Journal of Empirical Finance 46 (2018) 34–55

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

Behavioral biases in the corporate bond market

Jason Wei *

Department of Management, University of Toronto Scarborough, Canada
Joseph L. Rotman School of Management, University of Toronto, Canada

A R T I C L E I N F O

JEL classification:
G14

Keywords:
Corporate bond returns
Retail trades
Retail investors
Institutional trades
Institutional investors

A B S T R A C T

This paper investigates the behavioral biases in the corporate bond market through the cross-section association between retail and institutional trades and corporate bond returns. The study finds that bonds heavily bought by retail investors in one month underperform in the next month relative to bonds heavily sold, and the opposite holds for institutional investors. The alpha of the high-low portfolio (formed based on decile sorting on the buy–sell trade imbalance) relative to the usual market factors is significant for retail investors, but insignificant for institutional investors. The overall results indicate that retail investors in the corporate bond market suffer from behavioral biases but institutional investors do not. However, when the spread between the purchase and sell prices is factored into the returns, no profitable trading strategies exist, consistent with limits to arbitrage.

1. Introduction

Investors' sentiment can skew the demand for securities, which in turn causes prices to deviate from their fundamentals (e.g., De Long et al., 1990a; Shleifer and Summers, 1990). Spawned from this line of thinking is a strand of literature that examines how the trading of retail investors, who are considered as the most susceptible to behavioral biases, influences prices. Examples include Hvidkjaer (2008), Kaniel et al. (2008), Barber et al. (2009), and Han and Kumar (2013). While Han and Kumar (2013) focus on the pricing of stocks favored by retail investors, the rest of the cited studies examine the link between retail investors' trading and the cross-section of stock returns. The common methodology involves using retail trade imbalance in one period (e.g., a month) to predict the returns in the next. The trade imbalance is usually measured by excess buy over sell, scaled by the total trading volume or amount outstanding.

The empirical findings are mixed. Hvidkjaer (2008) finds that stocks heavily bought by retail investors in the past several months underperform those heavily sold, and this performance difference lasts from the current month to up to two years. Barber et al. (2009) present similar findings at the annual frequency. However, they show in the same study that the direction of prediction reverses itself at the weekly frequency: Stocks heavily bought by retail investors outperform those heavily sold. Kaniel et al. (2008) find that retail trade imbalance can also positively predict stock returns at the monthly frequency. Therefore, at the monthly frequency, the findings of Hvidkjaer (2008) and Kaniel et al. (2008) are diametrically opposite. The difference in sample selection and the construction of trade imbalance measure may be responsible for the opposite findings.

While the relation between retail trading and future stock returns has received increasing attention in the literature, little is known as to whether such a relation also exists in the corporate bond market, despite its large size and importance.

* Correspondence to: 105 St. George Street, Toronto, Ontario, Canada, M5S 3E6.
E-mail address: wei@rotman.utoronto.ca.

https://doi.org/10.1016/j.jempfin.2017.12.003
Received 17 February 2017; Received in revised form 17 November 2017; Accepted 12 December 2017
Available online 24 December 2017
0927-5398/

The current paper fills this gap. Based on data from TRACE Enhanced for the period of July 1, 2002 to December 31, 2014, the study finds that bonds heavily bought by retail investors in one month severely underperform in the next month relative to bonds heavily sold by retail investors. The zero-financing, high-low portfolio has a statistically and economically significant loss of 1.063% per month and its alpha survives the usual market factors. The results are the opposite for institutional investors: Heavily bought bonds *outperform* heavily sold bonds, and the high-low portfolio earns a statistically and economically significant return of 0.106% per month. However, its alpha vanishes once the Fama–French bond factor TERM (measuring the slope risk of the term structure of interest rates) is present. Additionally, when forming the high-low portfolio for institutional investors by sorting on the retail investors' trade imbalance, the alpha survives all market factors and is also significant in economic terms: 1.210% per month or 14.52% per year without compounding. Therefore, retail investors seem to suffer from behavioral biases while institutional investors do not. The retail investors' behavioral biases are consistent with overreactions in the sense of Daniel et al. (1998) and the broader impact of sentiments.

The above results are based on average bond prices without considering the spread between the purchase and sell prices, just as the findings in the equity-market literature are based on stock returns without accounting for the bid–ask spread. To gain further insights, I repeat the alpha analyses with returns based on transaction prices (e.g., a long position is initiated at the purchase price and liquidated at the sell price). The alpha becomes negative in all cases, indicating that the observed behavioral biases do not lead to profitable trading strategies, consistent with limits to arbitrage (Shleifer and Vishny, 1997).

While broadly related to the literature exploring the association between investors' trading behavior and the cross-section of security returns, the study is the first to examine the corporate bond market and makes contributions as such. To begin, although there are studies (e.g. Jackson, 2003; Hvidkjaer, 2008; Kaniel et al., 2008; Barber et al., 2009; Han and Kumar, 2013) that investigate the link between retail trades and stock returns, no such studies exist for the corporate bond market. The study by Abudy and Wohl (2015) does explore the general properties of retail trading, but it does not examine the link between retail trading and bond returns. Second, aside from examining the link between retail trading and bond returns, I also investigate institutional trades and their association with bond returns. Third, I exploit the predictability with trading strategies that properly account for the spread between purchase and sell prices, an investigation that has not been done in the equity-market literature. Overall, it is hoped that the various findings in this paper will stimulate further research on the link between investors' trades and the cross-section of bond returns.

The rest of this paper proceeds as follows. Section 2 offers a brief description of the corporate bond market and the related literature. Section 3 describes the data and the main variables. Sections 4 and 5 examine the link between retail and institutional trades and bond returns via sorting and regression analyses. Trading strategies incorporating the spread between purchase and sell prices are investigated in Section 6. Section 7 offers a closer look at the trading behavior of the retail and institutional investors, and examines the cross-sectional properties of bond trading. Section 8 delineates the potential mechanisms through which retail investors suffer from behavioral biases. The last section concludes.

2. The corporate bond market and related literature

Unlike stocks that are traded on organized exchanges, corporate bonds in the U.S. have mostly been traded in dealer-based, over-the-counter markets.[1] There does not exist a centralized quotation system where all participants can see the history and prevailing quotes. Instead, intended buyers and sellers must contact dealers directly to get quotes. Alternatively, they could broadcast their intended purchases or sells to some dealers through Bloomberg. Unlike market makers in the equity market, bond dealers do not post bid and ask quotes. They only provide quotes upon request, and the quotes are always one-sided: They only quote a purchase price if the customer wishes to sell, and a sell price if the customer wishes to buy. Their profits come from the markup or markdown in the sell/buy price they quote. Although most dealers carry some inventory, some also act as pure brokers. Even for inventory-carrying dealers, they act as an intermediary between buyer and sellers, and this intermediation function is facilitated by trading with other dealers (for a description of the recent trend in the market-making of corporate bonds, see Bessembinder et al., 2017).

The decentralized, opaque nature of the corporate bond market makes it almost impossible for investors to compare quotes and evaluate their trades against others on the same bond. It is especially challenging for retail investors and institutional investors of a smaller scale who have limited resources to establish a wide dealer network.

The situation has improved significantly since July 2002 when a bond-trade reporting system was put in place. On July 1, 2002, members of the National Association of Security Dealers (which was replaced by The Finance Industry Regulatory Authority, or FINRA since 2007) were required to report some of their trades to TRACE (Trade Reporting and Compliance Engine). Initially the reporting requirement only applied to bonds with large issue size and higher ratings, with a reporting time delay of up to 75 min. More bonds were added, and the allowable delay time was gradually shortened until 2005 when the phase-in period ended. Currently, TRACE covers almost all corporate bond transactions with virtually no time delay in reporting.

This centralized reporting makes it possible for investors to see the history of all transactions on a particular bond. The corporate bond market has become more transparent as a result. Historically, trading costs were lower for larger trades and smaller institutions incur higher trading costs than their larger counterparts (Schultz, 2001). The introduction of TRACE prompted researcher to examine the overall benefit of transparency. There is consensus that the overall post-TRACE transaction costs have gone down (see, e.g., Bessembinder et al., 2006; Edwards et al., 2007; Goldstein et al., 2007; Bessembinder and Maxwell, 2008). The deterioration

[1] For a brief description of the corporate bond market, see Schultz (2001) and Bessembinder et al. (2006). Although rare, corporate bonds have been traded on organized exchanges. See Biais and Green (2007) and Abudy and Wohl (2015) for such examples.

of liquidity in the corporate bond market during and after the financial crisis makes researcher wonder whether the increased transparency has discouraged some dealers from market making activities (e.g., Dick-Nielsen et al., 2012). Bessembinder et al. (2017) show that, the liquidity deterioration is not due to the increased transparency per se; instead, the tighter regulations such as the Dodd–Frank Act make the conventional market making less profitable and as a result, some dealers withdraw capital from market making and act as pure brokers.

The reporting of bond trades and its availability to all investors open up many new research avenues aside from transaction costs and liquidity as reviewed above. For instance, we can now examine whether individual or retail investors base their transactions on past trading prices and/or volume, and whether their transactions precede price increases or decreases, just as how researchers have addressed these questions for the stock market. Specifically, we are in a position to study the potential behavioral biases on the part of retail investors, and to ascertain whether large institutional investors are free of behavioral biases in addition to paying low transaction costs (Schultz, 2001). These are the issues the current paper attempts to address.

As stated earlier, little is known about the relation between retail trading and subsequent bond returns. There are several studies that examine bond trading by retail investors, albeit from different angles. Kalimipalli and Warga (2002) perform a microstructure analysis of bid–ask spreads, volatility and volume of bonds on the New York Stock Exchange which are typically transacted in retail-size trades (under 100 bonds). Biais and Green (2007) examine the microstructure of the bond market and provide an illuminating account of the evolution of the corporate bond market. They find that the migration of bond trading from NYSE to the now over-the-counter market has made retail investors worse off in the form of higher transaction costs. The study that closely examines retail trading of bonds is by Abudy and Wohl (2015). The corporate bonds under their study are quite unique in that they are traded on the Tel Aviv Stock Exchange, just like stocks. They estimate that retail trades of corporate bonds account for 12% to 18% of the total trades, indicating a more active participation of retail investors in the bond market than in the stock market. In addition, they find that retail bond investors incur lower transaction costs and narrower spreads than they do with stocks. To the best of my knowledge, no studies exist that examine how retail trades are related to future bond returns.

3. Data and variable descriptions

3.1. Data

The main data source is TRACE Enhanced for the period of July 1, 2002 to December 31, 2014. TRACE Enhanced provides, among other things, the date, time, price, size and buy–sell indicator for virtually all of the secondary market transactions of corporate bonds. The noticeable enhancements relative to the original TRACE dataset include (1) the wider coverage of bonds in the early years (i.e., from 2002 to 2005), (2) the removal of the $5 million and the $1 million caps (for investment grade bonds and speculative bonds, respectively) in the reporting of trading volume, and (3) the availability of the buy/sell indicator for all transactions in the entire sample period. Information on bond characteristics such as issue date, issue amount, maturity, coupon rate, and ratings is obtained from Mergent's FISD.

The screening procedure largely follows the literature, but is heavily influenced by Dick-Nielsen (2014), especially with respect to the handling of agency transactions and the data structure change made on February 6, 2012. Specifically, I eliminate the following bonds/transactions: when-issued, canceled, subsequently corrected, reversed trades, commission trades, agency transactions without commission, and trades with special sales conditions or longer than 2-day settlements. I also delete potentially erroneous records such as transactions whose par-value is not a multiple of $1,000, price is below $10 or above $200, and yield is either zero, negative or above 100%. Lastly, inter-dealer trades are excluded since they are mostly for order matching purposes.

Since my interest is in the different trading behaviors of retail and institutional investors, I classify all transactions into three size categories: small (size ≤ $100,000), medium ($100,000 < size < $500,000) and large (size ≥ $500,000). I then assume that small trades are executed by retail investors and large trades by institutional investors. The $100,000 and $500,000 cutoffs have been used in the literature (e.g., Warga, 2004; Edwards et al., 2007; Goldstein et al., 2007; Ronen and Zhou, 2013). In some cases (e.g., Edwards et al., 2007; Wei and Zhou, 2016), the $100,000 cutoff serves as a dividing point between retail and institutional trades. In the current study, I leave out a cushion range between $100,000 and $500,000 so that the small trades and large trades are different by a material amount. Specifically, the cushion range ensures a more accurate classification of large trades (e.g., a trade of $500,001 is less likely to be erroneously classified as an institutional trade than a trade of $100,001). However, one wonders whether some small-sized trades are executed by institutions via order splitting. This scenario is unlikely due to the following reasons. First, unlike the trading of stocks that can be done anonymously, bonds are traded over-the-counter by directly interacting with dealers. Anonymity is not an option and, as a result, submitting consecutive small orders to a dealer (or even a few dealers) will arouse too much suspicion and is not conducive to relationship building. Second, as will be seen in Table 1, the trivial total dollar-volume of small trades also rules out the order splitting possibility. Third, many researchers (e.g., Edwards et al., 2007; Schultz, 2001; Zitzewitz, 2010) have shown that the transaction cost for small trades is multifold higher than that for large trades. The higher transaction cost for small trades would prohibit order splitting. In fact, O'Hara et al. (2015) explicitly state: "*Unlike in equities where large orders are routinely chopped into smaller orders, bond orders are generally left intact because large trades receive better trade prices than small trades*".

