Do buy-side institutions supply liquidity in bond markets?

Evidence from mutual funds *

Amber Anand
Syracuse University
amanand@syr.edu

Chotibhak Jotikasthira,
Southern Methodist University
cjotikasthira@mail.smu.edu

Kumar Venkataraman
Southern Methodist University
kumar@mail.cox.smu.edu

Abstract

We examine the role of buy-side institutions as a channel of liquidity supply in corporate bonds. Using bond transactions data, we construct inventory cycles of dealers that reflect sustained trade imbalance of customers. Investor fund flows and dealer capital constraints influence commonality in cycles across bonds. We classify trading style of a bond fund as liquidity supplying (demanding) if changes in bond holdings help absorb (strain) dealers' inventory. Between 2003 and 2014, bond funds on average tend to demand liquidity; however, trading styles vary across funds and are persistent over time. A trading style that is liquidity supplying is associated with higher fund performance. Funds with stable investor base, skilled trading desks, and family affiliation with broker-dealers are more likely to supply liquidity. To tap into, and further encourage, the channel of liquidity supply identified by the study, bond trading platforms must exploit technology to facilitate direct participation by buy-side institutions. Our evidence contributes to the current debate on improving liquidity in bond markets.

Keywords: Corporate bond liquidity; buy-side institution; dealer inventory; mutual fund; performance.
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Abstract

We examine the role of buy-side institutions as a channel of liquidity supply in corporate bonds. Using bond transactions data, we construct inventory cycles of dealers that reflect sustained trade imbalance of customers. Investor fund flows and dealer capital constraints influence commonality in cycles across bonds. We classify trading style of a bond fund as liquidity supplying (demanding) if changes in bond holdings help absorb (strain) dealers' inventory. Between 2003 and 2014, bond funds on average tend to demand liquidity; however, trading styles vary across funds and are persistent over time. A trading style that is liquidity supplying is associated with higher fund performance. Funds with stable investor base, skilled trading desks, and family affiliation with broker-dealers are more likely to supply liquidity. To tap into, and further encourage, the channel of liquidity supply identified by the study, bond trading platforms must exploit technology to facilitate direct participation by buy-side institutions. Our evidence contributes to the current debate on improving liquidity in bond markets.

I. Introduction

Liquidity in the corporate bond market has received considerable attention in recent years. Several academic studies have documented a reduction in liquidity provision by corporate bond dealers between 2006 and 2016, attributable at least in part to regulations such as the Volcker Rule and bank-capital requirements (see, Bessembinder, Jacobsen, Maxwell, and Venkataraman (2017), Bao, O'Hara, and Zhao (2017), Dick-Neilsen and Rossi (2017), Schultz (2017), 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.[1] During the same decade, the outstanding amount of corporate bonds increased from $4.8 trillion to $8.5 trillion, alongside significant growth in assets under management by mutual funds and exchange traded funds (ETFs) that invest in corporate bonds.[2] Mutual funds trade frequently and their liquidity needs, while operating in illiquid secondary markets, led the U.S. Securities and Exchange Commission (SEC) to issue 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.[4]

The economic importance of buy-side institutions as a channel of liquidity supply cannot be overstated. In this study, we focus on unanswered questions relating to whether, and to what extent, buy-side institutions play a role as “shock absorbers” in the corporate bond market. Although this role appears similar to those played by bond dealers, the key distinction is that, unlike dealers, buy-side institutions do not incur inventory costs since they take positions for their portfolios. This flexibility allows institutions to

[1] "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."
[2] Statistics on the outstanding amount of corporate bonds are 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.
[3] https://www.sec.gov/divisions/investment/guidance/im-guidance-2014-1.pdf
[4] "Innovations ease corporate bond trading", Greenwich Associates, Quarter 2, 2017.

profit from opportunities to supply liquidity when dealers need to unwind inventory positions in an illiquid market. We examine whether bond mutual funds, an important category of buy-side institutions, serve as long-run suppliers of liquidity by helping dealers to offset their short-run inventory positions.[5] We focus on bond mutual funds since they trade frequently in secondary markets and are most likely among bond institutions to benefit from liquidity supply.

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. We use the enhanced version of the TRACE database of transactions in U.S. corporate bonds. The detailed dataset made available by FINRA represents all corporate bond transactions, and includes masked dealer identities for each transaction. 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 develop a methodology to classify the trading style of bond mutual funds. Our methodology is specifically designed for bond markets to take advantage of a market structure where liquidity suppliers (dealers) are clearly identified. Unlike the TAQ data that do not identify market makers, the TRACE data capture the entire history of dealers' trades with customers, implying that inventory positions of key intermediaries in corporate bonds can be observed with accuracy. We categorize a scenario with sustained customer selling (buying) activity as a positive (negative) dealer inventory cycle, to reflect the aggregate positive (negative) inventory of dealers. We 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.

Overall, the inventory cycles that we identify are long lasting, with the average cycle lengths of

[5] Further, unlike dealers, bond institutions do not post bid / offer quotes, or maintain a continuous market presence. The holding-period of market makers varies considerably across securities. In equities, high-frequency traders have very short horizon (in seconds) while in corporate bonds, Schultz (2017) estimates that half-life of active individual dealer inventory is four to five weeks. See Anand, Irvine, Puckett and Venkataraman (2013) for related discussions.

over 70 calendar days and peak inventory of $26 million. Inventory cycles are shorter and shallower in recent years. We observe a decline in the bond price when dealers' build-up inventory in a positive cycle followed by price reversals in the unload phase of the cycle. The former is consistent with dealers lowering indicative quotes to manage slow-moving inventory and the latter is consistent with price reversals that compensate liquidity suppliers for absorbing customer flow (see Kraus and Stoll (1972), Grossman and Miller (1988)). Price reversals are on average stronger in a positive cycle than a negative cycle, consistent with evidence of asymmetry in price impact of herding in corporate bonds (see Cai, Han, Li and Li (2017)).

Prior research shows that changes in market-level bond illiquidity explain a substantial part of time series variations in corporate bond yield spreads (see Bao, Pan and Wang (2011)). We first examine how inventory cycles vary over time. Instead of considering individual bonds, we focus on commonality in cycles by aggregating the price pressure incidences across bonds. We observe substantial level of commonality in bond-level inventory cycles. Notably, investors outflows (inflows) are positively associated with positive (negative) cycles indicating that bond funds *sell* (buy) a cross-section of bonds to dealers in response to investor *outflows* (inflows) and that the impact is material enough to generate commonality in cycles. There is a significant decline in both positive and negative cycles during the financial crisis, which likely reflects the capital constraints faced by bond dealers.

When we examine the influence of bond specific factors in a cross-sectional setting, we find that inventory cycles are less likely for bonds that have smaller issue sizes, higher credit risk, are closer to maturity, and older bonds. Inventory cycles are also more likely in the period surrounding credit upgrade or downgrade events that generate trading interest from customers. Overall, inventory cycles are less likely in bonds with lower trading activity and higher trading costs, which likely reflects the dealer's endogenous choice to build less risky inventory positions (see Goldstein and Hotchkiss (2017)).

Our measure of trading style captures the propensity of a fund's trades, which is measured by change in bond holdings over consecutive fund reporting periods, to further strain the inventory positions of bond dealers, or to help lay off dealer risk by absorbing the inventory positions of bond dealers. During our sample period, bond funds report most often at the monthly level (72%), followed by quarterly reporting

(25%). We overlay the change in bond holdings between reporting periods on the inventory cycle in a bond, and classify holdings changes as liquidity supply, demand, or unclassified.[6] Aggregating the classification across all corporate bond holdings for a reporting period, we obtain a fund's composite "*LS_score*" with higher (lower) values of *LS_score* signifying a propensity to absorb (strain) the inventory of bond dealers.

We present relevant empirical evidence on the following questions: First, do bond funds exhibit cross-sectional variation in trading style? Second, does trading style predict risk-adjusted fund performance, and further, whether the returns attributable to trading style vary over time? And third, what explains trading style? 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 find that mutual funds on average exhibit a trading style that demands liquidity from bond dealers. That is, the typical mutual fund tends to sell (buy) a bond when other market participants also sell (buy) the bond.[7] The funds' propensity to demand liquidity from dealers was pronounced during the financial crisis when risk bearing capacity of bond dealers was already strained. 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, and the sensitivity is higher when markets are stressed.

To understand the information content of trading style, we study the relation between trading style and future 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

[6] We classify the change in bond holdings as liquidity supply if the fund is buying the bond during an interval when bond dealers in aggregate are facing sustained selling activity from customers. The buying activity helps absorb the dealer's inventory. The opposite is classified as liquidity demand. Change in bond holdings that do not coincide with an inventory cycle, or meet a minimum overlap threshold are reported as unclassified.

[7] The bond market literature has identified many explanations for mutual funds to trade in the same direction, including herding behavior of institutions (Cai, Han, Li, and Li (2016)), index rebalancing (Dick-Neilsen and Rossi (2016)), credit rating events (Ellul, Jotikasthira and Lundblad (2011)), among others.

fund attributes and portfolio characteristics. Trading style has a larger impact on fund alpha when markets are illiquid, as measured by an elevated *Noise* measure (see Hu, Pan and Wang (2013)) or *VIX* index. The difference in fund alpha between low and high fund quintiles formed on trading style is 5.1 basis points per month, or approximately 60 basis points per year.

What determines trading style, and further, why do other funds not mimic the strategy? We estimate a panel predictive model where the dependent variable is trading style measured over a 12-month period, and the explanatory variables are the 12-month lagged fund attributes and portfolio characteristics. Investor inflows strengthen while investor redemptions weaken the ability to maintain a liquidity supplying trading style. When fund investors exhibit high flow-performance sensitivity, the fund is less likely to supply liquidity. These results suggest that funds with stable investor base are able to supply liquidity, as they are not forced into costly trading in response to investor flows. Funds that supply liquidity tend to hold older bonds and those with smaller issue size, suggesting that funds participate in segments of the market where dealer interest is lacking. The presence of a broker-dealer in the fund family is positively associated with the fund's propensity to supply liquidity. This suggests that affiliated broker-dealers confer informational advantages that are difficult to replicate by other funds. When we add fund fixed effects to the model, the R-square rises to 26%, from about 6% for the model with observable fund attributes, suggesting that the identity of the fund contains information on trading style. Possible explanations are that trading style reflects the fund manager's sensitivity to trading conditions in bond markets, the skill of trading desk, and the strength of the relationship between the buy-side desk and the dealer community.

Trading style is a fund attribute that is persistent over time. Sorting funds on trading style over a 12-month period, we show that trading style in the ranking period helps predicts the fund's trading style in the next 12 to 24 months. However, the strength of persistence declines when markets are stressed, implying that investor flows and market conditions affect the ability to maintain a trading strategy.

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. We present new evidence on a channel of liquidity supply in bond markets. Bond funds on average have a trading style that demands liquidity; however, there is significant dispersion in trading style, and some funds employ a strategy of absorbing dealer shocks. As noted by SEC Commissioner Michael S. Piwowar, while fixed income electronic platforms 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."[8] Despite the institutional frictions during our sample period, the evidence suggests that some funds help lay off dealer risk by absorbing the inventory. To tap into, and further encourage, the channel of liquidity supply identified by the study, alternative trading platforms must exploit technology and market data to facilitate direct participation by bond institutions.

We also 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 investor flows, as well as monthly index rebalancing, trade more frequently, and incur significant transaction costs. Indeed, funds in our sample trade 215% of their TNA in a year. 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 describe data sources and sample in Section II. Section III presents the methodology to identify dealer inventory cycles. Section IV describes the approach to classify trading style of funds. Section V examines the relation between trading style and fund returns. Section VI presents the relation between trading style and fund attributes. Section VII concludes.

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

II. Data and sample

The study's primary data sources are as follows. We obtain data on corporate bond transactions from FINRA's enhanced TRACE database, data on bond characteristics from Mergent's Fixed Income Securities Database (FISD), data on bond mutual fund holdings from Morningstar, the VIX index from the CBOE, and the Noise measure of arbitrage capital from Hu, Pan and Wang (2013).

Since July 2002, SEC-registered broker dealers report all the transactions that they facilitate in corporate bonds, as principal or agent, to FINRA's TRACE system. Research on market liquidity in corporate bonds received a significant boost with the availability of transaction data from TRACE. Notable findings in the bond literature include - (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) TRACE reporting is associated with a decline in customer's trading costs in 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 2007-09 financial crisis and contributed higher bond yields (Friewald, Jankowitsch and Subrahmanyam (2012)), and (d) there is a growth in the market share of electronic systems for actively traded bonds, large issue bonds, and among trades that are easier to complete (Hendershott and Madhavan (2015)).

The public version of the TRACE data include information on 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. The enhanced TRACE data made available to academics by FINRA includes 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 for individual dealers 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 from July 2002, the beginning of

TRACE data, to December 2014. The majority of cusips pertain to instruments other than corporate bonds. Following the approach in Bessembinder et al. (2017), 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 in 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 by FISD as zero, and (d) exclude 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. 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.[10]

We present descriptive statistics for the sample of bond funds in Table 1. Although mutual funds are required to disclose their holdings on a quarterly basis, many funds report monthly. We do not filter funds based on reporting frequency; instead, we condition on the available frequency in constructing the trading style measure. Panel A reports the statistics for 45,239 fund-reporting period observations in the sample. The snapshot of fund holding shows an average (median) of 431 (270) positions, representing total net assets (TNA) of approximately \$1.6 billion (\$0.39 billion). 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 50% (42%) of its portfolio in corporate bonds, of which corporate bonds in the TRACE sample account for 38% (28%) of TNA. Sample funds hold an average of

[9] Stated differently, 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.
[10] We find similar results for a sub-sample of bond funds with average corporate bond holdings of 50% or greater.

9% of TNA in cash and cash equivalents (as defined by Morningstar), 15% in government bonds and 25% in other securities. For the fund family, the average TNA is $8.3 billion with six funds per family in the sample. Consistent with Goldstein et al. (2017) and Cici and Gibson (2011), most bond funds are actively managed, with less than 3% of funds identified as index funds. The median bond fund has no rear load fee and only 5% of TNA owned by institutional share class; however, the averages are much higher than the median indicating that the distribution is right-skewed. The median monthly fund flow is 2% of TNA but the 25th and 75th percentile are -4.4% and 6.2%, respectively, indicating significant variation across funds and over time.

