Do Buyside Institutions Supply Liquidity in Bond Markets? Evidence from Mutual Funds*

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Abstract

This study presents new evidence on buy-side institutions as a channel of liquidity supply in the corporate bond market. Using bond transactions data, we aggregate the inventory positions of bond dealers, and identify inventory cycles. We classify a bond fund's trading style as liquidity supplying (demanding) if the changes in bond holdings exhibit a propensity to absorb (further strain) the aggregate dealer positions. Between 2003 and 2014, bond funds on average tend to demand liquidity; however, trading styles vary across funds and are persistent over time. Funds with higher flexibility in portfolio holdings and less volatile investor flows are associated with liquidity supply. Trading style that is liquidity supplying is associated with higher fund performance implying that bond funds have a market incentive to respond to dealer positions. Our results suggest that bond trading platforms should facilitate participation by buy-side institutions to enhance liquidity.

Keywords: Bond liquidity; buy-side institutions; dealer inventory; mutual funds; fund performance.

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Abstract

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I. Introduction

Liquidity in the corporate bond market has received considerable attention in recent years. Between 2006 and 2016, the outstanding amount of corporate bonds increased from $4.8 trillion to $8.5 trillion, alongside the growth in assets under management by mutual funds and exchange traded funds (ETFs) that invest in corporate bonds.[1] Several academic studies show that corporate bond dealers have reduced capital for market making activities during the same decade, attributable at least in part to regulation such as Volcker Rule and bank-capital requirements (see, Bessembinder, Jacobsen, Maxwell, and Venkataraman (2017), Schultz (2017), Bao, O'Hara, and Zhao (2016), Dick-Neilsen and Rossi (2016), among others). The Federal Reserve Bank of New York data indicate that primary dealer inventories of corporate bonds in 2016 appear to be at an all-time low, relative to market size.[2]

In this environment with significant bond issuance activity and decline in dealer inventory, many commentators are worried that a sudden rise in interest rates, or other credit market events, would lead to a liquidity crisis in corporate bonds. To address the potential risk posed by illiquid secondary markets, the U.S. Securities and Exchange Commission (SEC) has issued new guidelines for bond fund managers to "*assess funds' liquidity, and the ability to meet potential redemptions…during both normal and stressed environments, including assessing their source of liquidity*."[3] A 2017 Greenwich Associates study reports that 78% of credit investors surveyed by the study describe buy-side institutions as an important source of liquidity supply in the next 1-2 years.[4]

The economic importance of buy-side bond institutions as a channel of liquidity supply cannot be overstated. Yet, there is little empirical evidence on the most basic question regarding this possible channel – do buy-side institutions serve as "shock absorbers", similar to a role historically played by bond

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[1] Statistics on the outstanding amount of corporate bonds is obtained from SIFMA (http://www.sifma.org/research). "Corporate-bond markets need a reboot", *The Economist*, April 20, 2017, reports that U.S. equity issuance in 2016 amounted to just under $200 billion while the corporate bond issuance amounted to $1.5 trillion. Data reported by the Investment Company Institute (ICI) show that bond mutual funds and bond ETFs share of the corporate bond market has roughly doubled from 7.3% in 2006 to 17.9% in 2016.

[2] "Is there a liquidity problem post-crisis?", Speech by Stanley Fischer, Vice Chairman, Federal Reserve Board, on November 10, 2015, available at "https://www.federalreserve.gov/newsevents/speech/fischer20161115a.htm."

[3] https://www.sec.gov/divisions/investment/guidance/im-guidance-2014-1.pdf

[4] "Innovations ease corporate bond trading", Greenwich Associates, Quarter 2, 2017.

dealers? In this study, we develop a methodology to classify an institution's trading style, and present relevant empirical evidence for bond mutual funds, an important category of bond institutions, on the following questions: First, do some bond funds exhibit a trading style that is liquidity supplying? Our measure of trading style captures the propensity of a fund's trades (measured by change in bond holdings) to further strain the inventory positions of bond dealers (liquidity demanding (LD)), or to help lay off dealer risk by absorbing the inventory positions of bond dealers (liquidity supplying (LS)). Second, do fund attributes explain the trading style of mutual funds? Or, is trading style a manifestation of idiosyncratic fund preferences? Third, in the cross-section, does trading style predict risk-adjusted fund returns, and further, whether the returns attributable to trading style vary over time?

This study furthers our understanding of liquidity sources in fixed income markets. Additionally, we present an observable fund attribute that is useful for investors in selecting bond funds. We note that the returns attributable to a liquidity supplying trading style are distinct from the liquidity premium earned for holding illiquid bonds. Stated differently, we focus on *how* institutions choose to implement their trades, rather than *which bonds* they choose to hold in their portfolios.

We collect information from multiple sources on snapshots of funds' corporate bond holdings; fund characteristics such as TNA; the returns reported by funds; and bond characteristics such as age, issue size, and credit quality between July 2002 and December 2014. We use the enhanced version of the TRACE database of transactions in U.S. corporate bonds to classify the trading style of bond funds. Corporate bonds trade in over-the-counter (OTC) markets where virtually all transactions are intermediated by bond dealers, who historically have held inventories to facilitate principal trades with customers. The detailed dataset made available by FINRA represents all corporate bond transactions, and includes masked dealer identities for each transaction. The clear identification of bond dealers in the OTC market structure, along with information on how dealers allow trading to flow through to changes in inventory, present an ideal laboratory to quantify the aggregate imbalances faced by market makers.

Based on inventory positions aggregated across dealers, we identify inventory cycles in a bond, where dealers' build-up inventory in the load phase of a cycle and reverse inventory in the unload phase of the cycle, and the beginning and the end of a cycle is marked by inventory crossing zero. Consistent with price pressure, the bond prices decline when dealers build up inventory in a positive cycle, followed by a reversal in the unload phase. We overlay the change in bond funds' holdings between reporting periods on the inventory cycle in a bond, and classify the holdings changes as liquidity supplying or demanding.[5] Aggregating the classification across all corporate bond holdings, we calculate a fund's composite "*LS_score*" with higher (lower) values of *LS_score* signifying a propensity to absorb (strain) the inventory position of bond dealers.[6]

Existing empirical evidence suggests that corporate bond funds might strain the inventory absorbing capacity of bond dealers. In a recent study, Goldstein, Jiang and Ng (2017) show that outflows from corporate bond funds, both at fund level and for aggregate sector, are sensitive to bad performance, particularly when markets are stressed. Bessembinder, Maxwell, Jacobsen and Venkataraman (2017) show that the aggregate capital commitment of bond dealers declines during the financial crisis. We find that average fund *LS_score*, estimated for 963 funds over 2002 to 2014 sample period, is less than zero (-0.09). Notably, the *LS_score* declines from -0.09 in 2006 to -0.13 in 2009 and rebounds to -0.07 in 2010. On average, bond funds exhibit a liquidity demanding trading style, and the effect is stronger when dealers' risk bearing capacity is strained.

What determines trading style? We estimate a linear probability model where the dependent variable equals one for funds in the highest quintile of *LS_score* measured over a 12-month period, and equals zero otherwise. The explanatory variables are the 12-month lagged fund attributes and portfolio characteristics. The model coefficients suggest that a liquidity supplying trading style is associated with smaller and younger funds; funds with higher investor flows; funds with higher rear load fee; funds that

[5] For example, for a positive inventory cycle (where the dealer community absorbs net customer selling), we classify the change in funds' holdings in the bond as liquidity supplying (demanding) if the holdings change that overlaps with beginning and end date of the cycle is positive (negative). Any changes in funds' holdings that do not overlap with an inventory cycle in the bond are not classified. Section 3 provides the details.

[6] For the main measure (*LS_score*), the changes in bond holdings that correspond with issuance of a new bond are not classified. This allows the fund's trading style to be based on participation in secondary market activity alone. Given the record activity in bond issuance in recent years, we calculate a second measure (*LS_score_IPO*) that aggregates across all the changes in bond holdings, including those that correspond with issuance of a new bond.

hold liquid bonds, i.e., younger, higher credit quality and larger issue bonds; funds with lower portfolio risk; and funds with smaller volatility in investor flows. The results on rear load fee and the volatility in investor flow suggest that bond funds might be pushed into costly trading in response to investor flows. When we add fund fixed effects to the model, the R-square rises to 21%, from about 6% for the model with observable fund attributes, suggesting that the identity of the fund has information on trading style.

We explore the idea that trading style is a fund attribute that is persistent over time. Sorting funds on trading style over a 12-month period, we examine the *LS_score* of quintiles in the ranking and future periods. A fund's quintile assignment in the ranking period helps predict the fund's trading style in future periods. *LS_score* increases monotonically across quintiles, and the difference between high- and low-*LS_score* quintiles persists over the next 12 to 24 months. Thus some bond funds respond to dealer inventory shocks, or to a signal correlated with inventory shocks, such as a change in bond prices.

We hypothesize that funds with liquidity supplying trading style receive price concessions that lower the cost of building positions and further benefit from price reversals when demand shocks abate. To test this hypothesis, we study the relation between trading style and fund performance. In regressions where a fund's alpha in month *t* is the dependent variable, we obtain a positive coefficient on the fund's *LS_score* measured over months *t-12* to *t-1*, after controlling for fund attributes and portfolio characteristics. Trading style is associated with higher fund alphas when markets are illiquid, as measured by an elevated TED spread or VIX. In terms of economic significance, one standard deviation increase in *LS_score* is associated with higher alpha of two (four) basis points per month under normal (stressed) conditions. To put these numbers in context, the average fund alpha (gross of fees) for our sample is 3.3 basis points per month.

This study makes several contributions to the literature on bond markets. We present a methodology that can be implemented by researchers in over-the-counter markets to classify the trading style of bond funds. The approach uses a comprehensive database of virtually all corporate bond transactions and constructs a direct measure of shock to dealer inventory, and the funds' propensity to further strain versus absorb the dealer inventory. This methodology differs from approaches in equity markets that identify trading style based on exposure of fund returns to a contrarian long-short factor portfolio (see Jagadeesh (1990), Lehmann (1990), Nagel (2012), Jylha, Rinne and Souminen (2014)).

We present empirical evidence on a channel of liquidity supply in bond markets. Bond funds on average have a trading style that demands liquidity; however, we find significant dispersion in trading style, and some funds that employ a strategy of absorbing dealer shocks. To tap into, and further encourage, the channel identified by this study, the next generation of electronic platforms must develop features that facilitate participation by buy-side institutions. As noted by SEC Commissioner Michael S. Piwowar, while fixed income alternative trading systems hold much promise, many systems often restrict customer's request-for-quotation (RFQ) messages to participating bond dealers, and "seem content on relying on traditional methods of transacting in bonds."[7]

We contribute to the literature on the determinants of bond fund performance. Cici and Gibson (2012) find that bond managers on average do not demonstrate an ability to select corporate bonds that outperform risk-adjusted benchmarks. Our study highlights that it is important to understand *how* a fund builds portfolio positions, in addition to *which bonds* the fund holds in the portfolio.

Corporate bond transaction costs are high, with Bao, Pan and Wang (2011) estimating bid-ask spreads of 1.50% for a relatively liquid sample of corporate bonds. While buy and hold investors, such as insurance companies and pension funds, are less exposed to trading costs, bond mutual funds facing potentially daily inflows and outflows, as well as monthly index rebalancing, trade more frequently, and incur significant transaction costs. In an environment where fund outperformance is difficult to generate, the trading style we identify adds another dimension to a fund manager's ability to earn alpha by capturing a portion of the returns to liquidity provision in bond markets.

The article is organized as follows. We discuss the related literature in section 2. Section 3 describes the data, the methodology to identify dealer inventory cycles, and the approach to classify the trading style of funds. Section 4 presents summary statistics on trading style and its relation with fund attributes. Section 5 presents evidence on trading style persistence and the relation between trading style

[7] https://www.sec.gov/news/speech/piwowar-remarks-finra-2016-fixed-income-conference.html

and future fund performance. We present our conclusions in Section 6.