Table 1 reports the overall bond market profile and the trading activities for each size group. The total number of bonds in the first two years of TRACE initiation was slightly lower than other years. Since 2004, the number of bonds being traded has been largely steady until 2010 when an apparent upward trend merges. On average, about 90% of the bonds see retail trades, whereas institutional trades occur with only about 50% of the bonds. The higher percentage of institutional trades and the lower percentage of retail trades in the early years indicate a gradual catching-up by retail investors. In terms of trading frequency, smaller trades by far

Table 1

Summary statistics — overall trading activities. This table reports the overall trading activities of corporate bonds appearing in TRACE Enhanced for the period of July 1, 2002 to December 31, 2014. Transactions are classified into three categories according to their dollar size. Specifically, small = (size ≤ $100,000); medium = ($100,000 <size <$500,000); and inst = (size ≥ $500,000) where inst stands for institutions. Statistics are calculated for each year as well as the entire sample period. Since a particular bond may be traded in different dollar amounts even within the same day, it can belong to different size categories. Therefore the sum of percentages of distinct bonds across the three size categories is bigger than 100%. To calculate the average number of trades per bond per month, I first calculate the total number of transactions for each bond within each month, I then average this quantity within the year or within the entire sample period. This procedure gives more weights to more liquid bonds. Alternatively, we could first calculate the total number of trades within the year and then divide this total by the number of distinct bonds in that year and further divide the result by 12. This procedure amounts to equal weighting in the average which gives undue prominence to illiquid bonds. In other words, the procedure adopted for this table closely depicts the true picture. The average dollar value of trades per bond per month is calculated following the same procedure. For both the number of trades and the dollar value of trades, the percentage numbers represent the frequency of each trade size and they add up to 100% across the three size categories. Finally, the percentiles at the bottom of the table are calculated over the entire sample.

Sample	Number of distinct bonds				Number of trades per bond per month and % of total						Value of trades per bond per month and % of total					
	All	% of all			Small		Medium		Inst		Small		Medium		Inst	
		Small	Medium	Inst	Number	%	Number	%	Number	%	$ ('000)	%	$ ('000)	%	$ ('000)	%
2002	14,764	87.2	58.5	63.7	24.3	70.5	5.1	7.7	11.4	21.8	591	1.8	1,196	1.9	48,010	96.3
2003	19,069	88.0	61.4	61.8	21.5	69.5	5.0	8.0	11.6	22.5	529	1.9	1,167	2.2	43,266	95.9
2004	20,585	91.0	59.2	55.2	16.7	68.5	4.4	8.3	10.3	23.2	414	1.8	1,026	2.0	41,281	96.2
2005	21,458	92.2	54.7	50.5	15.8	68.6	4.5	8.4	10.3	23.0	404	2.1	1,042	2.4	35,153	95.5
2006	21,627	92.6	51.7	49.1	12.9	66.9	4.0	8.6	9.3	24.5	330	1.8	930	2.2	34,176	96.0
2007	22,294	93.0	50.2	46.2	11.8	66.1	3.8	8.5	9.4	25.4	305	1.6	900	1.9	37,235	96.4
2008	21,874	94.2	48.5	44.1	17.2	71.4	4.9	8.2	10.1	20.3	440	2.3	1,135	2.4	37,931	95.3
2009	21,545	94.3	55.3	49.4	27.8	75.2	6.4	8.2	12.0	16.6	702	3.0	1,500	3.1	42,562	93.9
2010	23,382	93.2	56.7	50.5	23.0	72.1	6.4	10.0	11.1	17.9	623	3.0	1,486	3.6	38,164	93.5
2011	24,005	92.0	58.2	50.9	20.6	69.1	6.3	11.2	10.8	19.7	571	2.8	1,476	3.8	35,448	93.4
2012	26,114	89.7	60.8	54.4	22.2	65.6	7.6	13.2	12.3	21.2	667	2.9	1,797	4.6	36,926	92.6
2013	25,897	89.7	64.1	56.0	21.2	62.4	7.6	14.6	12.2	23.0	639	2.6	1,814	4.7	36,435	92.7
2014	26,996	88.3	64.9	56.8	19.4	59.2	7.6	15.9	12.2	24.9	608	2.3	1,826	4.7	37,058	93.0
2002–2014	**80,442**	**87.6**	**64.7**	**57.9**	**19.4**	**67.8**	**6.0**	**10.7**	**11.1**	**21.5**	**526**	**2.3**	**1,411**	**3.2**	**38,208**	**94.4**
25th perctl					2		1		2		45		320		4,000	
Median					**5**		**3**		**5**		**134**		**710**		**13,365**	
75th perctl					15		7		12		404		1,605		38,250	
90th perctl					40		14		26		1,128		3,256		89,185	
99th perctl					229		44		87		6,410		10,117		361,922	

dominate medium-size or institutional trades. Over the entire sample period, 67.8% of all trades are of small size and only 21.5% are of institutional size. Each bond has, on average, 19.4 trades per month in small size and 11.1 trades in institutional size. As explained in the table, the average is calculated out of bond-month observations, hence giving higher weights to more liquid bonds. Because of this, the percentage numbers are quite different from the fractions of the number of trades. For instance, the average total number of trades per bond per month is (19.4 + 6.0 + 11.1) = 36.4, hence the percentage of small trades is 19.4/36.4 = 53.3%, different from 67.8%. A hypothetical, extreme case would help illustrate the difference: Bonds in all three size categories may trade, e.g., 10 times a month, but if there are more bonds with small trades, then the frequency of small trades will be higher.

The trading frequency is highly skewed. The median of average number of trades per month is much lower than the sample average. The skew is more pronounced with the small-trade group and the institutional-trade group, especially the former.

The total dollar value of trades per bond per month is shown in the last vertical panel of the table. In sharp contrast with the trading frequency, institutional trades overwhelmingly dominate, accounting for about 95% of all the transactions. Trading value is also highly skewed, especially for the institutional-trade group. Incidentally, that retail and medium-sized trades together account for only about 5% of the total dollar volume indicates the low likelihood of order splitting by institutional investors. In other words, there is no reason to believe that the retail trades classified in this study are contaminated by small orders from institutions.

3.2. Variable descriptions

The two main variables concern monthly bond returns and trading activities. I first delineate the calculation of bond returns. To begin, intra-day prices for the same bond are aggregated to the daily level by volume-weighted averaging. Second, when calculating bond returns for a specific size group, the initiation and liquidation prices are all from that group in question. To illustrate, suppose P_{t-1} and P_t are closing prices at the end of two consecutive months. Then the monthly return is $(P_t - P_{t-1})/P_{t-1}$ with some adjustment for accrued interest. Here, both P_{t-1} and P_t are calculated from trades belonging to the group in question. In the robustness checks in Section 4.2, an alternative return specification is examined: While P_t is the price based on trades pertaining only to that group (e.g., retail), P_{t-1} is based on trades of all sizes. This specification is based on the assumption that investor may initiate their trades in any size but would liquidate the positions in the group-specific size. Third, to facilitate sorting and regression analyses that are all anchored to calendar months, I interpolate the missing price at the end of the month, following Lin et al. (2011). For instance, to interpolate the end-of-month price for last month, I use the most recent price in the last month and the first available price in the current month. I require that neither price is more than 10 days away from the end of the last month. Otherwise the month-end price is treated as missing.[2] Finally, the group-specific returns are calculated as

$$r_t = \frac{\left(P_t + AI_t\right) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}}$$

where AI_t is the accrued interest and C_t is the coupon payment, and for the month in which there is a coupon payment, $AI_t = 0$ and for all other months, $C_t = 0$.

For each size group and for the entire bond population, excess bond returns are also calculated. This is to examine whether the trading behavior can predict bond returns after controlling for bond characteristics known to affect bond yields and returns. To this end, each month, I sequentially sort the observations along the following dimensions (with the number in parentheses being the number of cells): maturity (4), age (2), coupon rate (4), credit rating (3), and issue amount (2), resulting in 192 distinct portfolios.[3] Transaction-size-weighted average of returns is then calculated for each portfolio. The excess return for a bond is its raw return minus the return of the portfolio to which this bond belongs.

Investors trading activity is measured in a fashion similar to those in equity studies (e.g., Hvidkjaer, 2008; Kaniel et al., 2008). The essential idea is to calculate excess buy over sell, and divide this difference by a measure of the trading scale. Some researchers (e.g., Kaniel et al., 2008) use total trading volume while others (e.g., Hvidkjaer, 2008) use the security's total amount outstanding. I adopt the latter since it is more appropriate for bonds, many of which are not actively traded. Using the total trading volume to scale may lead to a less informative measure, especially in months when there are only buy or sell transactions. For instance, the measure is 1.0 if there are only buy transactions worth $10 million; but it is also 1.0 if the total volume is only $5,000 in another buy-only month.

The buy–sell imbalance for a particular bond scaled by its total amount outstanding is named "net buy over sell" or NetBOS in short. NetBOS is group specific. In other words, for the retail group, the total buy (sell) volume is tallied over trades with a size smaller than $100,000, and for the institutional group it is tallied over trades with a size larger than $500,000. To be free of potential data errors, the calculated NetBOS is winsorized at the 1% and 99% levels.

Summary statistics for the measure NetBOS are calculated, but are omitted for brevity. Nevertheless, the following observations are noteworthy. The average NetBOS is around zero for both the retail and the institutional group, as expected. However, the trading imbalance is skewed toward excess buy in the retail group and excess sell in the institutional group, and the skew appears more pronounced with the retail group. Interestingly, retail and institutional investors seem to go opposite ways in terms of trading directions. The average cross-section correlation between the retail NetBOS and the institutional NetBOS is −0.053, with a *t*-value of −7.24. This observation will be examined more closely in subsequent analyses.

[2] In unreported robustness checks, I repeat the sorting analysis without interpolations and the results are similar. In this robustness check, I simply assume that the last price of the month is the end-of-month price as long as it is no more than 10 days away from the month end.

[3] I numericalize the ratings with integers, with 1 presenting AAA/Aaa, 2 presenting AA^{+}/Aa, and so on. The average number of bonds within each cell is 51.2. The median is 57 and the 25th and 75th percentiles are respectively 47 and 64. The maximum number of bonds per cell is 126.

Table 2
Bond monthly returns sorted on previous month's NetBOS. This table reports portfolio returns based on a single-sort procedure. Each month, all bonds are sorted into deciles using previous month's NetBOS (net buy over sell). Equal-weighted average return is then calculated for each decile. This procedure is repeated for the entire sample period, resulting in a time-series of decile returns. The table reports the time-series average return of each decile and the "high minus low" difference and its Newey–West adjusted t-value. The sorting procedure is performed for bonds with any trading size, the small-trade group (trade size ≤ \$100,000), and the institutional-trade group (trade size ≥ \$500,000). They are respectively indicated by the headings "all", "small" and "inst". For completeness, I also report the "cross-sorting" results. For instance, when sorting based on $NetBOS_{small}$, decile returns are calculated for not only all the bonds and bonds in the small-trade group, but also bonds in the institutional-trade group. Results are presented for both raw returns and excess returns, all in percentage form. A bond's NetBOS in a particular month is the difference in dollars between all buy and all sell transactions (from the investors' perspective), divided by the total amount outstanding. A bond's monthly return is the percentage difference between the end-of-month prices, adjusted for accrued interest. A bond's excess return is its raw return minus the transaction-size-weighted average return of a characteristic-matched portfolio. The subtrahend is calculated as follows. Within each month, all bonds are sequentially sorted into sub-portfolios by maturity (4), coupon rate (4), credit rating (3), age (2), and issue size (2), where the numbers in parentheses are the number of bins for each bond characteristic. The sorting procedure results in 192 distinct portfolios. Transaction-size-weighted average of returns is then calculated for each sub-portfolio. A bond's excess return is arrived at by subtracting the return of the sub-portfolio to which the bond belongs. While the raw and excess returns under "all" are calculated using trades of all sizes, those under "small" and "inst" are calculated using only prices with a trade size belonging to that size group (e.g., returns under "small" are calculated using prices with a trade size equal to or smaller than \$100,000). The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

NetBOS	Raw returns						Excess returns					
	$NetBOS_{Small}$			$NetBOS_{Inst}$			$NetBOS_{Small}$			$NetBOS_{Inst}$		
	All	Small	Inst	All	Small	Inst	All	Small	Inst	All	Small	Inst
Low	1.238	1.260	1.718	0.567	0.508	0.625	0.586	0.608	0.903	−0.034	−0.098	0.020
2	0.818	0.860	0.886	0.540	0.533	0.617	0.217	0.267	0.277	−0.078	−0.088	−0.004
3	0.729	0.804	0.768	0.560	0.524	0.617	0.112	0.195	0.118	−0.063	−0.094	−0.008
4	0.735	0.835	0.753	0.595	0.569	0.660	0.116	0.222	0.082	−0.011	−0.030	0.050
5	0.619	0.638	0.762	0.579	0.567	0.636	0.007	0.024	0.124	−0.024	−0.022	0.030
6	0.542	0.487	0.694	0.633	0.632	0.641	−0.070	−0.124	0.014	0.003	0.018	0.006
7	0.508	0.433	0.614	0.601	0.635	0.571	−0.097	−0.167	−0.029	−0.014	0.028	−0.048
8	0.484	0.415	0.581	0.637	0.668	0.631	−0.112	−0.178	−0.058	0.013	0.049	0.001
9	0.438	0.388	0.516	0.694	0.725	0.678	−0.158	−0.207	−0.144	0.037	0.072	0.021
High	0.238	0.197	0.449	0.700	0.761	0.731	−0.353	−0.393	−0.271	0.080	0.134	0.110
High-low	−1.001	−1.063	−1.268	0.133	0.253	0.106	−0.939	−1.001	−1.174	0.114	0.232	0.090
t-value	−11.29***	−11.99***	−5.26***	2.53***	4.47***	2.58***	−13.47***	−14.30***	−5.40***	3.11***	6.04***	3.21***

4. Trading and cross-section of bond returns — sorting analysis

4.1. Main results

To see how bond returns are related to trading imbalance, I perform single-sort analyses. Each month, I sort bonds into deciles using the previous month NetBOS, and then calculate the average return for each decile. This procedure is repeated for the entire sample. The return difference between the high-NetBOS and low-NetBOS deciles is also calculated, together with its Newey–West adjusted t-value.

In this sorting exercise, while the trade imbalance measure NetBOS is group specific, the returns can belong to any of the groups. For instance, when we sort bonds into deciles according to the retail group's NetBOS, the most natural returns to examine would be the bond returns belonging to the retail group. This allows us to answer the question: How are the bond returns of the retail (institutional) group associated with excess buying or selling by retail (institutional) investors? Most of the ensuing analyses are of this nature.

For completeness and additional insights, I also perform a "cross-sorting" analysis in which, e.g., the retail group's returns are sorted on the institutional group's NetBOS. This exercise allows us to answer the question: Can one group of investors benefit from the trading behavior of the other group? To continue the above example, when the retail group's returns are sorted on the institutional investors' trade imbalance, we essentially attempt to ascertain whether retail investors can make a trading profit by mimicking institutional investors.