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 mutual funds and pension funds made available by Abel-Noser. A key empirical challenge for bond market research is that similar data on the corporate bond transactions of mutual funds and pension funds are not available.[11] We therefore follow the approach used by Da, Gao and Jagannathan (2011) for equity markets and infer the trades of the bond mutual funds by comparing their fund holdings over consecutive reporting periods.

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 (25%). 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 215% (148%). Thus, bond mutual funds trade frequently, which differentiates them from the typical buy-and-hold institutional investors in bonds (see Massa, Yasuda, and Zhang (2013)). Corporate bonds in the TRACE sample on average account for 35% of the total fund position changes in a fund-reporting period. Figure 1 shows the number and aggregate TNA of funds in our sample over time. Consistent with Goldstein et al. (2017), bond

[11] Transactions data of insurance companies are available from National Association of Insurance Companies (NAIC) database. Insurance companies tend to implement buy-and-hold strategies with reported annual turnover of 20 percent (http://www.naic.org/capital_markets_archive/110826.htm), suggesting they are less likely to supply liquidity.

funds' holdings increase over time, from about $600 billion to almost $1.8 trillion by the end of our sample period.

III. Inventory cycles

The theoretical literature on inventory management, such as Stoll (1978) and Amihud and Mendelson (1980), predicts that dealers will set a lower asking price to attract buyers when inventory position is larger than desired and a higher bid price to attract sellers when inventory position is smaller than desired. The "quote shading" attracts counterparties that lead to mean-reversion in dealer inventory. Empirical support from equity markets for these predictions is presented by Panayides (2007) and Hansch, Naik, and Viswanathan (1998) using data on NYSE specialists and LSE dealers, respectively.

We categorize a scenario with sustained customer selling activity as a positive inventory cycle, to reflect the aggregate positive inventory of dealers. Similarly, sustained customer buying activity leads to a negative inventory cycle, reflecting the aggregate negative inventory of dealers.[12] Figure 2 shows the interdealer network in an over-the-counter market (Figure 5 from Hollifield, Neklyudv and Spatt (2017)) where each circle represents a dealer, and the size of the circle is proportional to the size of the dealer. Dashed arrow represents a customer purchase from a dealer while the straight arrow represents a customer sale to a dealer. Panel A depicts a scenario where customer buying and selling activity aggregated across dealers is balanced and therefore does not generate an inventory cycle. Panel B depicts a scenario where customer selling activity is excessive and leads to a positive inventory cycle. Interdealer trading, which is depicted by light lines connecting the circles, offers an important channel for risk sharing among bond dealers (see Schultz (2017)); however, interdealer trades do not alleviate customer-driven imbalances aggregated across dealers.

Using TRACE transactions data, we calculate the (signed) inventory by cumulating dealers' trades with customers from the start date of the cycle. A common assumption in the microstructure literature is

[12] Large negative positions might cause some dealers to assume a short position. 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.

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.[13]

The cycle begins when the inventory crosses zero and ends when the inventory crosses zero again from the opposite direction. 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. In selecting inventory cycles, we require inventory to be material by imposing a minimum peak inventory of $10 million and a minimum inventory cycle length of 5 days.[14]

A. Descriptive statistics on inventory cycles

Table 2 summarizes the 156,234 inventory cycles identified by our methodology. There are 87,063 positive inventory cycles, representing persistent dealer buys to accommodate selling imbalance in customer trades, and 69,171 negative inventory cycles. Overall, inventory cycles are long lasting, with the average median cycle lengths of 72 (68) calendar days for positive cycles, and 75 (71) calendar days for negative cycles. [15] The loading and unloading phase of the inventory cycle is similar indicating that peak

[13] 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.
[14] We find similar results when we impose a minimum inventory cycle length of 15 days.
[15] For an individual dealer, Schultz (2017) finds that inventory position is mean-reverting, and the half-life of an active dealers' inventory position is about a month for actively traded investment grade bonds, and about five weeks for high yield bonds. In comparison, the inventory cycle reflects the position that is aggregated across all dealers.

inventory is observed half-way through the inventory cycle. The average peak inventory is $26 million for positive cycles and $22 million for negative cycles.

Figure 3 illustrates the aggregate dealer inventory, as a percentage of bond's issue size, and the mean/median cumulative abnormal return, normalized to zero on the peak inventory date, during positive (Panel A) and negative (Panel B) inventory cycles for a sample of investment grade, large issue bonds of age of at least one year. We calculate bond return as the change in volume weighted average price between two trading days. We then obtain abnormal return by subtracting the benchmark index return from the bond return. For positive cycles, Panel A shows the build-up in dealer inventory in the load phase and the reduction in dealer inventory in the unload phase. The abnormal returns are negative in load phase and positive in unload phase of the inventory cycle. The return patterns are consistent with dealers lowering indicative quotes to manage slow-moving inventory in the load phase, and subsequent price reversals that compensate liquidity suppliers for absorbing customer flow (see Kraus and Stoll (1972), Grossman and Miller (1988)). For negative cycles, the patterns in dealer inventory and abnormal returns are opposite to those observed for positive cycles. Cai, Han, Li, and Li (2018) find that price impact of herding by insurance companies in U.S. corporate bonds is highly asymmetric – while sell herding causes transitory price distortions, the price impact of buy herding is long lasting and facilitates price discovery. Consistent with their evidence, Panel A illustrates that price distortions in positive cycles (i.e., sell herding) almost entirely reverse while some component of price distortion in negative cycles (i.e., buy herding) appear permanent.

In Table 2, we report an analysis of bond returns for the full sample of inventory cycle.[16] During the buildup (loading) phase of inventory cycle, returns are negative for positive cycles and positive for negative cycles. The returns have the opposite sign for the unload phase of inventory cycle. For the full inventory cycle, the cumulative returns are marginally negative for positive cycles and significantly positive for negative cycles. Bao, Pan and Wang (2012) also report that reversals exhibit significant asymmetry – price reversals are on average stronger after a price reduction than a price increase.

[16] 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 investigate the length of inventory cycles and the dollar value of peak inventory by year. Since the TRACE data begins in July 2002 and calculation of trading style requires 12 months of data, we report the statistics between 2003 and 2014. Inventory cycle lengths decline over the sample period, with cycle length close to 80 days before the financial crisis to less than 70 days in recent years. Further, peak inventories declines over the sample period from close to $27 million before the financial crisis to $24 million in recent years. Thus, inventory cycles are shorter and shallower in recent years.

The results complement the evidence from related academic studies in the corporate bond market that dealer capital has declined over the 2006-2016 sample period. These studies conclude that declining dealer capital can be attributed to post-crisis banking regulation, such as the Volcker Rule, since the decline is observed mainly for 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) and Choi and Huh (2016) document a significant shift in dealer behavior from a market making role towards an agency role where dealers match buyers and sellers. Schultz (2017) shows that proportion of interdealer trading has declined in recent years. Friewald and Nagler (2016) find that the relation between dealer inventory positions and risk-adjusted returns have strengthened in recent years, indicating higher return to liquidity provision when dealer capital is constrained.

Figure 3, Panel C illustrates the patterns in aggregate dealer inventory surrounding the first downgrade of a bond from investment to speculative grade by at least one of the three credit rating agencies. On average, bond downgrades are associated with an increase in aggregate dealer inventory that is consistent with customer selling imbalance. About 36 percent of downgraded bonds experience a positive inventory cycle after announcement. At the same time, the percentage of bonds in negative cycles drops after the downgrade. These trends persist for over a month and gradually return to the pre-downgrade levels.

B. The determinants of inventory cycles

The evidence thus far suggests that a sustained customer buying or selling imbalance leads to large dealer inventory positions and transitory impact on bond prices. This supports the interpretation of inventory cycle as an empirical proxy for an abnormal price pressure event in a bond. Large customer imbalances could be driven by correlated trades of institutional investors in response to new information or induced by investor flows, and possibly exhibit commonality across bonds. Duffie, Garleanu, and Pedersen's (2007) model of the over-the-counter search frictions predicts that it takes longer to recover from transitory price dislocations when investors simultaneously face liquidity shocks, and in particular, when dealer capital is constrained. Empirically, Bao, Pan and Wang (2011) show that changes in market-level bond illiquidity explain a substantial part of time series variations in corporate bond yield spreads.

We first examine how inventory cycles vary over time. Instead of considering individual bonds, we focus on commonality in cycles by aggregating price pressure incidences across bonds. In Table 3, Panel A, we examine whether aggregate inventory cycles co-move with aggregate market conditions, including the VIX as a measure of market stress; the Noise measure constructed by Hu, Pan and Wang (2013) and the crisis variable to capture supply of arbitrage capital; customer demand as captured by aggregate bond fund flows, and market sentiment as captured by aggregate corporate bond issuance. The dependent variable is the number of bonds in positive (or negative) cycle for at least 10 days in a month divided by the number of sample bonds in the month.

The results indicate substantial level of commonality in bond-level price pressure, and point to both supply- and demand-side drivers of financial stability risk. The coefficient for *Flow* in column (2) is positive indicating that bond funds *purchase* a cross-section of bonds simultaneously from dealers in response to investor *inflows* while the coefficient for *Flow* in column (1) is negative indicating that bond funds *sell* a cross-section of bonds simultaneously to dealers in response to investor *outflows*. Notably the correlated activity of institutions across bonds is material enough to generate commonality in inventory cycles. New bond issuance activity is positively correlated with fraction of positive cycles and negatively correlated with fraction of negative cycles. Positive cycles could arise due to the "flipping" activity of institutions who are allocated bonds in the primary market, or if institutions sell “off-the-run” bonds to buy into new issues. The negative coefficient of *new issuance* on negative cycles indicates that primary market acts as a substitute for purchasing bonds from the secondary market.

Aggregate inventory cycles do not have a close connection with *VIX* index and the *Noise* measure of arbitrage capital. The likely explanation is that the explanatory power of these variables is subsumed by *crisis* variable, which equals one for the period from July 2007 to April 2009 and equals zero otherwise. For both positive and negative cycles, the coefficient on *crisis* indicator variable is negative and statistically significant indicating that commonality in inventory cycles is strongly associated with capital constraints faced by bond dealers after controlling for fund flows. Overall, the analysis indicates that there is substantial commonality in time variation of inventory cycles and that time variation is correlated with overall market conditions.

In Table 3, Panel B, we examine the connection between probability of observing inventory cycle in a bond and various bond characteristics studied in the liquidity literature. The dependent variable equals one if the bond is experiencing inventory cycle for at least 10 days in the month, and equals zero otherwise. Reported are the Fama-MacBeth estimates for monthly cross-sectional regressions. Results indicate that inventory cycles are less likely for bonds with smaller issuance size and those with higher credit risk. Inventory cycles are also less likely for older bonds and those closer to maturity. Building on evidence from Edwards, Harris and Piwowar (2007), our findings suggest that inventory cycles are less likely in bonds with lower trading activity and higher trading costs, which likely reflects the dealer’s endogenous choice to build inventory in liquid bonds.[17] The positive and highly significant coefficient on lagged dependent variable suggests that aggregate dealer inventory is slow-moving with a half-life of several weeks. Consistent with Figure 3, Panel C, an inventory cycle is more likely when the bond experiences an upgrade and downgrade event that generates trading interest from customers.

Conditional on observing an inventory cycle, we model the impact of market conditions and bond

[17] Goldstein and Hotchkiss (2017) find that dealers have a substantially higher propensity to offset trades within the same day rather than committing capital for riskier and less actively traded bonds.

characteristics on various attributes of inventory cycles. We focus on positive cycles (Panel C) in our discussion and note that results are similar but slightly weaker for negative cycles (Panel D). In column (1) of Panel C, the dependent variable is the cycle's *cumulative* dealer inventory calculated as the sum of daily ending inventory (in $) across all days in the given cycle, while column (2) is a similar measure that considers only the load phase of the cycle. The *cumulative* dealer inventory is likely to be higher when a cycle is longer, and the size of peak inventory commitment is large. We examine these two dimensions separately by modeling the length of inventory cycle (in days) in column (3), and the peak inventory commitment in column (4).

Our analysis of the attributes of inventory cycles is related to emerging literature on core-periphery dealer networks that shows highly connected dealers at the center and sparsely connected dealers at the periphery (see Li and Schurhoff (2016), DiMaggio, Kermani and Song (2016), Hollified, Neklyudov and Spatt (2017)). The evidence suggests that intermediation chains are shorter when central dealer is involved, and longer when markets are stressed, or when trades are difficult to complete. In comparison to this literature, inventory cycles that we examine are observed when customer flow to the dealer community is material and sustained. In other words, the higher peak inventory reflects intensity and the longer cycle length reflect the persistence in customer imbalance, holding all else the same.

In Table 3, Panel C, the results suggest that the *cumulative* dealer inventory is lower for cycles in smaller bonds, older bonds, and those closer to maturity. Further, smaller bond issues and older bonds are associated with slow moving cycles; i.e., smaller peak inventory and longer inventory cycles. An upgrade or downgrade credit event is associated with higher cumulative dealer inventory and the impact is via higher peak inventory alone. Notably, credit rating events do not affect cycle length suggesting that dealer inventory is quickly reversed. The likely explanation is that investor clientele in the new ratings category serve as a natural counterparty to dealers. We find weak empirical evidence that higher market uncertainty as captured by higher VIX index leads to reduction in cumulative dealer inventory; moreover, it is not clear whether the impact is via peak inventory and cycle length.

The conditional results are broadly consistent with the earlier results on observing a cycle suggesting that inventory cycles are more intense when cycles are more likely. Combining the results in Table 3, inventory cycles are less likely during the crisis, but are more likely to be longer. The analysis also shows that dealers are less willing to commit capital when market uncertainty is high. Reflecting an asymmetry in dealer preferences, we find that dealers appear to be more willing to accept deeper negative inventory cycles (reflecting customer buying) during the crisis than positive (customer selling). We also find that both upgrade and downgrade events lead to deeper positive inventory cycles but have no significant association with negative cycles. Since upgrades and downgrades alter the clientele, the results indicate that selling pressure is higher in both scenarios.

