BSI_t^{Retail}			
	(1)	(2)	(3)	(4)
$F\text{-}Score_t$	−0.479***	−0.754***	−0.831***	−0.896***
	(−4.112)	(−6.833)	(−8.083)	(−10.693)
Controls	Yes	Yes	Yes	Yes
Rating indicators	No	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,224,170	1,224,170	1,224,170	1,224,170
R^2	0.019	0.022	0.039	0.169

Panel C: Changes in CDS

	Dependent variable: BSI_t^{Retail}			
	(1)	(2)	(3)	(4)
ΔCDS_t	−2.476***	−2.512***	−2.525***	−2.184***
	(−16.255)	(−16.697)	(−16.963)	(−15.573)
Controls	Yes	Yes	Yes	Yes
Rating indicators	No	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	600,888	600,888	600,888	600,888
R^2	0.016	0.019	0.047	0.155

Panel D: Stock performance

	Dependent variable: BSI_t^{Retail}			
	(1)	(2)	(3)	(4)
$Ret6M_t$	−1.140***	−1.208***	−1.311***	−1.022***
	(−8.987)	(−9.582)	(−11.561)	(−10.349)
Controls	Yes	Yes	Yes	Yes
Rating indicators	No	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes
Bond fixed effects	No	No	No	Yes
Observations	1,222,175	1,222,175	1,222,175	1,222,175
R^2	0.019	0.023	0.040	0.169

This table examines whether retail investors select bonds based on contemporaneous firm fundamental signals. Panels A, B, C, and D proxy for firm fundamental signals available to investors using standardized unexpected earnings, Piotroski's F-Score, six-month changes in CDS spreads, and trailing six-month stock returns, respectively. All proxies are calculated as the intra-month quintile ranking of each measure and scaled to be increasing in fundamental strength. Untabulated controls include $Rating_t$, *Bond size*, and $Maturity_t$, as defined in Appendix A. Certain models also include indicators for each rating level and fixed effects for each year-month and bond, as specified in the lower rows of each column. All regressions are estimated using the full sample, subject to data availability. Clustered t-statistics, by bond and year-month, are included in parentheses. Levels of significance are presented as follows: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

We present our results in Panels A though D of Table 4. In all Panels, columns (1) through (4) examine retail investor BSI using the same progression of controls and fixed effects as in Table 3. All results find significantly negative associations between the four fundamental signals and retail BSI, indicating that retail investors trade in the opposite direction of standard predictions from fundamental analysis. The coefficients only slightly attenuate when adding bond fixed effects in columns (4), indicating that retail investors do not just "choose the wrong bonds" in general but also dynamically buy (sell) as bond fundamentals deteriorate (improve).[19]

In sum, these results indicate that retail investors trade in the opposite direction of fundamentals. This behavior is unlikely to be driven by their observing fundamentals and being contrarian, but it is instead likely an unintentional consequence of opting for higher yields.

5. Retail trading and future performance

This section examines the portfolio performance consequences of retail investors' trading. We proceed in two steps. First, we confirm that bonds that retail investors buy (sell) indeed have deteriorating (improving) credit risk, as measured based on future rating changes and defaults. These first tests investigate portfolio performance without relying on a specific pricing model (e.g., Becker and Ivashina, 2015; Choi and Kronlund, 2018). Second, we more directly examine retail investors' future risk-adjusted portfolio returns.

5.1. Future credit rating changes and defaults

We examine whether retail investors buy (sell) in advance of rating downgrades (upgrades) using the following OLS model, run separately for downgrades and upgrades:

$$RatingChg_{i,t+h} = \beta_1 \cdot BSI^{Retail}_{i,t} + Controls_{i,t} + Fixed\ Effects_{i,t} + \varepsilon_{i,t} \tag{4}$$

where BSI^{Retail}_t is measured in month t and $RatingChg_{t+h}$ is an indicator for whether a downgrade or upgrade occurs during the subsequent $h =$ one, six, or 12 months. *Controls* and *FixedEffects* are as previously defined. While a logit or probit specification can be more appropriate for binary dependent variables, we use OLS to accommodate high-frequency fixed effects and for easier interpretation of regression coefficients.

Panel A of Table 5 examines rating downgrades. Column (1) excludes rating indicators and fixed effects, and finds a significantly positive coefficient on BSI^{Retail}_t, indicating that retail investors tend to buy bonds that are more likely to be downgraded in the following month. A one-standard-deviation increase in BSI^{Retail}_t is associated with a 0.199% higher chance of being downgraded, which is economically meaningful, given the unconditional baseline monthly downgrade probability of 1.637%.[20] Column (2) adds rating level indicators, bond fixed effects, and year-month fixed effects and produces similar inferences. Because bond fixed effects restrict these analyses to within-bond variation, these findings indicate that retail investors dynamically buy (sell) when credit deteriorates (improves) during a given bond's life. Estimated effect sizes increase in columns (3) through (6) over a six-month and one-year horizon.

Panel B of Table 5 examines rating upgrades and finds symmetric results. Results in column (1) indicate that a one-standard-deviation increase in BSI is associated with a 0.153% lower chance of being upgraded in the subsequent month, which is again meaningful in relation to a baseline upgrade probability of just 1.082%. Estimated effect sizes again increase over longer measurement horizons.

Panel C of Table 5 examines future defaults, which may be more relevant to investors who hold bonds for long durations. For example, taken to the extreme, an investor who holds to maturity would only underperform if that person's bond actually defaults. Our default tests resemble model (4), except that bond fixed effects are impracticable because they absorb 100% of the variation in future defaults through maturity.[21] We instead replace bond fixed effects with two-digit SIC industry fixed effects. The dependent variable is an indicator for a default over the next three to five years or through the end of the bond's life.

As expected, Panel C of Table 5 finds that issuers of bonds with higher retail BSI are more likely to default. We find a statistically significant and positive relationship between the probability of observing defaults and retail BSI in all specifications. These relationships are also economically meaningful. For instance, column (5) indicates that a one-standard-deviation increase in retail BSI is associated with a 0.217% higher default probability, which is economically significant in relation to the baseline default rate of 2.153% in our sample.

In sum, the results in this section confirm that, by trading on $Y|RM_t$, retail investors systematically buy in advance of adverse credit events, and vice versa.

[19] Controls are untabulated for brevity but have similar coefficients as in the previous two tables. Our results are qualitatively unchanged when we also include $Y|RM_t$ as a regressor, but the coefficient magnitudes decline slightly. We do not include $Y|RM_t$ in our regressions because yield is a function of the firm's fundamental performance, so by including both in the same regression, we would likely understate the effect of either.

[20] 0.199% is calculated as the standard deviation of BSI, 61.528%, multiplied by the regression coefficient of 0.323. The baseline annual downgrade probability is 13.9% in our sample, which resembles the 11.7% probability reported by S&P for 1982 through 2019 (Kraemer et al., 2019).

[21] A bond either does or does not default before maturity, so fixed effects subsume all of the variation in the indicator $Default^{Maturity}_t$, as evidenced by the 0.000 residual standard deviation in Table 1 (deHaan, 2021).

Table 5
Retail bond trading and future credit events.

Panel A: Ratings downgrades

	Dependent variable:					
	$Downgrade_t^{1mo.}$		$Downgrade_t^{6mo.}$		$Downgrade_t^{12mo.}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BSI_t^{Retail}	0.323***	0.114***	1.645***	0.604***	2.832***	1.009***
	(6.114)	(2.934)	(12.195)	(6.854)	(13.959)	(8.607)
$Maturity_t$	−0.011***	−0.135*	−0.034***	−0.707**	−0.050**	−1.287**
	(−2.660)	(−1.934)	(−2.668)	(−2.072)	(−2.544)	(−2.231)
Bond size	−0.423***		−1.224***		−1.334***	
	(−6.306)		(−8.812)		(−7.266)	
$Rating_t$	0.093***		0.328***		0.351***	
	(4.248)		(6.027)		(4.853)	
Rating indicators	No	Yes	No	Yes	No	Yes
Month fixed effects	No	Yes	No	Yes	No	Yes
Bond fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,393,395	1,393,395	1,254,011	1,254,011	1,107,838	1,107,838
R^2	0.003	0.071	0.006	0.213	0.005	0.324

Panel B: Ratings upgrades

	Dependent variable:					
	$Upgrade_t^{1mo.}$		$Upgrade_t^{6mo.}$		$Upgrade_t^{12mo.}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BSI_t^{Retail}	−0.248***	−0.092***	−1.340***	−0.494***	−2.316***	−0.749***
	(−9.766)	(−3.964)	(−16.846)	(−8.084)	(−18.634)	(−8.404)
$Maturity_t$	−0.004*	0.044	−0.004	0.207	−0.005	0.418
	(−1.887)	(1.256)	(−0.470)	(1.156)	(−0.386)	(1.222)
Bond size	−0.049**		−0.103		−0.128	
	(−2.180)		(−1.373)		(−1.042)	
$Rating_t$	0.180***		0.962***		1.695***	
	(12.172)		(22.226)		(28.075)	
Rating indicators	No	Yes	No	Yes	No	Yes
Month fixed effects	No	Yes	No	Yes	No	Yes
Bond fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,393,395	1,393,395	1,254,011	1,254,011	1,107,838	1,107,838
R^2	0.004	0.042	0.022	0.171	0.038	0.298

Panel C: Defaults

	Dependent variable:					
	$Default_t^{3Y}$		$Default_t^{5Y}$		$Default_t^{Maturity}$	
	(1)	(2)	(3)	(4)	(5)	(6)
BSI_t^{Retail}	0.174***	0.258***	0.282***	0.441***	0.352***	0.559***
	(2.802)	(4.690)	(3.717)	(6.470)	(4.174)	(7.374)
$Maturity_t$	−0.004	0.013**	0.010	0.033***	0.058***	0.085***
	(−0.726)	(2.524)	(1.352)	(4.466)	(4.786)	(6.718)
Bond size	−0.128***	0.076**	−0.159***	0.152***	−0.236***	0.208***
	(−3.217)	(2.066)	(−3.144)	(3.086)	(−3.820)	(3.223)
$Rating_t$	0.777***		1.000***		1.160***	
	(21.646)		(21.721)		(21.248)	
Rating indicators	No	Yes	No	Yes	No	Yes
Month fixed effects	No	Yes	No	Yes	No	Yes
Industry fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,422,523	1,422,523	1,422,523	1,422,523	1,422,523	1,422,523
R^2	0.054	0.160	0.064	0.161	0.071	0.165

This table examines the relation between retail BSI on the probability of future credit rating changes and defaults (in percent). Panel A (Panel B) presents regressions of retail BSI on the probability of a bond experiencing future credit rating downgrade (upgrade) over the subsequent one, six, and twelve months. Panel C presents regressions of retail BSI on the probability of a bond defaulting over subsequent three years, five years, and the remaining bond life. Untabulated controls include $Rating_t$, *Bond size*, and $Maturity_t$, as defined in Appendix A. Certain models include indicators for each rating level and fixed effects for each year-month and bond or industry, as specified in the lower rows of each column. All regressions are estimated using the full sample, subject to data availability. Clustered t-statistics, by bond and year-month, are included in parentheses. Levels of significance are presented as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

5.2. Risk-adjusted portfolio performance

This section examines the portfolio performance consequences of retail investors' trading decisions. If bonds traded by retail investors are perfectly priced, then retail investors' portfolios should not underperform a diversified strategy on a risk-adjusted basis, at least when excluding the effects of transaction costs. Said differently, retail investors' portfolios would have high risk but not incur negative alpha if they are compensated for the additional risk taken.