II. Related literature

A. Bond Market Liquidity Literature

Research on market liquidity in corporate bonds received a significant boost with the introduction of transactions reporting via the TRACE system in July 2002. A number of studies examine the corporate bond market and show that (a) customers in corporate bonds incur transactions costs that are large relative to those observed in equity markets (e.g., Schultz (2001), Ederington, Guan and Yadav (2015), Harris (2015)), (b) the introduction of the TRACE system lowered trading costs for corporate bonds (Bessembinder, Maxwell and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007)), (c) the liquidity in corporate bonds deteriorated during the financial crisis, which contributed in part to higher bond yields (Friewald, Jankowitsch and Subrahmanyam (2012)), and (d) electronic systems are gaining market share in active, larger bonds, and among trades that are easier to complete (Hendershott and Madhavan (2015)).

Several studies examine the impact of bank-related regulation implemented after the financial crisis on the corporate bond market. The main findings are that dealers' capital commitment in corporate bonds has declined in recent years, driven mainly by bank-affiliated dealers, both under normal market conditions and on stressful days (Bessembinder, Maxwell, Jacobsen, and Venkataraman (2017), Schultz (2017)), and around bond-specific stress events, such as ratings downgrades (Bao, O'Hara, and Zhou (2016)) and index reconstitutions (Dick-Neilson and Rossi (2015)). Bessembinder et al. (2017) document a significant shift in dealer behavior from a market making role towards an agency role where dealers connect buyers and sellers. Friewald and Nagler (2016) find that the relation between dealer inventory positions and risk-adjusted returns have strengthened in recent years. Schultz (2017) shows that the proportion of interdealer trading has recently declined. Choi and Huh (2016) document that situations where a dealer is matching customer buy and sell trades are associated with smaller bid-ask spreads than principal commitment trades. The study interprets one leg of the matched trade as liquidity provision by customers; however, since the TRACE data do not identify customers, it is not possible to study the trading style of individual customers using only TRACE data.

Other studies examine the role of networks in dealer markets on execution quality. Di Maggio, Kermani and Song (2016) show that well connected dealers are able to obtain better prices than peripheral dealers, especially during periods of high uncertainty. Using insurance company transactions in corporate bonds, O'Hara, Wang, and Zhou (2015) show that less active institutions receive worse executions than more active institutions, which reflects in part the dealers' use of market power. Hendershott, Li, Livdan, and Schurhoff (2016) develop a model on costs and benefits of maintaining relationships with multiple dealers, and show that larger firms obtain better executions by fostering competition among dealers.

B. Institutional Trading Literature

The literature on trading behavior of buy-side institutions has largely focused on equities markets. Anand, Irvine, Puckett and Venkataraman (2013) study equity transactions data of buy-side institutions made available by Abel-Noser, and classify trading style by comparing the fund's transactions with daily stock return, or daily trade imbalance based on TAQ data. The main findings are that trading style is persistent, that trading costs of LS funds are smaller than LD funds, and that trading style influences the speed of liquidity recovery after the financial crisis. Da, Gao and Jagannathan (2011) construct a measure of impatient trading versus liquidity supply by comparing quarterly fund holding changes of equity mutual funds to trade imbalances calculated using the TAQ database. They attribute the majority of fund outperformance to impatient trading, although liquidity provision is important for income oriented funds. Cheng, Hameed, Subrahmanyam and Titman (2017) find that LS funds withdraw from stocks that are losers in a previous period, which affects the pattern of return reversals. Other studies classify trading style of equity funds based on exposure of funds' return to a contrarian long-short factor portfolio (see Nagel (2012)).

Unlike equity markets, where buy-side institutions can post limit orders in electronic markets, trading in OTC structure of bond markets is highly decentralized, and inserts the bond dealer in virtually all transactions between buyers and sellers. Corporate bonds trade less often than stocks. Furthermore, market participants have less information on order flow and quotations in bond markets than equities markets. The differences in market structure of equity and bond markets suggest that trading strategies that work in equity markets might be more difficult to implement in bond markets.

III. Data sources, inventory cycles and trading style classifications

The primary datasets used by the study are the enhanced TRACE data of corporate bond transactions, Mergent's Fixed Income Securities Database (FISD) on bond characteristics, and the Morningstar data of bond mutual fund holdings. We obtain data on the VIX index from the CBOE and the TED Spread from the Federal Reserve Bank of Saint Louis. In this section, we first describe the data and the selection of corporate bond funds. We then describe our approach to identifying inventory cycles and present their descriptive statistics. Next, we present our methodology that overlays the changes in bond holdings on the inventory cycles to classify trading style.

A. Data description

Since July 2002, all broker/dealers registered with the SEC are mandated to report all the transactions that they facilitate in corporate bonds, as principal or agent, to FINRA's TRACE system. The public version of the TRACE data include, among other things, information on the bond's CUSIP, the date and time of execution, the transaction price and volume (in dollars of par), and symbols indicating whether the trade represented a sale or purchase of bonds by a dealer to a (non-dealer) customer, or a trade between two dealers, and for customer trades, whether the customer is a buyer or a seller.[8] The enhanced TRACE data made available by FINRA includes additional information on disseminated and non-disseminated historical transactions, including those in privately-traded 144A bonds; unmasked trade sizes that are capped in the public version for large transactions; and masked identification numbers that identify the

[8] The dissemination of transaction reporting by TRACE was introduced in phases between July 2002 and March 2005 for registered bonds, and in June 2014 for unregistered bonds. See Bessembinder, Maxwell and Venkataraman (2006), Goldstein, Hotchkiss and Sirri (2007), and Edwards, Harris and Piwowar (2007), among others, for a description on the regulatory timeline and the impact of post-trade transparency on the corporate bond market.

dealer(s) participating in a transaction.

We obtain information on bond characteristics such as issue size, credit rating, and age from FISD database. The TRACE database includes over 131,000 unique cusips during our sample period, which runs from July 2002, the beginning of TRACE data, to December 2014. As noted by Bessembinder et al. (2017), the majority of cusips in the FISD database pertain to instruments other than corporate bonds. We follow the sample selection and trade screening approach outlined in Bessembinder et al. (2017). Specifically, we identify 29,127 corporate bonds in FISD database that are classified as non-puttable U.S. Corporate Debentures and U.S. Corporate Bank Notes (bond type-CDEB or USBN).[9] For these bonds, we select all transactions data between July 2002 and December 2014, and impose the following screens: (a) exclude bonds with less than five trades during the sample period, (b) exclude bonds with a reported trade size that exceeds the bond's offer size, (c) exclude trades that are reported after the bond's amount outstanding is reported as zero, and (d) excludes transactions that are flagged as primary market transactions. With these filters imposed, the sample comprises 68.6 million transactions in 26,207 distinct cusips.

From Morningstar, we obtain data on fund holdings and monthly (inferred) flows and returns for taxable bond mutual funds between 2002 and 2014. Since the transactions database provides information for corporate bonds, we focus on Morningstar's defined categories for which corporate bonds form a material part of portfolio holdings (average proportion of 30% or greater). These include Corporate Bond, High-Yield Bond, Multi-sector Bond, Nontraditional Bond, Bank Loan, Preferred Stock, Short-Term Bond, Intermediate-Term Bond, and Long-Term Bond funds.

We present descriptive statistics for the sample of bond funds in Table 1. Mutual funds are required to disclose their holdings on a quarterly basis; however, many funds report on a monthly basis. We do not filter funds based on reporting frequency; instead, we condition on the available frequency in

[9] Specifically, we exclude cusips that pertain to retail notes, foreign government bonds, U.S. agency debentures, asset backed securities, pay-in-kind bonds, medium term notes, convertible ad preferred securities, etc.

constructing the trading style measure. There are 48,808 fund-reporting period observations in the sample. The snapshot of fund holding reports an average (median) of 415 (258) positions, representing total net assets (TNA) of approximately $1.5 billion ($369 million). In addition to corporate bonds, bond mutual funds invest in other securities such as government bonds, international bonds, and structured products. The average (median) fund in the sample invests 48% (41%) of its portfolio in corporate bonds. Sample funds hold an average of 9% of TNA in cash, and invest the remainder in government bonds (15.7%) and other securities (27.1%). Consistent with Goldstein et al. (2017) and Cici and Gibson (2011), bond funds are actively managed, with less than 3% of funds identified as index funds.

Table 1, Panel B, reports statistics on funds' turnover (annualized), broken down by frequency of reporting. During our sample period, bonds funds report most often at the monthly level (72%), followed by quarterly reporting (26%). We define turnover as the change in holdings, including both increases and decreases, in a reporting period, excluding bonds' expiration, divided by the total holdings at beginning of the period. For the full sample, the average (median) annualized turnover is 219% (147%). Thus, bond mutual funds trade frequently, which differentiates them from other buy-and-hold institutional investors in bonds (see Massa, Yasuda, and Zhang (2013)). Figure 1 shows the number and aggregate TNA of funds in our sample over time. Consistent with Goldstein et al. (2017), bond funds' holdings increase over time, from about $600 billion to almost $1.8 trillion by the end of our sample period.

B. Identifying Dealer Inventory Cycles

Our methodology for identifying dealer inventory cycles is based on the theoretical literature on dealer inventory management. The models in Stoll (1978) and Amihud and Mendelson (1980) show that, when a dealer's inventory positions diverge from desired positions, the dealer responds by actively "shading" the quotations that lead to unwinding of inventory positions. Empirical evidence in support of these models from equity markets is presented by Panayides (2007) and Hansch, Naik, and Viswanathan (1998) using data on NYSE specialists and LSE dealers, respectively. Interdealer trading offers an important channel for risk sharing among bond dealers (see Schultz (2017)); however, interdealer trades do not alleviate customer-driven imbalances across all dealers.

In our framework, a trading style that is liquidity supplying alleviates the imbalance by absorbing the inventory positions of dealers. A common assumption in the microstructure literature is that the desired dealer inventory, which is not observable, is zero. Zero inventory is intuitively appealing because inventory requires capital and exposes a dealer to volatile prices. We therefore identify the beginning and ending dates of an inventory cycle in a bond when the cumulative inventory crosses zero. Cumulative inventory is the signed, aggregate dollar inventory based on all dealers' trades with customers in the bond. Interdealer trades are not included because they do not impact aggregate dealer positions.[10]

Using TRACE transactions data, we calculate the (signed) inventory by cumulating dealers' trades with customers from the start date of the cycle. The cycle begins when the inventory crosses zero and ends when the inventory crosses zero again from the opposite direction. However, if the cycle remains ongoing and becomes longer than three months (63 trading days), then inventory is the (signed) cumulative customer imbalance over the rolling three months, which helps reduce the cycle's sensitivity to reporting errors that may otherwise compound infinitely. We select a rolling three-month period to allow for the slow build-up and unwinding of inventory in an illiquid market. Appendix 1 provides details of our methodology.

When inventory cycles extend longer than three months, the inventory cycle can end on a day when there are no reported transactions in the data. This reflects a scenario where transactions that occurred earlier in the cycle fall out of the three-month rolling period. In this case, we reset the starting inventory of the new cycle to zero. [11] An alternate scenario is that the cycle ends on a day with reported

[10] We consider all customer trades including those trades that are reported to TRACE as "Agency" trades. When a dealer acts as agent, the dealer reports two legs of the facilitated trade as separate transactions on TRACE. When both legs involve customers, the net impact on the aggregate dealer positions is zero. When one leg involves a dealer and the customer and the other leg involves two dealers, we include the customer leg but not the inter-dealer leg.

[11] It is well known that bond dealers assume long term, proprietary positions (non market-making) but the TRACE data do not allow us to distinguish "prop" versus market making positions of dealers. To capture this effect, we reset the inventory to zero (instead of the three-month cumulative sum) when a previous cycle extends longer than three months and ends without transactions on the ending date of the cycle.

transactions in the bond. If the old transactions being dropped from Day[-63] are sufficient to bring the rolling three-month inventory to zero, the starting inventory of the new cycle is based on customer imbalance on Day[0]. On the other hand, if it is the combination of old transactions dropping out and the new trades that make the inventory cross zero, the starting inventory position for the new cycle is the residual of the Day[0] imbalance that is in excess of zero after offsetting the previous day inventory. As a robustness check, we identify inventory cycles based on a (mechanical) three-month rolling period without resetting inventory to zero, and obtain similar results.