IV. *Classifying bond 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 trades in the same direction as the dealer, i.e., 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 net selling activity from customers. The buying (selling) activity of the fund helps absorb (further strain) the dealers' inventory.

The market structure of corporate bonds offers a mechanism for dealers to "signal" their interest in unwinding positions by broadcasting indicative bids and offers on a list of bonds on their inventory (called "Runs") to potential institutional clients. In the early part of our sample period, dealers used to broadcast runs once a day. In recent years, runs are broadcast every hour using automated pricing models that use market data on similar bonds. Further, buy-side institutions subscribe to news feeds from data aggregators (such as Bloomberg) for recently completed transactions and quotations from electronic bond platforms, solicit quotations from multiple dealers simultaneously via electronic request-for-quote (RFQ) platforms, obtain "color" on market conditions by directly contacting dealers, and participate in all-to-all trading platforms that allow institutions to compete with dealers in response to an RFQ. New services (e.g., Bloomberg's RUNs) have emerged to help institutions parse information and identify the best price.

When a corporate bond experiences a positive inventory cycle, it is likely that dealers signal the larger than desired inventory position by lowering the indicative quotes in the runs. In our framework, a bond fund with a trading style that is liquidity supplying will alleviate the imbalance by absorbing the inventory positions of dealers. In the scenario depicted in Figure 2, Panel B, a liquidity supplying bond fund will purchase the bond, represented by the dashed arrow, coinciding with a positive inventory cycle. Institutions could contact dealers, via a messaging system or by phone, to obtain “color” on market conditions and negotiate the terms of a transaction.

Studies from equity markets classify a fund’s trading style by comparing the fund's transactions with the daily stock return (Anand et al. (2013), Cheng et al. (2017)), or daily trade imbalance from TAQ data (Da, Gai, and Jagannathan (2011)). Other studies classify trading style of equity funds based on exposure of funds' return to a contrarian long-short factor portfolio (see Nagel (2012)). The literature reports that trading style is persistent, influences the return and liquidity patterns of assets, and impacts trading costs and fund performance. Unlike equity markets, where any investor can participate in the provision of liquidity by submitting limit orders, trading in OTC structure of bond markets is highly decentralized, and inserts the bond dealer in virtually all transactions between buyers and sellers. Bond market participants have less information on order flow and quotations than equity market participants. The differences in market structure of equity and bond markets suggest that trading strategies that work in equity markets could be more difficult to implement in bond markets.

Our methodology is specifically designed for bond markets to take advantage of a market structure where liquidity suppliers (dealers) are clearly identified. Unlike the TAQ data that do not identify market makers, the TRACE data capture the entire history of dealers' trades with customers, implying that inventory positions of key intermediaries in corporate bonds can be measured with accuracy. Figure 4 illustrates the advantage of classifying trading style using dealer inventory cycle (IC) versus the change in dealer inventory (ΔI, or trade imbalance from TRACE) or bond returns (R_b). The figure depicts a fund with an increase in bond holdings (ΔH) over a reporting period that coincides with positive inventory cycle (IC), implying the fund helps absorb the dealers' inventory. Note that the load and the unload phase of inventory cycle encompass periods of opposite bond returns, or opposite sign changes in dealer inventory (ΔI), implying that the correlation between change in holdings and change in inventory (ΔH, ΔI), or the correlation between change in holdings and bond returns (ΔH, R_b) could be either positive or negative over a fund-reporting period. In our methodology, since we classify inventory cycle and then overlay change in bond holding, the correlation between change in holdings and inventory cycle (ΔH,IC) is always positive, and the position change is classified as liquidity supply, regardless of whether the fund's reporting period overlaps with the load or unload phase of the inventory cycle.[18]

After classifying the change in each bond holding for a fund-reporting period as liquidity supply, demand, or unclassified, we calculate the *LS_score* for the fund-reporting period, as follows: [19]

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

In equation (1), change in bond holdings over consecutive fund-reporting periods that do not coincide with inventory cycle are marked as unclassified. Further, 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 must overlap for at least 15 days for the holdings change to be classified.[20] Finally, we eliminate the change in bond holdings that overlap with primary market issuance, thereby focusing on secondary market transactions of the bond fund. To the extent that underwriters are reluctant to hold large positions in a newly issued bond, participation by a fund in the primary market can be viewed as liquidity supplying; however, this is not the focus of our study.

[18] It is of interest to examine whether participation in the load versus unload phase leads to similar outcomes. The monthly frequency of reporting period limits our ability to investigate this but presents an opportunity for future research.

[19] 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. We verify that a measure based on number of liquidity supplying and demanding holdings changes (equally weighting each holdings change) yields similar results.

[20] 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 4, about 46% of the holding changes over the sample period are not classified.

We recognize that data limitations introduce noise in the classification of a fund's trading style. As shown in Table 1, the position changes in TRACE corporate bonds account for 35% of total position changes in a fund-reporting period, and further, about 46% of these corporate bond position changes are not classified (see Table 4). Our assumption is that trading styles that we estimate based on a subset of funds' trades in corporate bonds are indicative of their overall trading style. As robustness, we replicate our analysis for funds that hold 50% of their portfolio in corporate bonds during our sample. The average corporate bond holdings for this sample are 78%. The sample yield similar results. Additionally, while the majority (72%) of funds report at the monthly level, the analysis is unable to capture the trades of funds within the reporting window. For equity markets, Puckett and Yan (2011) show that the interim trades of institutions contain useful information about trading skill.

Inventory cycles are also affected by changes in bond market structure over the sample period. Technological advancements, such as electronic dealer runs and bond trading platforms, reduce the search frictions in decentralized markets (see Hendershott and Madhavan (2015)) while banking regulation such as Volcker Rule cause dealers to commit less capital. In a related study, Choi and Huh (2016) show that dealers are increasingly relying in recent years on "prearranged" trades, where a bond is quickly passed on from one customer to another customer rather than remaining in dealer inventory, and that pre-arranged trades are associated with smaller bid-ask spreads than principal commitment trades. The focus of their analysis is to document an increase in liquidity provision by customers in recent years. Since TRACE data do not provide the identity of customer, Choi and Huh (2016) do not study the trading style of individual funds, and the heterogeneity in liquidity provision by mutual funds, which is the focus of our study. Further, while there is an uptick in pre-arranged trades in recent years, it represents a small slice of the overall activity. For example, Bessembinder et al. (2017) report that principal commitment by dealers still account for more than 90% of corporate bond transactions in 2014-2016 period. We recognize that as these trends intensify in the future, changes in market structure have the potential to lower the information content of trading style and weaken its association with fund performance, which is based on returns of all the fund's bond holdings.

Table 4, Panel A reports descriptive statistics for our trading style measure, *LS_score*, over the sample period. An *LS_score* of zero points to a trading style that is relatively balanced such that the fund's trading activities neither absorb nor strain the aggregate dealer inventory. A fund with a high *LS_score* exhibits a higher propensity to absorb dealer inventory in comparison to a fund with a low *LS_score*. For the 35,093 fund-period observations, the mean and the median value of *LS_score* is -0.055. Aggregating at the fund level, the mean *LS_score* estimated over 937 bond funds is -0.048 and the median score is -0.054.

In summary, on average, mutual funds exhibit a trading style that demands liquidity from bond dealers. That is, the typical mutual fund sells (buys) a bond when other market participants also sell (buy) the bond. The bond market literature has identified many explanations for mutual funds to trade in the same directions, including herding behavior of institutions (Cai, Han, Li, and Li (2016)), index rebalancing (Dick-Neilsen and Rossi (2016)), credit rating events (Ellul, Jotikasthira and Lundblad (2011)), among others.

Results in Panel A indicate that the average *LS_score* exhibits variation over time. In comparison with full sample mean of -0.055, trading style decreases three-fold during the financial crisis, from -0.027 in 2007 to -0.081 in 2008, before reversing to -0.044 in 2010. Goldstein et al. (2017) show that corporate bond fund outflows are sensitive to bad performance, and this sensitivity is higher when bond market is stressed. We estimate a significant decline in *LS_score* for bond funds in 2008 indicating that bond funds exhibit a trading style that demands liquidity from dealers in 2008. Other studies find that the risk bearing capacity of dealers is already strained during the 2007-2009 financial crisis, as evidenced by a significant decline in dealer inventory (see Bessembinder et al. (2017)). Future work need to investigate these patterns in light of regulatory concerns on bond funds' ability to meet investor redemptions (see Chernenko and Sunderam (2016)), and the impact of mutual fund trading on liquidity of the underlying bonds.

We observe significant cross-sectional variation in trading style, with the 25th percentile of -0.168 and the 75th percentile of 0.057. Thus, a significant percentage of bond funds exhibit a trading style that absorbs dealer inventory. Based on the average *LS_score* every year, we assign bond funds into quintiles and report descriptive statistics on fund attributes in Panel B. In comparison to low (Q1) quintile, bond funds in high (Q5) quintile are smaller in terms of TNA, hold bonds with shorter duration, and experience higher investor flows. Other fund attributes such as cash allocations, credit rating and turnover are similar across quintiles.

V. Trading style and fund performance

To understand the information content of trading style, we examine whether trading style is associated with future fund performance. We expect that funds with trading style that is liquidity supplying earn higher returns, partly from an immediate price concession for alleviating dealer positions and partly from future price reversals due to price pressure. We estimate fund performance by the fund's alpha relative to a four-factor benchmark model, following Chen and Qin (2017), as follows:

$$R_{i,t} - R_{ft} = \propto + \beta_{STK} STK_t + \beta_{BOND} BOND_t + \beta_{DEF} DEF_t + \beta_{OPTION} OPTION_t + \varepsilon_t \qquad (2)$$

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-17, t*]. The beta estimates are then used to calculate the expected return in month *t+1*. The difference between the actual fund return and the expected return yields the estimated alpha for month *t+1*.

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

$$\propto_{i,t+1} = \beta_1 LS\_score_{i,(t-11,t)} + \beta_2 LS\_score_{i,(t-11,t)} * MktLiq_{t+1} + \sum_{k=1}^{n} \beta_k X_{i,t} + \sum T_{t+1} + \sum FC_i + \varepsilon_{i,t+1} \qquad (3)$$

where $\propto_{i,t+1}$ is the funds' alpha as described above, $LS\_score_{i,(t-11,t)}$, the explanatory variable of interest, refers to funds' trading style measured over months [*t-11, t*] and $LS\_score_{i,(t-11,t)} * MktLiq_{t+1}$ represents interaction between trading style and market liquidity. Market liquidity is measures by VIX Index, the *crisis* indicator variable, and the *Noise* measure, as defined earlier. The observable fund attributes $X_{i,t}$ include log of TNA, log of fund age, log of number of bond holdings, institutional share fraction calculated as the fraction of TNA that is owned by institutional share classes, broker affiliated indicator variable that equals one if the fund family is associated with a broker-dealer and equals zero otherwise, rear load fees, proportion of assets held as holdings in cash and cash equivalents, 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, and the fund's net flows in the prior three months. These variables are designed to capture fund attributes in terms of its age and size, as well as characteristics of portfolios held by of the fund, and funding stability and liquidity. In addition, we include month fixed effects denoted by $\sum T_t$ and fund-category fixed effects denoted by $\sum FC_i$. Standard errors are double-clustered by fund family and month.

Results in Table 5 provide strong evidence that trading style is associated with future fund alphas. 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 regression coefficient on *LS_score* that is significant at the 5% level. The result suggests that liquidity supplying trading style has a positive impact on future fund performance after accounting for factor risk exposures of the fund.

In model 2, we introduce a non-linear specification with two indicator variables representing Q1 (liquidity demand) and Q5 (liquidity supply) quintiles based on trading style in the prior twelve months. The regression coefficient on low Q1 quintile is negative (-0.021) and highly significant implying that bond funds with a propensity to strain dealer inventory are associated with lower future monthly fund alphas of 2.1 basis points. The regression coefficient on high Q5 quintile is positive (0.030) and highly significant implying that bond funds with a propensity to absorb dealer inventory are associated with higher future monthly fund alphas of 3.0 basis points.

Model 3 to 5 report the interactions of trading style with market illiquidity on future fund performance. 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* variable in Model 3 is positive, indicating that benefits from liquidity supply are larger in the crisis period. We introduce interaction of *LS_score* with

Noise variable in Model 4 and *VIX* index in Model 5. In these models, the impact of *crisis* variable is subsumed while the market illiquidity coefficients are significant. We conclude that funds with a liquidity supplying trading style earn higher compensation when markets are stressed. This evidence is consistent with several studies showing that illiquidity factor is an important determinant of asset returns (Bao, Pan, and Wang (2011), Nagel (2012), Friewald, Jankowitsch, and Subrahmanyam (2012), among others).

Model 2 presents a straightforward estimate of the economic significance of trading style on future fund performance. The difference in coefficients between low (Q1) and high fund (Q5) quintiles exceed 5.1 basis points per month (p-value of difference = 0.02), or approximately 60 basis points per year, in terms of future fund alpha. The economic significance of market conditions on performance of trading style strategy is presented using Model 4. When *Noise* variable is at the mean of our sample period, bond funds with one standard deviation higher *LS_score* generate an additional 1.24 basis points of future monthly alpha. To put this number in perspective, the average monthly alpha of a fund in the sample is 3.40 basis points. When *Noise* variable is one standard deviation above its sample mean, bond funds with one standard deviation higher *LS_score* generate an additional future monthly alpha of 3.87 basis points. Overall, we conclude that trading style has an economically material impact on fund performance. Our 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 the benchmark (see Cici and Gibson (2012)).