Research provides several compelling reasons why bonds traded by retail investors are not perfectly priced, in which case retail investors' portfolios likely underperform. First, research finds that bond prices are slow to adjust to observable fundamental signals (e.g., Lee et al., 2018; Correia et al., 2012; Gebhardt et al., 2005), and our tests indicate that retail bond investors trade in the opposite direction of those signals. Second, we find that retail investors buy in advance of future downgrades and defaults, which indicate negative future performance. For example, studies, such as the work of Choi and Kim (2018) and Becker and Ivashina (2015), use future downgrades and defaults as proxies for negative future performance that do not rely on asset pricing models. Third, research finds that bonds in the highest quintiles of $Y|RM_t$ are overvalued because of reach-for-yield trading by mutual funds and insurance companies (e.g., Choi and Kim, 2018; Chen and Choi, 2021). Finally, bond mispricing can temporarily persist, due to the high costs of trading and shorting, known as limits to arbitrage (e.g., Gromb and Vayanos, 2010; Shleifer and Vishny, 1997; Edwards et al., 2007; O'Hara and Zhou, 2021).[22]

Our first tests of portfolio performance resemble those of Choi and Kronlund (2018) and Becker and Ivashina (2015), who examine the performance of bond trades by mutual funds and insurance companies. Specifically, we contrast the monthly alphas of equal-weighted portfolios of bonds that retail investors are most likely to buy (quintile 5) versus sell (quintile 1). We estimate alphas, conditional on the five factors proposed by Fama and French (1993), which includes three stock market factors and two bond market factors, supplemented by the Carhart (1997) momentum factor.[23]

Table 6 reports average alphas and factor loading estimates. The focus of these tests is on the high-low portfolio difference reported in the lowest row, which is the difference between the bonds that retail investors are most buying (quintile 5) versus selling (quintile 1). The high-low difference in column (1) is −51.4 basis points (t-statistic = −4.763), indicating that the bonds that retail investors purchase underperform by −51.4 bps in month $t + 1$, relative to the bonds they sell.[24] Fig. 3 plots cumulative high-low portfolio excess returns over time and confirms that underperformance is not concentrated in any particular period.[25] We also see that cumulative excess returns for value-weighted portfolios are smaller than when using equal-weighted portfolios, which we explore further in Section 6.2.

Our second set of tests examines longer-term returns predictability using a Fama-MacBeth regression framework.[26] Results in Column (1) of Table 7 control only for rating and maturity and show that a one-standard-deviation increase

Table 6
Retail bond trading and future portfolio returns.

	Factor-Adjusted Alphas and Factor Loadings						
	ALPHA	MKTRF	SMB	HML	UMD	DFR	TERM
1 (Low)	0.555	0.131	0.014	−0.096	−0.119	0.324	0.065
	(2.786)	(4.490)	(0.315)	(-2.332)	(-5.018)	(5.721)	(0.894)
2	0.280	0.073	−0.001	−0.097	−0.094	0.236	0.067
	(1.661)	(2.950)	(-0.024)	(-2.781)	(-4.685)	(4.920)	(1.089)
3	0.161	0.111	0.013	−0.096	−0.061	0.265	0.085
	(0.925)	(4.367)	(0.336)	(-2.657)	(-2.964)	(5.348)	(1.346)
4	0.150	0.062	−0.004	−0.102	−0.073	0.249	0.090
	(0.978)	(2.758)	(-0.122)	(-3.210)	(-3.992)	(5.684)	(1.615)
5 (High)	0.041	0.092	−0.014	−0.092	−0.063	0.204	0.080
	(0.236)	(3.642)	(-0.360)	(-2.579)	(-3.064)	(4.144)	(1.264)
High−Low	−0.514	−0.039	−0.028	0.004	0.056	−0.120	0.015
	(-4.763)	(-2.447)	(-1.159)	(0.169)	(4.348)	(-3.914)	(0.376)

This table reports the relation between retail BSI and future bond returns. The columns report factor loadings and abnormal monthly returns from the resulting calendar-time equal-weighted trading strategy. We estimate abnormal returns (ALPHA) using the Fama and French (1993) five-factor model for bonds with a market factor (MKTRF), a size factor (SMB), a value factor (HML), a term factor (TERM), a default spread factor (DFR), augmented with the momentum factor (UMD). All regressions are estimated using the full sample, subject to data availability. T-statistics in parentheses are based on regressions.

[22] Section 6.2 further discusses market efficiency and cross-sectional tests thereof.

[23] Our method for evaluating trading performance also resembles the tests of Boehmer et al. (2021), who examine retail investors in equities markets.

[24] Similar to other studies of bond portfolio alphas (e.g., Bai et al., 2019; Bali et al., 2021), the estimated alphas in all five quintiles are non-negative. This highlights the limitations in commonly used asset pricing models for corporate bonds, which may bias some portfolio alphas upwards, potentially due to capped downsides for bonds (relative to equities). While this bias is less likely to be present in our estimate of interest (the high-low portfolio), for robustness, we also examine performance using multiple methodologies, including examining outcomes such as downgrades and defaults that do not rely on an asset pricing model.

[25] The excess returns (alphas) are defined as returns that cannot be explained by the asset pricing factors in Table 6. Specifically, we estimate time-series regressions of long-short portfolio returns on factors, and excess returns (alphas) are computed as the regression intercept plus the regression residuals.

[26] Choi and Kronlund (2018) and Becker and Ivashina (2015) limit their performance analyses to just one month ahead, and Boehmer et al. (2021) examine up to three months ahead. We examine returns up to two years ahead to be thorough and because the retail investors tend to hold bonds for an estimated average of 1.36 years.

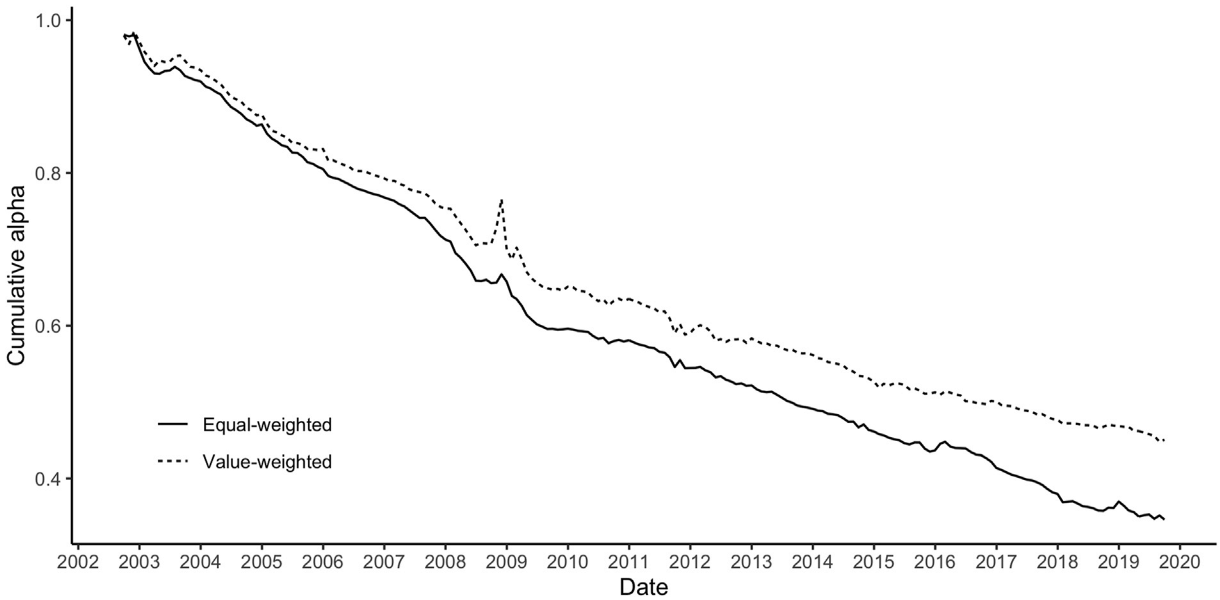


Fig. 3. Cumulative alpha of retail buy-sell imbalance portfolios. This figure plots the cumulative alpha of a portfolio strategy that is long (short) the top (bottom) quintile of bonds based on retail investor BSI. The solid line plots equal-weighted portfolios, and the dashed line plots value-weighted portfolios. The alphas are adjusted using full-sample time-series regressions with the Fama and French (1993) five-factor model for bonds augmented with the momentum factor.

in BSI equates to a 0.235% $\times$ 0.615 $\approx$ 14.5 bps lower monthly future return. Results in column (3) and (5) find that the magnitude of BSI's predictive power increases slightly over a one- and two-year horizon and statistical significance decreases. Columns (2), (4), and (6) show similar results when controlling for other variables that have been proposed to explain bond returns.

Table 7
Retail bond trading and future returns: Cross-sectional regressions.