Finally, it is also instructive to examine how the overall bond market returns are associated with a particular group's trade imbalance. In this case, the returns will be based on prices of all trade sizes (including the medium size from \$100,000 to \$500,000), for both the numerator and the denominator in the return calculation. Here, we answer the question: How would a random average investor (who sometimes trades small sizes and sometimes large sizes) perform if he/she follows a particular group of investors (i.e., either retail or institutional)? Table 2 reports the results for all three forms of sorting: returns of own group (within-group sorting), returns of the other group (cross-sorting), and returns of all sizes (general sorting).

For the within-group sorting, the most striking observation is that the trading imbalance, NetBOS, negatively predicts returns for retail investors while positively predicts returns for institutional investors, and the observation is valid for both the raw returns and the excess returns. The return difference between the high and low decile portfolios is highly significant, both statistically and economically. The magnitude of the high-minus-low return difference decreases only slightly from raw returns to excess returns, i.e., −1.063% to −1.001% and 0.106% to 0.090%, implying that the predictability in raw returns is not due to the risks captured by the five bond characteristics. For the retail group, in raw returns, if we go long in the lowest-NetBOS portfolio and short in the highest-NetBOS portfolio, then our monthly return is 1.063%, equivalent to 12.76% annually without compounding. For the institutional group, the long-short positions need to be reversed and the monthly return is 0.106%, equivalent to 1.272% annually without compounding.

Closer examinations of the decile returns reveal that the low-NetBOS side contributes more to the return difference for both investor groups. In other words, the return predictability is stronger when investors engage in excessive selling.

The "cross-sorting" leads to qualitatively similar results, except that when institutional returns are sorted on retail NetBOS, the results are even more dramatic: The long-short portfolio earns a monthly return of 1.268%. It is apparent from the table that this large long-short portfolio return results from the wider dispersion in decile returns of the institutional group. What drives the wider dispersion then? It is certainly not the return dispersion within the institutional group, since unreported summary statistics show that the bond returns of the two groups have similar means and standard deviations. As will be shown in Tables 7 and 8 and discussed in Section VIII, the main reason is retail investors' behavioral bias. They are positive feedback traders in the presence of return reversals. Fig. 1 provides two vivid examples. In November 2007, the bond issued by Tekni-Plex Inc. was in retail investors' decile that saw the most selling, apparently due to the price decline up to that point. However, the bond price rebounded in December 2007, providing an explanation of the large returns in the low-$\text{NetDOS}_{\text{small}}$ decile in Table 2. The prices in Fig. 1 are based on all trade sizes. A closer examination of bond prices within each group provides the ultimate answer as to why the institutional group return is higher in the low-$\text{NetBOS}_{\text{small}}$ decile. It turns out that, for the retail group, the end-of-month volume-weighted prices for November and December are respectively \$53.6667 and \$64.74, leading to a December return of 20.63% for this bond. The corresponding quantities for the institutional group are \$53.9688, \$70, and 29.70%. In other words, the price of the same bond in the institutional group rebounded more (equivalently speaking, prices with a trade size larger than \$500,000 rebounded more). Bonds with price profiles similar to that of Tekni-Plex Inc. collectively explain why the low-$\text{NetBOS}_{\text{small}}$-decile return for the institutional group (1.718%) is much higher than that of the low-$\text{NetBOS}_{\text{inst}}$-decile (0.625%).

The second plot in Fig. 1 provides an example for the case of extreme buying. As the plot shows, the price was on the rise up to January 2003, a month in which the bond saw the most buying by retail investors. The price dropped subsequently in February. In fact, the February return for the retail group was still positive at 12.82%, but that for the institutional group was −30.62%. Situations like this explain why the high-$\text{NetBOS}_{\text{small}}$-decile return for the institutional group (0.449%) is much lower than that of the high-$\text{NetBOS}_{\text{inst}}$-decile (0.731%). In a nutshell, the cross-sorting results demonstrate that the behavior bias of retail investors manifests itself even more when measured in bond returns of the institutional investors, who, as shown later, prove to be more rational.

Finally, perhaps not surprisingly, for the "general sorting" wherein returns are based on prices of all trade sizes, the results are in between those of the two separate groups. By definition, the general bond market returns are size-weighted average of the retail and institutional returns. As such, this version of returns does not offer additional insights relative to the returns of the retail and institutional groups. I therefore omit this version of returns in the subsequent analyses.

In summary, the upshot of Table 2 is the following. For retail investors, excessive buying (selling) is followed by lower (higher) bond returns; for institutional investors, excessive buying (selling) precedes higher (lower) returns. And the above is true no matter which group's bond returns are being examined. Tentatively, the results indicate that institutional investors are rational while retail investors are not. Before making further investigations, a few robustness checks are in order.

4.2. Robustness checks

The robustness checks are performed along four dimensions: alternative frequencies, alternative return and NetBOS calculations, alternative definitions of the retail trading size, and different ways of calculating excess returns. To see whether the predictive pattern also exists in shorter or longer horizons, I repeat the analysis with non-overlapping weekly and quarterly data. To this end, the NetBOS measure is re-calculated for the weekly and quarterly frequencies, but returns are aggregated from high-frequency quantities. Specifically, weekly returns are average daily returns within the week multiplied by 22; quarterly returns are simple average of the monthly returns within the quarter.[4] Panel A of Table 3 reports the results (for brevity, the cross-sorting results are omitted). The patterns in monthly data observed in Table 2 also prevail in the weekly and quarterly frequencies. Relative to the monthly case, the statistical significance is stronger in the weekly case, but slightly weaker in the quarterly case. More important is the fact that the economic significance does not diminish as we move from monthly to quarterly frequency.

Do the patterns reverse themselves beyond certain horizons? To answer this question, the analysis in Table 2 is repeated with one modification: Instead of calculating monthly returns upon sorting NetBOS_{t-1} each month, returns for horizons of 3, 6, 12, and 24 months are calculated (for brevity, the results are omitted from the table). It turns out that the statistical significance of the high-low portfolio return remains even at the 24-month horizon for both the small-trade and the institutional-trade groups. In other words, no reversals are observed.

The second set of robustness checks are along the dimension of alternative return and NetBOS calculations. As discussed in Section 3.2, the group-specific bond returns can be calculated in two ways. The analyses so far are based on returns whose initiation price is from the group in question. As a robustness check, I repeat the analysis by using returns whose initiation price is based on trades of all sizes. The implicit assumption behind this return definition is: Investors may acquire bonds in any trade size. The first part of Panel B reports the results. Qualitatively, the conclusions drawn from Table 2 remain valid under the alternative return calculation. In fact, the results are stronger for the institutional group.

[4] Calculating the actual weekly and quarterly returns would entail additional interpolations of the end-of-week and end-of-quarter prices. Insofar as our objective is to see whether the predictability exists at alternative frequencies (as opposed to precisely estimating the abnormal trading returns), the aggregation method will serve the purpose while maintaining consistency.

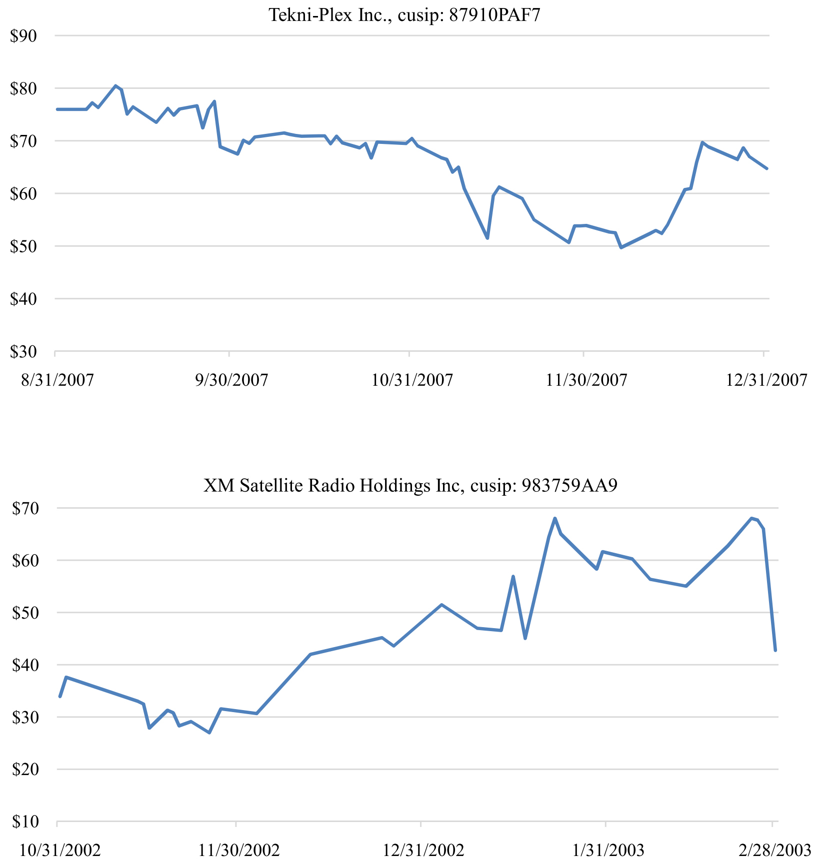

Fig. 1. Examples of bond price movements in the extreme deciles of buy–sell imbalance. This figure shows two examples of bond price movements in the extreme deciles of the buy–sell imbalance measure (NetBOS) for the retail group. The bond prices are in daily frequency. Each daily price is a volume-weighted average of trading prices of all transaction sizes within the day. The bond, 87910PAF7, issued by Tekni-Plex Inc. (a U.S. company specializing in plastic and rubber polymer technology) was in the lowest decile in November 2007. In other words, this bond saw the most selling by retail investors in November 2007. The intensive selling was propelled by the decline of prices in the recent months. However, the bond price recovered substantially in December 2007. The bond, 983759AA9, issued by XM Satellite Radio Holdings Inc. (a U.S. radio company producing music, sports, news, talk, entertainment, traffic, and weather channels) was in the highest decile in January 2003. In other words, this bond saw the most buying by retail investors in January 2003. The intensive buying was propelled by the increase of prices in the recent months. However, the bond price dropped substantially in February 2003. As shown in Table 8 and Section 8, the retail investors behavior is consistent with the so-called "extrapolation bias".

The alternative calculation of NetBOS is motivated by Kaniel et al. (2008) who use two versions of trading imbalance to carry out their investigations of stocks in weekly frequency. The first version is equivalent to the one used in the current study. The second version measures the so-called intensity of trade imbalance. Specifically, their sorting is based on the deviation of last week's trade imbalance from the average imbalance of the prior nine weeks. In the current setting, I use the deviation of last month's NetBOS from the average of the prior three months' NetBOS. The last part of Panel B in Table 3 reports the results. The previous conclusion remains valid, albeit with weaker statistical and economic significance, especially for the institutional group whose high-low difference in raw returns is no longer significant. In fact, as will be seen later, once all the risk factors are controlled for in a regression setting, the return predictability for the institutional group (using its own NetBOS) no longer exists.[5]

The next set of robustness checks deal with the size classification. It is already argued in Section 3.1 that the direct customer–dealer interactions and the small portion that the small-size trades account for the overall trading volume both imply a low probability of order splitting by institutional investors. Nevertheless, for additional assurance, I repeat the analysis in Table 2 by redefining small/retail trades with lower cutoffs at $50,000 and $25,000 respectively. Presumably, the smaller the trade size, the more likely that they come from retail investors. As shown in Panel C of Table 3, the results remain unchanged qualitatively.

[5] Etula et al. (2016) show that asset prices can be subject to undue selling pressures at the month end due to mutual funds' cash needs. Insofar as corporate bonds are widely held by mutual funds, their month-end prices might be affected too, which in turn might affect the monthly returns as calculated in this study. To see if my results are robust to this potential effect, I recalculate the monthly returns and NetBOS using the middle of the month as the month end (i.e., the monthly returns are based on mid-month prices and the trade imbalances are also calculated from mid-month to mid-month). It turns out that the results in Table 2 remain largely unchanged both qualitatively and quantitatively. To conserve space, the results are omitted from Table 3.