In Figure 5, 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 Model 2, the quintiles are formed in months *t-11* to *t*, and the difference in alphas are calculated in month *t+1*. The average monthly Q5-Q1 difference in alphas before the financial crisis is 2.2 basis points and in a recent 2012-2014 period is 3.2 basis points. Consistent with Table 5, the Q5-Q1 difference in alphas is highest during the crisis, averaging 28.4 basis points per month.[21] Acharya and Pedersen (2005) show that security characteristics could serve as an illiquidity hedge

[21] The average Q5-Q1 difference in fund alphas subsequent to the crisis (2010-2011) is -1.3 basis points, which is a puzzling finding. The negative performance of a liquidity supply strategy points to adverse selection risk borne by liquidity supplying strategies which can suffer losses when returns experience a continuation rather than reversal.

in a fund's portfolio. Our results suggest a fund's trading style that is liquidity supplying might help partially offset the decline in fund performance when markets are stressed.

Model 6 confirms that the results on the relation between trading style and future fund performance are robust to the inclusion of a number of fund attributes and portfolio characteristics. The coefficient estimates of low (Q1) and high fund (Q5) quintiles in Model 2 and Model 6 are similar in magnitude. We separate the bond funds into investment grade and non-investment grade samples based on the average credit rating of bonds in their portfolio over the sample period. In Model 7 and 8, the coefficient estimates of low (Q1) fund quintiles is negative and statistically significant for both samples, suggesting that a trading style that further strains the dealers' inventory positions is associated with lower fund performance. The coefficient estimates of high (Q5) fund quintiles is positive in both models but only significant in Model 8. Thus, the impact of trading style that absorbs the dealers' inventory positions has a stronger effect on fund performance for non-investment grade bonds, which are typically less liquid than investment grade bonds.

In Model 9, we examine a sample of bond funds with an allocation to corporate bonds over our sample period that exceed 50 percent. On average, these funds hold 78% of their portfolios in corporate bonds. For these bond funds, trading style can be estimated more precisely due to higher overlap between the fund's position changes and the inventory cycles that comprise of TRACE corporate bonds. The Q5-Q1 monthly difference in alphas in Model 9 is 6.5 basis points, which is marginal larger than those estimated in Model 2 at 5.1 basis points; however, the sample size of Model 9 is less than half of the sample size of Model 2, which highlights the tradeoff between precision and power.

VI. What explains trading style?

The evidence thus far indicates that a liquidity supplying trading style is associated with better fund performance. We observe significant cross-sectional variation in trading styles across funds. What explains trading style, and given the impact on fund performance, why do other funds not mimic the style? In this section, we consider several explanations. A mutual fund's ability to respond opportunistically to dealer inventory shocks may depend on flexibility afforded by investment strategy on asset side and the behavior of fund investors on liability side. To the extent that the fund holds cash or liquid bonds, or a variety of bonds in the portfolio, it might have greater ability to purchase bonds during a positive cycle, or sell bonds during a negative cycle. Similarly, flexibility to be liquidity supplying may come from positive investor fund flows, or from flows that are less sensitive to the fund's past performance.

Another potential explanation is market structure – corporate bonds trade in a fragmented market with limited amount of pre-trade transparency that presents trading advantages to well-connected market players. Research on the impact of dealer networks on execution quality in OTC markets is building. 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. Thus, fund attributes, such as the presence of an affiliated broker-dealer inside the fund family, may confer informational advantages that are difficult to replicate by other funds. A related explanation is that trading desks at some funds have the expertise in locating counterparties and implement a trading strategy that is liquidity supplying. Evidence from equity markets suggests that there is significant variation in trading skill across buy-side institutions (see Anand, Irvine, Puckett and Venkataraman (2012)).

Table 6 reports estimates from panel predictive regressions of the fund's *LS_score*, averaged over next twelve months, on fund attributes and other general characteristics as defined in Section III, as of the end of month *t*, as follows:

$$LS\_score_{i,(t+1,t+12)} = \sum_{k=1}^{n} \beta_k X_{i,t} + \sum T_t + \sum F_i + \varepsilon_{i,t} \tag{4}$$

All models include time fixed effects, and in addition, Model 5 includes fund family fixed effects while Model 6 includes fund fixed effects. In Model 1, we study the impact of the behavior of fund investors on trading style. Lagged fund flows have a positive and statistically significant impact on *LS_score* implying that fund inflows improve the propensity to supply liquidity while investor redemptions hurt the ability to supply liquidity. These findings are relevant in light of evidence in Goldstein et al. (2017) that investor redemptions are particularly sensitive to poor fund performance. In further support of the role of investor behavior, we find that funds with high flow-performance sensitivity are less likely to implement a liquidity supplying trading style. Fund design features such as the extent of rear load fee and the fraction of TNA owned by institutional share class could influence investor behavior; however, our results indicate that they convey no incremental information for trading style. Our results suggest that funds with a stable investor pool supply liquidity, as they are not forced into costly trading in response to investor flows.

In Model 2, the results suggest that the composition of the funds' portfolio holdings is related to future trading style. Funds that hold older bonds and those with smaller issue size have a higher propensity to exhibit a trading style that is liquidity supplying. The bond attributes are associated with lower liquidity (see Edwards, Harris and Piwowar (2007)), implying that bond funds participate in segments where dealer interest is lacking. A liquidity supplying trading style is not associated with the number of bond holdings or the percentage of portfolio held as cash, but shows an association with bonds with lower duration and lower credit risk. These results indicate that liquidity supplying funds carry lower level of interest rate and credit risk, but higher levels of liquidity risk. In Model 3, we find a positive and statistically significant coefficient on broker affiliation indicator variable, which points to informational advantage of being affiliated with a broker-dealer firm. Perhaps surprisingly, funds with liquidity supplying trading style tend to be younger funds and smaller funds in terms of TNA. With the exception of fund age, which loses statistical significance, the results are similar when we combine the variables in Model 4, with a corresponding increase in explanatory power to 6%.

We observe a significant increase in the explanatory power with fund-family fixed effects in Model 6 (15.3%) relative to Model 5 (6%). In the majority of bond fund families, fund managers are responsible for security selection, but the execution of the order is handled by a trading desk that aggregates order flows from fund managers within the family. The higher model R^2 with fund family fixed effects is consistent with variation in expertise in implementing the trading strategy across fund families. In model 6 with fund fixed effects, we observe a further increase in the explanatory power (26%) of the model, which provides further evidence that trading style is a fund-specific attribute that is not fully captured by observable fund characteristics. For example, trading style could reflect fund manager's sensitivity to demand-supply conditions, or the relationship between the fund manager and the trading desks.

Results are broadly similar when we estimate the model separately for investment grade and non-investment grade bond funds. Notable differences are that percentage of assets held as cash impacts trading style for non-investment grade bonds while broker affiliation and fund size do not impact trading style for investment-grade bonds. In Model 9, the results are broadly similar to Model 4 for bond funds with average corporate bond allocation that exceed 50 percent.

VII. Persistence in trading style

Results in Table 6 indicate that trading style is a fund attribute. If so, then is it persistent over time? In Table 7, 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*]. From Panel A, in the ranking period, the difference in trading style between the Q1 (liquidity demand) and Q5 (liquidity supply) quintiles is 0.255. This difference narrows in future periods, which reflects in part that some funds do not maintain a trading style, possibly due to funding and market circumstances, and also that trading style is measured with noise.

Nonetheless, Panel A clearly shows that the funds' past trading style contains information about trading style over next 12 to 24 months. In each of the non-overlapping and long-horizon periods, *LS_score* increases monotonically from Q1 to Q5. Further, *LS_score* in future months [*t+1, t+12*] for Q1 (-0.071) is significantly lower (at the 1% level) than Q5 (-0.034). It is also notable that point estimates of trading style for each quintile in future months [*t+1, t+12*] and [*t+13, t+24*] are almost identical.

To further investigate the persistence, we report a transition matrix in Panel A for funds assigned into quintiles based on average trading style in months [*t-11, t*] in future months [*t+1, t+12*] and [*t+13, t+24*]. If past trading style contains no information for future trading style, then funds randomly sort on trading style in future periods. Under this null, funds have an equal (20%) probability of being assigned to a quintile in future periods. Results in Panel A strongly reject the null hypothesis. Funds in the high liquidity supplying (Q5) quintile have a 29.77% probability in the next 12 months and 28.65% probability between months 13 and 24 of staying in the same quintile. Similarly, funds in the low liquidity supplying (Q1) quintile have a 32.50% probability in the next 12 months and 28.84% probability between months 13 and 24 of staying in the same quintile. The Pearson's chi-square test strongly rejects the null hypothesis that past trading style contains no information for future trading style.

We present further tests of persistence using a regression framework that builds on specifications in Table 6. Panel B reports OLS estimates for panel predictive regressions of funds' average *LS_score* on funds' past average *LS_score* and its interaction with market conditions. Average *LS_score* is calculated over the period from months t+1 to t+12 while past average *LS_score* is calculated over the period from months t-11 to t. All models include all explanatory variables and the time fixed effects identified in Model 4 of Table 6. For the full sample of bond funds (Model 1), and sub-samples based on investment grade funds (Model 7), non-investment grade funds (Model 8), and funds with high corporate bond allocation (Model 9), the coefficient on lagged *LS_score* is positive and highly significant, implying that the fund's past trading style contains relevant information about future trading style over the next 12 months. In Models 2, 3 and 4, the coefficient on interaction between lagged *LS_score* and market stress is negative indicating it is challenging for bond funds to maintain trading style in periods of market stress. In Model 5, we interact *LS_score* with aggregate investor flow to bond funds, a measure of market conditions. Results suggest that aggregate fund flows do not impact persistence in trading style; however, when we interact lagged *LS_score* with investors specific to the fund, the coefficient on interaction term is positive and statistically significant at the 10% level. The result indicates that fund inflows improve the ability of funds while fund outflows makes it more challenging to maintain trading style in future periods.

VIII. Conclusions

Regulators and market participants are worried that the growth in corporate bond markets and the reduction in dealer capital point to a liquidity problem. According to 2017 Greenwich Associates survey, many bond investors describe buy-side institutions as an important channel of liquidity supply in corporate bonds. 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.

Studies from equity markets classify a fund’s trading style by comparing the fund's transactions with the daily stock return (Anand et al. (2013), Cheng et al. (2017)), or daily trade imbalance from TAQ data (Da, Gai, and Jagannathan (2011)). These studies find that trading style is persistent, influences the return and liquidity patterns of assets, and impacts trading costs and fund performance. Unlike equity markets, where any investor can participate in the provision of liquidity by submitting limit orders, trading in OTC structure of bond markets is highly decentralized, and inserts the bond dealer in virtually all transactions between buyers and sellers. Bond market participants have less information on order flow and quotations than equity market participants. The differences in market structure of equity and bond markets suggest that strategies that work in equity markets could be more difficult to implement in bond markets.

Using bond transactions (TRACE) data between 2002 and 2014, we aggregate the inventory positions of bond dealers, and identify inventory cycles. There is commonality in inventory cycles across bonds that co-moves with aggregate market conditions. We classify a bond funds' trading style as liquidity supplying (demanding) if changes in bond holdings exhibit a propensity to absorb (strain) dealer inventory. We find that 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. Fund attributes, such as an affiliated broker-dealer in the fund family, the skill of the trading desk, and a stable investor base, allow bonds funds to opportunistically responds to dealer shocks. A trading style that is liquidity supplying is associated with higher fund performance after controlling for portfolio attributes and factor risk exposures. The impact is economically large and accentuated when markets are stressed.

This study present new evidence on a channel of liquidity supply in bonds market. In 2014, then SEC chair Mary Jo White noted that bond trading platforms are being used primarily to "provide information on the bonds their participating dealer would like to sell."[22] Survey evidence indicates that the majority of bond participants expect request-for-quote (RFQ) platforms based on traditional bond dealers to dominate.[23] Nonetheless, 45 percent of the larger investors expect all-in-all networks that allow access to buy-side institutions to play a significant role in the future.

The results of this study indicate that buy-side firms respond to aggregate liquidity shocks in a manner that absorb inventory position of dealers. We document this liquidity supplying behavior of buy-side firms in spite of the current bond market structure that impediments such activity. Given the regulatory concerns regarding liquidity problem in corporate bonds, an implication of our study is that RFQ platforms can significantly expand the liquidity pool of counterparties, and facilitate risk sharing for bond dealers, by allowing buy-side institutions to receive RFQs and directly compete with traditional bond dealers.

Trading style has useful information for investors in predicting fund performance. Our study shows that it is important to understand when institutions choose to implement trades, in addition to 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.

[22] https://www.sec.gov/news/speech/2014-spch062014mjw
[23] McKinsey&Company and Greenwich Associates report, "*Corporate bond E-Trading: same game, new playing field*", August 2013.

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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. Since inventory cycles reflect the opposite side of customer trading, a positive dealer inventory cycle occurs when there is sustained selling from customers.

Simply accumulating inventory over time is prone to several issues: potential reporting errors that may compound infinitely;[24] our inability to separate proprietary positions from market making; and the lack of any information on any inventory position dealers may hold for their market making operations. To avoid these concerns affecting our measure, we drop daily customer imbalances that occur more than three calendar months (63 trading days) ago from the cumulative inventory calculation. We select the rolling window of 63 trading days to allow for the slow build-up and unwinding of inventory in an illiquid market. The period is broadly consistent with the half-life of four to five weeks documented in Duffie (2013) and Schultz (2017) for an active, individual dealer. A consequence of this approach to accumulate inventory over a defined period of three months is that simply the dropping out of the 63-day old imbalance can cause a new inventory cycle to begin in the opposite direction.[25] We adjust our measure to avoid this possibility. A detailed description of our approach to handle four possible scenarios that can arise are given below.

In the first 63 trading days, we accumulate the dealer imbalances from the beginning of the cycle. For cycles that end during this three month period, the dealer inventory is simply this accumulation of daily imbalances absorbed by the dealer community. As the cycle becomes longer than 63 trading days, i.e., the inventory does not revert to zero during the three month period, we begin dropping the imbalances during the cycle that are outside the 63-trading day rolling window. As discussed above, the dropping of three month old imbalances can cause a new cycle to start in the opposite direction. We make an adjustment to

[24] An example of reporting "error" is a broker dealer who transfers all risk positions to trading desk of an European subsidiary who is not a FINRA member. These offset affiliated-trades are reported as customer trades on TRACE.
[25] As robustness, we construct a simple 63-day cumulative inventory measure (discussed later) and find similar results.

the starting inventory to avoid these mechanical effects. The adjustments are best explained in the context of a few different scenarios.