	Dependent variable:					
	Ret_{t+1}		Ret_{t+12}		Ret_{t+24}	
	(1)	(2)	(3)	(4)	(5)	(6)
BSI_t^{Retail}	−0.235***	−0.237***	−0.334***	−0.286***	−0.345**	−0.314**
	(−8.074)	(−7.012)	(−2.626)	(−2.623)	(−2.251)	(−2.362)
$Rating_t$	0.046*	0.038**	0.443**	0.338**	0.809***	0.623***
	(1.728)	(1.969)	(2.040)	(2.333)	(3.116)	(3.462)
$Maturity_t$	0.015**	0.015**	0.165***	0.166***	0.280***	0.286***
	(2.451)	(2.332)	(2.807)	(2.750)	(3.305)	(3.357)
Bond size		−0.013		−0.030		0.166
		(−0.613)		(−0.246)		(0.701)
$Volume_t$		−0.012*		−0.056		−0.191***
		(−1.680)		(−1.457)		(−3.086)
Mkt. $cap._t$		0.005		−0.031		−0.111
		(0.468)		(−0.281)		(−0.754)
Book-to-$market_t$		0.017		0.188**		0.151
		(1.187)		(2.193)		(1.436)
Asset $growth_t$		−0.003**		−0.026**		−0.053***
		(−2.153)		(−2.227)		(−2.865)
Return on $assets_t$		0.027*		−0.005		−0.015
		(1.716)		(−0.037)		(−0.082)
$Ret6M_t$		0.002		0.006		−0.014
		(1.315)		(0.419)		(−1.083)
Earnings $month_t$		0.034		−0.184		−0.356**
		(1.499)		(−1.353)		(−2.174)
Constant	0.063	0.334	1.025	2.888**	2.473	5.145***
	(0.446)	(1.275)	(0.807)	(2.028)	(1.466)	(2.590)
Observations	1,324,541	1,076,989	1,299,023	1,057,099	1,213,266	987,471
R^2	0.180	0.240	0.420	0.491	0.400	0.459

This table reports the results of Fama-Macbeth cross-sectional regressions of one, twelve, and twenty-four month-ahead corporate bond returns on retail BSI. All variables are as described in Appendix A, and all regressions are estimated using the full sample, subject to data availability. Newey-West adjusted t -statistics are shown in parentheses. Levels of significance are presented as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

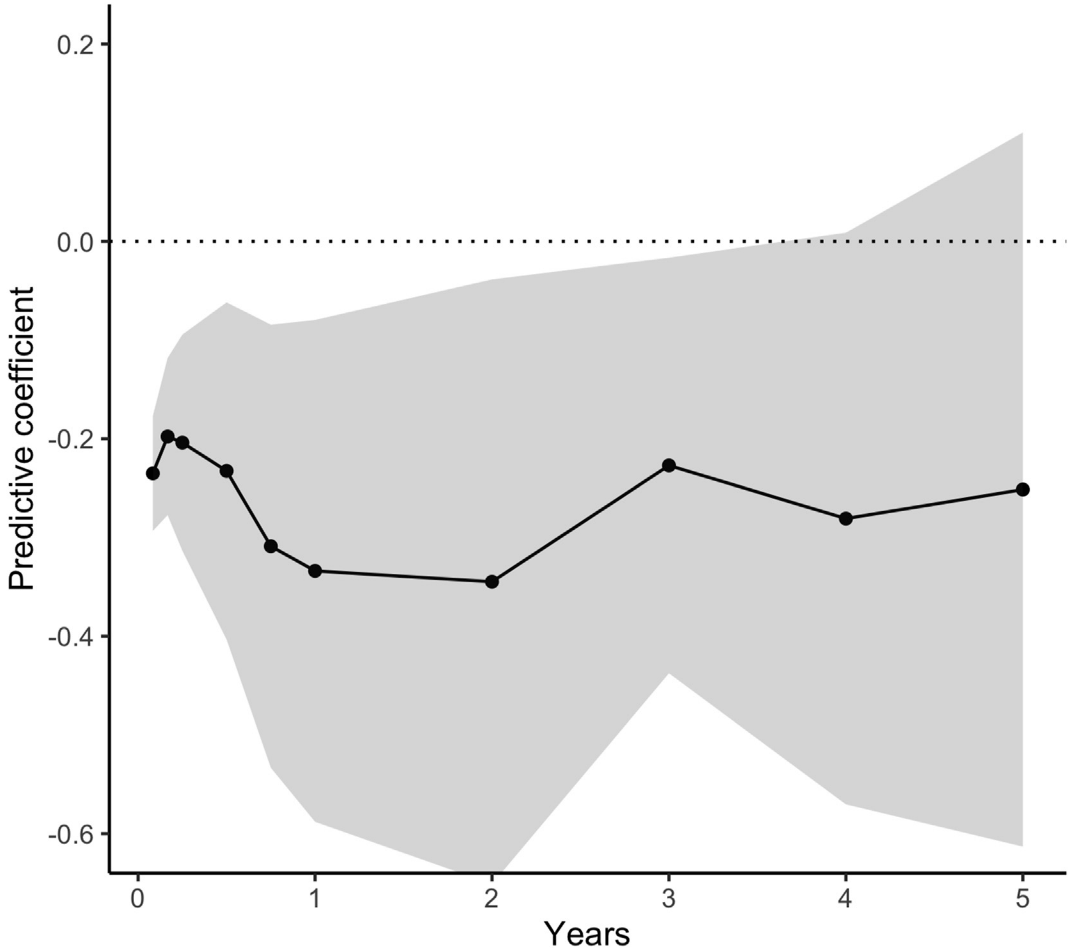


Fig. 4. Retail buy-sell imbalances and long horizon bond returns. In this figure, we extend Table 7 to plot the predictive coefficient estimates of BSI_t^{Retail} on corporate bond returns at horizons out to five years. The line plots return predicting coefficients, and the shaded area represents 95% confidence intervals. The regression specification follows column (1) in Table 7.

Contrasting the BSI_t^{Retail} coefficients over various horizons in Table 7 provides two insights. The first is that most of retail BSI's return predictability is concentrated within one month, indicating that the prices adjust relatively quickly. Second, there is no evidence of returns reversals, which indicates that the retail investors' one-month-ahead underperformance persists for long holding periods. Fig. 4 further examines returns for up to five years, which exceeds the median remaining maturity of bonds in our sample, and again finds no evidence of reversals (although confidence intervals naturally continue widening).

Overall our findings in this section indicate that, on average, retail investors’ trading underperform a broadly diversified strategy. This indicates that, for instance, retail investors could collectively improve their bond portfolio returns by investing in low-fee bond index funds. We explore this possibility in Section 6.3.

6. Empirical extensions

6.1. Alternative trade size cutoffs and heterogeneous effects

The analyses in this section examine trade sizes of below \$50,000, from \$50,000 to \$100,000, and \$100,000 or more and serve two purposes. First, these analyses provide more granularity on how trading varies with investor sophistication, given that the least sophisticated retail investors likely make trades below \$50,000 (e.g., Cuny et al., 2021), while most trades above \$100,000 are from institutions. Second, using a \$50,000 threshold likely further isolates retail investors from small institutions.[27]

[27] As mentioned, unsophisticated institutions may be prone to the same ill-informed trading as retail investors. Thus, while the focus of our paper is on retail investors, our findings may also speak to smaller and less sophisticated institutions.

Table 8
Heterogeneous effects across different trade size cutoffs.

Panel A: Determinants of BSI by trade size

	Dependent variable:		
	BSI_t^{0-50K}	$BSI_t^{50-100K}$	BSI_t^{100K+}
	(1)	(2)	(3)
IG_t	13.820***	6.494***	−0.391
	(7.702)	(4.361)	(−0.429)
$Y\|RM_t$	4.497***	2.535***	−3.301***
	(17.414)	(15.417)	(−18.480)
SUE_t	−0.912***	−0.496***	0.204***
	(−7.694)	(−4.938)	(2.957)
Controls	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes
Observations	1,144,789	1,144,789	1,144,789
R^2	0.173	0.084	0.025

Panel B: Future credit events by BSI trade size

	Dependent variable:		
	$Downgrade_t^{6mo.}$	$Upgrade_t^{6mo.}$	$Default^{Maturity}$
	(1)	(2)	(3)
BSI_t^{0-50K}	0.909***	−0.690***	0.325***
	(14.364)	(−15.000)	(7.135)
$BSI_t^{50-100K}$	0.335***	−0.204***	0.151***
	(8.453)	(−8.213)	(6.527)
BSI_t^{100K+}	−0.296***	0.064***	−0.059***
	(−9.615)	(3.017)	(−4.207)
Controls	Yes	Yes	Yes
Rating indicators	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	1,254,011	1,254,011	1,422,523
R^2	0.045	0.039	0.165

Panel C: Portfolio alphas by BSI trade size

	(1)	(2)	(3)
	BSI_t^{0-50K}	$BSI_t^{50-100K}$	BSI_t^{100K+}
Q1 (Low)	0.536	0.335	0.209
	(2.715)	(1.848)	(1.199)
Q5 (High)	0.054	0.120	0.204
	(0.306)	(0.732)	(1.110)
Diff. (High - Low)	−0.482	−0.214	−0.005
	(−4.566)	(−3.172)	(−0.106)

This table examines alternative BSI cutoffs for our primary results. Panel A presents regressions of various determinants of BSI by transaction size. Panel B examines the relation between BSI by transaction size and future credit events. Panel C presents the average factor-adjusted alphas, using the Fama and French (1993) five-factor model for bonds augmented with the momentum factor, of portfolios sorted based on BSI by various transaction sizes. All buy-sell imbalance measures have been standardized to have a mean of zero and standard deviation of one. Untabulated controls include *Rating*$_t$, *Bond size*, and *Maturity*$_t$, as defined in Appendix A. All regressions are estimated using the full sample, subject to data availability. Clustered robust t-statistics (Panels A and B) by bond and year-month and regression t-statistics (Panel C) are included in parentheses. Levels of significance are presented as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

Panel A of Table 8 re-examines the determinants of BSI across transaction sizes. For brevity, we focus on three representative determinants from Table 1 through 4 and only tabulate models with complete fixed effects. We examine investors' trading on credit ratings by testing for differences in BSI around the investment-grade threshold (variable IG_t), trading on yield-within-rating using $Y|RM_t$, and trading on fundamental information based on SUE_t. We standardize BSI within each size group to facilitate direct comparisons.