Table 3
Robustness results. This table reports results for various robustness checks performed against the main results in Table 2. Panel A reports sorting results for weekly and quarterly frequencies. For this purpose, the trade imbalance measure NetBOS is recalculated for each frequency. However, for simplicity, the bond returns are aggregated from high frequency returns. Specifically, weekly returns are average daily returns within the week, multiplied by 22 to make them equivalent to monthly returns; quarterly returns are average monthly returns within the quarter. Panel B presents results based on alternative calculations of bond returns and the NetBOS measure, all for the monthly frequency. The alternative NetBOS measure takes a relative form. Instead of using the NetBOS measure for month $t-1$, the sorting is done using the difference between the NetBOS measure for month $t-1$ and the average NetBOS over the previous three months. The alternative return calculation is slightly complicated. In the main analysis, for a particular trade-size group, returns are calculated using only bond prices belonging to that group. In contrast, in the robustness check, returns for a particular trade-size group are calculated using bond prices of all trades. The reader is referred to the text for details. For brevity, in both Panels A and B, "cross-sorting" results are omitted. In other words, decile returns are only calculated based on the sorting variable relevant for that trade-size group. Panel C demonstrates the robustness of the cutoff used to classify retail trades. Specifically, the sorting analyses in Table 2 (pertaining to small-trade returns) are repeated for two alternative cutoffs: \$50,000 and \$25,000. For instance, under the cutoff of \$50,000, all trades with a size ≤ \$50,000 are classified as retail. The cutoff used to classify institutional trades remains at \$500,000. Therefore, all results pertaining to institutional returns are omitted. In all panels, results are presented for both raw returns and excess returns as defined in Table 2. All returns are in percentage form. The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

Panel A. Alternative frequencies

Weekly frequency				Quarterly frequency			
Raw return		Excess return		Raw return		Excess return	
Small	Inst	Small	Inst	Small	Inst	Small	Inst
0.766	0.010	0.565	−0.035	1.086	0.606	0.393	0.016
0.180	−0.010	0.093	−0.051	0.738	0.582	0.119	−0.012
0.027	0.018	−0.023	−0.023	0.681	0.610	0.064	0.009
0.005	0.037	−0.041	0.003	0.700	0.653	0.081	0.050
−0.020	0.065	−0.093	0.021	0.646	0.697	0.017	0.091
0.005	0.049	−0.056	0.009	0.609	0.802	−0.009	0.163
0.023	0.024	−0.018	−0.014	0.549	0.713	−0.038	0.092
0.064	0.043	0.015	0.002	0.529	0.707	−0.042	0.076
0.100	0.051	0.021	0.006	0.509	0.685	−0.070	0.052
−0.005	0.062	−0.170	0.010	0.434	0.762	−0.127	0.129
−0.771	0.052	−0.735	0.045	−0.652	0.156	−0.519	0.113
−19.45***	4.79***	−19.96***	4.15***	−4.29***	2.73***	−5.40***	3.16***

Panel B. Alternative return and NetBOS calculations

NetBOS	Alternative return calculation				Alternative NetBOS calculation			
	Raw return		Excess return		Raw return		Excess return	
	Small	Inst	Small	Inst	Small	Inst	Small	Inst
Low	1.197	0.553	0.544	−0.051	0.731	0.655	0.131	0.029
2	0.712	0.545	0.117	−0.076	0.665	0.641	0.091	0.013
3	0.565	0.580	−0.045	−0.045	0.630	0.619	0.055	0.007
4	0.577	0.627	−0.037	0.018	0.649	0.637	0.061	0.020
5	0.497	0.678	−0.117	0.074	0.672	0.635	0.060	0.020
6	0.485	0.753	−0.126	0.119	0.630	0.617	0.016	0.003
7	0.497	0.670	−0.103	0.052	0.528	0.596	−0.078	−0.019
8	0.535	0.700	−0.059	0.071	0.518	0.596	−0.080	−0.012
9	0.538	0.726	−0.057	0.069	0.513	0.608	−0.077	−0.002
High	0.328	0.768	−0.262	0.147	0.526	0.652	−0.124	0.061
High-low	−0.869	0.215	−0.806	0.198	−0.205	−0.003	−0.255	0.032
t-value	−12.02***	4.47***	−11.75***	5.69***	−3.03***	−0.15	−5.52***	1.89*

Panel C. Alternative cutoffs for the definition of small-size trades

NetBOS	Raw return				Excess return			
	$NetBOS_{Small}$		$NetBOS_{Inst}$		$NetBOS_{Small}$		$NetBOS_{Inst}$	
	\$50k	\$25k	\$50k	\$25k	\$50k	\$25k	\$50k	\$25k
Low	1.220	1.142	0.505	0.501	0.566	0.481	−0.097	−0.098
2	0.844	0.818	0.526	0.528	0.255	0.231	−0.091	−0.085
3	0.761	0.728	0.515	0.518	0.162	0.137	−0.101	−0.093
4	0.804	0.765	0.546	0.546	0.199	0.169	−0.045	−0.041
5	0.624	0.598	0.557	0.555	0.012	−0.014	−0.024	−0.020
6	0.488	0.491	0.635	0.624	−0.119	−0.109	0.026	0.020
7	0.456	0.486	0.638	0.612	−0.140	−0.102	0.035	0.016
8	0.441	0.463	0.672	0.663	−0.147	−0.120	0.057	0.053
9	0.399	0.424	0.701	0.701	−0.194	−0.168	0.056	0.061
High	0.225	0.272	0.759	0.739	−0.366	−0.320	0.135	0.119
High-low	−0.995	−0.869	0.254	0.238	−0.932	−0.801	0.232	0.217
t-value	−11.36***	−9.89***	4.24***	4.21***	−14.05***	−12.79***	5.59***	5.98***

Lastly, it is useful to know whether the results concerning excess returns are sensitive to the benchmarks. To this end, instead of using the maturity/coupon/rating/age/size stratified returns, I use Barclays U.S. corporate bond indices to calculate the excess returns and then repeat the analyses in Table 2. Specifically, the monthly returns of the following nine Barclays indices are used to adjust the corresponding raw returns: U.S. Aggregate Corporate AAA/AA/A/BAA long, U.S. Aggregate Corporate AAA/AA/A/BAA intermediate, and U.S. Corporate High-Yield Index. Barclays defines "intermediate" maturity as ranging from 1 to 9.99 years; and "long" maturity as being 10 years and longer. It turns out that, the results are not sensitive to the choice of benchmarks. If anything, the high-low returns are larger in magnitude than those in Table 2. This makes perfect sense in that the risk-adjustment by using only nine sub-indices is not as fine as the one employed in the paper. The results are omitted from the table for brevity.

In summary, the negative predictability for the retail group is strong and survives in all alternative settings; the positive predictability for the institutional group survives most of the checks, but is less robust compared with the retail group.

5. Additional risk investigations

5.1. Return volatility and illiquidity

To this point, cross-sectional predictability in bond returns has been established for retail investors. The results also hold with excess returns obtained via crude risk adjustments based on bond characteristics or Barclays corporate bond indices. It is possible that the predictability is explained by other risks that have not been controlled for. Kaniel et al. (2008) consider return standard deviation as a risk measure when investigating individual trading and stock returns. They also consider liquidity as a potential explanation for the association between individual investors trading and stock returns. In fact, Chen et al. (2007) and others have shown that illiquidity is priced in bond yields and returns. To see whether risk and illiquidity can explain the predictability in returns, I run Fama–MacBeth regressions with these two factors as control variables.

Bond risk is measured by the standard deviation of daily returns over the past six months excluding the current month (at least 15 daily observations are required for a valid standard deviation to be calculated). Bond illiquidity is gauged by turnover, number of trades, zero-return days, and price range. Turnover is the total trading volume within the month divided by the total amount outstanding. The number of trades is the total number of transactions within the month. A negative sign is attached to the value of these two proxies so that they measure illiquidity. The third measure of illiquidity is "days of zero return", which is the number of days within the month on which the bond return is zero. This measure has been used by Chen et al. (2007) and others. Finally, following Downing et al. (2005), and Helwege et al. (2014), I also use "price range" to measure illiquidity. The daily price range is calculated as $[(P_{\max} - P_{\min})/P_{\text{avg}}]/(\text{daily volume})$, where $P_{\max}$, $P_{\min}$ and P_{avg} stand for, respectively, the maximum, minimum and average bond price within the day. The monthly "price range" is simply the average of the daily price range within the month.

The Fama–MacBeth regression is then run with one illiquidity measure at a time. Specifically, each month, bond returns are regressed cross-sectionally on lagged values of NetBOS, return, and standard deviation, together with one of the four illiquidity measures. For brevity, I omit the table and summarize the main results below.

First and foremost, the negative relation between trade imbalance and bond returns for the retail group remains highly significant in the presence of all control variables; the same can be said about the positive relation for the institutional group. Therefore, bond risks and illiquidity cannot explain the association between trade imbalance and bond returns.

Moreover, bond returns are indeed positively associated with their return volatility for both groups, consistent with the usual risk-return pricing relationship. However, compared with the retail group, the risk impact on returns is much stronger for the institutional group. Finally, the coefficient of the lagged return variable is highly significant for both groups, but with opposite signs. It is negative for the retail group, indicating monthly reversals in returns, and positive for the institutional group, indicating momentum. Section 7 will provide an in-depth analysis of this reversal/momentum phenomenon.

5.2. Fama–French and liquidity factors

While the previous section examines the traditional risk-return relations, this section investigates whether a statistically and economically significant alpha exists after the usual market factors are accounted for. To this end, the monthly Fama–French equity factors (i.e., MKT, SMB and HML) are downloaded from the webpage of Ken French. The Fama–French bond factors (i.e., DEF and TERM in Fama and French, 1993) need to be calculated from corporate bond returns and returns of government bonds and T-bills, the latter of which are downloaded from the webpage of the Federal Reserve Board. TERM is simply the monthly return of long-term government bond minus the 30-day T-bill rate. DEF measures the return differential between corporate bonds and government bonds, and its calculation varies slightly among researchers. Lin et al. (2011), and Acharya et al. (2013) are two studies employing this measure. It turns out that the two versions of DEF in these two papers lead to similar results. So I only report results based on the version used by Acharya et al. (2013).

While the Fama–French equity and bond factors are commonplace in many asset pricing tests, there does not exist a commonly accepted liquidity factor for corporate bonds. Lin et al. (2011) is the only known study that systematically examines the liquidity risk in bond returns. I therefore follow their procedure and construct two versions of the aggregate liquidity factor based on, respectively, Amihud (2002) and Pastor and Stambaugh (2003). In the end, the results are similar between the two versions of the aggregate

Table 4
Alpha of the high-minus-low portfolio. This table reports the alpha of the high-minus-low portfolios resulting from the sorting procedures in Table 2. Specifically, once the monthly returns of the high-minus-low portfolio (i.e., the difference between the returns of the highest-NetBOS decile and the lowest-NetBOS decile) are obtained, they are regressed on the Fama–French equity factors (i.e., Mkt_RF, SMB and HML), the Fama–French bond factors (i.e., DEF and TERM), and a liquidity factor. The equity factors are downloaded from Ken French's webpage while the bond factors are calculated following the procedures in Acharya et al. (2013). The liquidity factor is based on Amihud (2002) and its calculation follows the procedure in Lin et al. (2011). Alpha is already in percentage form. The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

Panel A. Raw returns

	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
	Sorting by $NetBOS_{Small}$						
Coef.	−1.008	0.087	0.127	0.013	−0.180		
t-value	−16.76***	0.42	0.38	0.04	−4.20***		
Coef.	−0.858	0.064	0.176	0.005	−0.171	−0.648	
t-value	−6.13***	0.31	0.53	0.02	−3.95***	−1.18	
Coef.	−0.880	0.073	0.184	0.061	−0.205	−0.508	0.001
t-value	−6.26***	0.35	0.55	0.20	−4.10***	−0.91	1.36
	Sorting by $NetBOS_{Inst}$						
Coef.	0.082	−0.104	−0.115	0.236	0.089		
t-value	3.16***	−0.98	−0.67	1.46	4.03***		
Coef.	0.051	−0.100	−0.125	0.237	0.087	0.137	
t-value	0.69	−0.93	−0.72	1.47	3.89***	0.48	
Coef.	0.037	−0.094	−0.120	0.274	0.065	0.228	0.001
t-value	0.50	−0.88	−0.70	1.69*	2.51**	0.79	1.70*

Panel B. Excess returns

	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
	Sorting by $NetBOS_{Small}$						
Coef.	−0.992	0.249	0.189	0.325	−0.095		
t-value	−20.21***	1.48	0.70	1.28	−2.72***		
Coef.	−0.864	0.230	0.231	0.318	−0.088	−0.554	
t-value	−7.56***	1.36	0.85	1.25	−2.48**	−1.24	
Coef.	−0.916	0.250	0.249	0.454	−0.170	−0.217	0.002
t-value	−8.42***	1.57	0.97	1.88*	−4.39***	−0.50	4.22***
	Sorting by $NetBOS_{Inst}$						
Coef.	0.083	−0.109	−0.138	0.090	0.053		
t-value	3.57***	−1.37	−1.07	0.74	3.21***		
Coef.	0.044	−0.103	−0.151	0.092	0.051	0.172	
t-value	0.80	−1.29	−1.16	0.76	3.03***	0.80	
Coef.	0.035	−0.100	−0.148	0.114	0.038	0.227	0.000
t-value	0.65	−1.25	−1.15	0.94	1.93*	1.05	1.37

market liquidity factor. Therefore, for brevity, I only report the results based on the Amihud liquidity factor.[6] Table 4 contains the results.

First and foremost, the alpha of the high-low portfolio for the retail group is negative and significant, both statistically and economically, re-affirming the sorting results in Table 2 and the regression analyses controlling for risk and liquidity. The alpha survives all the factors, both in raw returns and excess returns. In contrast, the positive alpha for the institutional group prevails only in the absence of the TERM factor. Therefore, the positive return of the high-low portfolio for the institutional group appears to compensate for the slope risk of the term structure of interest rates. The positive coefficient of DEF and TERM for the institutional group is consistent with the findings in Lin et al. (2011). The coefficient of DEF for the retail group is negative, mostly due to flight-to-quality when the credit condition deteriorates.[7] Finally, the coefficient of the aggregate liquidity factor is mostly positive, consistent with the findings in Lin et al. (2011), although it is highly significant only in Panel B when the sorting is done with the retail group's trade imbalance. Regardless, the aggregate liquidity factor does not weaken the alpha.

To this point, one can conclude that institutional investors appear to be rational and their trading can generate a positive abnormal return. However, this abnormal return is subsumed by the TERM bond factor. In sharp contrast, retail investors seem to be irrational

[6] The contemporaneous correlation between the two liquidity factors is 0.31 in Lin et al. (2011) whereas it is 0.25 in the current study. One potential reason is the difference in samples. For one, their TRACE sample has limited coverage in the period of 2002–2005, and their sample ends at March 2009; for another, they extend the sample period backward to 1994 with NAIC data. My sample is from 2002 to 2014 with full coverage of corporate bonds.

[7] The specific reasoning is as follows. As shown later, retail investors prefer safer and liquid bonds. When the default risk increases in the market place (i.e., as DEF increases), a flight-to-quality would ensue as noted by Pastor and Stambaugh (2003) in a more general context. Investors offload risky bonds and shift to safer and liquid bonds, exerting price pressure on the latter, causing their expected returns to go down. Although prices of all bonds tend to go down when the overall default risk increases, the flight-to-quality phenomenon alleviates the price decline of the safer and more liquid bonds. As a result, after controlling for all risks, relatively speaking, the price of safer bonds actually go up, leading to a lower expected return.