First, it's possible that an inventory cycle ends 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. Second, a cycle ends on a day with reported transactions in the bond but we also drop older transactions on that day. In this case, if the old transactions being dropped are sufficient to bring the rolling three-month inventory to zero, the starting inventory of the new cycle is based on the reported transactions on that day. 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 new trades that is in excess of zero after offsetting the previous day inventory.

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

In the example below, 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 count of the days that the bond is in an inventory cycle, the third column presents the (signed) daily aggregate dealer imbalance. The dealer imbalance is the opposite of the customer imbalance and represents the incremental inventory taken on by dealers on that day. Column 4 presents the cumulative dealer imbalance from the start of the cycle. The fifth 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 sixth column presents the inventory. Column 7 indicates whether the inventory cycle clears our minimum threshold for inclusion and if it does whether it is a positive or a negative cycle, and the last column indicates the cycle length.

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

The inventory is either the cumulative imbalance or the rolling sum. We highlight the inventory in bold and italics. The column where the inventory is drawn from (either the cumulative imbalance in column 4 or the rolling sum in column 5) is highlighted in bold, while the other series is de-emphasized in a lighter font. In example 1, since all the cycles are shorter than 63 trading days, the inventory is always the cumulative imbalance.

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 we require a minimum cycle length of five day, this cycle does not clear our threshold and is excluded from our analysis.

There is no further trading until day 19 when a new positive cycle begins with the dealers buying bonds worth $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 day 64 when two large daily negative imbalances on days 64 and 65 close the positive cycle. We start a new negative cycle on day 65 at -$8 million. The new negative cycle then lasts until day 82 when 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	Day of Cycle	Daily imbalance	Cumulative Imbalance	63-Day Rolling	***Inventory***	Cycle	Cycle Length
1	1	$12	**$12**	$12	***$12***	Positive	81
2	2	$12	**$24**	$24	***$24***	Positive	81
3	3	$0	**$24**	$24	***$24***	Positive	81
4	4	$0	**$24**	$24	***$24***	Positive	81
5	5	$0	**$24**	$24	***$24***	Positive	81
…	6 to 18	$0	**$24**	$24	***$24***	Positive	81
19	19	$12	**$36**	$36	***$36***	Positive	81
20	20	$12	**$48**	$48	***$48***	Positive	81
…	21 to 62	$0	**$48**	$48	***$48***	Positive	81
63	63	$0	**$48**	$48	***$48***	Positive	81
64	64	$0	$48	**$36**	***$36***	Positive	81
65	65	$0	$48	**$24**	***$24***	Positive	81
66	66	-$20	$28	**$4**	***$4***	Positive	81
67	67	$0	$28	**$4**	***$4***	Positive	81
…	68 to 81	$0	$28	**$4**	***$4***	Positive	81
82	-	$0	**$0**	-$8	***$0***	None	-
83	-	$0	**$0**	-$20	***$0***	None	-

Example 2 illustrates the case of one long inventory cycle that eventually ends as older trades are dropped from the inventory. As discussed earlier, 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, ignoring all trades that are part of the ended inventory cycle. Since the cycle has ended, the dealer inventory equals the cumulative imbalance of zero. In contrast, the rolling sum on day 82 is -$8 million, which reflects that the $12 million trade on day 19 is dropped, more than offsetting the $4 million inventory held on day 81. 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

Example 3 is a minor variation of Example 2. The key difference is that Example 3 reports a trade of $12 million on day 82, whereas Example 2 reports no trades on day 82. As noted above, dropping the earlier imbalance on day 19 is sufficient to end the cycle on its own. Therefore, we keep the entire new trade on day 82 as the beginning inventory of the new cycle. In the illustration below, 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	Day of Cycle	Daily imbalance	Cumulative Imbalance	63-Day Rolling	***Inventory***	Cycle	Cycle Length
1	1	$12	**$12**	$12	***$12***	Positive	81
2	2	$12	**$24**	$24	***$24***	Positive	81
3	3	$0	**$24**	$24	***$24***	Positive	81
4	4	$0	**$24**	$24	***$24***	Positive	81
5	5	$0	**$24**	$24	***$24***	Positive	81
…	6 to 18	$0	**$24**	$24	***$24***	Positive	81
19	19	$12	**$36**	$36	***$36***	Positive	81
20	20	$12	**$48**	$48	***$48***	Positive	81
…	21 to 62	$0	**$48**	$48	***$48***	Positive	81
63	63	$0	**$48**	$48	***$48***	Positive	81
64	64	$0	$48	**$36**	***$36***	Positive	81
65	65	$0	$48	**$24**	***$24***	Positive	81
66	66	-$20	$28	**$4**	***$4***	Positive	81
67	67	$0	$28	**$4**	***$4***	Positive	81
…	68 to 81	$0	$28	**$4**	***$4***	Positive	81
82	1	-$12	**-$12**	-$20	***-$12***	Negative	> 2
83	2	$0	**-$12**	-$32	***-$12***	Negative	> 2

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

Example 4 is a minor variation of example 3. The key difference is that example 4 reports a trade of $8 million on day 66, whereas example 3 reports a trade of $20 million on day 66. Up to day 65, the cycle looks exactly the same as in Example 3. On day 66, the sale of $8 million in example 4 is smaller than $20 million in example 3, and therefore only decreasing the inventory to $16 million. On day 82, due to the $12 million imbalance on day 19 being dropped, the inventory further decreases from $16 million to $4 million. In contrast to example 3, the dropping out of the day 19 trade does not end the inventory cycle. Here, the inventory cycle ends only because the -$12 million daily imbalance on day 82 further pushes the inventory to -$8 million (+$4 million - $12 million). The positive cycle ends on day 81. A new negative cycle starts on day 82 with the residual of the new imbalance, -$8 million, as the starting inventory. We again ignore 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	Day of Cycle	Daily imbalance	Cumulative Imbalance	63-Day Rolling	***Inventory***	Cycle	Cycle Length
1	1	$12	**$12**	$12	***$12***	Positive	81
2	2	$12	**$24**	$24	***$24***	Positive	81
3	3	$0	**$24**	$24	***$24***	Positive	81
4	4	$0	**$24**	$24	***$24***	Positive	81
5	5	$0	**$24**	$24	***$24***	Positive	81
…	6 to 18	$0	**$24**	$24	***$24***	Positive	81
19	19	$12	**$36**	$36	***$36***	Positive	81
20	20	$12	**$48**	$48	***$48***	Positive	81
…	21 to 62	$0	**$48**	$48	***$48***	Positive	81
63	63	$0	**$48**	$48	***$48***	Positive	81
64	64	$0	$48	**$36**	***$36***	Positive	81
65	65	$0	$48	**$24**	***$24***	Positive	81
66	66	-$8	$40	**$16**	***$16***	Positive	81
67	67	$0	$40	**$16**	***$16***	Positive	81
…	68 to 81	$0	$40	**$16**	***$16***	Positive	81
82	1	-$12	**-$8**	-$8	***-$8***	Negative	> 2
83	2	$0	**-$8**	-$20	***-$8***	Negative	> 2

Robustness: Rolling Sum as Alternative Inventory Measure

We construct inventory cycles using a simple rolling sum of imbalances over 63 trading days as a robustness measure. We obtain the results similar to those reported in the paper. The rolling sum is easier 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. As an illustration, in example 2, the 63-day rolling sum would yield the start of a new negative cycle on day 82. Our main specification avoids the problem of these mechanical 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.

Table 1
Summary Statistics for Taxable Bond Funds

This table presents summary statistics for fund 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 flow and return, and fund-month (family-month) or coarser, depending on each fund's reporting frequencies, for other variables at the fund (family) level. 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 total net assets (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. TRACE positions are positions in TRACE sample bonds. 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. Institutional share fraction is the fraction of TNA that is owned by institutional share classes. Rear load is the value-weighted average across all share classes of the maximum charge, in percentage points, for redeeming the mutual fund shares. Family definition is as reported by Morningstar, and the total net assets and number of funds reported here only include taxable bond funds. Total (TRACE) position change is the par value of changes in all (TRACE) bond positions. Turnover is the annualized ratio of total position change and prior-reporting date TNA. The statistics are reported by length of time in months between two reporting dates.

Panel A: Fund Characteristics

	N	Mean	Std. Dev.	Pct. 25	Median	Pct. 75
Total net assets (TNA, $ Million)	45,239	1,590	5,764	121	390	1,175
Number of positions	45,239	431	710	149	270	470
Asset allocation (%)						
Cash	45,239	8.894	11.275	3.302	6.581	12.272
Corporate bonds	45,239	50.105	29.849	25.410	42.378	80.597
Government bonds	45,239	15.534	18.160	1.085	11.879	24.525
Others	45,239	25.467	26.732	5.403	24.268	41.956
TRACE positions/TNA (%)	45,239	38.434	30.128	15.559	28.150	63.393
Average duration	45,239	3.922	1.672	3.162	4.200	4.800
Average credit rating	45,239	10.184	4.077	7.000	10.000	14.000
Institutional share fraction (%)	45,239	32.760	40.092	0.000	5.736	73.999
Rear load (%)	45,239	0.388	0.836	0.000	0.000	0.264
Index fund dummy	45,239	0.031	0.174	0.000	0.000	0.000
Monthly return (%)	72,489	0.425	1.198	-0.154	0.445	1.087
Monthly flow (%)	72,489	1.971	16.560	-4.467	0.205	6.233
Family total net assets ($ Million)	11,964	8,327	27,626	254	1,262	7,564
Number of funds in family	11,964	6	7	2	4	8

Table 1 -*continued*

Panel B: Fund Trading

	N	Mean	Std. Dev.	Pct. 25	Median	Pct. 75
Total pos. change ($ Million)	45,239	365	910	15	59	217
TRACE pos. change ($ Million)	45,239	54	102	3	13	51
TRACE/Total pos. change (%)	45,239	35.452	32.653	7.960	22.838	63.418
Turnover by reporting period (annualized)						
1 month	32,510	2.230	2.266	0.801	1.507	2.738
2 months	1,230	2.523	3.192	0.945	1.550	2.645
3 months	11,499	1.880	1.657	0.855	1.395	2.263
All reporting periods	45,239	2.149	2.166	0.821	1.475	2.599

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. Only cycles with peak inventory of $10 million or greater and with cycle length of 5 days or longer are included. 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 = 87,063)			Negative Inventory Cycle (N = 69,171)			Diff.
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean
Cycle length (Days)							
Loading	34.453	35.765	21.000	36.240	33.691	26.000	-1.787**
Unloading	36.646	31.015	28.000	37.753	32.455	28.000	-1.107
Full	71.944	55.670	68.000	74.805	56.508	71.000	-2.861**
Cycle length by year (Full cycle - Days)							
2003	80.042	59.654	77.000	87.282	60.858	91.000	-7.240***
2004	74.527	58.280	66.000	80.163	59.416	80.000	-5.635***
2005	79.137	59.961	76.000	80.986	58.550	84.000	-1.849*
2006	78.038	59.395	71.000	80.229	58.569	79.000	-2.191**
2007	81.010	60.563	79.000	82.282	59.687	84.000	-1.272
2008	77.158	60.704	72.000	87.593	63.921	90.000	-10.436***
2009	66.680	56.378	51.000	75.310	58.535	68.000	-8.630***
2010	73.079	55.243	68.000	73.854	56.135	69.000	-0.775
2011	73.468	57.086	69.000	75.662	57.381	70.000	-2.194**
2012	65.935	50.313	63.000	66.036	51.698	57.000	-0.100
2013	63.686	48.324	62.000	61.029	45.734	56.000	2.657***
2014	67.891	50.813	70.000	66.620	49.143	65.000	1.271*

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Table 2 -*continued*

	Positive Inventory Cycle (N = 87,063)			Negative Inventory Cycle (N = 69,171)			Diff.
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean
							Cont'd from previous page
Peak inventory ($ Million)	25.705	21.097	18.749	22.389	17.812	16.772	3.316***
Peak inventory by year ($ Million)							
2003	27.816	22.346	19.946	25.716	19.813	18.871	2.100***
2004	27.151	22.157	19.523	25.684	20.076	18.680	1.468***
2005	26.562	21.659	19.058	25.332	19.994	18.244	1.229***
2006	27.071	22.215	19.379	24.672	19.110	18.292	2.399***
2007	28.053	22.414	20.599	24.776	19.421	18.294	3.276***
2008	24.026	19.950	17.840	22.011	18.119	16.449	2.015***
2009	25.123	20.673	18.188	21.867	17.688	16.316	3.255***
2010	27.709	22.351	20.263	23.325	18.266	17.555	4.384***
2011	26.704	21.823	19.425	22.438	17.417	17.238	4.266***
2012	24.990	20.711	18.335	18.956	14.821	15.087	6.035***
2013	23.626	19.419	17.623	19.406	14.869	15.391	4.219***
2014	23.345	19.006	17.591	19.297	14.779	15.378	4.048***
Bond return (%)							
Loading	-0.168	2.684	-0.030	0.578	2.973	0.102	-0.746***
Unloading	0.170	2.714	0.050	-0.048	2.883	-0.022	0.218***
Full	-0.016	3.945	-0.001	0.517	4.390	0.085	-0.534***

Table 3

Determinants of Probability and Characteristics of Dealer Inventory Cycles

Panel A reports OLS estimates for time-series regressions of fractions of bonds in positive (column (1)) and negative (column (2)) inventory cycles on various market variables. The sample period is from July 2003 to December 2014, and the frequency is monthly. Fraction of bonds in positive (negative) inventory cycle is calculated as the number of bonds that are in a positive (negative) cycle for at least ten days in a given month divided by the number of all sample bonds that exist at the end of the month. NOISE is the standard deviation of Treasury pricing errors as constructed by Hu, Pan, and Wang (2013). VIX is the CBOE implied volatility index. Both NOISE and VIX are averaged across all days in the month. Crisis is a dummy variable that equals one for the period from July 2007 to April 2009, and zero otherwise. ln(Total bond issuance) is natural log of par value (in dollars) of all corporate bonds issued in the month. Flow is the sum of dollar flows to all sample funds, as a percentage of the sum of prior-month TNAs. Newey-West standard errors calculated using three lags are in parentheses. Panel B reports Fama-MacBeth estimates for cross-sectional regressions of dummies for being in a positive (column (1)) or negative (column (2)) cycles on various bond characteristics. In each month, all bonds that exist are included, each as one observation. Dummy for being in a positive (negative) cycle equals one if a given bond is in a positive (negative) cycle for at least 10 days in the particular month, and zero otherwise. ln(Bond maturity), ln(Bond issue size), and ln(Bond age) natural logs of maturity (in years), issue size (in dollars) and age (in years) of a given bond as of the beginning of the month. Upgrade (Downgrade) [t-2, t+2] is a dummy variable that equals one if a given bond is upgraded (downgraded) within two months from the particular month, and zero otherwise. Fama-MacBeth standard errors, with three-lag Newey-West adjustment, are in parentheses. Panels C and D report OLS estimates for regressions of cycle characteristics on various market variables and bond characteristics. Observations are inventory cycles. The dependent variables in columns (1)-(4) are ln(Inventory x Day), ln(Inventory x Day during loading), ln(Peak inventory), and ln(Cycle length), respectively. ln(Inventory x Day) is calculated as natural log of the sum of ending inventory (in dollars) across all days in a given cycle, while ln(Inventory x Day during loading) considers only the loading phase of the cycle. ln(Peak inventory) is natural log of the cycle's peak inventory (in dollars). ln(Cycle length) is natural log of the cycle length (in days). Market variables as well as Upgrade and Downgrade [t-2, t+2] are merged to the month in which the cycle reaches its peak. All models include issuer fixed effects. Standard errors, two-way clustered by issuer and year, are in parentheses. $*$, $**$, and $***$ refer to statistical significance at 10%, 5%, and 1% levels.