We categorize a scenario with large customer selling imbalance as a positive inventory cycle, to reflect the aggregate positive inventory of dealers. Similarly, large customer buying imbalance leads to a negative inventory cycles.[12] In selecting inventory cycles, we require inventory to be material by imposing (a) a minimum peak inventory of $5 million for investment-grade bonds or bonds with issue sizes greater than $1 billion, and $3 million for other bonds, and (b) a minimum inventory cycle length of 5 days.[13]

Table 2 summarizes the 166,299 inventory cycles identified by our methodology. There are 86,876 positive inventory cycles, representing persistent dealer buys to accommodate selling imbalance in customer trades, and 79,423 negative inventory cycles. Overall, inventory cycles are long lasting, with the average cycle lengths of 79 calendar days for positive cycles, and 77 calendar days for negative cycles. Our findings contrast sharply with those of Madhavan and Smidt (1993) and Hansch et al. (1998) for equity markets (the mean half-lives are 7.3 trading days for NYSE specialists and 2.5 trading days for dealers at the LSE). The average peak inventory is approximately $20 million.

We investigate the length of inventory cycles and the dollar value of peak inventory by year. Since the TRACE data begins in July 2002 and the trading style calculation requires 12 months of data,

[12] Asquith, Au, Covert and Pathak (2013) show that the cost of borrowing corporate bonds is comparable to the cost of borrowing stocks, and has fallen over time.

[13] The choice of thresholds reflect that corporate bond transactions are large and that the public version of TRACE reports transactions in investment-grade (high-yield) bonds that exceed $5 million ($1 million) as "$5 million or larger" ($1 million or larger), as opposed to actual size. We find similar results when we impose a minimum peak inventory of $5 million for investment grade bonds and $1 million for high-yield bonds.

the first inventory cycles are identified in 2003. The time trend shows declining inventory cycles over time, with average cycle length that exceed 80 days in the beginning of the sample to cycle lengths that are closer to 70 days towards the end of the sample. The time trend also shows that peak inventory has declined over time. Our results indicate that dealer inventory cycles are shorter and shallower in recent years. These findings complements the evidence from related studies that dealers are less willing to commit capital in recent years (see Bessembinder et al. (2017), Bao et al. (2016), Dick-Neilsen and Rossi (2016), Schultz (2017), among others).

To validate our approach to identifying inventory cycles, we also report an analysis of total bond returns during the inventory cycle.[14] During the buildup (loading) phase of inventory cycle, returns are negative for positive cycles, which is consistent with customer selling pressure, and positive for negative cycles, which is consistent with customer buying pressure. The returns are the opposite sign for the unload phase of inventory cycle, which is consistent with price reversals that compensate dealers for absorbing customer order flow. For the full cycle, the returns are negative for positive cycles and positive for negative cycles, which suggests that aggregate customer flows result in a small permanent price impact. Figure 2 presents a schematic on the change in dealer inventory and the bond returns in the load, peak, and unload phase of a positive inventory cycle.

C. Classifying Funds Based on Trading Style

To measure trading style, we overlay the change in a fund's bond holdings on the inventory cycle in a bond. We classify the holdings change as liquidity supplying if the fund increases (reduces) its bond holdings during a positive (negative) inventory cycle. The opposite is considered liquidity demanding. Stated differently, a liquidity supplying (demanding) bond fund is buying (selling) the bond during an interval when bond dealers in aggregate are facing selling pressure from customers, and the buying (selling) activity of the fund helps absorb (further strain) the dealers' inventory.

[14] We calculate returns as percentage changes in bond's clean price from the beginning of the cycle to the peak for the buildup phase and from the peak to the end of the cycle for the unloading phase. We use volume-weighted price across all transactions in the day for return calculation.

Our methodology differs in important ways from the return based, contrarian trading approach used in equities literature to identify trading style. The main advantage of our approach is that corporate bonds trade in a market structure where liquidity suppliers (dealers) are clearly identified. A second advantage is that the TRACE dataset captures the entire history of dealers' transactions with customers, which allows us to relate changes in bond holdings to a direct measure of stress in dealer positions; that is, changes in bond holdings observed without a dealer inventory cycle are not included in trading style classification. Third, as shown in Figure 2, the load and the unload phase of an inventory cycle encompass periods of opposite bond returns, which introduces noise in other classification schemes, particularly in illiquid securities, based on the correlation between holdings change and the corresponding bond returns over reporting window. In our methodology, we first identify an inventory cycle as positive or negative, and then overlay the change in bond holdings; thus, an increase in bond holdings that overlaps with beginning and end dates of a positive cycle is classified as liquidity supplying, regardless of whether the increase in bond holdings occurred in the load, peak, or unload phase of the inventory cycle.

After classifying the change in each bond holding in a reporting period, we calculate the fund's *LS_score* for the reporting period, as follows: [15]

$$LS_{score} = \frac{Liquidity\ supplied\ (\$) - Liquidity\ demanded\ (\$)}{Liquidity\ supplied\ (\$) + Liquidity\ demanded\ (\$) + Unclassified\ (\$)} \qquad (1)$$

Since the reporting periods of mutual funds' holdings are unlikely to perfectly overlap with inventory cycles, we require a minimum overlap of 50% between the fund's reporting window and the inventory cycle. That is, for the one-month reporting period, the reporting window and inventory cycle have to overlap for at least 15 days for the holdings change to be classified.[16] The main measure of the trading style, *LS_score*, focuses on the fund's participation in the secondary market alone. We therefore remove

[15] The use of dollar liquidity supplied and demanded places greater weight on larger holdings changes, which we believe is an appropriate reflection of a fund's willingness to provide liquidity. However, we verify that a measure based on the number of liquidity supplying and demanding holdings changes (equally weighting each holdings change) yields similar results.

[16] Similarly, the overlap requirement is 30 days for two-month reporting periods, and 45 days for three-month reporting periods. The overlap requirement of 50% also ensures that each position change can only be classified in one way. As reported in Table 3, about 14% of the holding changes over the sample period are not classified.

the changes in bond holdings that correspond with bond issuance from equation (1). In Section IV.C, we present a trading style measure (*LS_score_IPO*) that includes all changes in holdings, including those changes that correspond with the initial issuance of a bond.

We recognize that data limitations and many developments in the bond markets have the potential to influence the trading style measure. First, as shown in Table 1, the average fund in the sample invests 48% of its portfolio in corporate bonds. Our assumption is that trading style that we identify based on the funds' behavior in corporate bonds apply to other instruments as well. To the extent that this assumption is violated, the fund's trading style is estimated with noise, and weakens the relation between trading style and fund performance. Second, although our sample funds often (72%) report at the monthly level, we are still unable to incorporate in equation (1) the trades of funds within the reporting period. Puckett and Yan (2011) show that the interim trades of institutional investors in equity markets contain valuable information about trading skill. Third, the length and depth of dealer inventory cycles are affected by market structure developments in bond markets. For example, alternative trading systems have captured market share in corporate bond market in recent years (see Hendershott and Madhavan (2015)). Although bond dealers play a prominent role as liquidity suppliers in these electronic markets, the technological advancements imrpove the nature of search for counterparties. Further, bank-regulation such as Volcker Rule has caused dealers to participate more in agency capacity that directly match a buyer and a seller. These developments have the potential to lower the information content of the trading style measure.

Table 3, Panel A reports descriptive statistics for *LS_score* over the sample period. An *LS_score* of zero implies that the fund's trading style is relatively balanced such that the fund's trading activity neither absorbs nor strains the dealer positions, on average. A fund with a higher *LS_score* exhibits a higher propensity to absorb dealer inventory in comparison to a fund with a lower *LS_score*.

For the 40,828 fund-period observations, the average and the median value of *LS_score* is -0.09. Aggregating at the fund level, the average *LS_score* estimated over 962 bond funds is -0.08 and the median score is -0.09. Thus, a typical bond mutual fund exhibits a trading style that demands liquidity from bond dealers. This implies that a typical bond mutual fund buys (sells) when other funds and buy-side investors are buying (selling). Reasons may include herding (Cai, Han, Li, and Li (2016)), index rebalancing (Dick-Neilsen and Rossi (2016)), rating upgrades and downgrades (Ellul, Jotikasthira and Lundblad (2011)), among others. The table also reports annual statistics of *LS_score* over the sample period. Although the proportion of bond holding changes that are unclassified remains fairly constant, the *LS_score* exhibits significant variation over time. The measure more than doubled from -0.05 in 2007 to -0.11 in 2008, and further increased to -0.13 in 2009, before reversing to -0.07 in 2010. These patterns suggest that bond mutual fund exhibit a higher propensity to demand liquidity from dealers in a crisis period. Goldstein et al. (2017) find that corporate bond fund outflows are sensitive to bad performance, and this sensitivity is higher when bond market is stressed. Collectively, the evidence suggests that fund outflows increase the demand for dealer intermediation during periods when dealer's risk bearing capacity is already strained. Future work should further investigate these patterns in light of the regulatory concerns on liquidity risk in bond markets.

We observe significant cross-sectional variation in *LS_score*, with the 25^{th} percentile of -0.29 and the 75^{th} percentile of 0.10. Thus, while the average bond fund demands liquidity, some funds exhibit a trading style that absorbs dealer inventory. Table 3, Panel B presents fund characteristics based on quintile of funds formed every year by average *LS_score*. In comparison to other quintiles, the bond funds in the highest *LS_score* quintile are smaller in terms of TNA; hold a smaller number of bond positions; and hold shorter duration bonds. The credit rating of bond holdings and fund turnover are similar across quintiles. We next explore the determinants of trading style in a multivariate framework.

IV. Results

A. Determinants of Trading Style

What are the observable fund attributes that are associated with a (relative) propensity to supply liquidity? To model the determinants of fund *i*'s trading style, we estimate a linear probability regression model of the fund's trading style on fund attributes and portfolio characteristics regress the average *LS_score* of the fund calculated over a rolling 12-month period [$t+1,t+12$] on fund attributes at time t, as follows:

$$LS\_score\_Q5_{i,(t+1,t+12)} = \sum_{k=1}^{n} \beta_k X_{i,t} + \sum T_t + \sum F_{i,t} + \varepsilon_{i,t} \quad (2)$$

$LS\_score\_Q5_{i,(t+1,t+12)}$ is an indicator variable that equals one for the highest *LS_score* quintile of funds in months [$t+1$, $t+12$] and zero otherwise. The observable fund attributes $X_{i,t}$ include log of TNA, log of fund age, institutional indicator variable that equals one if fund targets institutional investors and equals zero otherwise, rear load fees, proportion of assets held as cash holdings, proportion of assets held as corporate bond holdings, average duration of bonds held by the fund, average credit rating of bonds held by the fund, average issue size of bonds held by the fund, average age of bonds held by the fund, the average and standard deviation of a fund's net flows over months [t-11, t], and the average and standard deviation of a fund's returns over months [t-11, t]. These variables are designed to capture fund attributes in terms of its age and size, as well as the characteristics of portfolios held by funds. In addition, we include month fixed effects denoted by $\sum T_t$ and either fund-category, or fund-specific fixed effects denoted by $\sum F_{i,t}$.

Table 4, Panel A presents the results. We include fund category fixed effects (as described in section III.A) in model 1 and fund fixed effect in models 2.[17] In model 1, in terms of portfolio characteristics, the coefficient on bond issue size is positive and the coefficients on bond duration, bond age, and bond credit ratings are negative. Bonds with larger issue size, shorter duration, higher credit rating and younger bonds tend to be more liquid. Our results indicate that the fund's ability to respond opportunistically to dealer shocks is explained by the liquidity of portfolio holdings. The negative coefficient on volatility of fund returns indicates that lower portfolio risk exposure is associated with a higher propensity to supply liquidity. The coefficients on fund size and fund age are negative implying that younger and smaller funds have higher tendency to supply liquidity.