A clear pattern emerges in Panel A — there is an ordinal relationship between transaction size and each of our variables of interest. The IG_t coefficient for the smaller retail trades (column 1) has a greater magnitude than for larger retail trades (column 2) and is statistically insignificant for institutional trades (column 3). These results indicate that smaller retail investors rely mostly on ratings while, in aggregate, institutional investors do not.[28] Sorting on $Y|RM_t$ and trading against SUE_t are most pronounced among smaller retail trades, while institutional trades display the opposite behaviors.

Panel B of Table 8 re-examines BSI and future credit events. Estimated effects are again most pronounced for smaller retail trades, relative to larger retail trades, and signs reverse for institutional trades. Specifically, row 1 of column (1) indicates that BSI for small retail trades most strongly predicts downgrades, while BSI for large retail trades less strongly predicts downgrades (row 2), and institutions trade in the opposite direction of downgrades (row 3). Columns (2) and (3) provide inferentially similar results for upgrades and defaults.

Panel C of Table 8 re-examines BSI and factor-adjusted long-short alphas. Column (1) finds that smaller retail investors underperform by −48.2 bps per month, and column (2) finds that larger retail investors underperform by −21.4 bps per month. Column (3) finds that institutional investors earn insignificant alpha.

Collectively, these results indicate that trading on yield-within-rating and the negative consequences thereof are concentrated among smaller retail investors. In contrast, institutional investors tend to demonstrate the opposite behavior.

6.2. Portfolio performance and market efficiency

As discussed in Section 5.2, if bonds are perfectly priced, then retail investors' trades should be unassociated with future risk-adjusted returns, and thus their portfolios should not underperform. Our finding that retail investors do underperform indicates that bonds in the extreme quintiles of BSI_t^{Retail} are not perfectly priced. This section investigates whether retail investors' underperform to a lesser degree when trading bonds that are more efficiently priced.

Our first analysis repeats the portfolio alpha tests from Table 6 but using value-weighted instead of equal-weighted portfolios. Extensive research indicates that larger bonds, which are generally issued by larger firms, have more efficient pricing (e.g., Fama, 1998). As expected, Panel A of Table 9 shows that high-low portfolio differences are −38.3 bps on a value-weighted basis, as compared to −51.4 bps on an equal-weighted basis in Table 6. Still, underperformance of −38.3 bps remains economically meaningful in relation to the unconditional value-weighted average monthly bond return of 51.2 bps over our sample period.[29]

We next expand the Fama-MacBeth regressions from Table 7 to examine two cross-sectional determinants of the extent of bond mispricing. The first determinant is bond issue size. The second is whether the bond issuer has CDS coverage. We expect that bonds with CDS coverage should be more efficiently priced because their issuers tend to be larger and have stronger information environments and because of information spillovers from the CDS market (e.g., Batta et al., 2016; Lee et al., 2018).

Columns (1) through (3) of Panel B of Table 9 re-estimate our Fama-MacBeth regressions while interacting BSI_t with an indicator variable for bonds in the top tercile of size in month t($Large\ size_t$). Column (1) indicates that a one-unit increase in BSI is associated with a −34.3 bps lower returns in the following month. The difference for large bonds is a statistically significant 33.2 bps, indicating that the net association between BSI_t is (−34.3 + 33.2 =) just −1.1 bps. Untabulated results show that the net −1.1 bps is statistically insignificant, indicating that retail investors do not underperform when trading in the largest bonds. Columns (3) and (5) provide inferentially similar results over 12- and 24-month horizons. The even-numbered columns interact BSI_t^{Retail} with an indicator for the roughly 36% of bonds with CDS coverage ($HasCDS_t$) and again offer similar results.

Overall these results are consistent with the idea that retail investors' underperformance is mitigated for more efficiently priced bonds, highlighting the role of market inefficiencies in their portfolio underperformance.

6.3. Could retail investors easily do better?

The simplest alternative strategy for retail bond investors would be to invest in low-cost index mutual funds, which earn zero alpha. Investing in index funds should permit retail investors to not only avoid the underperformance observed in their buy-sell portfolios (estimated at 38.3/2 ≈ 19 bps per trade, based on the value-weighted results in Table 9) but also largely avoid the high transaction costs of retail bond trades (estimated at 66 bps per trade).[30]

Back-of-the-envelope calculations can help contextualize retail investors' potential savings from switching to index funds. Retail trading totaled $150.7 billion in the last 12 months of our sample, indicating that underperformance was −19 bps × $150.7 billion ≈ -$286 million in terms of alpha and −0.66% × $150.7 ≈ -$995 million in transaction costs, for a total of approximately -$1.281 billion. Vanguard offered a variety of index bond funds during the same period with average expense

[28] The insignificant IG_t coefficient does not imply that no institutional investors rely on credit ratings but rather that their ratings-based trades offset one another. Research shows that some institutions, for example, those with regulatory capital requirements, do heavily use ratings in portfolio decisions. However, many other institutions do not have incentives to trade on ratings, and some institutions choose to specialize in sub-investment grade debt. Given bond market-makers cannot hold significant risk for long periods (e.g., Goldstein and Hotchkiss, 2020), in the aggregate, these institutions' heterogeneous trading on ratings offset each another.

[29] We focus on equal-weighted portfolios in our main specifications to be consistent with closely related prior studies (e.g., Becker and Ivashina, 2015; Choi and Kim, 2018; Cornaggia et al., 2018). In Table IA-5 of the Internet Appendix, we confirm all other inferences derived from analyses on portfolio alphas are qualitatively unchanged when using value-weighted portfolios, although the economic magnitudes are mitigated.

[30] As detailed in Appendix B.2, 66 bps is based on the method of Hong and Warga (2000) and is very close to the 62 bps cost of retail trades reported by Bessembinder et al. (2020).

Table 9
Retail bond trading and future returns: Exploring the role of market efficiency.

Panel A: Value-weighted portfolio returns

	Factor-Adjusted Alphas and Factor Loadings						
	ALPHA	MKTRF	SMB	HML	UMD	DFR	TERM
1 (Low)	0.498	0.070	0.021	−0.107	−0.132	0.365	0.010
	(1.910)	(1.838)	(0.368)	(-1.987)	(-4.273)	(4.926)	(0.111)
2	0.302	0.055	−0.014	−0.097	−0.093	0.281	0.032
	(1.714)	(2.136)	(-0.368)	(-2.662)	(-4.442)	(5.599)	(0.493)
3	0.215	0.073	0.004	−0.101	−0.077	0.255	0.052
	(1.143)	(2.647)	(0.102)	(-2.613)	(-3.432)	(4.769)	(0.762)
4	0.172	0.055	−0.023	−0.116	−0.069	0.270	0.082
	(1.046)	(2.301)	(-0.644)	(-3.398)	(-3.509)	(5.767)	(1.372)
5 (High)	0.116	0.083	−0.024	−0.107	−0.066	0.242	0.090
	(0.629)	(3.079)	(-0.598)	(-2.817)	(-3.010)	(4.629)	(1.345)
High−Low	−0.383	0.013	−0.046	0.000	0.067	−0.124	0.079
	(-2.515)	(0.563)	(-1.353)	(0.008)	(3.696)	(-2.864)	(1.433)

Panel B: Fama-Macbeth regressions with interactions

	Dependent variable:					
	Ret_{t+1}		Ret_{t+12}		Ret_{t+24}	
	(1)	(2)	(3)	(4)	(5)	(6)
BSI_t^{Retail}	−0.343***	−0.300***	−0.443***	−0.470***	−0.466***	−0.512***
	(−8.076)	(−7.119)	(−3.961)	(−3.879)	(−3.591)	(−3.569)
$BSI_t^{Retail} \times$ Large $Size_t$	0.332***		0.500***		0.459**	
	(9.266)		(2.756)		(2.097)	
$BSI_t^{Retail} \times$ Has CDS_t		0.136***		0.393***		0.423***
		(4.857)		(5.016)		(5.729)
Large $size_t$	−0.003		0.128*		−0.139	
	(−0.090)		(1.711)		(−0.906)	
Has CDS_t		−0.036***		−0.142		−0.267**
		(−3.584)		(−1.465)		(−2.097)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,076,989	1,076,989	1,057,099	1,057,099	987,471	987,471
R^2	0.242	0.241	0.492	0.491	0.460	0.460

This table examines the role of market efficiency on the predictability of retail BSI on future returns. Panel A re-examines Table 6 on a value-weighted basis. Panel B re-examines Table 7 by interacting BSI_t^{Retail} with indicator variables associated with more efficiently priced securities. The set of control variables used is identical to the full set of controls shown Table 7. All variables are as described in Appendix A, and all regressions are estimated using the full sample, subject to data availability. Panel A presents t-statistics in parentheses based on regressions, and Panel B presents Newey-West adjusted t-statistics in parentheses. Levels of significance are presented as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

ratios of 0.12%.[31] Using the methodology of He et al. (2022), we estimate that the average holdings by retail investors is $206 billion during the last year of our sample. Therefore investing in index funds would earn zero alpha and incur transaction costs of −0.12% × $206 billion ≈ -$247 million, for one-year savings of over $1 billion.

For a retail investor insistent upon trading individual bonds, potential alternative strategies include trading on any of the four fundamental signals that we examine in Section 4.2.2. We investigate the performance of fundamentals-based strategies by examining whether the strategies avoid future downgrades and defaults (similar to the analyses in Table 5) and mitigate portfolio underperformance (similar to Table 6).

Panel A of Table 10 investigates rating changes over the following six months. Column (1) investigates actual retail trading and shows that bonds in the lowest quintile of retail BSI have an average downgrade of 0.015 notches while bonds in the highest quintile have average downgrades of 0.080. Thus, consistent with Table 5, retail investors tend to buy bonds that are more likely to be downgraded, and vice versa. Column (2) shows that bonds in the lowest quintile of SUE_t have an average downgrade of 0.179 notches while those in the highest quintile have an average downgrade of 0.017 notches, confirming that firms with more positive SUE_t are less likely to be downgraded. Column (3) shows that the difference-in-differences between (2) and (1) is highly significant, indicating that trading on SUE_t would produce 0.226 fewer notches of downgrades over the next six months. Columns (4) through (9) provide similar results for $F\text{-}Score_t$, ΔCDS_t, and $Ret6M_t$.

Results in Panel B examine future defaults. The difference-in-differences tests are all positive and statistically significant, indicating that trading on SUE_t, $F\text{-}Score_t$, ΔCDS_t, or $Ret6M_t$ would also help avoid defaults.