Table 3 -*continued*

Panel A: Fractions of Existing Bonds in Positive and Negative Cycles

	Dependent Variable	
	Fraction of Bonds in ***Positive*** Cycle	Fraction of Bonds in ***Negative*** Cycle
	(1)	(2)
NOISE	-0.0000	0.0002
	(0.001)	(0.001)
VIX	-0.0008*	0.0000
	(0.000)	(0.000)
Crisis	-0.0351***	-0.0167***
	(0.006)	(0.006)
ln(Total corporate bond issue size)	0.0089***	-0.0138***
	(0.003)	(0.003)
ln(Total corporate bond issue size) *t*-1	0.0072***	-0.0129***
	(0.003)	(0.004)
Flow	-0.0004***	0.0003**
	(0.000)	(0.000)
Flow *t*-1	-0.0001	-0.0001
	(0.000)	(0.000)
Intercept	-0.1159*	0.6041***
	(0.070)	(0.110)
Observations	137	137
R-squared	0.748	0.377

Table 3 -*continued*

Panel B: Probability for Being in Positive and Negative Cycles (Fama-MacBeth)

	Dependent Variable	
	Dummy for Being in ***Positive*** Cycle	Dummy for Being in ***Negative*** Cycle
	(1)	(2)
Dependent variable *t*-1	0.722***	0.754***
	(0.004)	(0.004)
ln(Bond maturity)	0.003***	0.004***
	(0.000)	(0.001)
ln(Bond issue size)	0.027***	0.022***
	(0.001)	(0.001)
ln(Bond age)	-0.019***	-0.019***
	(0.001)	(0.001)
Investment grade	0.017***	0.014***
	(0.001)	(0.001)
Upgrade [*t*-2, *t*+2]	0.033***	0.013***
	(0.006)	(0.004)
Downgrade [*t*-2, *t*+2]	0.030***	0.008**
	(0.005)	(0.003)
Intercept	-0.282***	-0.229***
	(0.007)	(0.008)
Observations	1,603,701	1,603,701
Months	137	137
R-squared	0.589	0.626

Table 3 -*continued*

Panel C: Characteristics of Positive Cycles

	Dependent Variable			
	ln(Inventory x Day)	ln(Inventory x Day during Loading)	ln(Peak Inventory)	ln(Cycle Length)
	(1)	(2)	(3)	(4)
NOISE	-0.010	-0.011	0.004	-0.002*
	(0.016)	(0.019)	(0.009)	(0.001)
VIX	-0.007**	-0.006*	-0.005	0.000
	(0.003)	(0.003)	(0.003)	(0.000)
Crisis	0.077	0.036	-0.054	0.017***
	(0.086)	(0.095)	(0.051)	(0.003)
ln(Bond maturity)	0.134***	0.129***	0.011	0.012***
	(0.014)	(0.012)	(0.010)	(0.001)
ln(Bond issue size)	0.057*	0.181***	0.275***	-0.033***
	(0.026)	(0.023)	(0.012)	(0.002)
ln(Bond age)	-0.351***	-0.303***	-0.399***	0.013***
	(0.026)	(0.024)	(0.016)	(0.002)
Upgrade [*t*-2, *t*+2]	0.240*	0.352***	0.205***	0.004
	(0.114)	(0.092)	(0.060)	(0.005)
Downgrade [*t*-2, *t*+2]	0.214**	0.292***	0.204***	0.003
	(0.096)	(0.090)	(0.038)	(0.008)
Issuer fixed effects	YES	YES	YES	YES
Observations	85,028	85,028	85,028	85,028
R-squared	0.068	0.074	0.148	0.108

Table 3 -*continued*

Panel D: Characteristics of Negative Cycles

	Dependent Variable			
	ln(Inventory x Day)	ln(Inventory x Day during Loading)	ln(Peak Inventory)	ln(Cycle Length)
	(1)	(2)	(3)	(4)
NOISE	-0.017	-0.007	-0.002	-0.002
	(0.018)	(0.020)	(0.013)	(0.001)
VIX	-0.004	-0.004	-0.005	0.001*
	(0.006)	(0.006)	(0.004)	(0.000)
Crisis	0.226***	0.196***	0.041	0.029***
	(0.055)	(0.053)	(0.045)	(0.003)
ln(Bond maturity)	0.069***	0.113***	0.086***	0.004***
	(0.013)	(0.013)	(0.010)	(0.001)
ln(Bond issue size)	-0.012	0.082***	0.319***	-0.046***
	(0.020)	(0.025)	(0.016)	(0.002)
ln(Bond age)	-0.277***	-0.335***	-0.384***	0.011***
	(0.027)	(0.031)	(0.018)	(0.002)
Upgrade [*t*-2, *t*+2]	-0.116	-0.221	0.058	-0.020**
	(0.133)	(0.134)	(0.077)	(0.007)
Downgrade [*t*-2, *t*+2]	-0.134	-0.128	0.057	-0.027***
	(0.093)	(0.085)	(0.047)	(0.007)
Issuer fixed effects	YES	YES	YES	YES
Observations	67,626	67,626	67,626	67,626
R-squared	0.061	0.068	0.164	0.140

Table 4

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 ($ Million), (monthly) flow (%), allocations to cash and equivalents (%), portfolio effective duration, average credit rating, turnover, and fraction of position changes that are unclassified. 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	35,093	-0.055	0.209	-0.168	-0.055	0.057	0.464
Fund average	937	-0.048	0.108	-0.088	-0.054	-0.014	0.443
Fund average by year							
2003	505	-0.046	0.163	-0.129	-0.040	0.038	0.394
2004	544	-0.078	0.150	-0.146	-0.073	-0.005	0.402
2005	523	-0.038	0.166	-0.111	-0.044	0.030	0.418
2006	530	-0.045	0.153	-0.124	-0.044	0.024	0.440
2007	542	-0.027	0.161	-0.105	-0.036	0.024	0.421
2008	543	-0.081	0.168	-0.163	-0.076	-0.006	0.406
2009	558	-0.062	0.117	-0.119	-0.063	-0.012	0.483
2010	554	-0.044	0.122	-0.107	-0.050	0.008	0.476
2011	570	-0.048	0.128	-0.101	-0.052	-0.001	0.465
2012	590	-0.047	0.128	-0.104	-0.051	0.009	0.521
2013	606	-0.066	0.130	-0.113	-0.063	-0.016	0.515
2014	616	-0.051	0.131	-0.113	-0.057	0.005	0.510

Table 4 -*continued*

Panel B: Means of Funds' Characteristics by LS_score Quintile

Net LS Fraction Quintile	TNA	Flow	Cash Allocation	Effective Duration	Average Credit Rating	Turnover	Unclass'd Fraction
1 (Low)	2,272	1.914	5.781	3.975	9.341	2.651	0.404
2	2,093	1.919	6.791	4.281	11.042	2.391	0.485
3	2,766	3.410	5.573	4.107	11.263	2.369	0.494
4	2,068	3.086	6.867	4.099	10.841	2.429	0.482
5 (High)	1,138	3.830	6.339	3.681	9.489	2.673	0.417
5 - 1	-1,134***	1.916***	0.558	-0.294***	0.149	0.022	0.013

Table 5

Funds' Liquidity Supply and Performance

This table reports OLS estimates for panel predictive regressions of alpha in month *t*+1 on liquidity supply measures calculated over the period from months *t*-11 to *t*. Observations are fund-month, and only those with at least five identifiable CUSIPS traded per reporting period during months *t*-11 to *t* are included. Alpha is calculated by subtracting benchmark return from actual fund return:

$$R_{i,t+1} - R_{f,t+1} = \propto_{t+1} + [\, \beta_{STK} STK_{t+1} + \beta_{BOND} BOND_{t+1} + \beta_{DEF} DEF_{t+1} + \beta_{OPTION} OPTION_{t+1} \,]$$

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 downloaded from DataStream. The parameters, β_{STK}, β_{BOND}, β_{DEF}, and β_{OPTION}, are estimated on a rolling basis. For alpha in month *t*+1, the estimation period is from months *t*-17 to *t*. 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*-11 to *t*. *LS_score* Q1, and *LS_score* Q5 are dummy variables that equal one if the fund's average *LS_score* is in the bottom and top quintiles, respectively, on month *t*, and zero otherwise. Crisis is a dummy variable that equals one if month *t*+1 falls in the period from July 2007 to April 2009, and zero otherwise. NOISE is the standard deviation of Treasury pricing errors as constructed by Hu, Pan, and Wang (2013). VIX is the CBOE implied volatility index. Both NOISE and VIX are averaged across all days in month *t*+1. Institutional share fraction is the fraction of TNA that is owned by institutional share classes. Rear load is the value-weighted average across all share classes of the maximum charge, in percentage points, for redeeming the mutual fund shares. Three lags of flows (%) are included. ln(Number of holdings) is natural log of the number of CUSIPs. % Cash is fund's percentage allocations to cash and equivalents. 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 value-weighted average issue size (in dollars) and average age (in years) of corporate bonds in fund's portfolio. Broker affiliated is a dummy variable that equals one if the fund's family is affiliated with a broker-dealer bank, and zero otherwise. ln(TNA) and ln(Age) are natural logs of fund's TNA and age. Unless specified, all control variables are as of the latest reporting period prior to month *t*+1. All models include fund classification and month fixed effects. Standard errors, two-way clustered by fund family and month, are in parentheses. $*$, $**$, and $***$ refer to statistical significance at 10%, 5%, and 1% levels.

Table 5 -*continued*

	Full Sample						Sub Samples		
							Avg. Bond Rating *Higher* than BB+	Avg. Bond Rating *Lower* than BB+	Avg. Corp. Bond Allocation ≥ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Main Variables									
Avg. LS-score [*t*-11, *t*]	0.176**		0.103***	0.168***	0.155***				
	(0.071)		(0.039)	(0.061)	(0.058)				
Avg. LS-score [*t*-11, *t*] Q1		-0.021***				-0.020***	-0.020***	-0.020*	-0.043***
		(0.006)				(0.005)	(0.005)	(0.012)	(0.013)
Avg. LS-score [*t*-11, *t*] Q5		0.030***				0.028***	0.013	0.028*	0.022**
		(0.009)				(0.009)	(0.009)	(0.015)	(0.011)
Crisis x Avg. LS-score [*t*-11, *t*]			0.385***	-0.011	0.077				
			(0.140)	(0.120)	(0.108)				
NOISE x Avg. LS-score [*t*-11, *t*]				0.074**					
				(0.032)					
VIX x Avg. LS-score [*t*-11, *t*]					0.022***				
					(0.009)				
Control Variables									
Institutional share fraction						0.027**	0.008	0.057***	0.049***
						(0.012)	(0.014)	(0.017)	(0.012)
Rear load						0.002	-0.009	0.014***	0.008
						(0.005)	(0.011)	(0.005)	(0.006)
Flow *t*						0.000	0.000	0.001	-0.000
						(0.000)	(0.000)	(0.000)	(0.000)
Flow *t*-1						-0.000	0.000	0.000	-0.000
						(0.001)	(0.000)	(0.001)	(0.001)
Flow *t*-2						0.000	-0.000	-0.000	-0.000
						(0.001)	(0.000)	(0.001)	(0.001)

Cont'd next page

Table 5 -*continued*

	Full Sample						Sub Samples		
							Avg. Bond Rating *Higher* than BB+	Avg. Bond Rating *Lower* than BB+	Avg. Corp. Bond Allocation ≥ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cont'd from previous page									
ln(Number of holdings)						-0.004	-0.004	-0.013	-0.000
						(0.007)	(0.007)	(0.014)	(0.013)
% Cash						-0.000**	-0.000**	-0.001***	-0.000
						(0.000)	(0.000)	(0.000)	(0.000)
Average duration						0.006	0.013	-0.007	0.010
						(0.007)	(0.008)	(0.005)	(0.008)
ln(Average bond issue size)						0.001	-0.005	-0.005	-0.005
						(0.009)	(0.007)	(0.009)	(0.010)
ln(Average bond age)						0.065**	-0.012	0.028	0.097**
						(0.032)	(0.007)	(0.039)	(0.044)
Average credit rating						0.012**			0.020***
						(0.005)			(0.008)
Broker affiliated						0.028*	0.003	0.001	0.020***
						(0.016)	(0.012)	(0.014)	(0.002)
ln(TNA)						0.002	0.002	0.003	0.001
						(0.005)	(0.004)	(0.007)	(0.006)
ln(Age)						0.013*	0.010	0.012	0.004
						(0.007)	(0.011)	(0.012)	(0.009)
Fund classification fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	61,753	61,753	61,753	61,753	61,753	61,753	35,783	25,970	26,021
R-squared (total)	0.242	0.241	0.242	0.243	0.243	0.245	0.260	0.443	0.415

Table 6

Determinants of Funds' Liquidity Supply

This table reports OLS estimates for panel predictive regressions a fund's liquidity supply measure, *LS_score*, averaged over the period from months *t*+1 to *t*+12, on the fund's funding, asset, and other general characteristics. Observations are fund-month (unbalanced). Explanatory variables are funds' characteristics as of the end of month *t*. Institutional share fraction is the fraction of TNA that is owned by institutional share classes. Rear load is the value-weighted average across all share classes of the maximum charge, in percentage points, for redeeming the mutual fund shares. Average and standard deviation of flow, as well as the correlation between flow and lagged alpha, as well as standard deviations of flow and return, are calculated over the period from months *t*-11 to *t*. ln(Number of holdings) is natural log of the number of CUSIPs. % Cash is fund's percentage allocations to cash and equivalents. 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 value-weighted average issue size (in dollars) and average age (in years) of corporate bonds in fund's portfolio. Broker affiliated is a dummy variable that equals one if the fund's family is affiliated with a broker-dealer bank, and zero otherwise. ln(TNA) and ln(Age) are natural logs of fund's TNA and age. Fixed effects are as indicated in the table. Standard errors, two-way clustered by fund family and month, are in parentheses. ∗, ∗∗, and ∗∗∗ refer to statistical significance at 10%, 5%, and 1% levels.