We observe three notable findings in model 2, which includes fund fixed effects. First, the

[17] We estimate two alternative models. One, where we use a continuous *LS_score* measure as the dependent variable; and two, where we do not include fund category or fund fixed effects. The results are qualitatively similar to those presented in Table 4, and are available from the authors upon request.

coefficient on rear load is positive and the coefficient on standard deviation of investor flows is negative. These variables are proxies for the sensitivity of investor flows to fund performance. Our results suggest that funds that discourage outflows using higher fees, or benefit from a stable investor pool can supply liquidity because they might not be forced into costly trading in response to investor flows. Second, while the results in model 2 are similar to model 1, the coefficients in model 2 are smaller. Thus, the cross-sectional variation in fund observables is informative about trading style, in addition to the time-series variation within a fund. Third, the R-square jumps from 0.08 in model 1 to 0.23 in model 2 with inclusion of fund fixed effects, indicating that trading style is a fund-specific attribute that is not fully captured by observable fund characteristics. For example, trading style can reflect fund manager's sensitivity to demand-supply conditions, or the relationship between the fund's trading desk and the dealer community.

B. Persistence in Trading Style

If trading style is a fund attribute, then is it persistent over time? In Table 4, Panel B.1, we examine persistence in two ways. First, we sort funds into *LS_score* quintiles using a 12-month ranking period [*t-11, t*]. Then, we calculate the average *LS_score* for each quintile in future months [*t+1, t+12*] and [*t+13, t+24*]. In the ranking period, the difference in trading style between the lowest and highest quintiles is 0.48. This difference narrows in future months, which reflects in part that some funds do not adhere to a trading style, and that trading style is measured with noise.

Nonetheless, the evidence clearly shows that the funds' past trading style is informative about the fund's future trading style. First, in each of the non-overlapping and long-horizon periods, the *LS_score* increases monotonically from the lowest (Q1) quintile to the highest (Q5) quintile. Second, the *LS_score* in future months [*t+1, t+12*] for the lowest quintile is -0.11, which is smaller (at the 1% level of significance) than that for the highest quintile (-0.04). Notably, *LS_score* for each quintile in future months [*t+1, t+12*] and [*t+13, t+24*] are almost identical.

To confirm this relationship further, we include a transition matrix in Table 4, Panel B.1. In this analysis, we assign funds into quintiles based on average *LS_score* in months [*t-11, t*] and report the proportion of funds in each quintile in future months [*t+1, t+12*]. The null hypothesis is that trading style is not informative, implying that funds randomly sort on trading style in future periods. Thus, under the null, funds have an equal (20%) probability of being in an *LS_score* quintile in future periods. Instead, the results show that highest (Q5) quintile funds exhibit a 33% probability of being in the highest (Q5) quintile in future periods. Similarly, the lowest (Q1) quintile funds exhibit a 28% probability of being in the lowest (Q1) quintile in future periods. The Pearson's chi-square test significantly rejects the null that probabilities in months [*t+1, t+12*] of *LS_score* quintiles do not depend on the fund's *LS_score* quintile in months [*t-11, t*].

C. Bond Issuance and Trading style

Participation in a new bond issue allows the fund to build a position in the bond. Given that fund holdings are reported at a monthly frequency at best, it is not possible to decompose changes in bond holdings into those acquired at initial issuance versus those acquired in the secondary market. The main measure *LS_score* does not consider changes in bond holdings that overlap with issue date of a new bond. To the extent that underwriters are reluctant to hold large positions in a newly issued bond, we recognize that participation by a fund in the initial bond issuance can be viewed as liquidity supply.

Issuance in the corporate bond market has been at record highs in recent years. Fund managers increasingly view participation in primary bond issuance as being important to meet fund objectives, which is in part attributable to the addition of new bond issues to relevant indexes at the end of the issuance month. In light of the importance of primary issues, we construct a trading style measure (*LS_score_IPO*) based on equation (1) that includes all changes in bond holdings, including those that overlap with the issuance date of a new bond. As discussed earlier, any change in bond holdings that is observed without an overlap with dealer inventory cycle is considered "unclassified" for measuring trading style.

In untabulated results, the average and median value of *LS_score_IPO* is 0.02. In comparison, the average and median value of *LS_score* is -0.09, suggesting that bond funds on average participate with a liquidity supplying trading style around the issuance of a new bond.[18] In the time series, the distribution of *LS_score_IPO* is shifted to right of the distribution of *LS_score*, and the shift is more striking in recent years. These patterns are consistent with the record level of new bond issues and the importance of primary markets for bond funds in recent years.

In models 3 and 4 of Table 4, Panel A, we present coefficient estimates of equation (2) but with the fund's *LS_score_IPO_Q5* on the left-hand side. The results are broadly similar to those observed for *LS_score*. One notable result is that past investor flow is highly significant in model 3 (with fund category fixed effects), suggesting that the ability to participate in new issuance is influenced by investor flow. In Panel B.2., the difference in *LS_score_IPO* between the lowest and highest quintiles during the ranking period is 0.40, and the difference narrows to 0.05 in future months. *LS_score_IPO* increases monotonically from the lowest (Q1) quintile to the highest (Q5) quintile in months [*t+1*, *t+12*] and [*t+13*, *t+24*]. The transition matrix shows that highest (Q5) quintile funds exhibit a 31% probability of being in the highest (Q5) quintile, and the lowest (Q1) quintile funds exhibit a 30% probability of being in the lowest (Q1) quintile in the next twelve months. These results are broadly similar to those reported for the *LS_score* measure.

D. Trading Style and Fund Performance

The evidence thus far shows that trading style is a fund-specific attribute that persists over time. We next examine whether trading style contains information about future fund performance. We expect that funds that supply liquidity should obtain additional returns, partly from an immediate price concession for alleviating dealer positions and partly from future price reversals due to the price pressure. We capture fund performance by the fund's alpha relative to a benchmark model. We use the four-factor model, following Chen and Qin (2017), as follows:

$$R_{i,t} - R_{ft} = \propto + \beta_{STK} STK_t + \beta_{BOND} BOND_t + \beta_{DEF} DEF_t + \beta_{OPTION} OPTION_t + \varepsilon_t \qquad (3)$$

[18] Not surprisingly, bond funds increase holdings in the new bond around issuance date. We find that inventory cycles, if they are observed, tend to be positive around the issuance date. One possibility is that some market participants, who received allocations at the time of issuance, are selling their bonds in the secondary market.

where *STK* is the stock market factor calculated as the excess return on the CRSP value-weighted stock index, *BOND* is the bond market factor calculated as the excess return on the U.S. aggregate bond index, *DEF* is a measure of default risk premium calculated as the return spread between the high-yield bond index and the intermediate government bond index, and *OPTION* is the option factor which accounts for possible bond fund investments in mortgage-backed securities, which contain an option feature. *OPTION* is the return spread between the GNMA mortgage-backed security index and the intermediate government bond index. We estimate the betas using monthly observations over a rolling 18-month period [*t-18, t-1*]. The betas estimates are then used to calculate the expected return in month *t*. The difference between the actual fund return and the expected return yields the estimated alpha for month *t*.

We next examine whether a fund's trading style predicts future alphas using the following model:

$$\propto_{i,t} = \beta_1 LS\_score_{i,(t-12,t-1)} + \beta_2 LS\_score_{i,(t-12,t-1)} * FundLiq_t + \sum_{k=1}^{n} \beta_k X_{i,t} + \sum T_t + \sum FC_{i,t} + \varepsilon_{i,t} \qquad (4)$$

where $\propto_{i,t}$ is the funds' alpha as described above, $LS\_score_{i,(t-12,t-1)}$, the explanatory variable of interest, refers to funds' trading style measured over months [*t-12, t-1*] and $LS\_score_{i,(t-12,t-1)} * MktLiq_t$ represents interaction variables between trading style and market liquidity measures. We use the TED spread; a dummy that equals one during the financial crisis (07/2007 to 04/2009) and zero otherwise; and, the US VIX as measures of funding liquidity. $X_{i,t}$ represents variables that account for fund attributes and bond characteristics, as defined in equation (2). Equation (4) also includes month fixed effects denoted by $\sum T_t$ and fund-category fixed effects denoted by $\sum FC_{i,t}$.

Results in Table 5.A provide strong evidence that trading style is associated with future fund alphas. Table 5.A, model 1 presents the baseline model with the lagged *LS_score* as the only explanatory variable, along with fund-category, and month, fixed effects. We estimate a positive coefficient on *LS_score* that is significant at the 5% level. Our results suggest that a liquidity supplying trading style is associated with higher future fund performance, after accounting for factor risk exposures.

In model 2, we introduce a non-linear specification with dummy variables representing the lowest (most liquidity demanding) and the highest (most liquidity supplying) *LS_score* quintiles formed using trading style in months [*t-12*, *t-1*]. We estimate a negative coefficient (-0.032) for the lowest (Q1) quintile suggesting that bond funds that have a propensity to strain the inventory positions of bond dealers are associated with lower monthly fund alphas of 3.2 basis points. In contrast, we estimate a positive coefficient (0.033) for the highest (Q5) quintile suggesting that bond funds that have a propensity to absorb the inventory positions of bond dealers are associated with higher monthly fund alphas of 3.3 basis points. The difference in coefficients between these *LS_score* quintiles is 6.5 basis points, and is statistically significant at the 5% level.

We consider the interactions of trading style with market illiquidity in models 3 to 7. In all models, the coefficient on *LS_score* is positive and statistically significant at the 1% level. The interaction coefficient of *LS_score* with the crisis dummy in model 3 is positive, indicating that liquidity supplying trading style is associated with higher alphas during the crisis period. When we include the interaction of the *LS_score* with the TED spread and the VIX in models 4 and 5, the crisis period effect is subsumed in both models, but the coefficients on the direct measures of funding liquidity are positive and significant at the 1% level. Higher compensation for liquidity supply during stressful times is consistent with prior evidence that investors earn a risk premium when markets are stressed (see Nagel (2012), and Friewald, Jankowitsch, and Subrahmanyam (2012)).

Models 6 and 7 confirm that the results showing higher alphas for funds with higher *LS_scores*, and even higher returns during period of market stress, are robust to the inclusion of a number of fund attributes and portfolio characteristics. To assess the economic significance of these effects, we standardize the TED and VIX variables to have a mean of zero. Model 6 coefficients indicate that, when the TED spread is at the mean during our sample period, bond funds with a one standard deviation higher *LS_score* generate an additional 1.95 basis points per month, or approximately 24 basis points per year, in terms of future portfolio alpha. To put this number in perspective, the average alpha of a fund in the sample is 3.4 basis points per month. Based on model 6, an increase of one-standard deviation for *LS_score* is associated with 4.05 basis points per month in future alpha when the TED spread is one standard deviation above its mean value. Overall, our results indicate that trading style contributes in an economically significant way to fund performance.

In Figure 3, we plot the cumulative difference in alphas for funds in the top (Q5) and bottom (Q1) *LS_score* quintiles over our sample period. Similar to equation (4), the quintiles are formed in months *t-12* to *t-1*, and the difference in alphas are calculated in month *t*. Consistent with Table 5, the Q5-Q1 difference in alphas is the highest during the crisis, averaging 23.3 basis points per month. The large magnitudes suggest that a liquidity supplying trading style might offset the low returns earned by institutional portfolio when markets are stressed. This evidence adds to the literature on security characteristics that serve as illiquidity hedge in a fund's portfolio (Acharya and Pedersen (2005)). We do not find a significant change in Q5-Q1 spreads in the period before and after the crisis. The average Q5-Q1 difference is 2.4 basis points per month in both non-crisis periods.

Table 5.B, uses *LS_score_IPO* that incorporates the fund holding changes that occur around bond issuance date. We find similar results – *LS_score_IPO* constructed over months [*t-12, t-1*] has a significant (at the 1% level) association with fund returns in month *t* in all seven specifications. Similar to Table 5.A, the return to liquidity provision is higher in periods of market stress as measured by the crisis dummy, the TED spread or the VIX. The economic significance of the coefficients is also similar, although smaller than that in Table 5.A. For example, Model 6 coefficients indicate that, when the TED spread is at the sample mean, bond funds with a one standard deviation higher *LS_score_IPO* generate an additional 1.81 basis points per month (compared to 1.95 for *LS_score*), in terms of future portfolio alpha. When the TED spread is one standard deviation above its mean, an increase of one-standard deviation for *LS_score_IPO* is associated with 3.72 basis points per month of future alpha (compared to 4.05 basis points for *LS_score*).