[31] For example, Vanguard offered funds VFIDX (intermediate-term investment-grade bonds), VWETX (long-term investment-grade bonds), and VWEAX (high-yield bonds) during our entire sample period. The average annual expense ratios were 0.13% over our full sample period or 0.12% in the last year of our sample.

Table 10
Observed retail trading vs. alternative low-cost trading strategies.

Panel A: Future ratings change (more positive value indicates larger downgrade)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	BSI_t^{Retail}	SUE_t	Diff.	$F\text{-}Score_t$	Diff.	ΔCDS_t	Diff.	$Ret6M_t$	Diff.
			(1)–(2)		(1)–(4)		(1)–(6)		(1)–(8)
Q1 (Low)	0.015	0.179	−0.163	0.142	−0.127	0.223	−0.208	0.199	−0.184
	(1.895)	(12.039)	(-16.842)	(10.385)	(-14.800)	(13.317)	(-17.202)	(14.781)	(-21.317)
Q5 (High)	0.080	0.017	0.062	−0.028	0.108	−0.035	0.115	−0.042	0.121
	(13.812)	(2.307)	(9.029)	(-6.399)	(18.886)	(-4.197)	(14.499)	(-7.374)	(20.288)
Diff.-in-Diff.			−0.226		−0.234		−0.323		−0.305
			(-15.626)		(-18.509)		(-18.979)		(-22.951)

Panel B: Future defaults (more positive value indicates higher probability of default)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	BSI_t^{Retail}	SUE_t	Diff.	$F\text{-}Score_t$	Diff.	ΔCDS_t	Diff.	$Ret6M_t$	Diff.
			(1)–(2)		(1)–(4)		(1)–(6)		(1)–(8)
Q1 (Low)	0.023	0.043	−0.020	0.030	−0.007	0.058	−0.035	0.048	−0.025
	(16.502)	(20.548)	(-16.830)	(18.904)	(-7.758)	(16.365)	(-14.173)	(19.972)	(-16.887)
Q5 (High)	0.030	0.028	0.002	0.014	0.016	0.030	0.000	0.016	0.014
	(22.618)	(19.828)	(1.862)	(22.236)	(14.880)	(15.161)	(0.052)	(15.007)	(13.882)
Diff.-in-Diff.			−0.022		−0.023		−0.035		−0.039
			(-11.700)		(-13.844)		(-10.450)		(-17.368)

Panel C: Factor-adjusted alphas (more positive value indicates higher abnormal return)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	BSI_t^{Retail}	SUE_t	Diff.	$F\text{-}Score_t$	Diff.	ΔCDS_t	Diff.	$Ret6M_t$	Diff.
			(1)–(2)		(1)–(4)		(1)–(6)		(1)–(8)
Q1 (Low)	0.554	0.127	0.426	0.203	0.351	0.196	0.358	0.193	0.360
	(2.776)	(0.603)	(3.291)	(1.193)	(3.292)	(0.738)	(2.093)	(0.857)	(2.684)
Q5 (High)	0.040	0.301	−0.261	0.267	−0.227	0.165	−0.125	0.299	−0.258
	(0.232)	(1.626)	(-3.394)	(1.554)	(-3.600)	(0.798)	(-1.384)	(1.718)	(-3.344)
Diff.-in-Diff.			0.688		0.579		0.483		0.619
			(3.837)		(3.977)		(2.227)		(3.167)

This table examines whether retail bond investors could improve their performance by using alternative low-cost trading strategies. Panel A presents the average six-month ahead future ratings changes of portfolios sorted based on observed retail BSI (column 1), alternative portfolio strategies (columns 2, 4, 6, 8), and their differences (columns 3, 5, 7, 9). Panel B presents similar analyses for future bond defaults. Panel C presents similar analyses for factor-adjusted alphas, using the Fama and French (1993) five-factor model for bonds augmented with the momentum factor. Each portfolio strategy is based on an equal-weighted quintile portfolio created at the end of month *t* based on information available at that time. SUE_t, $F\text{-}Score_t$, ΔCDS_t, and $Ret6M_t$ indicate investment strategies based on standardized unexpected earnings, Piotroski's F-Score, six-month changes in CDS spreads, and trailing six-month stock returns, respectively. All proxies are scaled to be increasing in fundamental strength. All calculations are based on the full sample observations, subject to data availability. T-statistics are presented in parentheses based on a two-sided *t*-test, and regression t-statistics for the portfolio alphas (Panel C).

Finally, Panel C examines alphas of equal-weighted portfolios based on retail BSI and alternative fundamental strategies. The difference-in-differences portfolios are all significant, indicating that trading on fundamentals would outperform retail investors' current strategies.

In sum, the results in this section indicate that retail investors could materially improve their trading performance following several simple alternative strategies.

6.4. Disagreements in credit ratings

A limitation of our approach is that we cannot observe which agency's credit ratings each retail investor uses. Our analyses use the credit ratings in the WRDS Bond Returns file, which primarily uses S&P ratings. This choice adds measurement error into our analyses because some retail investors likely trade on Moody's or Fitch ratings, which often differ from S&P ratings.

We assess the implications of rating disagreements on our inferences through two analyses. First, in Table 11, we reperform our main analyses in Tables 2 and 3 using credit ratings constructed using: only S&P ratings, only Moody's ratings, the lowest and highest among them, and broad ratings (which agree across S&P and Moody's approximately 75% in our sample). Our inferences are largely unchanged. Second, in Table IA-6 of the Internet Appendix, we replicate our analyses presented in Tables 2 and 3 for instances of split ratings (i.e., S&P and Moody's disagree) and non-split ratings. Consistent with split ratings being a source of noise, our results are somewhat weaker (but still significant) in cases of rating disagreements.

Table 11
Robustness analyses: Alternative rating assignment.

Panel A: Credit ratings and retail trading imbalances

	Dependent variable: BSI_t^{Retail}				
	S&P	Mdys	Max	Min	Broad
	(1)	(2)	(3)	(4)	(5)
IG_t	17.094***	15.239***	17.787***	14.625***	17.002***
	(19.243)	(17.609)	(19.856)	(17.999)	(19.637)
Controls	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	Yes	Yes	No	Yes
Bond fixed effects	No	No	Yes	No	No
Observations	1,345,586	1,370,332	1,413,773	1,410,774	1,419,114
R^2	0.136	0.154	0.153	0.153	0.156

Panel B: Bond pricing, conditional on credit rating, and retail trading imbalances

	Dependent variable: BSI_t^{Retail}				
	S&P	Mdys	Max	Min	Broad
	(1)	(2)	(3)	(4)	(5)
$Y\|RM_t$	1.637***	1.917***	1.719***	1.705***	1.807***
	(13.219)	(15.467)	(13.627)	(13.863)	(13.568)
$Yield_t^{Rank}$	0.717**	0.420	0.425	0.527*	0.383
	(2.383)	(1.430)	(1.455)	(1.808)	(1.310)
Controls	Yes	Yes	Yes	Yes	Yes
Rating indicators	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,301,528	1,316,267	1,354,681	1,354,681	1,358,537
R^2	0.139	0.147	0.146	0.146	0.147

This table provides robustness analyses for our ratings-based analyses for different definitions of ratings. Panel A (Panel B) replicates the primary results presented in Table 2 (Table 3) for each subsample indicated by the column headers. Columns (1) through (2) present these analyses using *only* S&P and Moody's, respectively. Columns (3) and (4) use the highest and lowest rating of the two, respectively. Column (5) presents "Broad" ratings, which is the broad/round rating assignment (e.g., AA, A, BBB) in the WRDS Bond Returns database. All controls and specifications are as described in Tables 2 and 3. All regressions are estimated using the full sample, subject to data availability. Clustered t-statistics, by bond and year-month, are included in parentheses. Levels of significance are presented as follows: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

7. Alternative or complementary explanations

Our findings indicate that retail bond investors simultaneously prefer bonds with safer credit ratings but also prefer the riskiest (i.e., highest yielding) bonds within each credit rating level, leading to the downward-sloping seesaw pattern in Fig. 2. A simple explanation for these behaviors is that retail investors select bonds by first screening on a rating level and then sorting on yield, which is a selection method that is available on common trading platforms. Observing these behaviors both across bonds and within the life of individual bonds (i.e., when including bond fixed effects) rules out many alternative explanations. This section further investigates plausible alternative or complementary explanations for retail investors' buying and selling choices.

7.1. Time-varying liquidity and availability

Some corporate bonds are highly illiquid, so our findings could be affected by temporal variation in bond liquidity or availability.[32] At the extreme, retail investors may be forced to trade the bonds in the extreme quintiles of $Y|RM_t$ if those are the only bonds that they have access to in a given month. While our inclusion of bond and year-month fixed effects control for market-wide liquidity shocks and bond-specific time-invariant heterogeneity, they do not address temporal variation in liquidity within a given bond. We perform several tests to mitigate this concern.

First, we explore whether we observe trading on $Y|RM_t$ among the most liquid and widely available bonds, for which retail investors should have minimal frictions to trading, however they choose. We rerun the analyses from column (4) of Panel A of Table 3 using three subsamples of such bonds in each year-month. Column (1) of Panel A of Table 12 includes only the highest

[32] Our sample requires that all bonds have at least one trade during a month, which mitigates concerns about complete illiquidity.

Table 12
Robustness analyses: Bond availability and liquidity.