Table 5

Alpha of the high-minus-low portfolio from cross-sorting. This table has exactly the same structure as Table 4, except that the sorting is done in a cross-group fashion. For instance, the first portion of Panel A reports alpha for the institutional high-minus-low portfolio when returns are sorted on the trade imbalance of the retail group. Please see Table 4 for other descriptions. Alpha is already in percentage form. The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

Panel A. Raw returns							
	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
	R_{Inst} sorted by $NetBOS_{Small}$						
Coef.	−1.405	−0.288	0.715	−1.324	−0.159		
t-value	−8.33***	−0.59	0.91	−1.79*	−1.56		
Coef.	−1.290	−0.262	0.658	−1.315	−0.168	0.750	
t-value	−3.31***	−0.53	0.82	−1.77*	−1.63	0.57	
Coef.	−1.210	−0.324	0.604	−1.726	0.081	−0.267	−0.007
t-value	−3.07***	−0.70	0.80	−2.44**	0.72	−0.21	−4.36***
	R_{Small} sorted by $NetBOS_{Inst}$						
Coef.	0.231	−0.281	0.121	−0.337	0.108		
t-value	5.04***	−1.79*	0.48	−1.42	3.31***		
Coef.	0.148	−0.269	0.093	−0.333	0.103	0.362	
t-value	1.38	−1.70*	0.37	−1.40	3.12***	0.86	
Coef.	0.105	−0.251	0.108	−0.219	0.034	0.645	0.002
t-value	1.01	−1.66*	0.44	−0.95	0.92	1.58	3.73***

Panel B. Excess returns							
	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
	R_{Inst} sorted by $NetBOS_{Small}$						
Coef.	−1.429	0.600	0.593	−0.485	0.007		
t-value	−9.02***	1.43	0.88	−0.77	0.09		
Coef.	−1.343	0.632	0.524	−0.474	−0.004	0.903	
t-value	−3.69***	1.50	0.77	−0.75	−0.05	0.81	
Coef.	−1.345	0.602	0.499	−0.669	0.114	0.421	−0.003
t-value	−3.66***	1.45	0.74	−1.06	1.13	0.37	−2.32**
	R_{Small} sorted by $NetBOS_{Inst}$						
Coef.	0.231	−0.282	0.035	−0.435	0.064		
t-value	7.09***	−2.52**	0.20	−2.58***	2.75***		
Coef.	0.163	−0.271	0.013	−0.432	0.060	0.296	
t-value	2.14**	−2.42**	0.07	−2.56**	2.54**	0.99	
Coef.	0.129	−0.257	0.025	−0.341	0.005	0.520	0.002
t-value	1.78*	−2.43**	0.14	−2.12**	0.19	1.81*	4.21***

in that they buy imminent losers and sell imminent winners. As shown in the next section, they are momentum traders in the presence of return reversals, which necessarily leads to losses.

It is tempting to dismiss the significance of the findings concerning the retail investors since, as apparent in Table 1, their trading accounts for only a small portion of the entire bond market in dollar terms. However, Table 1 also shows that most of the bonds are traded by retail investors and most of the trades on each bond originate from them too. In addition, it is interesting to know whether we can obtain a positive alpha by trading bonds in the institutional group based on the retail NetBOS. Results in Table 5 provide a positive answer to this question. While the trade imbalance of the institutional group cannot always lead to a positive alpha for the returns in the retail group, the negative alpha of the institutional returns can survive all pricing factors. In other words, a contrarian trading strategy relative to retail investors will lead to a positive alpha in bonds traded by institutional investors. The following section examines this trading strategy further by considering the spread between the buy and sell prices.

6. Evaluation of trading strategies with buy/sell transaction prices

This section addresses a practical question: Can the uncovered predictability lead to a realistic, profitable trading strategy? The analyses in Tables 4 and 5 inform us of the relationship between trades and returns from a theoretical asset pricing perspective, but the alphas are not necessarily achievable. The main reason is that the bond returns are calculated out of the average of buy and sell prices. The spread between the buy and sell prices has not been taken into consideration.[8] To evaluate the performance from a trading strategy perspective, the bond returns are recalculated with separate buy and sell prices coming from a particular size group,

[8] The term "bid–ask spread" is purposely avoided in this paper. Unlike a typical market maker in the equity market who posts bid and ask prices and is prepared to transact at those prices, a market maker in the corporate bond market does not post bid and ask prices for any bond. Instead, he/she only provides an indicative price when being contacted. Naturally, a market maker would mark the price up (down) relative to what he/she considers as the fair price when being approached to sell (buy). It is only in this sense that there is a spread. In order to avoid misperceptions, I will use the term "spread between buy and sell prices" or its equivalents.

Table 6
Alpha of the high-low portfolio based on buy/sell transaction prices. This table reports results of sorting analysis for raw returns, carried out in the same fashion as in Panel A of Tables 4 and 5, with a key modification concerning the calculation of bond returns. As described in Section 2, the bond returns within each group (viz. retail or institutional) are based on prices averaged over both the buy and sell prices, and the denominator in the return calculation is the average price across trades of all sizes. These bond returns reflect the overall price movements, and they are not attainable through regular transactions. The results in the current table are based on transaction prices, i.e., depending on the direction of the transaction, buy or sell price is used to calculate returns. Specifically, the return from a long position is calculated as $(sell_t/buy_{t-1} - 1)$, indicating that we need to acquire the bond at buy_{t-1} in month $(t-1)$ and liquidate it at $sell_t$ in month t. Analogously, the return from a short position is calculated as $(buy_t/sell_{t-1} - 1)$, indicating the borrowing and selling in month $(t-1)$ and the buying-back in month t. Additionally, since the alpha under the sorting by $\text{NetBOS}_{\text{small}}$ in Tables 4 and 5 is negative, the proper transaction is to long the low-decile bonds and short the high-decile bonds. In other words, the portfolio in Panel B is high-minus-low and that in Panel A is low-minus-high. The other aspects of Panels A and B are identical to Tables 4 and 5. Please refer to those tables for details. Alpha is already in percentage form. In order to provide a direct comparison with the sorting results in Table 2, in each group in Panels A and B, the low-minus-high or high-minus-low return and its associated t-value are also reported. They are in the first entry of each group, denoted by L–H or H–L. The last panel of the table, Panel C, reports the mean and selected percentiles of the difference between buy and sell prices for both the small-trade group and the institutional-trade group. The dollar difference is simply the average difference between buy and sell prices per \$100 par; the percentage difference is the dollar difference divided by the average of the buy and sell prices, multiplied by 100. The specific calculation procedure is as follows. We first calculate the volume-weighted buy and sell prices for each bond within the same day and find the difference between the two volume-weighted prices (this is only done for bonds/days where there are both buy and sell prices within the same day). We then average the time-series differences within the sample for each bond. Finally, the mean and percentiles are calculated across bonds. In Panels A and B, the *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

Panel A. Sorted by $\text{NetBOS}_{\text{Small}}$

	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
	Bond returns of the retail group						
L–H	−5.194						
t-value	−46.63***						
Coef.	−5.228	1.330	−1.440	1.008	−0.055		
t-value	−47.68***	3.54***	−2.39**	1.78*	−0.70		
Coef.	−5.049	1.303	−1.381	0.998	−0.044	−0.777	
t-value	−19.72***	3.45***	−2.27**	1.76*	−0.56	−0.77	
Coef.	−5.177	1.354	−1.337	1.337	−0.250	0.061	0.006
t-value	−21.56***	3.85***	−2.36**	2.50**	−2.92***	0.06	4.75***
	Bond returns of the institutional group						
L–H	−0.893						
t-value	−5.23***						
Coef.	−0.964	1.939	−2.199	2.010	0.034		
t-value	−5.95***	3.49***	−2.46**	2.40**	0.30		
Coef.	−0.631	1.888	−2.089	1.992	0.054	−1.445	
t-value	−1.67*	3.38***	−2.32**	2.38**	0.46	−0.97	
Coef.	−0.782	1.949	−2.038	2.392	−0.189	−0.456	0.007
t-value	−2.14**	3.64***	−2.36**	2.95***	−1.46	−0.32	3.69***

Panel B. Sorted by $\text{NetBOS}_{\text{Inst}}$

	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
	Bond returns of the retail group						
H–L	−4.046						
t-value	−33.67***						
Coef.	−4.009	1.662	−1.267	0.973	−0.294		
t-value	−34.45***	4.17***	−1.98**	1.62	−3.55***		
Coef.	−3.369	1.565	−1.055	0.939	−0.257	−2.776	
t-value	−12.67***	3.99***	−1.67*	1.59	−3.13***	−2.67**	
Coef.	−3.470	1.605	−1.020	1.207	−0.419	−2.115	0.004
t-value	−13.48***	4.25***	−1.68*	2.11**	−4.57***	−2.07**	3.50***
	Bond returns of the institutional group						
H–L	−0.928						
t-value	−19.19***						
Coef.	−0.906	0.591	−0.370	0.306	−0.128		
t-value	−19.15***	3.65***	−1.42	1.25	−3.82***		
Coef.	−0.624	0.548	−0.277	0.291	−0.112	−1.225	
t-value	−5.80***	3.46***	−1.08	1.22	−3.37***	−2.91***	

(*continued on next page*)

i.e., either the retail group or the institutional group. This is to ensure that bond purchases are executed at prices higher than bond liquidations, and that the prices are relevant for the group in question. Importantly, the return calculation is position specific. For a long position, the return is the percentage difference between the selling price and the initial purchase price; for a short position, it is the percentage difference between the purchase price in period t and the selling price in period $(t-1)$, reflecting the short selling transactions. Moreover, since the alpha under the sorting by $\text{NetBOS}_{\text{small}}$ in Tables 4 and 5 is negative, a profit-seeking trading strategy should consist of buying bonds in the low-$\text{NetBOS}_{\text{small}}$ decile and shorting bonds in the high-$\text{NetBOS}_{\text{small}}$ decile.

Table 6 (*continued*)

Panel B. Sorted by $NetBOS_{Inst}$							
	Alpha	Mkt_RF	SMB	HML	DEF	TERM	LIQ
Coef.	−0.654	0.561	−0.266	0.372	−0.161	−1.024	0.001
t-value	−6.16***	3.60***	−1.06	1.57	−4.27***	−2.44**	2.57***

Panel C. Mean and percentiles of difference or spread between buy and sell prices						
Mean	10th	25th	Median	75th	90th	
	$buy–sell spread per $100 par					
Small	$1.92	$0.55	$1.10	$1.82	$2.62	$3.36
Institution	$0.36	$0.02	$0.13	$0.28	$0.48	$0.80
	% buy–sell spread					
Small	2.00	0.53	1.06	1.80	2.69	3.57
Institution	0.39	0.02	0.13	0.27	0.49	0.85

The counterparts of Tables 4 and 5 based on the transaction returns are produced in Table 6 (since the results for the excess returns are similar, they are omitted for brevity). For completeness, the sorting analysis in Table 2 is also repeated with separate buy and sell prices. The first entry of each sub-panel contains such results. It is seen that, once the spread between the buy and sell prices is factored into the return calculations, all the trading strategies end up losing money. Moreover, whether we control for various pricing factors does not make much difference — i.e., the raw high-low return difference is comparable to alphas in magnitude.

Closer examinations reveal some interesting observations. To begin, the alphas change drastically from average-price-based returns (i.e., Table 4) to transaction-price-based returns (i.e., Table 6). Take as an example the retail group returns sorted by the net trade imbalance within the retail group. In the fully specified model, the trading strategy leads to a net profit or alpha of 0.88% per month when the average of buy and sell prices is used to calculate returns. In contrast, when returns are calculated based on transaction prices, the same trading strategy leads to a loss of 5.177% per month, a multi-fold of the previous alpha. The net change in alpha is 0.88% +5.177% = 6.057%. As for the institutional group, although the losses in Table 6 appear to be small compared with those for the retail group, the alpha change is actually also multi-fold. Again, under the fully specified model, the alpha is 0.037% and insignificant with the average-price-based returns. In contrast, the alpha is −0.654% with the transaction-price-based returns. The net change in alpha is 0.691%.

What explains the drastic change in alphas? How come the change in alpha for the retail group is so much larger than the institutional group? As one might expect, the answers mostly lie in the spread between the buy and sell prices. To gain further insights in this regard, I report in Panel C the mean and selected percentiles of the difference between buy and sell prices for both the retail group and the institutional group (please see the table note for calculation details). It turns out that the average buy–sell price spread is 2% for the retail group, and 0.39% for the institutional group. It is immediately evident that retail investors incur a much larger transaction cost compared with institutional investors. This is the reason why the alpha change for the retail group is much more sizable. Moreover, since the monthly return of a zero-financing portfolio involves four one-way transactions (e.g., for the high-minus-low portfolio, we need to buy and then sell for the high decile, and short and buy-back for the low decile), the total transaction cost in the form of price mark-up and mark-down should be around 4% for the retail group and 0.78% for the institutional group. These quantities are comparable in magnitude to the net alpha changes calculated above: 6.057% and 0.691%.

It is interesting to notice that the transaction costs do a much better job in explaining the alpha change for the institutional group, but not so for the retail group. Specifically, the alpha change of 6.057% for the retail group is larger than the average four-way transaction cost of 4%. There are two plausible reasons. First, due to the imperfect specification of the pricing model, the alpha can measure things other than trading profits and/or transaction costs. Second, the returns in Table 6 are calculated between buy and sell prices that are one month apart. In contrast, the summary statistics in Panel C of Table 6 are based on the difference in buy and sell prices within the same day. Other things being equal, the one-month time elapse will enlarge the price difference due to price volatility.

Incidentally, that retail investors' irrationality is observed with average returns but does not lead to profitable trading strategies is an interesting discovery in its own right. In the equity literature reviewed earlier (e.g., Hvidkjaer, 2008; Kaniel et al., 2008; Barber et al., 2009; Han and Kumar, 2013), biases on the part of retail investors are uncovered; however, none of the studies investigates feasible trading strategies based on these biases. Kaniel et al. (2008) are keenly aware of this and offer the following comment (p295): "...we emphasize that although we find that individual investor trades contain information that can be used to forecast returns over short horizons, this does not necessarily imply that individual investors, who have much longer holding periods, realize abnormal returns. The question of interest to us is not whether individuals realize these excess returns, but rather why we observe them". It will be interesting to evaluate the trading strategies in the equity literature using buy/sell prices or incorporating bid–ask spreads.