V. Conclusions

Market commentators are concerned that the growth in corporate bond market and the reduction in dealer capital point to a liquidity problem in corporate bonds. According to a 2017 Greenwich Associates survey, the majority of credit investors describe buy-side institutions as an important channel of liquidity supply in the next few years. Yet we know relatively little about the role of buy-side institutions as liquidity suppliers in bond markets. This study attempts to fill this gap in the literature.

We develop a methodology to classify an institution's trading style. Using bond transactions (TRACE) data between 2002 and 2014, we aggregate the inventory positions of bond dealers, and identify inventory cycles. We overlay the change in portfolio holdings, obtained from Morningstar, on inventory cycles to classify the trading style of bond mutual funds. We classify a bond funds' trading style as liquidity supplying (demanding) if the changes in bond holdings exhibit a propensity to absorb (further strain) the aggregate dealer positions.

Between 2003 and 2014, the typical bond mutual fund has a trading style that demands liquidity from bond dealers. Trading styles vary across bond funds, and are persistent over time. Greater flexibility in portfolio holdings, as evidenced by liquid bonds, and more stable investor base allow bonds funds to opportunistically responds to dealer shocks. A liquidity supplying trading style is associated with higher future fund performance after controlling for portfolio attributes and factor risk exposures. The difference in alpha between fund quintiles based on trading style is 6.5 basis points per month. The differences are further accentuated during times when market liquidity declines.

We present evidence on a new channel of liquidity supply in the corporate bonds market. In 2014, then SEC chair Mary Jo White expressed a concern that the majority of bond trading electronic platforms are being used primarily to "provide information on the bonds their participating dealer would like to sell."[19] A 2013 industry study reports that over 70 percent of institutional corporate bond investors expect request-for-quote (RFQ) platforms that are based on bond dealer as intermediary to dominate.[20] Nonetheless, 45 percent of the larger investors expect crossing networks that involve buy-side firms to play a significant role in the future. Our study shows that liquidity supplying buy-side firms respond to aggregate shocks in a manner that absorb the inventory position of dealers. One implication is that multi-

[19] https://www.sec.gov/news/speech/2014-spch062014mjw

[20] McKinsey&Company and Greenwich Associates report, "*Corporate bond E-Trading: same game, new playing field*", August 2013.

dealer RFQ platforms can significantly expand the liquidity pool, and facilitate better risk sharing for bond dealers, by developing capabilities that allow buy-side institutions to receive RFQs, and respond with their trading interests.

Trading style has useful information for investors in predicting fund performance. This evidence is noteworthy in light of the prior evidence in the bond literature that bond managers exhibit limited ability to select corporate bonds that outperform (see Cici and Gibson (2012)). Our study shows that it is important to understand when institutions choose to implement trades, in addition to the bond selection. The fund outperformance is especially important in the current low interest rate environment, where the cost of implementing bond trades has a measurable impact on the yield that bond investors receives from the fund. The trading style we identify adds another dimension to the fund's ability to earn alpha by capturing a portion of the returns to liquidity provision in bond markets.

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Appendix 1: Inventory Cycles

Our inventory cycle starts and ends at zero inventory. On the start date, the inventory departs from zero in either the positive or the negative directions as a result of new trades. The end date is the date immediately before the inventory reaches zero again. We refer to a cycle during which the inventory is positive (negative) as a positive (negative) inventory cycle. Let t denote the start date of an inventory cycle and B_i denote the (signed) aggregate dealer imbalance on trading day i. Then, the inventory on trading day $t+s$, denoted by I_{t+s}, is given by:

$$I_{t+s} = \begin{cases} \sum_{i=t}^{t+s} B_i & if\ s < 63 \\ \sum_{i=t+s-62}^{t+s} B_i & if\ s \geq 63 \end{cases}$$

In the first 63 trading days (upper part of the formula), we simply accumulate the dealer imbalances from the beginning of the cycle. As the cycle becomes longer than 63 trading days (lower part of the formula), i.e. the inventory not crossing zero during the period from t to $t+62$, we begin dropping the imbalances during the cycle that are outside the 63-trading day rolling window. We drop older trades to help keep the inventory cycle at a reasonable length and reduce its sensitivity to potential reporting errors that may otherwise compound infinitely. We select the rolling window of 63 trading days to allow for the slow build-up and unwinding of inventory in an illiquid market.

Below, we present four different examples to illustrate our implementation of the above formula. The examples illustrate different ways in which an inventory cycle may end and how we account for the imbalances on the end date. The first example provides the simplest case, in which the cycles end as a result of new trades pushing the inventory across the zero line. The remaining three examples demonstrate more complicated cases, in which dropping older trades plays a role in ending a long inventory cycle.

Example 1: Short Cycles Ending by New Trades

	Cycle ending only by new trade						
Trading Day	Imbalance	Cumulative Imbalance	63-Day Rolling	**Inventory**	Cycle	Day of Cycle	Cycle Length
1	$12	$12	$12	**$12**	Excluded	1	4
2	$12	$24	$24	**$24**	Excluded	2	4
3	$0	$24	$24	**$24**	Excluded	3	4
4	-$12	$12	$12	**$12**	Excluded	4	4
5	-$12	$0	$0	**$0**	None	-	-
…	$0	$0	$0	**$0**	None	-	-
19	$12	$12	$12	**$12**	Positive	1	46
20	$12	$24	$24	**$24**	Positive	2	46
…	$0	$24	$24	**$24**	Positive	3 to 44	46
63	$0	$24	$24	**$24**	Positive	45	46
64	-$12	$12	$0	**$12**	Positive	46	46
65	-$20	-$8	-$32	**-$8**	Negative	1	18
66	-$12	-$20	-$44	**-$20**	Negative	2	18
67	$0	-$20	-$32	**-$20**	Negative	3	18
…	$0	-$20	-$20	**-$20**	Negative	4 to 17	18
82	$10	-$10	-$22	**-$10**	Negative	18	18
83	$10	$0	-$24	**$0**	None	-	-

In the above example, we present several cycles during period from trading days 1 to 83. Besides the first column, which indexes the trading day, the table has seven other columns. The second column presents the (signed) daily imbalance, and the third column presents the cumulative imbalance from the start of the cycle. The fourth column presents the 63-trading day rolling sum of daily imbalances. We assume that the bond starts trading for the first time on trading day 1 so that the cumulative imbalance and the rolling sum are the same up to day 63. The fifth column presents the inventory, which as in the formula above, equals the cumulative imbalance during the first 63 days of the cycle and the rolling sum after that. Since all of our cycles in this example are shorter than 63 trading days, the inventory here is always the cumulative imbalance. The seventh column indexes the trading day within the cycle, and the last column presents cycle lengths in trading day unit.

The first cycle begins on day 1 when the dealers buy $12 million. On day 2, the dealers buy another $12 million, resulting in the cumulative imbalance and the inventory of $24 million. On day 4, a sale of $12 million decreases the inventory to $12 million. Another sale of $12 million on day 5 ends the cycle. By our definition, the first cycle ends on day 4 (immediately before crossing zero), and therefore the cycle length is only 4 days. Since the cycle length is shorter than 5 days, we exclude the cycle from our analysis.

There is no trading until day 19 when a new positive cycle begins with the dealers buying $12 million. The dealers continue to load the inventory with another $12 million on day 20, pushing the cumulative imbalance and the inventory cycle to its peak at $24 million. The inventory remains $24 million until two large negative imbalances close the positive cycle on day 64 and start a new negative cycle on day 65 at -$8 million. The new negative cycle then lasts until day 82 as the two large positive imbalances on days 82 and 83 together close the cycle at zero.

Example 2: Long Cycle Ending by Old Trades Dropping Out

	Cycle ending only by old trade dropping out						
Trading Day	Imbalance	Cumulative Imbalance	63-Day Rolling	**Inventory**	Cycle	Day of Cycle	Cycle Length
1	$12	$12	$12	**$12**	Positive	1	81
2	$12	$24	$24	**$24**	Positive	2	81
3	$0	$24	$24	**$24**	Positive	3	81
4	$0	$24	$24	**$24**	Positive	4	81
5	$0	$24	$24	**$24**	Positive	5	81
…	$0	$24	$24	**$24**	Positive	6 to 18	81
19	$12	$36	$36	**$36**	Positive	19	81
20	$12	$48	$48	**$48**	Positive	20	81
…	$0	$48	$48	**$48**	Positive	21 to 62	81
63	$0	$48	$48	**$48**	Positive	63	81
64	$0	$48	$36	**$36**	Positive	64	81
65	$0	$48	$24	**$24**	Positive	65	81
66	-$20	$28	$4	**$4**	Positive	66	81
67	$0	$28	$4	**$4**	Positive	67	81
…	$0	$28	$4	**$4**	Positive	68 to 81	81
82	$0	$0	-$8	**$0**	None	-	-
83	$0	$0	-$20	**$0**	None	-	-

In the above example, we present one long inventory cycle in a table similar to that in Example 1. As our formula indicates, when a cycle becomes longer than 63 trading days, we switch from using the simple cumulative imbalance to the 63-trading day rolling sum as our measure of inventory. As a result, old trades at the beginning of the cycle get sequentially dropped out, and the example here shows that the sequential dropping out can eventually end a long cycle.

Here, a positive cycle starts on day 1 with the $12 million imbalance. The dealers continue to load the inventory further on days 2, 19, and 20, resulting in the peak inventory of $48 million which lasts until day 63. On day 64, we switch to use the rolling sum as our measure of inventory, and therefore the inventory decreases to $36 million despite no trading. Notice that while the cumulative imbalance remains at $48 million, the rolling sum decreases to $36 million due to the $12 million imbalance on day 1 being dropped (outside the 63-trading day window). On day 65, the $12 million imbalance on day 2 also gets dropped, pushing the inventory down further to $24 million. On day 66, the dealers sell another $20 million, further reducing their inventory to $4 million. On day 81, the cycle ends as the $12 million imbalance on day 19 is dropped on day 82, pushing the inventory across the zero line. There is no additional imbalance on day 82, and therefore we do not have a new cycle that begins on that day. The long positive cycle lasts 81 days, and peaks at $48 million. Importantly, the use of rolling sum helps end the cycle at a reasonable length by dropping trades earlier in the cycle.

After the cycle ends, we reset the cumulative imbalance to zero on day 82, forgetting all trades that are part of the ended inventory cycle. In contrast, the rolling sum on day 82 is -$8 million, which reflects that $12 million on day 19 is dropped, more than offsetting the $4 million inventory. The rolling sum becomes further negative on day 83 as the imbalance of $12 million on day 20 is dropped. Notice here that the rolling sum is never reset, and may span across cycles.

Example 3: Long Cycle Ending by Old Trades Dropping Out - New Trades Occurring on the Same Day

This example is a minor variation on Example 2. If a trade occurs on day 82, but the dropping of the earlier imbalance on day 19 would have ended the cycle on its own, then we keep the entire new trade on day 82 as the beginning inventory of the new cycle. In the above illustration, a new negative inventory cycle starts on day 82 to reflect the new trade of -$12 million. Once again, we reset the inventory to zero after the end of the positive cycle, and switch back to using the cumulative imbalance as our measure of inventory in the first 63 days of the new negative cycle.