Panel A: Trading on yield-within-rating, limited to the most liquid and available bonds

	Dependent variable:		
	BSI_t^{Retail}		
	Large size	High volume	Low B-A spread
	(1)	(2)	(3)
$Y\|RM_t$	3.686***	4.695***	1.170***
	(25.371)	(31.560)	(9.145)
$Yield_t^{Rank}$	2.961***	2.198***	−1.200***
	(7.553)	(5.884)	(−3.907)
Controls	Yes	Yes	Yes
Rating indicators	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes
Observations	541,844	538,097	377,693
R^2	0.225	0.245	0.219

Panel B: Trading on yield-within-rating, controlling for time-varying liquidity

	Dependent variable:		
	BSI_t^{Retail}		
	(1)	(2)	(3)
$Y\|RM_t$	1.756***	2.594***	1.280***
	(14.905)	(23.977)	(10.948)
$Yield_t^{Rank}$	0.928***	0.733***	0.236
	(3.189)	(2.684)	(0.863)
$Volume_t$	4.296***		
	(38.039)		
B-A $spread_t$		8.092***	
		(21.659)	
Num. $trades_t$			0.084***
			(15.213)
Controls	Yes	Yes	Yes
Rating indicators	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes
Observations	1,358,537	1,181,686	1,358,537
R^2	0.158	0.187	0.161

This table examines the impact of bond liquidity and availability on the relation between $Y|RM_t$ and BSI_t^{Retail}. Panel A presents regressions of BSI_t^{Retail} on $Y|RM_t$ and controls that are the same as in Table 3, but limited to sub-samples of highly liquid and available bonds. Column headers Large size, High volume, and Low B-A spread indicate that the sub-samples are restricted to those in the upper tercile of issuance size and trading volume and lowest tercile of bid-ask spread for each month, respectively. Panel B presents regressions of BSI_t^{Retail} on $Y|RM_t$ and controls that are the same as in Table 3, but with additional (tabulated) controls for time-varying liquidity. Clustered robust t-statistics, by bond and year-month, are included in parentheses. Levels of significance are presented as follows: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

tercile of bonds based on issuance size, which should be broadly available to across brokers. Column (2) includes only the highest tercile of realized trading volume. Column (3) includes only the lowest tercile of bid-ask spread. We find qualitatively unchanged results in all subsamples.

Second, we re-run the same models but add additional controls for time-varying bond liquidity and availability.[33] Results in Panel B of Table 12 each add a control for one of several commonly used measures of bond trading and liquidity (e.g., Schestag et al., 2016): logged trading volume in column (1), average bid-ask spread in column (2), and the total number of trades in column (3). We find that all controls load in the expected directions, and we continue to find evidence of trading on $Y|RM_t$ across all specifications.

Third, we rerun the analyses from Table 3 using only retail investor sells instead of BSI. The logic for these tests is that retail investors may have limited buying options on a given date, but brokers should always allow clients to sell bonds already in their portfolios. Results presented in Panel A of Table IA-2 of the Internet Appendix find qualitatively unchanged results only for selling transactions, indicating that inability to trade is unlikely to drive our findings.

[33] We omit these variables from our primary analyses because they are likely mechanical *outcomes* of greater retail trading. For example, more retail trading will cause higher realized volume and higher average bid-ask spreads (because retail investors pay higher spreads). Also, spread is unavailable for all bond-months.

Fourth, to reduce concerns that retail investors trade in fundamentally different bonds than institutional investors, in Panel C of Table IA-2 of the Internet Appendix, we limit our sample to only observations where we observe both retail and institutional trading in the same month. Our results are qualitatively unchanged from those in Table 3.

Fifth, in untabulated analyses, we find little evidence that the volume of retail-sized transactions as a fraction of total market activity systematically differs across time-varying bond and firm characteristics. These results alleviate concerns that our results may be driven by time-varying bond and firm characteristics that correlate with $Y|RM_t$ and that also reduce the optimal transaction sizes of large investors.

7.2. Ratings-based regulations and internal policies

Ratings-based regulations and investment policies typically use broad ratings (e.g., AA versus A) instead of notched ratings (e.g., AA versus AA-). Similar to Cornaggia et al. (2018), we exploit this institutional feature to reduce concerns that our results in Section 4.2.1 are driven by investors that have some institutional reason for sorting on yield-within-ratings. First, we re-estimate model (2) using only the neutral-rated bonds within each broad rating category (i.e., just AA without a + or - modifier). Within this subsample, investors are unlikely to have institutional reasons to prefer higher-yielding bonds within each credit rating, but untabulated analyses continue to find strong evidence of sorting on yield-within-ratings.[34] Second, untabulated analyses find that BSI for the top $Y|RM_t$ quintile of neutral-rated securities (i.e., BB) is significantly higher than the lowest $Y|RM_t$ quintile of the adjacent negative rating (i.e., BB-), indicating that retail investors change their buying across notched rating boundaries.

7.3. Agency issues of brokerage firms and financial advisors

As discussed in Section 2, some retail bond investors use financial advisors. We expect that retail advisors are susceptible to the same ill-informed trading as retail investors, and therefore we follow many prior studies in treating advisors as extensions of retail investors. Here we discuss the possibility that advisors recommend trading on yield-within-rating not because they overrely on ratings but because the strategy somehow maximizes advisors' compensation at clients' expense.

Most advisors are compensated based on assets under management, in which case they are incentivized to preserve and grow client wealth.[35] In these situations, a financial advisor has no apparent incentive to underperform by recommending that clients trade on yield-within-ratings.

Depending on the account type, advisors can also earn transaction fees for each bond trade. Research (e.g., Egan, 2019) and discussions with practitioners indicate that transaction fees can differ across types of bonds, such as those with different rating levels, maturities, or features, such callability or sector. However, our tests account for rating level and maturity and include fixed effects to control for basic bond features. Conditional on an investor wanting to trade, we are unaware of a pervasive reason why advisors would earn higher fees per trade by recommending trading on yield-within-rating.

One possibility is that advisors sort on yield-within-rating because doing so motivates clients to trade more often, in which case advisors could earn more fees in aggregate. For instance, when a retail investor seeks advice, the advisor may recommend a five-year AA bond with a 3% versus a 2% yield because the former appears more attractive to the client and is more likely to result in trade. Similarly, brokerages' external search tools sort on yield-within-rating because doing so plausibly makes offerings appear more attractive and generates more trading. The premise of this story is still that the retail investors make their decisions based on the recommended bond's yield, relative to other bonds in the same rating level. Thus this explanation is not an alternative to investors overrelying on credit ratings, but it instead provides context as to how the behaviors occur in practice.

In sum, while financial advisors plausibly facilitate retail investors' trading on yield-within-rating, we are unaware of a reason why advisors intentionally do so to their clients' detriment. That said, we cannot empirically rule out the possibility that advisors drive our findings.

8. Conclusion

We find that, on average, retail investors appear to select corporate bonds by first screening on a credit rating level and then sorting on yield, buying the highest-yielding bonds within a rating level. Because credit ratings lag prices, selecting on yield-within-rating leads retail investors to trade in the opposite direction of fundamental signals, buy in advance of downgrades and defaults, and underperform in future returns. In short, retail investors appear to overrely on credit ratings as a sufficient statistic for risk, to their financial detriment.

[34] This exercise also addresses a possible concern related to the work of Kisgen (2006), who finds that firms with notched ratings (e.g. AA- or AA+), relative to those with neutral ratings (e.g, AA), tend to issue less debt. Kisgen (2006) argues that this is consistent with firms on rating boundaries trying to improve their rating by adjusting capital structure. By showing that our results are robust to only using neutral ratings, we alleviate the concern that his findings generate our results.

[35] Egan et al. (2019) report that 94.1% of financial advisors are compensated, at least in part, based on assets under management.

While our findings are based on corporate bond trading, our inferences likely generalize to retail trading in other debt markets, where information environments tend to be weaker, so credit ratings likely play an even more significant role. For example, Cornaggia et al. (2018) find that retail investors rely on credit ratings in the municipal debt market, in which they hold 75% of all assets. While Cornaggia et al. (2018) do not examine how retail investors select municipal bonds within a rating category or the consequences of their rating usage, our results suggest that municipal debt investors' reliance on ratings likely also harms their wealth.[36]

Our study informs the academic literature on credit ratings and has potential regulatory implications. Past studies find that ratings are slow to respond to changes in market conditions and fundamentals. Our findings suggest an additional cost associated with slow credit ratings, specifically monetary harm to retail investors. Due to the SEC's focus on protecting retail investors (e.g., SEC, 2018, 2014), our findings suggest that greater emphasis may be warranted on how retail investors use credit ratings. More broadly, our study builds on extensive findings that retail equity investors can, on average, improve their performance by holding low-cost index funds instead of individual securities. Our study indicates that similar findings extend to the bond market, which has traditionally been thought of as more sophisticated.

Our study is also subject to several caveats. First, it is based on archival data, and we cannot directly observe how retail investors select bonds. Section 7 investigates plausible alternative explanations for our findings, but ruling out all alternative explanations is impossible. Second, while our method for identifying retail investors is widely used, it is imperfect and likely captures some trades by small (and likely less sophisticated) institutions that may trade like retail investors. Finally, by studying retail investors using their aggregate transactions, our inferences speak to the representative retail investor and likely do not accurately characterize specific sub-groups of retail investors.

Appendix A: Variable Definitions

This table contains descriptions of the primary variables used throughout this paper. These include bond trading activity and pricing data, bond characteristics, bond CDS spreads, and bond issuer-level fundamentals. Sources include: Enhanced TRACE (TRACE), WRDS Bond Returns data (WRDS), Compustat (COMP), the Center for Research in Security Prices (CRSP), Markit (MARK), and Mergent FISD (FISD). All continuous variables are Winsorized at 1% and 99%. All fundamentals-based data are calculated using the most recently available data available as of the end of month *t*.