7. Dynamics of returns and trade imbalance and the cross-sectional properties of bond trading

7.1. A closer examination of the dynamics of returns and trade imbalance

To better understand why trade imbalances can predict bond returns, I first investigate the lead–lag relationship between returns and NetBOS in a vector autoregression (VAR) framework, following Jackson (2003). Specifically, I run the following cross-section

Table 7

Vector autoregression (VAR) results. This table reports VAR results for monthly frequency involving bond returns and the NetBOS measure. The VAR system contains three lags for each variable and is run in a Fama–MacBeth fashion. Specifically, the system $\{R_t = (R_{t-1}, R_{t-2}, R_{t-3}, \text{NetBOS}_{t-1}, \text{NetBOS}_{t-2}, \text{NetBOS}_{t-3}), \text{NetBOS}_t = (R_{t-1}, R_{t-2}, R_{t-3}, \text{NetBOS}_{t-1}, \text{NetBOS}_{t-2}, \text{NetBOS}_{t-3})\}$ is run each month cross-sectionally and the Newey–West adjusted t-values for all coefficients are calculated from the resulting time-series output. For ease of presentation, the coefficients of the lagged returns in the NetBOS regression are multiplied by 1,000 (since NetBOS is smaller than returns in magnitude). The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

	R_{t-1}	R_{t-2}	R_{t-3}	NetBOS_{t-1}	NetBOS_{t-2}	NetBOS_{t-3}
	Small trade size, raw return					
R_t	−0.155	−0.003	0.040	−7.210	−1.585	−1.066
t-value	−11.55***	−0.19	3.00***	−14.06***	−2.97***	−2.04**
NetBOS_t	0.077	−0.022	−0.026	0.091	0.094	0.075
t-value	3.95***	−1.37	−1.53	9.19***	16.59***	12.88***
	Small trade size, excess return					
R_t	−0.205	−0.034	0.016	−7.447	−1.872	−0.938
t-value	−18.61***	−1.14	1.68*	−14.57***	−4.64***	−2.24**
NetBOS_t	0.096	−0.002	−0.016	0.092	0.094	0.075
t-value	5.46***	−0.17	−1.15	9.31***	16.62***	12.85***
	Institutional trade size, raw return					
R_t	0.115	0.037	0.049	0.638	0.272	−0.045
t-value	9.91***	2.93***	4.17***	6.04***	3.02***	−0.46
NetBOS_t	−0.552	−0.286	−0.141	−0.091	−0.061	−0.040
t-value	−8.77***	−4.85***	−2.22**	−15.27***	−14.62***	−11.53***
	Institutional trade size, excess return					
R_t	0.092	0.034	0.041	0.645	0.283	−0.072
t-value	9.04***	3.50***	4.99***	6.60***	3.57***	−0.87
NetBOS_t	−0.502	−0.284	−0.134	−0.091	−0.061	−0.040
t-value	−9.11***	−4.69***	−2.45**	−15.03***	−14.46***	−11.42***

system in a Fama–MacBeth fashion:

$$\begin{aligned} R_t = &\ (R_{t-1}, R_{t-2}, R_{t-3}, NetBOS_{t-1}, NetBOS_{t-2}, NetBOS_{t-3}), \\ NetBOS_t = &\ (R_{t-1}, R_{t-2}, R_{t-3}, NetBOS_{t-1}, NetBOS_{t-2}, NetBOS_{t-3}), \end{aligned}$$

where, month by month, the returns are demeaned and divided by the cross-section standard deviation in order to cleanse the effects of any common movements in returns and/or time-varying cross-section dispersion in returns. Table 7 contains the results.[9]

First and foremost, the negative (positive) coefficient of $NetBOS_{t-1}$in the return equation for the retail (institutional) group corroborates the sorting results in Table 2. The predictability is significant after controlling for the autocorrelation in returns. In fact, for the institutional group, the second lag $NetBOS_{t-2}$ also significantly and positively predicts bond returns. Second, the trade imbalance for retail investors is highly persistent while that for institutional investors takes a reversal pattern. Third, judging by the coefficient of R_{t-1} in the trade imbalance equation, retail investors are momentum traders while institutional investors are contrarian.[10] Fourth and last, returns in the retail group exhibit first-order negative autocorrelation while those in the institutional group exhibit positive autocorrelation for all three lags.[11] Taken together, the results imply the following. Retail investors pursue a money-losing momentum strategy since the winners they identify immediately become losers, and vice versa. In contrast, institutions are able to identify winners and losers and trade on a monthly basis to capture the return momentum (i.e., buy the winner this period and sell it in the next, leading to a reversal in NetBOS). In short, institutions are trading wisely while retail investors are not.

Table 8 offers a closer look at the winner and loser portfolios before and after sorting. To this end, bonds are sorted according to their current month NetBOS, and the returns of extreme deciles for this month as well as the preceding and succeeding three months

[9] A VAR system with four or five lags are also run and the main results remain the same qualitatively.

[10] This is in sharp contrast with stock trading in the U.S. where institutional investors are momentum traders (Grinblatt et al., 1995; Griffin et al., 2003) while individual investors are contrarian (Barber and Odean, 2000; Griffin et al., 2003). The same investor behavior is also observed in the stock market of other countries such as Korea (Choe et al., 1999), Finland (Grinblatt and Keloharju, 2000, 2001), and Australia (Jackson, 2003).

[11] At first blush, the return reversal in the retail group and the return momentum in the institutional group appear to contradict each other, which begs the question as to how the returns based on all trades would behave. To address this question, I repeat the analysis in Table 7 with returns based on all trades. Return reversals are still observed in all cases. To obtain a clear picture, I have also run a simple Fama–Macbath regression with only the three lagged returns as dependent variables. Again, the return reversal prevails. The main reason for the overall returns to also exhibit reversals is the higher frequency of small trades as apparent in Table 1. In other words, returns in most of the months are calculated out of prices of small trades. They dominate the sample. This is why Bali et al. (2017) also observe bond return reversals when they consider all trade sizes.

Table 8

Past, contemporaneous and future returns for low and high deciles. This table reports the returns and the corresponding t-values for the extreme deciles (low and high) resulting from sorting on NetBOS. Decile returns and their Newey–West adjusted t-values are reported for the current month t, the past three months $t-3$, $t-2$, $t-1$, and the future three months $t+1$, $t+2$, $t+3$. Two versions of the extreme deciles are examined. For instance, for the low NetBOS case, "low1_avg" refers to the average return within the decile with the lowest NetBOS whereas "low1&2_avg" refers to the average return of bonds belonging to the lowest NetBOS decile as well as the decile with the second lowest NetBOS. The high NetBOS case is handled analogously. Results are presented for both raw returns (Panel A) and excess returns (Panel B) as defined in Table 2. Panel C reports return differences and associated t-values for the extreme deciles. For each extreme NetBOS decile in each month, four return differences are calculated: (1) month $(t+1)$ minus month $(t-1)$, (2) month $(t+2)$ minus month $(t-1)$, (3) month $(t+3)$ minus month $(t-1)$, and (4) the average of months $(t+1)$, $(t+2)$, $(t+3)$ minus the average of month $(t-1)$, $(t-3)$, $(t-3)$. This is repeated every month and the resulting differences are averaged across time and the associated Newey–West adjusted t-values are also calculated. All returns are in percentage form. The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

Panel A. Raw returns

	Month $t-3$	Month $t-2$	Month $t-1$	Month t	Month $t+1$	Month $t+2$	Month $t+3$
	$NetBOS_{Small}$						
Low1_avg	0.823	0.863	0.683	0.535	1.202	0.897	0.781
Low1_t_value	3.95***	3.76***	2.74***	2.32**	5.82***	3.95***	3.47***
Low1&2_avg	0.738	0.774	0.634	0.478	0.983	0.759	0.669
Low1&2_t_value	3.74***	3.70***	2.82***	2.22**	5.00***	3.56***	3.12***
High10_avg	0.659	0.606	0.764	0.895	0.294	0.433	0.583
High10_t_value	3.51***	3.46***	4.29***	5.81***	2.00**	2.54**	3.72***
High9&10_avg	0.618	0.583	0.683	0.777	0.354	0.474	0.564
High9&10_t_value	3.54***	3.47***	4.12***	5.18***	2.46**	3.01***	3.70***
	$NetBOS_{Inst}$						
Low1_avg	0.670	0.724	0.809	0.404	0.595	0.622	0.641
Low1_t_value	3.50***	3.65***	4.02***	2.15**	3.49***	3.22***	3.42***
Low1&2_avg	0.684	0.719	0.778	0.421	0.600	0.609	0.628
Low1&2_t_value	3.74***	3.80***	4.14***	2.33**	3.63***	3.28***	3.42***
High10_avg	0.587	0.547	0.478	0.965	0.720	0.685	0.653
High10_t_value	2.68***	2.64***	2.33**	4.72***	3.75***	3.50***	3.24***
High9&10_avg	0.623	0.574	0.525	0.917	0.697	0.653	0.647
High9&10_t_value	3.05***	2.93***	2.76***	4.68***	3.83***	3.46***	3.45***

Panel B. Excess returns

	Month $t-3$	Month $t-2$	Month $t-1$	Month t	Month $t+1$	Month $t+2$	Month $t+3$
	$NetBOS_{Small}$						
Low1_avg	0.090	0.136	0.012	−0.103	0.516	0.220	0.099
Low1_t_value	1.19	2.04**	0.15	−2.11**	7.43***	3.34***	1.44
Low1&2_avg	0.068	0.091	−0.005	−0.130	0.347	0.127	0.045
Low1&2_t_value	1.42	1.83*	−0.08	−2.01**	6.73***	2.60***	0.87
High10_avg	−0.001	−0.034	0.150	0.280	−0.329	−0.144	−0.001
High10_t_value	−0.02	−0.84	3.54***	8.66***	−9.80***	−3.40***	−0.04
High9&10_avg	−0.017	−0.030	0.086	0.171	−0.250	−0.099	−0.015
High9&10_t_value	−0.49	−0.87	2.69***	6.87***	−8.74***	−3.24***	−0.54
	$NetBOS_{Inst}$						
Low1_avg	0.006	0.064	0.134	−0.200	−0.010	0.013	0.033
Low1_t_value	0.28	2.29**	3.85***	−6.57***	−2.83***	0.49	1.36
Low1&2_avg	0.021	0.048	0.106	−0.193	−0.011	−0.001	0.024
Low1&2_t_value	1.25	2.24**	4.41***	−8.57***	−2.72***	−0.06	1.29
High10_avg	−0.043	−0.080	−0.138	0.334	0.099	0.063	0.032
High10_t_value	−1.20	−2.75***	−4.13***	7.93***	3.74***	2.72***	1.26
High9&10_avg	−0.018	−0.066	−0.103	0.276	0.061	0.026	0.020
High9&10_t_value	−0.73	−3.12***	−4.74***	7.91***	3.58***	1.47	1.28

Panel C. Test of differences in returns before and after sorting

	Raw returns							
	$(t+1)-(t-1)$		$(t+2)-(t-1)$		$(t+3)-(t-1)$		$[(t1,2,3)-(t-1,-2,-3,)]/3$	
	Ret_diff	t-value	Ret_diff	t-value	Ret_diff	t-value	Ret_diff	t-value
Low1_small	0.429	2.43**	0.120	0.55	0.020	0.08	−0.078	−0.38
Low1_inst	−0.246	−2.05**	−0.207	−1.00	−0.216	−0.92	−0.202	−1.03

(*continued on next page*)

are calculated. This is repeated for every month and the time-series mean and its corresponding t-value are calculated for each decile. For completeness, the average return and its t-value of the two extreme deciles on the same side are also calculated, as is done in Kaniel et al. (2008).

The results in Panels A and B clearly explain why the strategy of retail investors loses money while that of the institutional investors is profitable. In the month of sorting, indeed, the lowest-NetBOS portfolio has the lowest return, and the highest-NetBOS portfolio

Table 8 (*continued*)

High10_small	−0.476	−3.31***	−0.311	−1.71*	−0.222	−1.10	−0.236	−1.37
High10_inst	0.230	1.98**	0.207	0.89	0.132	0.51	0.096	0.42
	Excess returns							
	$(t+1)-(t-1)$		$(t+2)-(t-1)$		$(t+3)-(t-1)$		$[(t1,2,3)-(t-1,-2,-3,)]/3$	
	Ret_diff	*t*-value	Ret_diff	*t*-value	Ret_diff	*t*-value	Ret_diff	*t*-value
Low1_small	0.430	5.41***	0.148	1.53	0.066	0.62	0.035	0.41
Low1_inst	−0.174	−3.78***	−0.143	−0.104	−2.15**	−0.107	−2.31**	
			−3.05***					
High10_small	−0.462	−9.76***	−0.260	−4.42***	−0.137	−2.37**	−0.153	−2.83***
High10_inst	0.238	5.35***	0.201	4.10***	0.178	4.10***	0.135	3.52***

Table 9

Link between small and institutional trades. This table reports the contemporaneous and lagged links between the small-trade NetBOS and the institutional-trade NetBOS. The investigation is carried out in the sorting context. The setup is exactly the same as that in Table 2, except that both the sorting and sorted variables are the NetBOS measure. The arrow in the headings indicates the sorting direction. For instance, $\text{NetBOS}_{\text{small},t-1} \rightarrow \text{NetBOS}_{\text{inst},t}$ indicates that the current month NetBOS for the institutional trades is sorted on the last month NetBOS for the small trades. In other words, $\text{NetBOS}_{\text{small},t-1}$ is used to predict $\text{NetBOS}_{\text{inst},t}$. The NetBOS values are multiplied by 100 for ease of presentation. The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

	Panel A. Sorting on $\text{NetBOS}_{\text{Small}}$			Panel B. Sorting on $\text{NetBOS}_{\text{Inst}}$		
	$\text{NetBOS}_{\text{small},t} \rightarrow \text{NetBOS}_{\text{inst},t}$	$\text{NetBOS}_{\text{small},t-1} \rightarrow \text{NetBOS}_{\text{small},t}$	$\text{NetBOS}_{\text{small},t-1} \rightarrow \text{NetBOS}_{\text{inst},t}$	$\text{NetBOS}_{\text{inst},t} \rightarrow \text{NetBOS}_{\text{small},t}$	$\text{NetBOS}_{\text{inst},t-1} \rightarrow \text{NetBOS}_{\text{inst},t}$	$\text{NetBOS}_{\text{inst},t-1} \rightarrow \text{NetBOS}_{\text{small},t}$
Low	−0.552	0.084	−0.565	0.243	0.838	0.149
2	−0.071	−0.021	−0.068	0.079	0.212	0.062
3	−0.028	−0.007	−0.015	0.051	0.024	0.042
4	−0.013	0.001	0.001	0.033	−0.065	0.031
5	0.004	−0.002	−0.045	0.024	−0.107	0.021
6	0.038	−0.002	0.011	0.016	−0.129	0.014
7	0.059	0.016	0.049	0.022	−0.120	0.019
8	0.046	0.036	0.018	0.030	−0.093	0.021
9	−0.037	0.077	−0.042	0.045	−0.108	0.026
High	−0.622	0.296	−0.359	0.169	−0.044	0.060
High-low	−0.070	0.212	0.206	−0.074	−0.882	−0.089
t-value	−0.392	5.81***	1.52	−4.42***	−15.68***	−9.33***

has the highest return. However, the lowest return (0.535% per month) immediately turns to the highest return (1.202%), and the highest (0.895%) immediately turns to the lowest (0.294%), all of which are consistent with the first-order negative autocorrelation observed in the previous table. In contrast, institutional investors trade to capture the momentum in returns. Similar to the sorting using $\text{NetBOS}_{\text{small}}$, sorting using $\text{NetBOS}_{\text{inst}}$ also leads to the lowest/highest return for the lowest-NetBOS/highest-NetBOS decile. However, unlike the retail group, the losers and winners remain for at least one month, allowing profits to be made. In fact, the post-sorting returns for the lowest-NetBOS decile are all lower than those in the pre-soring months, and the post-sorting returns for the highest-NetBOS decile are all higher than those in the pre-soring months. In contrast, the opposite is observed with the retail group.