	Cycle ending by old trade dropping out; a trade occurring on the same day						
Trading Day	Imbalance	Cumulative Imbalance	63-Day Rolling	**Inventory**	Cycle	Day of Cycle	Cycle Length
1	$12	$12	$12	**$12**	Positive	1	81
2	$12	$24	$24	**$24**	Positive	2	81
3	$0	$24	$24	**$24**	Positive	3	81
4	$0	$24	$24	**$24**	Positive	4	81
5	$0	$24	$24	**$24**	Positive	5	81
…	$0	$24	$24	**$24**	Positive	6 to 18	81
19	$12	$36	$36	**$36**	Positive	19	81
20	$12	$48	$48	**$48**	Positive	20	81
…	$0	$48	$48	**$48**	Positive	21 to 62	81
63	$0	$48	$48	**$48**	Positive	63	81
64	$0	$48	$36	**$36**	Positive	64	81
65	$0	$48	$24	**$24**	Positive	65	81
66	-$20	$28	$4	**$4**	Positive	66	81
67	$0	$28	$4	**$4**	Positive	67	81
…	$0	$28	$4	**$4**	Positive	68 to 81	81
82	-$12	-$12	-$20	**-$12**	Negative	1	> 2
83	$0	-$12	-$32	**-$12**	Negative	2	> 2

Example 4: Long Cycle Ending by a Combination of New Trades and Old Trades Dropping Out

The final scenario is one where the combination of the dropping out of the day 19 imbalance and the new trades on day 82 cause the inventory cycle to end. Up to day 65, the cycle looks exactly the same as in Examples 2 and 3 where the loading ends on day 20 with the peak inventory of $48 million, and on days 64 and 65, the earlier imbalances on days 1 and 2 drop out, reducing the inventory to $24 million. However, the sale trade on day 66 is smaller than in the other examples, only decreasing the inventory to $16 million. On day 82, the inventory would further decrease from $16 million to $4 million due to the $12 million imbalance on day 19 being dropped. This alone would not end the inventory cycle. Hence, the inventory cycle ends only because the new -\$12 million imbalance further pushes the inventory to -\$8 million (+\$4 million -\$12 million). The positive cycle ends on day 81, and the new negative cycle starts on day 82 with the residual of the new imbalance, -\$8 million, as the starting inventory. We again forget all trades in the previous positive cycle, and switch back to using the cumulative imbalance as our measure of inventory in the first 63 days of the new negative cycle.

	Cycle ending by a combination of new trade and old trade dropping out						
Trading Day	Imbalance	Cumulative Imbalance	63-Day Rolling	**Inventory**	Cycle	Day of Cycle	Cycle Length
1	\$12	\$12	\$12	**\$12**	Positive	1	81
2	\$12	\$24	\$24	**\$24**	Positive	2	81
3	\$0	\$24	\$24	**\$24**	Positive	3	81
4	\$0	\$24	\$24	**\$24**	Positive	4	81
5	\$0	\$24	\$24	**\$24**	Positive	5	81
…	\$0	\$24	\$24	**\$24**	Positive	6 to 18	81
19	\$12	\$36	\$36	**\$36**	Positive	19	81
20	\$12	\$48	\$48	**\$48**	Positive	20	81
…	\$0	\$48	\$48	**\$48**	Positive	21 to 62	81
63	\$0	\$48	\$48	**\$48**	Positive	63	81
64	\$0	\$48	\$36	**\$36**	Positive	64	81
65	\$0	\$48	\$24	**\$24**	Positive	65	81
66	-\$8	\$40	\$16	**\$16**	Positive	66	81
67	\$0	\$40	\$16	**\$16**	Positive	67	81
…	\$0	\$40	\$16	**\$16**	Positive	68 to 81	81
82	-\$12	-\$8	-\$8	**-\$8**	Negative	1	> 2
83	\$0	-\$8	-\$20	**-\$8**	Negative	2	> 2

Robustness: Rolling Sum as Alternative Inventory Measure

We use the simple rolling sum of imbalances over 63 trading days as a robustness measure of inventory. We obtain the results similar to those reported in the paper. The rolling sum is simple and easy to understand, and yields cycles that are similar in length and peak to our main specification. However, one important disadvantage of the rolling sum is that dropping an older trade could by itself start a new cycle in the opposite direction. For example, suppose the dealers buy \$20 million of a bond on day t and close out their inventory by selling \$20 million on day $t + 10$. Despite the fact that the positive cycle has ended and there are no new trades, the original trade on day t will drop out on $t + 64$, and the inventory on that day will be -\$20 million as a result of the remaining trade on day $t + 10$. This starts a new cycle on day $t + 64$, which lasts for another ten days (until the trade on $t + 10$ also drops out). In Example 2 above, we can observe the same problem. The rolling sum would have started a new negative cycle on day 82, despite no trading activities.

Our main specification avoids the problem of spurious cycles by resetting the inventory to zero at the end of each cycle, and removing all prior dealer imbalances from the calculation of future inventory beyond that point. Our underlying assumption is that once the cycle has ended, the dealer inventory is completely flat and *imbalances in prior cycles* can no longer affect future inventories. However, as the cycle becomes longer than 63 trading days, our inventory measure and the alternative rolling sum measure converge and *earlier imbalances within the cycle* may drop and change the inventory even without new trading.

As discussed above, by construction, our main specification and the rolling sum are most different at the beginning of a new cycle. Spurious cycles aside, the evolution of inventory over the cycle may also differ, which may result in different lengths and peaks (though capped at 63 trading days). Let us go back to Example 1. Our inventory and the rolling sum start diverging on day 64. The rolling sum on that day is 0, as a result of dropping the \$12 million imbalance on day 1 and adding the -\$12 million imbalance on day 64. On day 65, the rolling sum moves further negative to -\$32 million due to the \$12 million imbalance on day 2 dropping out and the new imbalance of -\$20 million on day 65. The rolling sum peaks at -\$44 million on day 66, and the cycle based on the rolling sum lasts beyond day 83. This is because the negative cycle is amplified by positive imbalances in the previous cycles dropping out of the rolling sum calculation. On the other hand, our inventories on day 64 and after are unaffected by the imbalances in previous cycles, e.g. imbalances on days 1 and 2, as it accumulates the imbalances only from the beginning of the current cycle, and forgets any imbalances before that date. Only new imbalances affect our inventory when a cycle lasts 63 days or less.

Table 1

Summary Statistics for Taxable Bond Funds

This table presents summary statistics for general characteristics (Panel A) and turnover (Panel B) of taxable bond funds. The data are from Morningstar, and the sample period is from July 2003 to December 2014. The sample includes only open-ended funds in the following Morningstar classifications, for which the average allocation to corporate bonds is 30% or greater: Corporate Bond, High-Yield Bond, Multisector Bond, Nontraditional Bond, Bank Loan, Preferred Stock, Short-Term Bond, Intermediate-Term Bond, and Long-Term Bond. The observation frequencies are fund-month for total net assets (TNA), flow, and return, and fund-month or coarser, depending on each fund's reporting frequencies, for other variables. Number of positions is the number of unique bond CUSIPs held by each fund on each report date. Flows and returns are measured as a percentage of prior-month TNA while the allocations to cash and equivalents, corporate bonds, government bonds, and others (including municipal bonds, securitized bonds, and derivatives) are measured as a percentage of current-month TNA. Average duration and average credit rating are the value-weighted averages of bonds' modified duration and credit rating (1 = AAA, 2 = AA+, etc.), respectively, as reported by Morningstar. Index fund dummy equals one if Morningstar classifies the fund as index fund, and zero otherwise. Turnover is the annualized ratio of dollar volume traded between two reporting dates and TNA on the earlier reporting date. The statistics are reported by length of time in months between two reporting dates.

Panel A: General Characteristics

	N	Mean	Std. Dev.	Pct. 25	Median	Pct. 75
Total net assets (TNA, $ Million)	48,808	1,544	5,627	111	369	1,138
Number of positions	48,808	415	696	137	258	456
Asset allocation (%)						
Cash	48,808	9.212	12.018	3.301	6.680	12.553
Corporate bonds	48,808	47.987	30.686	23.614	40.509	78.719
Government bonds	48,808	15.725	18.575	1.022	11.724	24.595
Others	48,808	27.076	27.877	5.702	25.535	43.480
Average duration	48,808	3.899	1.670	3.110	4.180	4.800
Average credit rating	48,808	10.026	4.216	6.000	10.000	14.000
Index fund dummy	48,808	0.029	0.169	0.000	0.000	0.000
Monthly return (%)	78,110	0.417	1.180	-0.156	0.437	1.070
Monthly flow (%)	78,110	1.930	16.633	-4.530	0.171	6.149

Panel B: Turnover by Reporting Period

	N	Mean	Std. Dev.	Pct. 25	Median	Pct. 75
Reporting period						
1 month	34,989	2.265	2.409	0.761	1.486	2.757
2 months	1,329	2.658	3.639	0.931	1.550	2.717
3 months	12,490	1.932	1.789	0.841	1.403	2.321
All	48,808	2.191	2.317	0.793	1.465	2.627

Table 2

Summary Statistics for Dealer Inventory Cycles

This table presents summary statistics for characteristics of dealer inventory cycles. Each inventory cycle begins when the cumulative inventory of all dealers changes from zero and ends when it comes back to zero. A positive (negative) inventory cycle is a cycle during which the cumulative inventory is positive (negative), i.e. dealers buying more than selling (buying less than selling) in aggregate. For each bond on each trading day, cumulative inventory is calculated using all customer trades from the beginning of the cycle if the beginning of the cycle is less than three months ago, or over the past three months if the beginning of the cycle is more than three months ago. Bond trading data, including trade size, trade price, and whether the trade is between two dealers or between dealer and customer, are from TRACE, and the sample period is from July 2003 to December 2014. Cycle length is the number of calendar days in an inventory cycle. Loading (unloading) period is the period over which the cumulative inventory moves away from (back to) zero. Peak inventory is the largest cumulative inventory, most positive or most negative in par value terms, during the cycle. Bond return between two trading days is calculated using volume-weighted average price (VWAP) of all trades. Tests of difference in mean between the positive and negative inventory cycles are conducted using heteroscedasticity-robust standard errors. ∗, ∗∗, and ∗∗∗ refer to statistical significance at 10%, 5%, and 1% levels.

	Positive Inventory Cycle (N = 86,876)			Negative Inventory Cycle (N = 79,423)			Diff.
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean
Cycle length (Days)							
Loading	38.391	35.984	28.000	37.760	33.171	29.000	0.631
Unloading	40.031	30.750	33.000	39.246	31.906	31.000	0.786
Full	79.319	53.789	77.000	77.783	54.100	76.000	1.535
Cycle length by year (Full cycle - Days)							
2003	89.805	57.495	90.000	91.932	58.474	92.000	-2.126
2004	84.386	56.755	86.000	85.496	57.259	89.000	-1.111
2005	88.532	57.905	90.000	86.307	55.745	90.000	2.225**
2006	88.266	57.666	90.000	85.633	55.949	90.000	2.633**
2007	90.047	58.404	91.000	87.150	57.254	90.000	2.896**
2008	87.249	58.116	90.000	91.619	61.788	91.000	-4.370***
2009	77.757	55.357	73.000	80.148	57.129	76.000	-2.391**
2010	80.698	53.428	84.000	77.556	54.333	76.000	3.141***
2011	80.811	55.599	83.000	79.962	55.105	79.000	0.849
2012	72.199	49.063	77.000	69.841	50.128	64.000	2.357***
2013	69.710	46.996	73.000	63.411	43.873	61.000	6.300***
2014	73.198	48.838	75.000	67.632	46.481	66.000	5.567***
Peak inventory ($ Million)	22.209	20.701	14.864	18.049	16.967	11.921	4.160***
Bond return (%)							
Loading	-0.222	2.980	-0.064	0.615	3.207	0.122	-0.838***
Unloading	0.188	3.035	0.084	-0.082	3.114	-0.070	0.270***
Full	-0.056	4.455	-0.016	0.527	4.817	0.067	-0.583***

Table 3

Summary Statistics for Funds' Liquidity Supply and Its Association with Funds' Characteristics

This table presents summary statistics for mutual funds' liquidity supply measure (Panel A) and its association with other mutual funds' characteristics (Panel B). Observations are fund-month or coarser, depending on each fund's reporting frequencies. Liquidity supply score (*LS_score*) is calculated as:

$$LS\_score = \frac{Liquidity\ supplied\ (\$) - Liquidity\ demanded\ (\$)}{Liquidity\ supplied\ (\$) + Liquidity\ demanded\ (\$) + Unclassified\ (\$)}$$

For each fund-bond-period, the fund is considered "supplying" ("demanding") liquidity if the change in the fund's position in that particular bond is on the same (opposite) side as the dealer inventory cycle, and the overlap between the fund's reporting period and the dealer inventory cycle is at least half of the fund's reporting period. Changes in the fund's position in a bond that coincide with the bond's initial public offering are excluded. Changes in the fund's positions that do not meet the criteria but are not excluded are considered "unclassified." Changes in par value are then aggregated across all corporate bonds, grouped into liquidity supplied, liquidity demanded, and unclassified. The three aggregate changes, for each fund-period, are used in the above calculation. In Panel A, the statistics for *LS_score* are calculated for the entire sample (pooled, counting each observation as one unit) and for the cross section of funds' time-series averages, both over the full sample period and each calendar year. The last column reports the mean fraction, in par value terms, of unclassified position changes. In Panel B, fund-period observations, in each calendar year, are sorted by *LS_score* into five quintiles. The mean statistics for each *LS_score* quintile are reported for the following funds' characteristics: TNA, number of positions, allocations to cash and equivalents and corporate bonds, average portfolio duration, average credit rating, and turnover. Tests of difference in mean between the top and bottom LS_score quintiles are conducted using heteroscedasticity-robust standard errors. ∗, ∗∗, and ∗∗∗ refer to statistical significance at 10%, 5%, and 1% levels.