Variable	Description
$Asset\ growth_t$	The bond issuer's asset growth for bond *i* in month *t*, relative to the previous four quarters. (COMP)
$B\text{-}A\ spread_t$	Average trade-weighted bid-ask spread for bond *i* in month *t*. (WRDS)
Bond size	The natural logarithm of issuance size for bond *i*. (WRDS)
$Book\text{-}to\text{-}market_t$	The natural logarithm of the book-to-market ratio for the issuer of bond *i* in month *t*. (COMP, CRSP)
BSI_t^{Retail}	Retail investor buy-sell imbalances for bond *i* in month *t*. (TRACE)
BSI_t^{L-U}	Buy-sell imbalances for bond *i* in month *t* generated from different groups of transaction sizes from lower-bound *L* to upper-bound *U*. These include 0 to \$50,000 (BSI_t^{0-50K}), \$50,000 to \$100,000 ($BSI_t^{50K-100K}$), and greater than \$100,000 (BSI_t^{100K+}). (TRACE)
$Default_t^x$	An indicator of whether the bond's issuer defaults over the next period, *x*, from month *t*. (WRDS)
ΔCDS_t	The six-month change in 5-year, U.S. dollar-denominated, senior unsecured CDS spreads for the issuer of bond *i* in month *t*. (MARK)
$\Delta Rating_{t+1}$	The ratings change for bond *i* from month *t* to month $t+1$. A positive (negative) value indicates a downgrade (upgrade). Credit ratings are as defined in the WRDS Bond Returns data. (WRDS)
$Downgrade_t^x$	An indicator of whether bond *i* experienced a downgrade over the next period, *x*, from month *t*. Credit ratings are as defined in the WRDS Bond Returns data. (WRDS)
$Earnings\ month_t$	An indicator of whether it is an earnings announcement month for the issuer of bond *i* in month *t*. (COMP)
$F\text{-}Score_t$	The fundamental strength score from Piotroski (2000), F-Score, for the issuer of bond *i* in month *t*. (COMP)
$Has\ CDS_t$	An indicator which takes the value of one if the issuer of bond *i* has traded CDS in month *t*. (MARK)
IG_t	An indicator of whether the rating for bond *i* in month *t* is investment grade (i.e., at least BBB- or Baa3). (WRDS)
$Mkt.\ cap._t$	The natural logarithm of stock market capitalization for the issuer of bond *i* in month *t*. (CRSP)
$Large\ size_t$	An indicator which takes the value of one if bond *i* is in the top tercile of bond size, as measured by issue amount, in month *t*. (WRDS)
$Maturity_t$	The remaining time to maturity for bond *i* in month *t*. (WRDS)
$Num.\ trades_t$	The total number of trades for bond *i* in month *t*. (WRDS)
$Rating_t$	The rating for bond *i* in month *t*, increasing in value from 1 (AAA) to 22 (D). The WRDS Bond Returns data assigns the value of S&P ratings, where available, and Moodys if missing. If both S&P and Moodys ratings are missing, it assigns the value of Fitch ratings. WRDS updates the ratings continuously throughout the life of a bond. (WRDS)
Ret_{t+x}	Bond returns for bond *i* from the end of month *t* through month $t+x$. One-month returns are provided pre-calculated in the WRDS Bond Returns file. For longer-period returns, we follow WRDS methodology and compute *x*-months ahead returns for month *t* as: $Ret_{i,t+x} = \frac{Price_{i,t+x} + AI_{i,t+x}}{Price_{i,t}} - 1$ where $AI_{i,t+x}$ is the accrued coupon interest over the period *t* to $t+x$. Bond prices and coupon rates for the accrued interest calculations are obtained from the WRDS Bond Returns file. (WRDS)
$Ret6M_t$	The stock return over the trailing six months for the issuer of bond *i* in month *t*. (CRSP)
$Return\ on\ assets_t$	The return on assets for the issuer of bond *i* in month *t*. (COMP)

[36] Data limitations make such analyses in municipal markets infeasible, given the lack of reliable pricing data or data on issuers' fundamental performance outside of credit ratings themselves.

(*continued*)

Variable	Description
SUE_t	Standardized unexpected earnings. Defined as the realized EPS minus EPS from four quarters prior, scaled by price, for the issuer of bond i in month t. (COMP)
$Upgrade_t^x$	An indicator of whether bond i experienced an upgrade over the next period, x, from month t. Credit ratings are as defined in the WRDS Bond Returns data. (WRDS)
$Volume_t$	The natural logarithm of total trading volume for bond i in month t. (WRDS)
$Y\|RM_t$	The within-rating quintile of yield after controlling for maturity for bond i in month t. (WRDS)
$Yield_t$	The average bond yield for bond i in month t. (WRDS)
$Yield_t^{Rank}$	The quintile rank of yield for bond i in month t. (WRDS)

Appendix B. Additional Supporting Calculations

This section provides supporting details for several calculations mentioned in the paper.

Retail investor holding periods

While we cannot observe the holdings of retail investors, He et al. (2022) provide a method for estimating their holdings using cumulative trades. We calculate bond-month changes in retail holdings using the following:

$$Holding_{i,t}^{Retail} = Holding_{i,t-1}^{Retail} + Buy_{i,t}^{Retail} - Sell_{i,t}^{Retail} \tag{5}$$

where $Buy_{i,t}^{Retail}$ and $Sell_{i,t}^{Retail}$ are the number of bond shares bought and sold by retail investors in the month.[37]

A drawback of this method is that we do not know investors' holdings before the start of TRACE in 2002, so we must assume that holdings are zero at the beginning of our sample. Month-end holdings are therefore underestimated for the earlier years of our sample, and are most accurate for bonds issued after the beginning of our sample. By the end of our sample, 96.6% bonds were issued during the sample period, so estimated holdings at the end of our sample should be relatively unaffected by not knowing starting positions.

Untabulated results find that retail investors' hold an average of total of $206.5 billion in bonds during the last 12-months of our sample, which amounts to roughly 2.85% of the market.[38] Retail investors trading in the last 12-months of our sample totaled $150.7 billion. Thus, estimated portfolio turnover is 150.7/206.5 ≈ 73% per year, for an average holding period of 1/73% ≈ 1.369 years.

Retail investor transaction costs

We estimate retail investors' transaction costs using the method from papers such as Hong and Warga (2000), Edwards et al. (2007), and Bessembinder et al. (2018). For each bond i on day d, we estimate one-way transaction cost as:

$$Transaction\ Cost_{i,d}^{Retail} = \frac{\left(Buy\ Price_{i,d}^{Retail} - Sell\ Price_{i,d}^{Retail}\right)\Big/2}{Price_{i,d}}$$

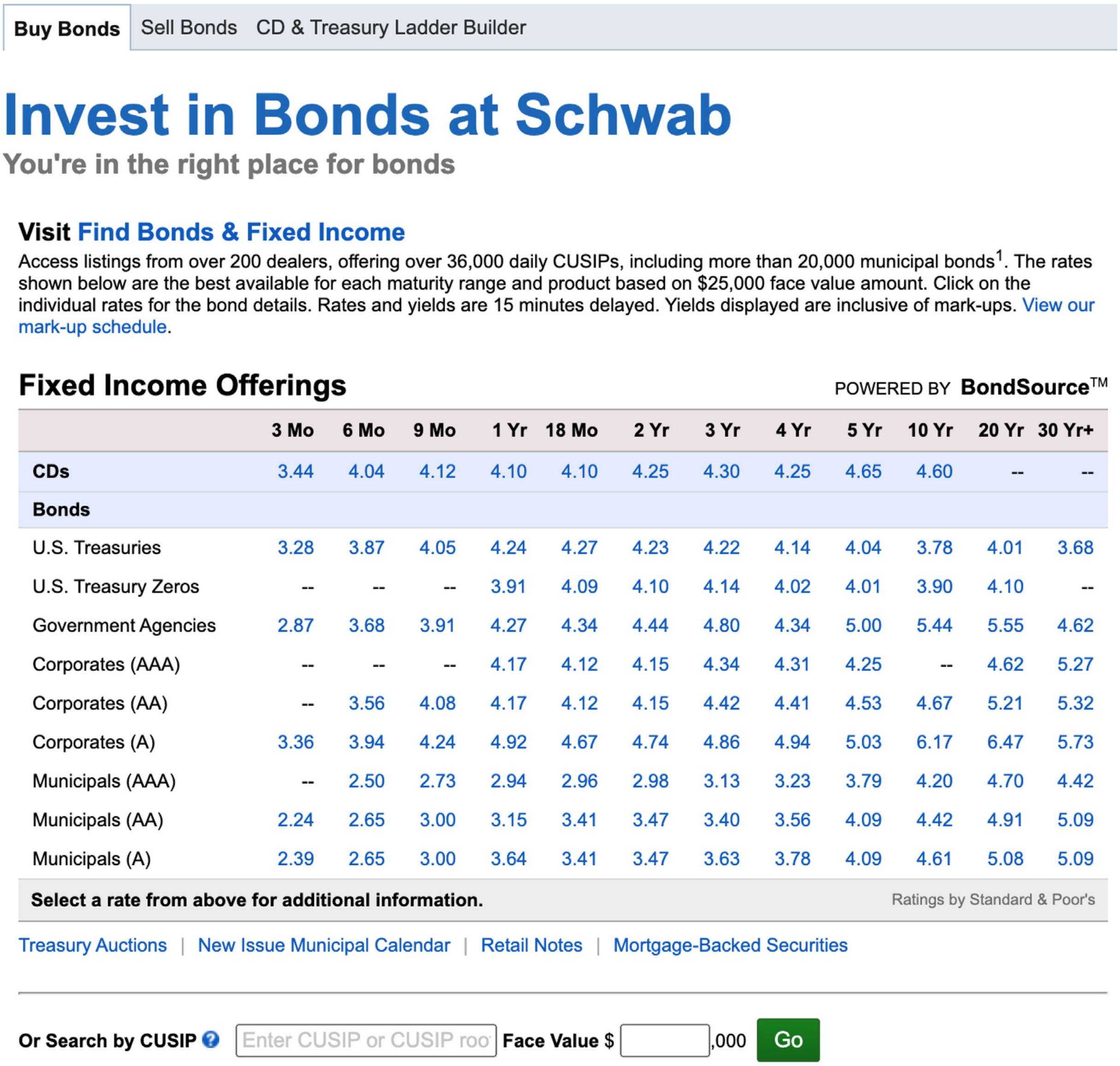
where the variables in the numerator represent value-weighted average buying and selling prices by retail investors, and the denominator is the value-weighted average bond price. We only compute this measure if there are both retail buys and sells on the same day, meaning that we effectively capture more liquid bonds, and thus err on the side of underestimating transaction costs.

Untabulated results estimate weighted-average one-way retail transaction costs to be 66 bps over our sample period. These estimates are close to the 62 bps reported by Bessembinder et al. (2020), with the small difference likely due to different sample periods.

[37] If $Holding_{i,t}^{Retail}$ is negative or exceeds issue size, we trim the variable to be between zero and the issue size.

[38] Retail investors' holdings as a proportion of the market are fairly stable from 2009 onwards, ranging from 2.5% to 3.0%.

Appendix C: Illustrative Examples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Access listings from over 200 dealers, offering over 36,000 daily CUSIPs, including more than 20,000 municipal bonds[1]. The rates shown below are the best available for each maturity range and product based on $25,000 face value amount. Click on the individual rates for the bond details. Rates and yields are 15 minutes delayed. Yields displayed are inclusive of mark-ups. View our mark-up schedule.