To provide a statistical assessment, I test the significance of four versions of return difference: (1) month $(t+1)$ minus month $(t-1)$, (2) month $(t+2)$ minus month $(t-1)$, (3) month $(t+3)$ minus month $(t-1)$, and (4) the average of months $(t+1)$, $(t+2)$ and $(t+3)$ minus the average of months $(t-1)$, $(t-2)$ and $(t-3)$. The objective is to see how investors perform when they first observe price patterns in month $(t-1)$, then form portfolios in month t, and finally liquidate portfolios in month $(t+1)$ or later. As seen in Panel C of Table 8, the return difference between months $(t+1)$ and $(t-1)$ is mostly significant at the 1% level. For retail investors, the returns would go up after they sell and go down after they buy. In contrast, for institutional investors, the returns do go down after they sell and go up after they buy. In fact, after adjusting for risks (i.e., with the excess returns), the return difference is significant for up to three months.

Finally, turning to the trade imbalance, to ascertain whether one group's excess buying or selling is related to the other group's, the sorting analysis in Table 2 is repeated with one modification: Instead of using NetBOS to predict returns, we now use NetBOS to predict NetBOS. Table 9 reports the results. The middle column in each panel simply confirms the positive (for the retail group) and negative (for the institutional group) autocorrelation uncovered in the VAR analysis. The remaining columns are more revealing. In Panel A, none of the high-low difference is statistically significant, indicating that the trading of institutional investors is not related to the trading of retail investors. In contrast, in Panel B, the high-low difference is negative and highly significant, implying that when institutions trade actively (either excessive buying or excessive selling), the retail investors unwittingly become their counterparts. As seen in Panel B, moving from the middle deciles (i.e., deciles 5 and 6) to the "low" decile (i.e., as institutions sell more and more), the trade imbalance for the retail group increases. When institutions sell intensively, retail investors are on the buying side. As noted in Wei and Zhou (2016), most of the informed trading in corporate bonds occurs when institutional investors sell before negative news. It is then not surprising that retail investors' NetBOS negatively predicts returns while institutional investors' NetBOS positively predict returns.

7.2. Cross-sectional properties of the retail and institutional bond trades

This section performs sorting analyses to address the following questions: How is bond trading related to the bond's characteristics and the characteristics of the firm/stock? Do retail and institutional traders prefer certain types of bonds? Essentially, we would like to know what type of bonds attracts a particular group of investors. To this end, I measure the trading activity by the trading proportion used in Han and Kumar (2013) for the stock study. Specifically, the retail trading proportion, TP_{small}, is the total trading volume within the month with a trade size less than \$100,000 divided by the total monthly volume of all trade sizes; the institutional trading proportion, TP_{inst}, is defined analogously with trades larger than \$500,000 in size.

The bond characteristics have already appeared in earlier analyses, namely: rating, issue size, coupon rate, age, maturity, returns standard deviation, and the four illiquidity measures (negative turnover, negative number of trades in the month, zero returns in the month, and price range). Additionally, I examine three firm characteristics (firm size, book–market ratio and leverage) and two stock characteristics (return standard deviation and skewness), and for ease of exposition, I refer to all five as stock characteristics. The book–market ratio and leverage, estimated using data from Compustat, are in annual frequency; firm size, return standard deviation and skewness, estimated with data from CRSP, are in monthly frequency and are lagged by one month (results based on a six-month horizon are qualitatively similar).

Table 10 contains the results whereby each of the aforementioned characteristics is sorted on the previous month's trading proportion (either TP_{small} or TP_{inst}). Among the five stock characteristics in Panel A, firm size and return standard deviation exhibit a clear monotonicity and a large t-value for the high-low difference. Large firms and stocks with a lower return standard deviation attract more retail trading, and smaller firms and stocks with a higher standard deviation attract more institutional trading. As for book-to-market ratio and leverage, it appears that low leverage and value firms attract retail trading while high leverage and growth firms attract institutional trading. Overall, the results in Panel A indicate that retail investors prefer bonds issued by safer firms while institutional investors prefer bonds issued by risky firms (i.e., small size, low book–market ratio, high leverage, and high standard

Table 10
Sorting trading proportions on stock and bond characteristics. This table reports results of a single-sort analysis based on "trading proportion" defined as the monthly trading volume for a particular size group over the total trading volume. Specifically, TP_{small} is the total trading volume within the month with trade-size smaller than \$100,000, divided by the total monthly trading volume of that bond, and TP_{inst} is defined analogously with trade-size larger than \$500,000. Each month, the bond trading proportion is sorted into quintiles and the corresponding stock and bond characteristics are calculated for each quintile as simple, equal-weighted averages. This sorting procedure is repeated for the entire sample period and the time-series average is then calculated for each characteristic within each quintile. The high-minus-low difference is also calculated for each characteristic, together with its Newey–West adjusted t-value. The stock characteristics include: (1) logarithm of firm size based on the previous month's stock price and shares outstanding, (2) book-to-market ratio of the previous year, (3) firm's leverage of the previous year, which is long-term debt divided by the sum of long-term debt and market value of equity, and (4) stock return standard deviation and skewness of the previous month. The bond characteristics include: (1) credit rating, measured in 1, 2, 3, . . . , with a higher number corresponding to a lower rating, (2) logarithm of the bond issue size, (3) coupon rate, (4) age of issue in years, (5) maturity in years, (6) standard deviation of daily bond returns over the previous six months, and (7) four illiquidity measures (i.e., negative of turnover, negative of number of trades, days of zero returns, and price range), which are defined in the text. For ease of presentation, the original quantities of price range are multiplied by 10^8. The *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels for two-tail tests.

Panel A. Stock characteristics

	log(size)	BM	Leverage	STD	Skew
	Sorting by TP_{Small}				
Low	22.518	0.571	0.317	0.358	0.043
2	22.772	0.599	0.318	0.341	0.035
3	23.031	0.594	0.311	0.327	0.033
4	23.256	0.587	0.305	0.318	0.042
High	23.267	0.611	0.312	0.317	0.048
High-low	−0.749	0.040	−0.005	−0.041	0.006
t-value	21.674***	4.856***	−2.786***	−15.400***	0.775
	Sorting by TP_{Inst}				
Low	23.227	0.605	0.305	0.320	0.044
2	23.126	0.594	0.310	0.321	0.040
3	22.943	0.597	0.320	0.333	0.035
4	22.746	0.585	0.323	0.349	0.035
High	22.468	0.587	0.317	0.363	0.045
High-low	−0.759	−0.019	0.012	0.042	0.002
t-value	−25.571***	−2.272**	7.811***	20.227***	0.255

Panel B. Bond characteristics

	Rating	log(issue size)	Coupon rate	Age	Maturity
	Sorting by TP_{Small}				
Low	10.199	12.955	5.667	2.773	11.407

(continued on next page)

Table 10 (*continued*)

Panel B. Bond characteristics					
	Rating	log(issue size)	Coupon rate	Age	Maturity
2	9.640	13.035	5.895	3.077	10.332
3	8.934	13.060	5.937	3.506	8.985
4	8.237	13.035	5.924	4.149	7.922
High	8.159	12.784	6.164	5.711	8.141
High-low	−2.040	−0.171	0.497	2.938	−3.266
t-value	−23.445***	−19.105***	23.929***	120.013***	−28.139***
	Sorting by TP_{Inst}				
Low	8.187	12.922	6.041	4.718	7.913
2	8.608	13.048	5.962	3.740	8.500
3	9.184	13.070	5.933	3.257	9.608
4	9.711	13.036	5.831	2.998	10.577
High	10.151	12.865	5.551	3.148	10.749
High-low	1.964	−0.057	−0.490	−1.571	2.836
t-value	27.988***	−6.963***	−23.397***	−61.097***	20.226***

Panel C. Bond characteristics (continuing)					
	STD	(-)turnover	(-) no. of trades	Zero return days	Price range
	Sorting by TP_{Small}				
Low	0.016	−2.035	−33.223	14.318	2.346
2	0.015	−0.148	−38.848	13.059	4.130
3	0.014	−0.098	−51.042	12.300	5.780
4	0.014	−0.041	−67.391	11.659	7.610
High	0.016	−0.061	−75.514	12.097	11.881
High-low	0.000	1.974	−42.291	−2.221	9.535
t-value	0.773	1.294	−20.331***	−31.224***	28.340***
	Sorting by TP_{Inst}				
Low	0.014	−0.041	−74.833	11.608	8.829
2	0.013	−0.044	−63.149	11.883	6.488
3	0.014	−0.308	−52.880	12.176	5.376
4	0.015	−0.579	−44.001	12.850	4.148
High	0.017	−1.931	−33.070	15.127	3.169
High-low	0.003	−1.890	41.763	3.519	−5.660
t-value	11.215***	−1.235	18.530***	39.067***	−25.052***

deviation of stock returns). This makes intuitive sense in that retail investors lack the resources to research bonds issued by smaller and less known firms and they therefore avoid them.

Turning to bond characteristics, bonds that attract more retail trading tend to have a higher credit rating, a higher coupon rate, an older age, a shorter maturity, a higher liquidity measured by number of trades and zero return days, and a wider price range. The bond return standard deviation and turnover do not seem to be associated with the trading proportion (not significantly anyway). Bonds with a smaller issue size seem to attract more active retail trading, but the relationship is not strictly monotonic and the effect is small compared with the firm size effect. The opposite is true for institutional trades: Bonds that attract more institutional trading tend to have a lower credit rating, a lower coupon rate, a younger age, a longer maturity, a lower liquidity measured by number of trades and zero return days, and a narrower price range.[12] The more active trading of younger bonds may reflect the simple fact that institutional investors are the main players right after the bonds are issued. The narrower price range for the actively traded bonds means that institutional investors mostly trade bonds on which they can get a better pricing from dealers. Every other characteristic on the above list can be considered as a measure of risk — credit risk (rating), interest rate risk (coupon rate and maturity), and liquidity risk (trading frequencies). The association between these characteristics and the trading proportion suggests that institutional investors are more active with risky bonds, while retails investors are more active with less risky bonds. Therefore,

[12] There are two exceptions. First, the high-low difference in issue size is negative for both the retail trading proportion and the institutional trading proportion, although much less so with the latter. Second, the bond return standard deviation is positively associated with the trading proportion for the institutional group.

the stock and bond characteristics are consistent in revealing the retail and institutional investors' proclivity for the riskiness of the bond.

8. Summary of results and discussions of fundamental mechanisms[13]

Measured with the overall returns without differentiating buy and sell transactions, the institutional segment of the bond market appears to be efficient in that the trade imbalance of the institutional group does not entail a profitable trading strategy after controlling for the usual risk factors; in contrast, retail investors seem irrational since their intensive buying (selling) is followed by lower (higher) bond returns. Moreover, the retail group's trade imbalance can also lead to a profitable trading strategy for the institutional group. However, when the spread between purchase and sell prices is factored into the bond returns, none of the trading strategies is profitable anymore, consistent with limits to arbitrage (Shleifer and Vishny, 1997). As a whole, the empirical results indicate that institutional investors are rational while rational investors suffer from behavior biases.

What is the fundamental mechanism in which the retail investors' behavioral biases are related to bond prices and returns? As in other studies of this nature, the empirical findings are often consistent with multiple behavioral channels. Two plausible channels are identified below, with the first rooted in investors' sentiment and overreaction, and the second rooted in extrapolative expectations. The two channels are not mutually exclusive.

The retail investors' behavior in the corporate bond market is similar to what Hvidkjaer (2008) uncovers in the stock market in that, intensive buying (selling) is followed by lower (higher) returns. Hvidkjaer (2008) states that his findings are consistent with the hypothesis that stocks favored by retail investors are overvalued and hence suffer from extended underperformance subsequently. However, he leaves open the question as to why investors favor overvalued stock in the first place. One potential explanation is investors' overreaction in the sense of Daniel et al. (1998). In the current setting, the retail investors' overreaction manifests itself in the following ways. To begin, Table 7 indicates that retail investors are momentum traders. They buy (sell) after seeing an upward (downward) trend. Meantime, Table 7 also reveals that retail investors' trade imbalance is persistent, indicating overreaction. In other words, as soon as retail investors see an upward (downward) trend, they keep buying (selling) the same bond. As they push the price to the highest level (in the case of intensive buying) or the lowest level (in the case of intensive selling), price reversals will follow, as evident in Table 8.

More broadly, the findings are consistent with the impact of investors' sentiment on asset returns. As pointed out by De Long et al. (1990a), and Shleifer and Summers (1990), sentiments of some investors can cause prices to deviate from their fundamentals when rational investors are subject to limits of arbitrage. At the same time, retail investors are the most likely to be influenced by sentiments or behavioral biases as shown in previous studies (e.g., Barber and Odean, 2000). Baker and Wurgler (2006) point out that sentiments can propagate into the cross-section through either cross-sectional variations in sentiment (while limits to arbitrage remains constant) or cross-sectional variations in arbitrage (while sentiments remain constant). Either way, according to Baker and Wurgler (2006), the sentiment-prone investors will then choose stocks according to whatever salient characteristics consistent with their prevailing sentiment.