Panel A: Summary Statistics of LS_score

	N	Mean	Std. Dev.	Pct. 25	Median	Pct. 75	Mean Unclass'd Fraction
Pooled	40,828	-0.090	0.355	-0.291	-0.093	0.103	0.136
Fund average	962	-0.081	0.145	-0.139	-0.091	-0.030	0.145
Fund average by year							
2003	525	-0.080	0.243	-0.223	-0.086	0.040	0.112
2004	590	-0.107	0.234	-0.217	-0.104	0.000	0.128
2005	558	-0.055	0.237	-0.164	-0.069	0.039	0.140
2006	575	-0.086	0.232	-0.199	-0.073	0.032	0.129
2007	568	-0.052	0.224	-0.172	-0.068	0.051	0.122
2008	580	-0.109	0.228	-0.227	-0.107	-0.002	0.123
2009	587	-0.131	0.192	-0.227	-0.125	-0.032	0.147
2010	589	-0.072	0.171	-0.166	-0.088	0.022	0.175
2011	603	-0.070	0.198	-0.164	-0.082	0.007	0.175
2012	618	-0.076	0.195	-0.170	-0.083	-0.007	0.175
2013	641	-0.106	0.193	-0.189	-0.112	-0.028	0.185
2014	652	-0.085	0.208	-0.176	-0.098	0.002	0.178

Table 3 -*continued*

Panel B: Means of Funds' Characteristics by LS_score Quintile

LS_score Quintile	TNA	Number of Positions	% Cash	% Corporate Bonds	Average Duration	Average Credit Rating	Turnover
1 (Low)	1,943.271	381.959	6.576	44.104	3.894	9.455	2.456
2	2,375.195	526.015	5.204	51.537	4.125	10.993	2.286
3	2,604.717	579.241	5.534	51.979	4.167	10.988	2.345
4	1,842.607	489.981	7.386	52.859	4.031	10.840	2.389
5 (High)	1,183.824	355.309	6.888	43.317	3.666	9.292	2.466
5 - 1	-759.447**	-26.650	0.312	-0.787	-0.228***	-0.163	0.010

Table 4

Determinants of Funds' Liquidity Supply

Panel A reports OLS estimates of linear models for the probability that a fund's liquidity supply measure, averaged over the period from months *t*+1 to *t*+12, is in the top quintile during that particular rolling period. Observations are fund-period. In columns (1)-(2), the liquidity supply measure is *LS_score*, calculated using only changes in corporate bond positions that do not coincide with the bonds' initial public offering dates. In columns (3)-(4), the liquidity supply measure is *LS_score_IPO*, calculated in the same manner as *LS_score* but also considering changes in corporate bond positions that coincide with the bonds' initial public offering dates. Explanatory variables are funds' characteristics as of the end of month *t*. Institutional fund dummy equals one if the majority of the fund's shares are of institutional classes, and zero otherwise. Rear load is the maximum rear load, in percentage points, that investors in the fund have to pay if they redeem their shares within a certain period after purchasing. ln(TNA) and ln(Age) are natural logs of fund's TNA and age. % Cash and % Corporate bonds are fund's percentage allocations to cash and equivalents and corporate bonds. Average duration and average credit rating are the value-weighted averages of bonds' modified duration and credit rating (1 = AAA, 2 = AA+, etc.). ln(Average bond issue size) and ln(Average bond age) are natural logs of average issue size (in dollars) and average age (in years) of corporate bonds in fund's portfolio. Average flow and return, as well as standard deviations of flow and return, are calculated over the period from months *t*-11 to *t*. Models in columns (1) and (3) include period and fund classification fixed effects while models in columns (2) and (4) include period and fund fixed effects. Standard errors, two-way clustered by fund and period, are in parentheses. Panel B-1 (B-2) reports various metrics of funds' future liquidity supply conditional on funds' past *LS_score* (*LS_score_IPO*). At the end of each month *t*, funds are sorted into five quintiles by their *LS_score* (*LS_score_IPO*) averaged over the period from months *t*-11 to *t*. The reported statistics are across funds in each *LS_score* (*LS_score_IPO*) quintile. The first two columns report the mean number of traded CUSIPs and *LS_score* (*LS_score_IPO*) during the sorting period. The third and fourth columns report the mean *LS_score* (*LS_score_IPO*) over the periods from months *t*+1 to *t*+12 and months *t*+13 to *t*+24, respectively. The last five columns report the mean percentages that the funds in each *LS_score* (*LS_score_IPO*) quintile during the sorting period will move into different *LS_score* (*LS_score_IPO*) quintiles in the period from months *t*+1 to *t*+12. In the first four columns, the tests of difference in mean between the top and bottom quintiles are conducted using standard errors, two-way clustered by fund and period. In the last five columns, the reported chi-square statistic is for the test of null hypothesis that the probability for being in each *LS_score* (*LS_score_IPO*) quintile in the period from months *t*+1 to *t*+12 is independent of the fund's *LS_score* (*LS_score_IPO*) quintile during the sorting period. $*$, $**$, and $***$ refer to statistical significance at 10%, 5%, and 1% levels.

Table 4 -*continued*

Panel A: Linear Probability Models for Future LS_score or LS_score_IPO Being in Top Quintile

	Dep. Var. = Avg. *LS_score* [*t*+1, *t*+12] Q5 dummy		Dep. Var. = Avg. *LS_score_IPO* [*t*+1, *t*+12] Q5 dummy	
	(1)	(2)	(3)	(4)
Non-Investment Characteristics				
Institutional fund dummy	-0.001	-0.038	-0.003	-0.021
	(0.013)	(0.035)	(0.014)	(0.035)
Rear load	0.012	0.020**	0.018**	0.027**
	(0.008)	(0.010)	(0.008)	(0.011)
ln(TNA)	-0.024***	-0.015**	-0.016***	-0.013*
	(0.004)	(0.007)	(0.004)	(0.008)
ln(Age)	-0.024***	-0.006	-0.020**	0.014
	(0.009)	(0.025)	(0.010)	(0.025)
Investment Characteristics				
% Cash	0.011	0.008	0.001	0.004
	(0.011)	(0.010)	(0.010)	(0.011)
% Corporate bonds	-0.017	0.013	0.030	0.036
	(0.027)	(0.022)	(0.027)	(0.023)
Average duration	-0.015***	-0.009	-0.012***	-0.011
	(0.004)	(0.006)	(0.004)	(0.007)
Average credit rating	-0.010***	-0.008***	-0.014***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Average bond issue size)	0.166***	0.069***	0.095***	0.052**
	(0.020)	(0.020)	(0.021)	(0.022)
ln(Average bond age)	-0.013***	0.000	-0.014***	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Flows and Returns				
Avg. flow [*t*-11, *t*]	0.001*	0.000	0.001***	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Avg. return [*t*-11, *t*]	-0.016	-0.014	-0.008	-0.009
	(0.015)	(0.014)	(0.013)	(0.013)
Std. dev. flow [*t*-11, *t*]	-0.001	-0.003**	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Std. dev. return [*t*-11, *t*]	-0.046***	-0.034**	-0.052***	-0.033**
	(0.014)	(0.014)	(0.014)	(0.014)
Classification fixed effects	YES	NO	YES	NO
Time fixed effects	YES	YES	YES	YES
Fund fixed effects	NO	YES	NO	YES
Observations	39,517	39,517	39,618	39,618
R-squared (total)	0.078	0.232	0.064	0.212

Table 4 -*continued*

Panel B-1: Future LS_score and Percentages in Different LS_score Quintiles Conditional on Past LS_score Quintile

Avg. *LS_score* Quintile	Avg. Number of Traded CUSIPs	Avg. *LS_score* [*t*-11, *t*]	Avg. *LS_score* [*t*+1, *t*+12]	Avg. *LS_score* [*t*+13, *t*+24]	Percentage in Avg. *LS_score* [t+1, t+12] Quintile: 1 (Low)	2	3	4	5 (High)
1 (Low)	18.964	-0.319	-0.108	-0.103	28.36	19.18	17.09	16.42	18.94
2	36.619	-0.164	-0.104	-0.101	19.79	24.71	22.47	19.18	13.85
3	40.825	-0.091	-0.089	-0.090	16.29	22.48	24.13	21.82	15.29
4	35.632	-0.015	-0.077	-0.080	16.94	18.84	21.54	23.09	19.59
5 (High)	17.392	0.159	-0.044	-0.046	18.86	14.55	14.54	19.24	32.80
5 - 1	-1.572	0.478***	0.063***	0.056***	H0: Rows and Columns are Independent				
Std. Error	(1.540)	(0.008)	(0.010)	(0.010)	χ^2 > 2,000***				

Panel B-2: Future LS_score_IPO and Percentages in Different LS_score_IPO Quintiles Conditional on Past LS_score_IPO Quintile

Avg. *LS_score _IPO* Quintile	Avg. Number of Traded CUSIPs	Avg. *LS_score_IPO* [*t*-11, *t*]	Avg. *LS_score_IPO* [*t*+1, *t*+12]	Avg. *LS_score_IPO* [*t*+13, *t*+24]	Percentage in Avg. *LS_score_IPO* [t+1, t+12] Quintile: 1 (Low)	2	3	4	5 (High)
1 (Low)	23.008	-0.182	0.005	0.006	29.71	18.90	15.59	15.62	20.18
2	46.620	-0.042	0.013	0.020	19.36	24.85	22.18	19.28	14.32
3	49.524	0.018	0.021	0.022	15.52	23.00	24.57	22.28	14.64
4	42.539	0.078	0.036	0.034	15.49	18.89	21.75	23.68	20.19
5 (High)	18.076	0.217	0.047	0.054	20.17	14.08	15.77	18.84	31.15
5 - 1	-4.932***	0.398***	0.042***	0.048***	H0: Rows and Columns are Independent				
Std. Error	(1.365)	(0.007)	(0.009)	(0.009)	χ^2 > 2,200***				

Table 5

Funds' Liquidity Supply and Performance

This table reports results from panel predictive regressions of alpha in month *t* on liquidity supply measures calculated over the period from months *t*-12 to *t*-1. Observations are fund-month, and only those with at least five identifiable CUSIPS traded per month during months *t*-12 to *t*-1 are included. Alpha is calculated by subtracting benchmark return from actual fund return:

$$R_{i,t} - R_{ft} = \propto_t + [\beta_{STK} STK_t + \beta_{BOND} BOND_t + \beta_{DEF} DEF_t + \beta_{OPTION} OPTION_t]$$

where *STK* is the excess return on the CRSP value-weighted stock index, *BOND* is the excess return on the U.S. aggregate bond index, *DEF* is the return spread between the high-yield bond index and the intermediate government bond index, and *OPTION* is the return spread between the GNMA mortgage-backed security index and the intermediate government bond index. All bond indices are from Bank of America Merrill Lynch. The parameters, β_{STK}, β_{BOND}, β_{DEF}, and β_{OPTION}, are estimated on a rolling basis. For alpha in month *t*, the estimation period is from months *t*-19 to *t*-1. In Panel A, the main independent variables are average *LS_score*, *LS_score* Q1, and *LS_score* Q5, all of which are calculated over the period from months *t*-12 to *t*-1. *LS_score* Q1, and *LS_score* Q5 are dummy variables that equal one if the fund's average *LS_score* in the bottom and top quintiles, respectively, of all funds on month *t*, and zero otherwise. In Panel B, *LS_score* is replaced by *LS_score_IPO*. Crisis is a dummy variable that equals one for the period from July 2007 to April 2009, and zero otherwise. TED is the yield spread in percentage points between the three-month Eurodollar futures contract and the three-month Treasury bill, averaged across all days in month *t* and demeaned to center at zero. VIX is the CBOE implied volatility index, averaged across all days in month *t* and demeaned to center at zero. All other variables are as defined in Table 4 and as of the latest period prior to month *t*. All models include period and fund classification fixed effects. In Panel B, control variables are omitted for brevity. Standard errors, two-way clustered by fund and period, are in parentheses. $*$, $**$, and $***$ refer to statistical significance at 10%, 5%, and 1% levels.