	Full Sample						Sub Samples		
							Avg. Bond Rating *Higher* than BB+	Avg. Bond Rating *Lower* than BB+	Avg. Corp. Bond Allocation ≥ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Funding									
Institutional share fraction	0.006			-0.002	-0.002	0.003	-0.002	0.002	0.005
	(0.005)			(0.004)	(0.005)	(0.009)	(0.006)	(0.006)	(0.007)
Rear load	0.001			0.001	-0.000	0.001	0.001	-0.001	0.001
	(0.003)			(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Avg. flow [*t*-11, *t*]	0.001***			0.001***	0.001**	0.000*	0.001**	0.001***	0.000*
	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Std. dev. flow [*t*-11, *t*]	-0.000			-0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corr. flow and lagged return [*t*-11, *t*]	-0.010***			-0.010***	-0.010***	-0.008***	-0.007**	-0.012***	-0.016***
	(0.002)			(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Assets									
ln(Number of holdings)		-0.002		0.002	-0.000	0.000	0.005	-0.004	0.001
		(0.003)		(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)

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Table 6 -*continued*

	Full Sample						Sub Samples		
							Avg. Bond Rating *Higher* than BB+	Avg. Bond Rating *Lower* than BB+	Avg. Corp. Bond Allocation ≥ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
									Cont'd from previous page
		(0.003)		(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
% Cash		0.031		0.022	0.001	0.008	0.006	0.069**	0.023
		(0.027)		(0.027)	(0.022)	(0.021)	(0.028)	(0.033)	(0.041)
Average duration		-0.006***		-0.006***	-0.005***	-0.002	-0.006***	-0.006***	-0.006***
		(0.001)		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Average bond issue size)		-0.004**		-0.003**	-0.001	0.000	-0.009***	-0.000	-0.005***
		(0.002)		(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
ln(Average bond age)		0.026***		0.027***	0.019**	0.012	0.022**	0.027**	0.041***
		(0.009)		(0.009)	(0.009)	(0.008)	(0.011)	(0.011)	(0.010)
Average credit rating		-0.002*		-0.002**	-0.001	-0.000			-0.003
		(0.001)		(0.001)	(0.001)	(0.001)			(0.002)
<u>Fund and family characteristics</u>									
Broker affiliated			0.012**	0.009**			0.007	0.016***	0.009*
			(0.006)	(0.004)			(0.006)	(0.004)	(0.005)
ln(TNA)			-0.003**	-0.004***	-0.005***	-0.007***	-0.003	-0.006***	-0.005**
			(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
ln(Age)			-0.008**	-0.006	-0.000	0.003	-0.010**	0.003	-0.008
			(0.004)	(0.004)	(0.003)	(0.009)	(0.005)	(0.005)	(0.005)
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Family fixed effects	NO	NO	NO	NO	YES	NO	NO	NO	NO
Fund fixed effects	NO	NO	NO	NO	NO	YES	NO	NO	NO
Observations	34,710	34,710	34,710	34,710	34,710	34,710	18,919	15,791	15,364
R-squared (total)	0.028	0.044	0.032	0.060	0.153	0.260	0.072	0.092	0.087

Table 7

Persistence in Funds' Liquidity Supply

Panel A reports various metrics of funds' future liquidity supply, *LS_score*, conditional on funds' past *LS_score*. At the end of each month *t*, funds are sorted into five quintiles by their *LS_score*, averaged over the period from months *t*-11 to *t*. The reported statistics are across funds in each *LS_score* quintile. The first two columns report the mean number of traded CUSIPs and *LS_score* during the sorting period. The third and fourth columns report the mean *LS_score* over the periods from months *t*+1 to *t*+12 and months *t*+13 to *t*+24, respectively. The next (last) five columns report the mean percentages that the funds in each *LS_score* quintile during the sorting period will move into different *LS_score* quintiles in the period from months *t*+1 to *t*+12 (months *t*+13 to *t*+24). 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 family and month. In the next (last) five columns, the reported chi-square statistic is for the test of null hypothesis that the probability for being in each *LS_score* quintile in the period from months *t*+1 to *t*+12 (months *t*+13 to *t*+24) is independent of the fund's *LS_score* quintile during the sorting period. Panel B reports OLS estimates for panel predictive regressions funds' average *LS_score* on funds' past average *LS_score* and its interaction with various market and funding variables. Observations are fund-month (unbalanced). Average *LS_score* is calculated over the period from months *t*+1 to *t*+12 while past average *LS_score* is calculated over the period from months *t*-11 to *t*. All models include all explanatory variables and month fixed effects as in column (4) of Table 6 (omitted here for brevity). Standard errors, two-way clustered by fund family and month, are in parentheses. ∗, ∗∗, and ∗∗∗ refer to statistical significance at 10%, 5%, and 1% levels.

Panel A: 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*			Percentage in Avg. *LS_score* [*t*+1, *t*+12] Quintile					Percentage in Avg. *LS_score* [*t*+13, *t*+24] Quintile				
		[*t*-11,*t*]	[*t*+1,*t*+12]	[*t*+13,*t*+24]	1 (Low)	2	3	4	5 (High)	1 (Low)	2	3	4	5 (High)
1 (Low)	24.008	-0.178	-0.071	-0.069	29.77	21.00	17.87	16.15	15.21	28.65	20.72	17.81	16.08	16.74
2	35.442	-0.096	-0.064	-0.063	21.45	23.39	22.18	19.30	13.69	20.24	23.25	21.36	19.15	16.00
3	35.244	-0.055	-0.054	-0.056	16.81	22.25	22.00	21.91	17.03	17.23	21.63	22.45	21.21	17.49
4	32.295	-0.014	-0.049	-0.049	16.05	18.76	22.33	22.46	20.40	15.93	18.62	21.75	23.40	20.30
5 (High)	21.981	0.076	-0.034	-0.043	15.42	15.17	16.35	20.57	32.50	17.51	16.08	17.41	20.17	28.84
5 - 1	-2.027	0.255***	0.037***	0.027***	H0: Rows and Columns are Independent					H0: Rows and Columns are Independent				
Std. Error	(3.059)	(0.010)	(0.009)	(0.006)	$\chi^2 > 1{,}400$***					$\chi^2 = 744.64$***				

Table 7 -*continued*

Panel B: Regressions of Future LS_score on Past LS_score

	Full Sample						Sub Samples		
							Avg. Bond Rating *Higher* than BB+	Avg. Bond Rating *Lower* than BB+	Avg. Corp. Bond Allocation ≥ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Avg. LS-score [*t*-11, *t*]	0.093***	0.123***	0.098***	0.094***	0.094***	0.094***	0.081**	0.108***	0.131***
	(0.032)	(0.033)	(0.031)	(0.031)	(0.032)	(0.031)	(0.032)	(0.041)	(0.048)
Crisis x Avg. LS-score [*t*-11, *t*]		-0.147***							
		(0.036)							
NOISE x Avg. LS-score [*t*-11, *t*]			-0.013***						
			(0.004)						
VIX x Avg. LS-score [*t*-11, *t*]				-0.003*					
				(0.002)					
Agg. flow x Avg. LS-score [*t*-11, *t*]					0.687				
					(0.869)				
Avg. flow x Avg. LS-score [*t*-11, *t*]						0.002*			
						(0.002)			
Controls and fixed effects as in column (4) of Table 6	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	34,710	34,710	34,710	34,710	34,710	34,710	18,919	15,791	15,364
R-squared (total)	0.069	0.072	0.070	0.069	0.069	0.069	0.078	0.102	0.103

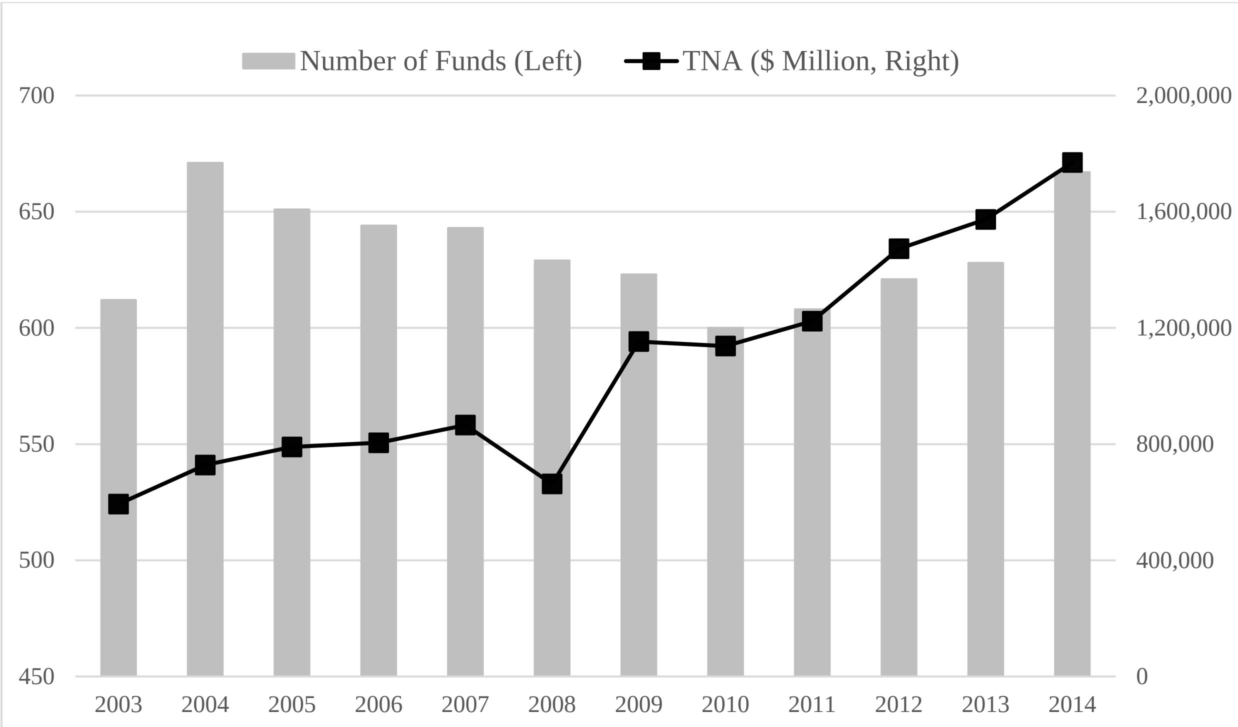
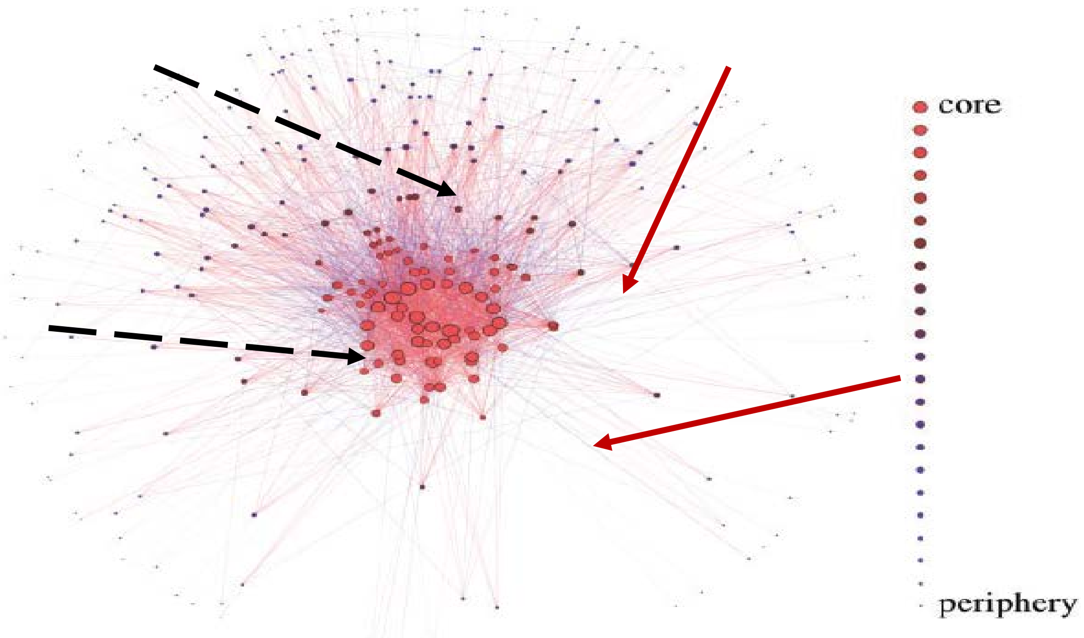


Figure 1. Taxable bond mutual funds over time. This figure presents the total net assets (TNA, in $ Million) of taxable bond funds and the numbers of these funds, as reported by Morningstar, over the sample period from 2003 to 2014. The sample includes only open-ended funds in the following Morningstar 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.