This theoretical framework can be applied to the current setting. Specifically, retail bond investors are sentiment-prone and tend to make investment decisions based on non-fundamental factors. Chasing returns with dumb money is one such investment decision (e.g., Frazzine and Lamonti, 2008). In the stock market, sentiment can be gauged by many factors, but in the bond market, past returns are the readily available measure. In other words, retail investors' sentiment is formed by observing the past returns, and this is also how they choose the bonds to invest. This explains why retail investors are momentum investors. Since their behavioral biases collectively push the price either too low or too high, reversals ensue subsequently.

That retail bond investors follow a moment or positive feedback trading strategy is also consistent with "extrapolation bias", a behavior in which individuals overly rely on recent events when forming expectations. Evidence of extrapolation bias was first observed in experimental settings (e.g., Tversky and Kahneman, 1974; Andreassen and Kraus, 1990) and subsequently confirmed in surveys of future-return forecasts (e.g., De Bondt, 1993; Clarke and Statman, 1998; Greenwood and Shleifer, 2014). Cutler et al. (1990), and De Long et al. (1990b) postulate that some irrational investors extrapolate past returns while some other rational investors trade with the extrapolative investors. This framework is subsequently expanded by Barberis et al. (2015) by incorporating features such as infinite-horizon investors. Applying this framework to the current setting, retail investors, who suffer from the extrapolation bias, overreact to the recent bond performance. They mistakenly believe that realized higher (or lower) returns are indicative of future returns, hence engage in positive feedback trading.

In order for the extrapolation bias to be a valid theoretical explanation for retail investors' behavior, the bond returns need to exhibit short-term reversals. In fact, Tables 7 and 8 already demonstrate that retail investors tend to engage in positive feedback trading and the bonds they trade exhibit strong short-term reversals in returns (both raw and excess). To begin, in the return regression equation reported in Table 7, the t-value of the first-lag coefficient is negative and highly significant: −11.55 for raw returns and −18.61 for excess returns, which serves as strong evidence of monthly reversals (in contrast, returns in the institutional group exhibit

[13] It is useful to note that, in an early version of the paper, I also investigated the potential predictive relationship between the bond and stock markets. The imbalance measure of stocks was calculated using the TAQ data and the Lee–Ready algorithm to classify buy and sell transactions. It turns out that, no trade imbalance in one market can predict the other market's returns, regardless of the combination in size group (for instance, stocks' NetBOSsmall predicting bonds' Rsmall; bonds' NetBOSinst predicting stocks' return, etc.). Therefore, one market's trade imbalance does not seem to carry information for the future returns of the other market. Nevertheless, the monthly returns of bonds and stocks are positively correlated in the cross-section, both contemporaneously and in lagged fashion, both ways, as noted by, e.g., Baele et al. (2010).

strong short-term momentums).[14] Meanwhile, Table 8 provides a combined picture of positive feedback trading and return reversals within the retail group. Specifically, as the returns in months $t-3$, $t-2$, $t-1$, and t demonstrate, retail investors buy bonds whose returns are on the rise, and sell bonds whose returns are on the decline. Unfortunately, due to the strong subsequent reversals, the retail investors end up losing money on both buys and sells. For instance, as already illustrated in Section 7.1, right after retail investors sell the bond when it earns a meager return of 0.535%, the bond earns a handsome return of 1.202%. Likewise, right after they acquire a bond with an appealing return of 0.895%, the bond produces a lackluster return of 0.294%. This is how retails investor suffer under the extrapolation bias in the presence of short-term reversals, as vividly demonstrated by the two examples in Fig. 1. The institutional investors, on the other hand, act as the rational investors and accommodate the retail investors. In conclusion, the empirical results in Tables 7 and 8 are consistent with the "extrapolation bias" channel.

9. Conclusion

This paper examines, in a cross-section fashion, the link between retail and institutional trades and the corporate bond returns. While there are already studies that examine the association between retail trades and the cross-section of stock returns, no such studies exist for corporate bonds. Therefore, this study is the first of its kind for corporate bonds, and it examines both the retail and the institutional investors. The main findings can be summarized as follows.

For institutional investors, intensive buying/selling in one month is followed by higher/lower bond returns in the next month. The difference in returns between the high and low trade-imbalance (defined as excess buy over sell within the month, scaled by total outstanding amount) portfolios is positive, and statistically and economically significant. However, when the high-low portfolio return is regressed on the usual risk factors (viz. the Fama–French equity factors the bond factors) and the aggregate liquidity factor, the alpha is insignificant in the encompassing model. Therefore, the institutional segment of the bond market appears efficient in that risk-adjusted excess returns cannot be earned.

The opposite results are obtained for retail investors: Intensive buying/selling in one month is followed by lower/higher bond returns in the next month, and this is true in both the sorting and regression analyses. The negative relationship between trade imbalance and bond returns is consistent with the stock market findings in Hvidkjaer (2008). The alpha of the high-low portfolio is negative and significant, both statistically and economically. More important, the alpha survives the liquidity factor and all the Fama–French factors. The return predictability does not reverse in the long run either. That retail investors' transactions are followed by unfavorable movements in bond prices after controlling for known risk factors is an indication of their behavioral biases.

The study goes one step further by exploring feasible trading strategies based on the findings. Specifically, the alpha of the high-low portfolio is re-examined by properly accounting for the spread between the buy and sell prices. It turns out all the alphas (no matter whether the high-low portfolio is formed by within group sorting or cross-group sorting) are significantly negative. In other words, once the spread is factored into the returns, there does not exist a profitable trading strategy. Therefore, retail investors suffer from behavioral biases and their biases make the bond prices systematically deviate from the fundamental values. However, limits to arbitrage prevent the apparent profits from being exploited.

Acknowledgments

Previously titled "Retail and Institutional Trades and the Cross-Section of Corporate Bond Returns". Financial support from the Social Sciences and Humanities Research Council of Canada (435-2012-0191) is gratefully acknowledged. I thank Jennie Bai, Melanie Cao, Siu Kai Choy, Bing Han, Alan Huang, Madhu Kalimipalli, Thomas Ruf, Xing Zhou, an anonymous referee, and seminar participants at the Australia National University, the National University of Singapore, and the University of Saskatchewan for helpful comments and suggestions.

References

Abudy, Menachem, Wohl, Avi, 2015. Corporate bond trading by retail investors in a limit order book exchange. Working paper.
Acharya, Viral, Amihud, Yakov, Bharath, Sreedhar, 2013. Liquidity risk of corporate bond returns: A conditional approach. J. Financ. Econ. 110 (2), 358–386.
Amihud, Yakov, 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Markets 5, 31–56.
Andreassen, Paul, Kraus, Stephen, 1990. Judgmental extrapolation and the salience of change. J. Forecast. 9 (4), 347–372.
Baele, Lieven, Bekaert, Geert, Inghelbrecht, Koen, 2010. The determinants of stock and bond return comovements. Rev. Financ. Stud. 23, 2374–2428.
Baker, Malcolm, Wurgler, Jeffrey, 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.
Bali, Turan, Subrahmanyam, Avanidhar, Wen, Quan, 2017. Return-based factors for corporate bonds. Working paper.
Barber, Brad M., Odean, Terranee, 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. J. Finance 55, 773–806.
Barber, Brad, Odean, Terrance, Zhu, Ning, 2009. Do retail trades move markets? Rev. Financ. Stud. 22, 151–1185.
Barberis, Nicholas, Greenwood, Robin, Jin, Lawrence, Shleifer, Andrei, 2015. X-CAPM: An extrapolative capital asset pricing model. J. Financ. Econ. 115, 1–24.
Bessembinder, Hendrik, Jacobsen, Stacey, Maxwell, William, Venkataraman, Kumar, 2017. Capital commitment and illiquidity in corporate bonds. Working paper.
Bessembinder, Hendrikand, Maxwell, William, 2008. Markets: Transparency and the corporate bond market. J. Econ. Perspect. 22, 217–234.
Bessembinder, Hendrik, Maxwell, William, Venkataraman, Kumar, 2006. Optimal market transparency: Evidence from the initiation of trade reporting in corporate bonds. J. Financ. Econ. 82, 251–288.
Biais, Bruno, Green, Richard, 2007. The microstructure of the bond market in the 20th century. Working paper.

[14] The strong monthly reversals in corporate bond returns are also documented by Bali et al. (2017) who study bond returns but not investors' trading behavior. It should be noted that they lump trades of all sizes together whereas I examine returns within groups of small and large trades and I omit trades of medium trade size.

Chen, Long, Lesmond, David, Wei, Jason, 2007. Corporate yield spreads and bond liquidity. J. Finance 61, 119–149.
Choe, Hyuk, Kho, Bong-Chan, Stulz, Rene, 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. J. Financ. Econ. 54, 227–264.
Clarke, Roger, Statman, Meir, 1998. Bullish or bearish? Financ. Anal. J. 54, 63–72.
Cutler, David, Poterba, James, Summers, Lawrence, 1990. Speculative dynamics and the role of feedback traders. Amer. Econ. Rev. Papers Proc. 80, 63–68.
Daniel, Kent, Hirshleifer, David, Subrahmanyam, Avanidhar, 1998. Investor psychology and security market under- and overreactions. J. Finance 53, 1839–1886.
De Bondt, Werner, 1993. Betting on trends: Intuitive forecasts of financial risk and return. Int. J. Forecast. 9, 355–371.
De Long, J. Bradford, Shleifer, Andrei, Summers, Lawrence, Waldmann, Robert, 1990a. Noise trader risk in financial markets. J. Political Econ. 98, 703–738.
De Long, J. Bradford, Shleifer, Andrei, Summers, Lawrence, Waldmann, Robert, 1990b. Positive feedback investment strategies and destabilizing rational speculation. J. Finance 45, 379–395.
Dick-Nielsen, Jens, 2014. How to clean Enhanced TRACE data. Working paper.
Dick-Nielsen, Jens, Feldhutter, Peter, Lando, David, 2012. Corporate bond liquidity before and after the onset of the subprime crisis. J. Financ. Econ. 103, 471–492.
Downing, Chris, Underwood, Shane, Xing, Yuhang, 2005. Is liquidity risk priced in the corporate bond market? Working paper.
Edwards, Amy, Harris, Lawrence, Piwowar, Michael, 2007. Corporate bond market transaction costs and transparency. J. Finance 62, 1421–1451.
Etula, Erkko, Rinne, Kalle, Suominen, Matti, Vaittinen, Lauri, 2016. Dash for cash: month-end liquidity needs and the predictability of stock returns. Working paper.
Fama, Eugene, French, Kenneth, 1993. Common risk factors in the returns of stocks and bonds. J. Financ. Econ. 33, 3–56.
Frazzine, Andrea, Lamonti, Owen, 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. J. Financ. Econ. 88, 299–322.
Goldstein, Michael, Hotchkiss, Edith, Sirri, Erik, 2007. Transparency and liquidity: a controlled experiment on corporate bonds. Rev. Financ. Stud. 20, 235–273.
Greenwood, Robin, Shleifer, Andrei, 2014. Expectations of returns and expected returns. Rev. Financ. Stud. 27, 714–746.
Griffin, John, Harris, Jeffrey, Topaloglu, Selim, 2003. The dynamics of institutional and individual trading. J. Finance 58, 2285–2320.
Grinblatt, Mark, Keloharju, Matti, 2000. The investment behavior and performance of various investor types: A study of Finland's unique data set. J. Financ. Econ. 55, 43–67.
Grinblatt, Mark, Keloharju, Matti, 2001. What makes investors trade? J. Finance 56, 589–616.
Grinblatt, Mark, Titman, Sheridan, Wermers, Russ, 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. Amer. Econ. Rev. 85, 1088–1105.
Han, Bing, Kumar, Alok, 2013. Speculative retail trading and asset prices. J. Financ. Quant. Anal. 48, 377–404.
Helwege, Jean, Huang, Jing-zhi, Wang, Yuan, 2014. Liquidity effects in corporate bond spreads. J. Bank. Finance 45, 105–116.
Hvidkjaer, Soeren, 2008. Small trades and the cross-section of stock returns. Rev. Financ. Stud. 21, 1123–1151.
Jackson, Andrew, 2003. The aggregate behavior of individual investors. Working paper.
Kalimipalli, Madhu, Warga, Arthus, 2002. Bid–ask spread, volatility, and volume in the corporate bond market. J. Fixed Income 13, 31–42.
Kaniel, Ron, Saar, Gideon, Titman, Sheridan, 2008. Individual investor trading and stock returns. J. Finance 63, 273–310.
Lin, Hai, Wang, Junbo, Wu, Chunchi, 2011. Liquidity risk and the cross-section of expected corporate bond returns. J. Financ. Econ. 99, 628–650.
O'Hara, Maureen, Wang, Yihui, Zhou, Xing, 2015. The best execution of corporate bonds. Working paper.
Pastor, Lubos, Stambaugh, Robert, 2003. Liquidity risk and expected stock returns. J. Political Econ. 111, 642–685.
Ronen, Tavy, Zhou, Xing, 2013. Trade and information in the corporate bond market. J. Financ. Markets 16, 61–103.
Schultz, Paul, 2001. Corporate bond trading costs: A peek behind the curtain. J. Finance 56, 677–698.
Shleifer, Andrei, Summers, Lawrence, 1990. The noise trader approach to finance. J. Econ. Perspect 4, 19–33.
Shleifer, Andrei, Vishny, Robert, 1997. The limits of arbitrage. J. Finance 52, 35–55.
Tversky, Amos, Kahneman, Daniel, 1974. Judgment under uncertainty: Heuristics and biases. Science 185, 124–1131.
Warga, Arthur, 2004. An overview of the regulation of the bond markets. Report to the Senate Banking Committee.
Wei, Jason, Zhou, Xing, 2016. Informed trading in corporate bonds prior to earnings announcements. Financ. Manag. 45, 641–674.
Zitzewitz, Eric, 2010. Paired corporate bond trades. Working paper.