Fixed Income Offerings POWERED BY **BondSource**™

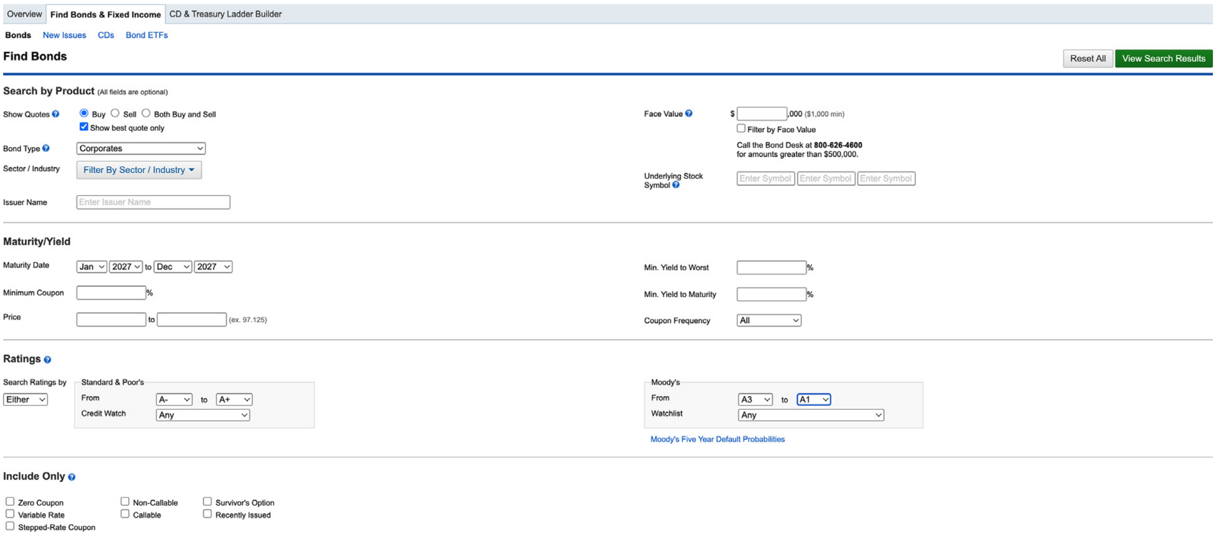
	3 Mo	6 Mo	9 Mo	1 Yr	18 Mo	2 Yr	3 Yr	4 Yr	5 Yr	10 Yr	20 Yr	30 Yr+
CDs	3.44	4.04	4.12	4.10	4.10	4.25	4.30	4.25	4.65	4.60	--	--
Bonds												
U.S. Treasuries	3.28	3.87	4.05	4.24	4.27	4.23	4.22	4.14	4.04	3.78	4.01	3.68
U.S. Treasury Zeros	--	--	--	3.91	4.09	4.10	4.14	4.02	4.01	3.90	4.10	--
Government Agencies	2.87	3.68	3.91	4.27	4.34	4.44	4.80	4.34	5.00	5.44	5.55	4.62
Corporates (AAA)	--	--	--	4.17	4.12	4.15	4.34	4.31	4.25	--	4.62	5.27
Corporates (AA)	--	3.56	4.08	4.17	4.12	4.15	4.42	4.41	4.53	4.67	5.21	5.32
Corporates (A)	3.36	3.94	4.24	4.92	4.67	4.74	4.86	4.94	5.03	6.17	6.47	5.73
Municipals (AAA)	--	2.50	2.73	2.94	2.96	2.98	3.13	3.23	3.79	4.20	4.70	4.42
Municipals (AA)	2.24	2.65	3.00	3.15	3.41	3.47	3.40	3.56	4.09	4.42	4.91	5.09
Municipals (A)	2.39	2.65	3.00	3.64	3.41	3.47	3.63	3.78	4.09	4.61	5.08	5.09

Select a rate from above for additional information. Ratings by Standard & Poor's

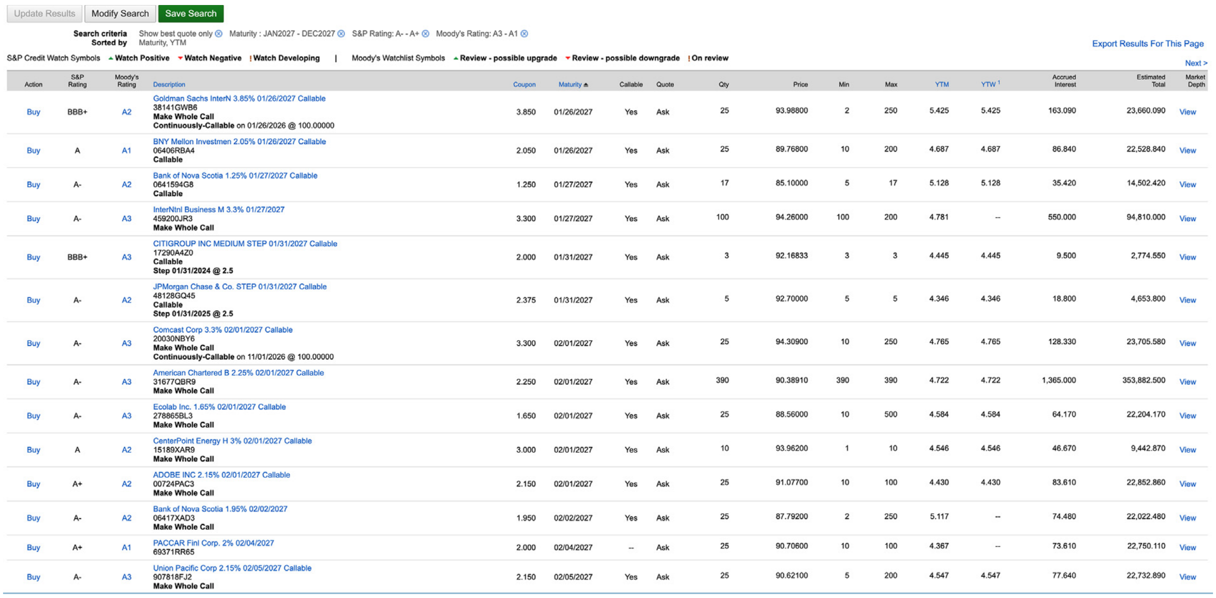
Treasury Auctions | New Issue Municipal Calendar | Retail Notes | Mortgage-Backed Securities

Or Search by CUSIP Enter CUSIP or CUSIP roo **Face Value $** ,000 Go

(a) Introductory screen



(b) Bond search screen



Action	S&P Rating	Moody's Rating	Description	Coupon	Maturity	Callable	Quote	Qty	Price	Min	Max	YTM	YTW [1]	Accrued Interest	Estimated Total	Market Depth
Buy	BBB+	A2	Goldman Sachs InterN 3.85% 01/26/2027 Callable 38141GWB6 **Make Whole Call** **Continuously-Callable** on 01/26/2026 @ 100.00000	3.850	01/26/2027	Yes	Ask	25	93.98800	2	250	5.425	5.425	163.090	23,660.090	View
Buy	A	A1	BNY Mellon Investmen 2.05% 01/26/2027 Callable 06406RBA4 **Callable**	2.050	01/26/2027	Yes	Ask	25	89.76800	10	200	4.687	4.687	86.840	22,528.840	View
Buy	A-	A2	Bank of Nova Scotia 1.25% 01/27/2027 Callable 0641594G8 **Callable**	1.250	01/27/2027	Yes	Ask	17	85.10000	5	17	5.128	5.128	35.420	14,502.420	View
Buy	A-	A3	InterNtnl Business M 3.3% 01/27/2027 459200JR3 **Make Whole Call**	3.300	01/27/2027	Yes	Ask	100	94.26000	100	200	4.781	--	550.000	94,810.000	View
Buy	BBB+	A3	CITIGROUP INC MEDIUM STEP 01/31/2027 Callable 17290A4Z0 **Callable** **Step 01/31/2024 @ 2.5**	2.000	01/31/2027	Yes	Ask	3	92.16833	3	3	4.445	4.445	9.500	2,774.550	View
Buy	A-	A2	JPMorgan Chase & Co. STEP 01/31/2027 Callable 48128GQ45 **Callable** **Step 01/31/2025 @ 2.5**	2.375	01/31/2027	Yes	Ask	5	92.70000	5	5	4.346	4.346	18.800	4,653.800	View
Buy	A-	A3	Comcast Corp 3.3% 02/01/2027 Callable 20030NBY6 **Make Whole Call** **Continuously-Callable** on 11/01/2026 @ 100.00000	3.300	02/01/2027	Yes	Ask	25	94.30900	10	250	4.765	4.765	128.330	23,705.580	View
Buy	A-	A3	American Chartered B 2.25% 02/01/2027 Callable 31677QBR9 **Make Whole Call**	2.250	02/01/2027	Yes	Ask	390	90.38910	390	390	4.722	4.722	1,365.000	353,882.500	View
Buy	A-	A3	Ecolab Inc. 1.65% 02/01/2027 Callable 278865BL3 **Make Whole Call**	1.650	02/01/2027	Yes	Ask	25	88.56000	10	500	4.584	4.584	64.170	22,204.170	View
Buy	A	A2	CenterPoint Energy H 3% 02/01/2027 Callable 15189XAR9 **Make Whole Call**	3.000	02/01/2027	Yes	Ask	10	93.96200	1	10	4.546	4.546	46.670	9,442.870	View
Buy	A+	A2	ADOBE INC 2.15% 02/01/2027 Callable 00724PAC3 **Make Whole Call**	2.150	02/01/2027	Yes	Ask	25	91.07700	10	100	4.430	4.430	83.610	22,852.860	View
Buy	A-	A2	Bank of Nova Scotia 1.95% 02/02/2027 06417XAD3 **Make Whole Call**	1.950	02/02/2027	Yes	Ask	25	87.79200	2	250	5.117	--	74.480	22,022.480	View
Buy	A+	A1	PACCAR Finl Corp. 2% 02/04/2027 69371RR65	2.000	02/04/2027	--	Ask	25	90.70600	10	100	4.367	--	73.610	22,750.110	View
Buy	A-	A3	Union Pacific Corp 2.15% 02/05/2027 Callable 907818FJ2 **Make Whole Call**	2.150	02/05/2027	Yes	Ask	25	90.62100	5	200	4.547	4.547	77.640	22,732.890	View

(c) Bond screen results (default sort)

Fig. C-1. Placing a bond trade through Charles Schwab's platform. This figure highlights the various steps taken to place a trade on the Charles Schwab platform, and highlights several pieces of key functionality. Panel (a) shows a screenshot of their intro screen. Panel (b) shows a screenshot of their bond search tool. Panel (c) highlights the default search results (by maturity, then yield).

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jacceco.2023.101587.

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