Panel A: Customer buying and selling activity are balanced



Panel B: Customer selling activity is excessive

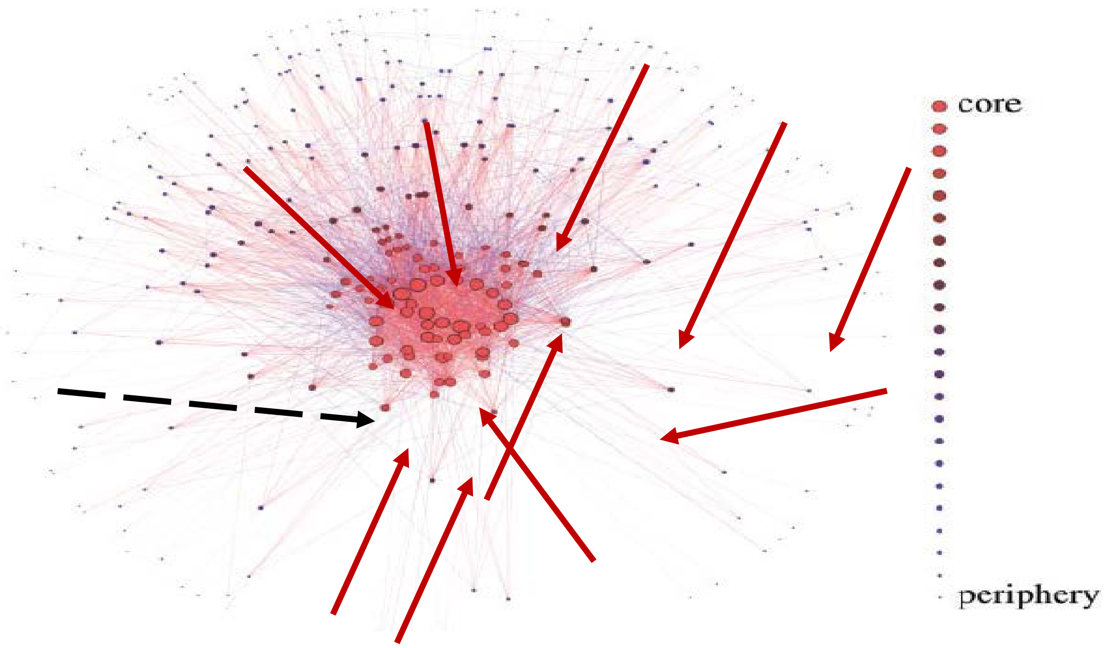
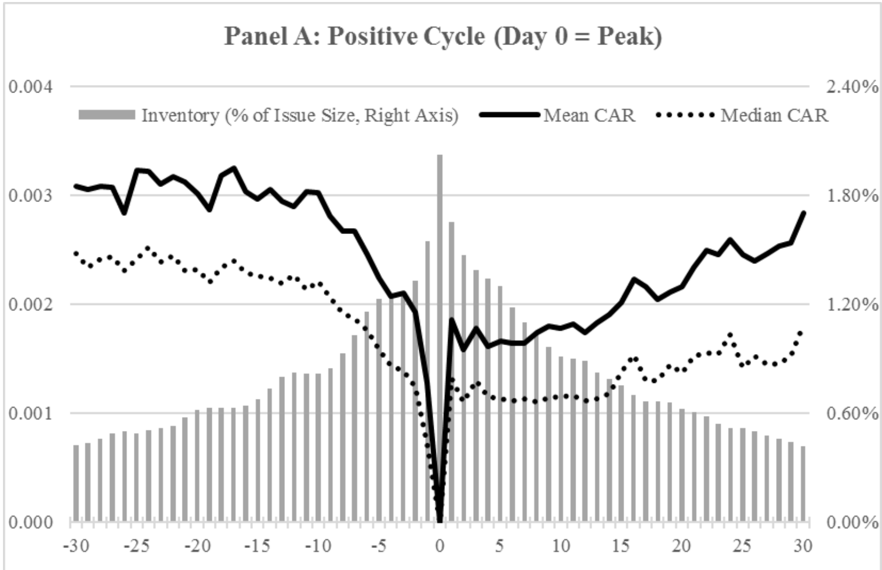


Figure 2. Interdealer network. This is figure 5 from Hollified, Neklyudov and Spatt (2017) showing the interdealer network in bond markets. Each circle represents a dealer, where the size of circle is proportional to importance of the dealer, and the connections between dealers are depicted as lines connecting the circles. Dashed arrow represents a customer purchase from a dealer while the straight arrow represents a customer sale to a dealer.



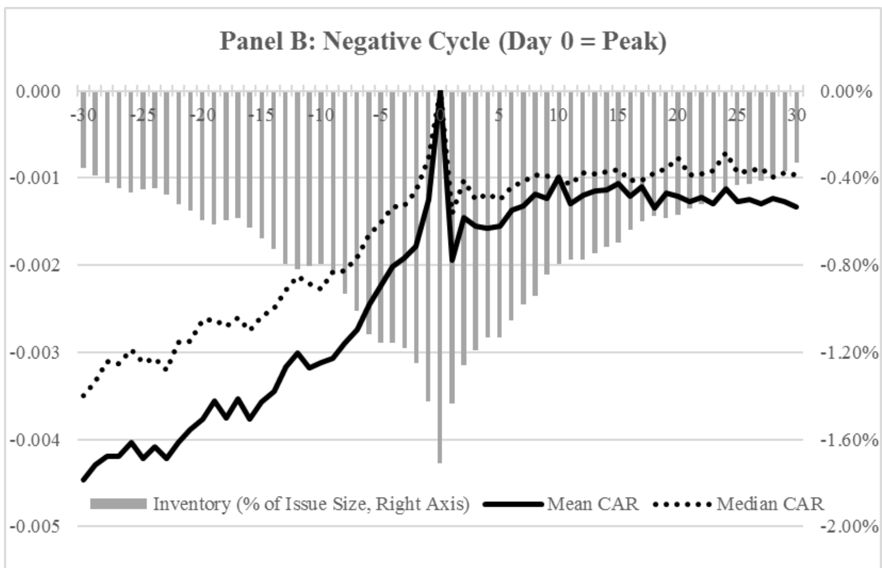


Figure 3. Dealer inventory and cumulative abnormal returns during positive and negative cycles and around bond rating downgrades. This figure presents average dealer inventory, as a percentage of bond's issue size, and mean/median cumulative abnormal returns, normalized to zero on the event day, during positive (Panel A) and negative (Panel B) inventory cycles and around the downgrades of corporate bonds from investment to speculative grades (Panel C). In Panels A and B, the event day (day 0) is the day on which the inventory reaches the cycle peak. Only inventory cycles on investment grade bonds with maturity of at least one year, issue size of at least $1 billion, and age of at least one year, are included. In Panel C, the event day (day 0) is the day on which the bond is first downgraded from investment to speculative grades by at least one of the three rating agencies-- S&P, Moody's, and Fitch. Only bonds with maturity of at least one year on the event day are included. Bond return is calculated as change in VWAP between two trading days, and abnormal return is obtained by subtracting the bond return by Bank of America Merrill Lynch's Investment Grade Corporate Bond's return.

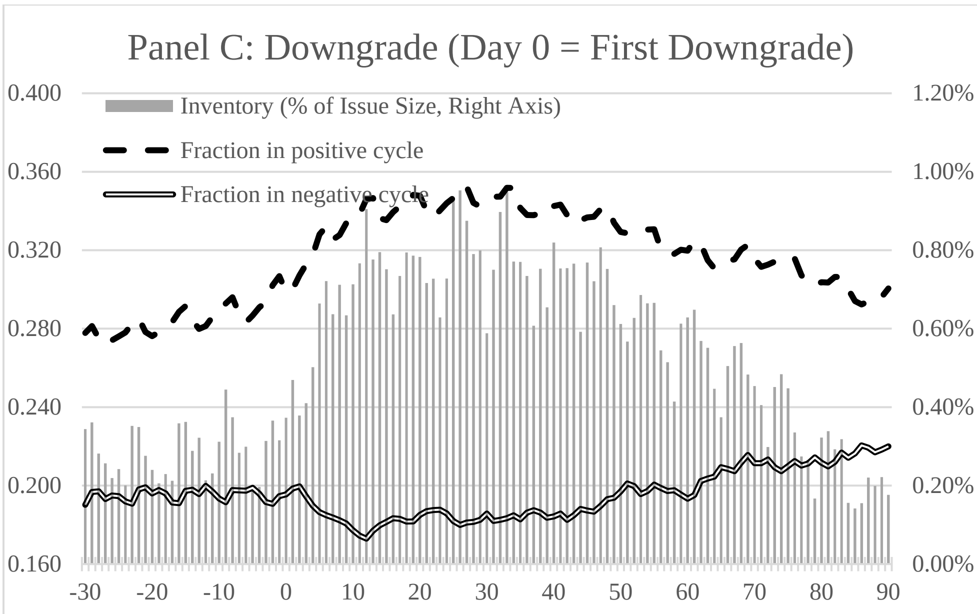
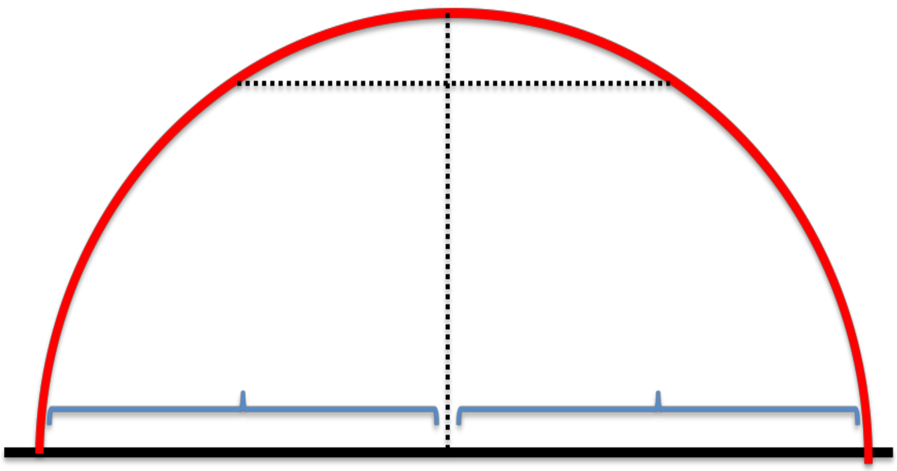


Figure 3 -*continued.*



	Load Phase		Unload Phase
Change in dealer inventory (ΔI)	+		-
Bond return (r)	-		+
Inventory cycle (IC)		+	
Change in fund holdings (ΔH)		+	
Correlation(ΔH,ΔI)	+		-
Correlation(ΔH,r)	-		+
Correlation(ΔH,IC)	+		+
Trading style	**Liquidity supply**		**Liquidity supply**

Figure 4. Classifying changes in fund holdings during in a positive inventory cycle.

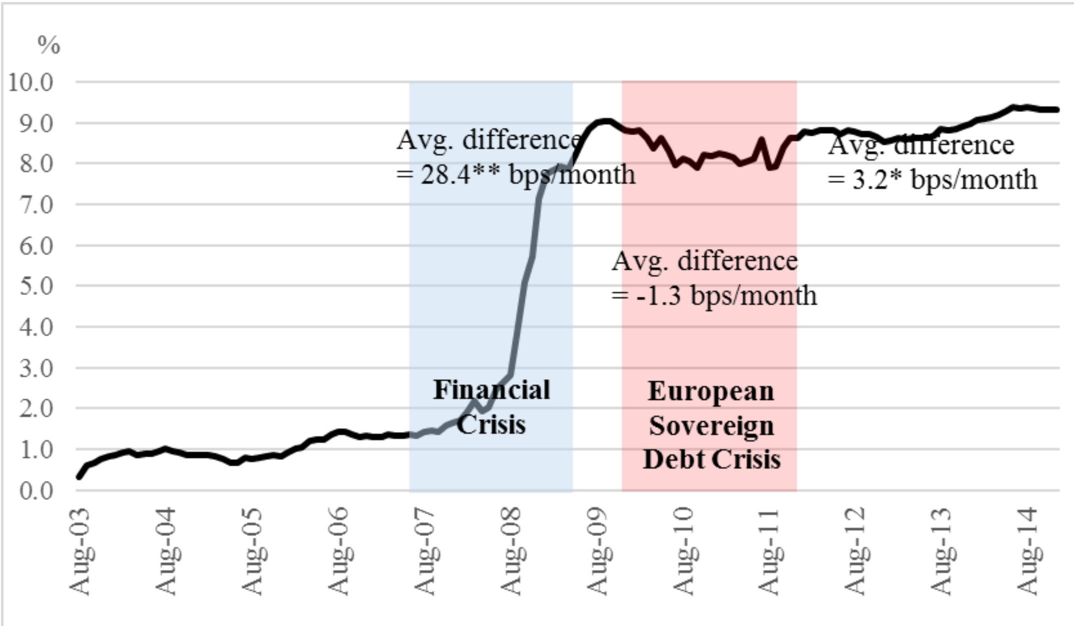


Figure 5. Cumulative difference in performance between funds in the top and bottom *LS_score* quintiles. This figure plots cumulative difference in average alpha of funds in the top and bottom *LS_score* quintiles. Alpha is calculated by subtracting benchmark return, based on a four-factor model as described in Table 5, from actual fund return. The model parameters are estimated on a rolling basis. For alpha in month *t*+1, the estimation period is from months *t*-17 to *t*. 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*+1, the sorting variable is the average *LS_score* over the period from months *t*-11 to *t*. The shaded areas highlight the financial crisis period, defined as the period from July 2007 to April 2009, and the European sovereign debt crisis period in 2010-2011 (Becker and Ivashina (2017)).