Panel A: Regressions of Fund Alphas on LS_score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Main Variables							
Avg. *LS_score*	0.152**		0.087***	0.128***	0.129***	0.122***	0.123***
	(0.066)		(0.033)	(0.039)	(0.044)	(0.039)	(0.040)
Avg. *LS_score* Q1		-0.032**					
		(0.015)					
Avg. *LS_score* Q5		0.033**					
		(0.016)					
Crisis x Avg. *LS_score*			0.312**	0.020	0.073	0.013	0.063
			(0.126)	(0.109)	(0.104)	(0.111)	(0.102)
TED x Avg. *LS_score*				0.300***		0.298***	
				(0.046)		(0.041)	
VIX x Avg. *LS_score*					0.018***		0.018***
					(0.006)		(0.006)

Cont'd next page

Table 5 -*continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
						Cont'd from previous page	
Control Variables							
Institutional fund dummy						0.012	0.011
						(0.009)	(0.009)
Rear load						0.006	0.005
						(0.005)	(0.005)
ln(TNA)						0.000	0.000
						(0.003)	(0.003)
ln(Age)						0.006	0.005
						(0.007)	(0.007)
% Cash						-0.000**	-0.000**
						(0.000)	(0.000)
% Corporate bonds						0.000	0.000
						(0.000)	(0.000)
Average duration						0.009	0.009
						(0.008)	(0.008)
Average credit rating						0.011**	0.011**
						(0.005)	(0.005)
ln(Average bond issue size)						-0.000	-0.001
						(0.010)	(0.010)
ln(Average bond age)						0.054*	0.054*
						(0.030)	(0.030)
Flow *t*-1						0.000	0.000
						(0.000)	(0.000)
Flow *t*-2						-0.000	-0.000
						(0.001)	(0.001)
Flow *t*-3						0.000	0.000
						(0.001)	(0.001)
Classification fixed effects	YES	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	58,428	58,428	58,428	58,428	58,428	58,428	58,428
R-squared (total)	0.246	0.246	0.247	0.248	0.249	0.251	0.252

Table 5 -*continued*

Panel B: Regressions of Fund Alphas on LS_score_IPO

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. *LS_score_IPO*	0.100***		0.071***	0.111***	0.101***	0.113***	0.107***
	(0.030)		(0.027)	(0.034)	(0.034)	(0.036)	(0.032)
Avg. *LS_score_IPO* Q1		-0.015***					
		(0.006)					
Avg. *LS_score_IPO* Q5		0.021**					
		(0.010)					
Crisis x Avg. *LS_score_IPO*			0.145***	-0.126	-0.029	-0.117	-0.037
		(0.041)	(0.079)	(0.061)	(0.079)	(0.057)	(0.107)
TED x Avg. *LS_score_IPO*				0.280***		0.272***	
				(0.076)		(0.071)	
VIX x Avg. *LS_score_IPO*					0.012***		0.013***
					(0.004)		(0.004)
Controls variables	NO	NO	NO	NO	NO	YES	YES
Classification fixed effects	YES	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	58,822	58,822	58,822	58,822	58,822	58,822	58,822
R-squared (total)	0.232	0.232	0.232	0.232	0.233	0.237	0.237

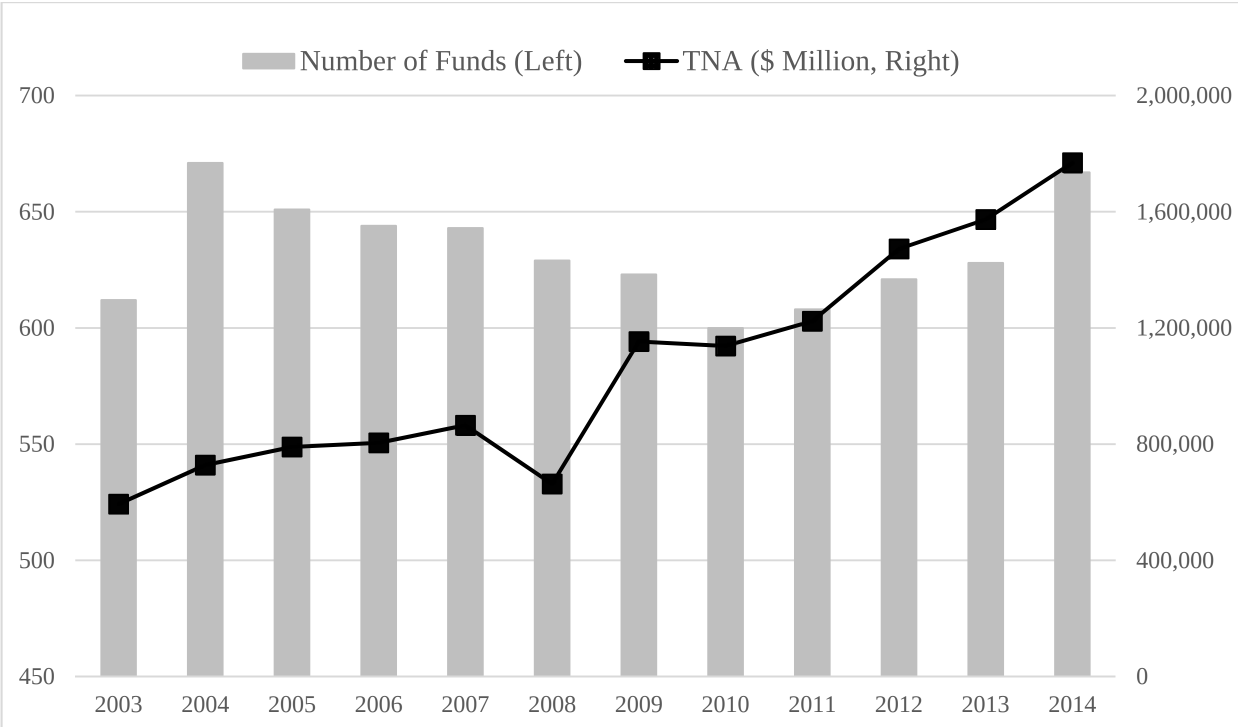
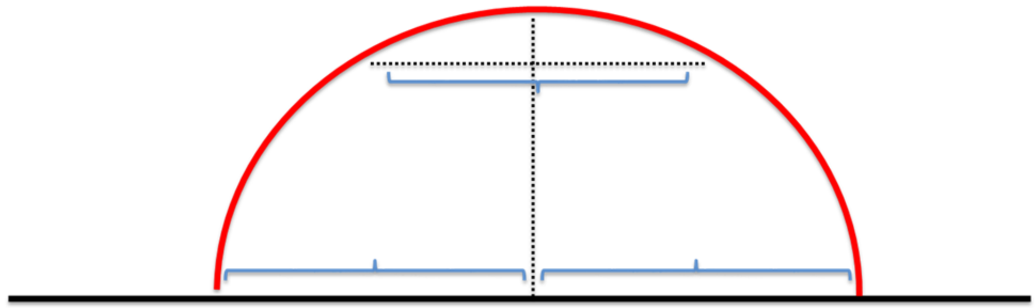


Figure 1. Taxable bond mutual funds over time. This figure presents the total net assets (TNA, in $ Million) of taxable bond funds and the numbers of these funds, as reported by Morningstar, over the sample period from 2003 to 2014. The sample includes only open-ended funds in the following Morningstar classifications, for which the average allocation to corporate bonds is 30% or greater: Corporate Bond, High-Yield Bond, Multisector Bond, Nontraditional Bond, Bank Loan, Preferred Stock, Short-Term Bond, Intermediate-Term Bond, and Long-Term Bond.



	Load Phase	Peak Phase	Unload Phase
Change in dealer inventory	Increase	No Change	Decrease
Bond return	Negative	Zero	Positive
Change in fund’s holding	Increase	Increase	Increase
Classification based on correlation with inventory change	Liquidity Supply	Not Classified	Liquidity Demand
Classification based on inventory cycle	Liquidity Supply	Liquidity Supply	Liquidity Supply

Figure 2. Classifying trades in a positive inventory cycle.

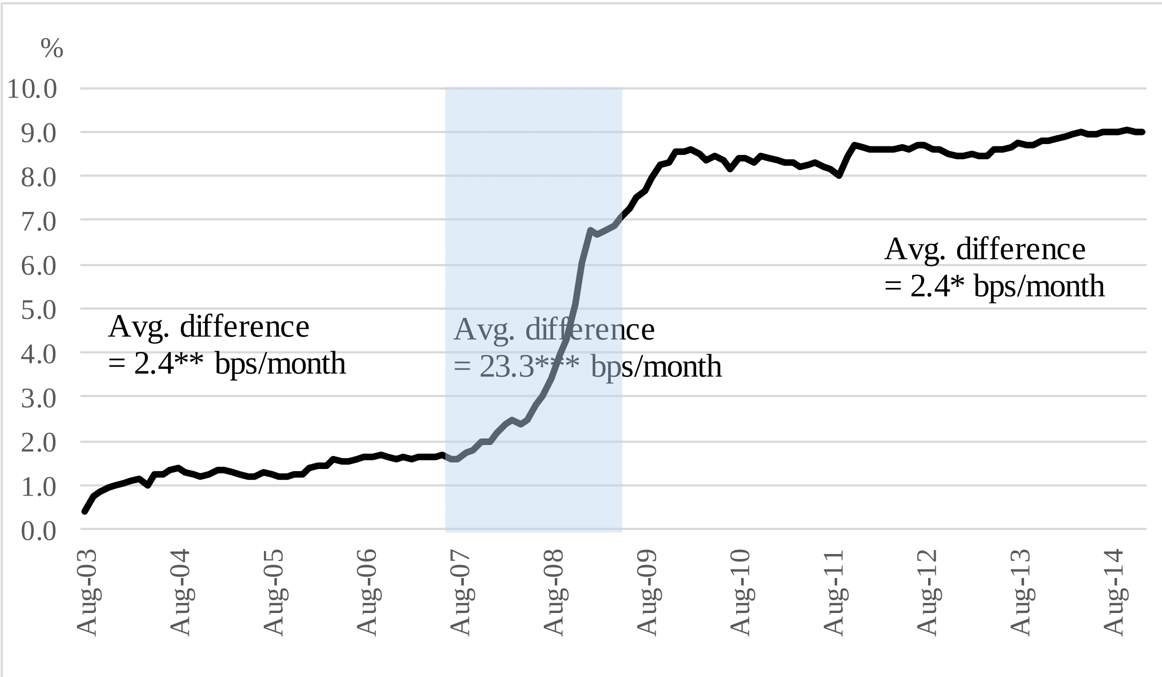


Figure 3. Cumulative difference in performance between funds in the top and bottom *LS_score* quintiles. This figure plots cumulative difference in average alpha of funds in the top and bottom *LS_score* quintiles. Alpha is calculated by subtracting benchmark return, based on a four-factor model as described in Table 5, from actual fund return. The model parameters are estimated on a rolling basis. For alpha in month *t*, the estimation period is from months *t*-19 to *t*-1. The average alpha is calculated each month on an equally weighted basis across all funds in each of the five *LS_score* quintiles, and the difference between the average alphas of the top and bottom quintiles is accumulated and plotted over time. For month *t*, the sorting variable is the average *LS_score* over the period from months *t*-12 to *t*-1. The shaded area highlights the crisis period, defined as the period from July 2007 to April 2009.