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 liquidity suppliers in bond markets. Focusing on mutual funds, we classify a fund's trading style as liquidity supplying (demanding) if the fund helps absorb (strain) dealers' inventory. While mutual funds in aggregate demand liquidity, persistent cross-sectional variation exists – stable funding, family affiliation with dealers, and fund manager skill are associated with liquidity supply. Liquidity supplying trading style earns higher alpha, especially in illiquid markets. Our evidence suggests that bond market liquidity can be enhanced by removing institutional frictions that impede broad investor participation in liquidity provision.

Keywords: Corporate bonds; dealer inventory; bond mutual fund; liquidity supply; performance.
This Draft: July 11, 2018

---

* We thank Hank Bessembinder, Yong Chen, Zhi Da, Jack Bao, Jaewon Choi, Paul Calluzzo, Itay Goldstein, Stacey Jacobsen, Ryan Israelsen, Eric Kelley, Amar Kuchinad, David Krein, Bill Maxwell, Mike Piwowar, Andy Puckett, Alex Reyfman, Tavy Ronen, Marco Rossi, Mehrdad Samadi, Norman Schurhoff, Pradeep Yadav, and participants at 2018 Chicago Financial Institutions conference, 2018 Bank of Canada-Laurier Market Structure conference, 2017 Emerging Markets Finance conference, 2017 Financial Economics and Accounting conference, 2018 Financial Intermediation Research Society Conference, 2018 Midwest Finance Association conference, FINRA/Columbia University Market Structure and Capital Formation conference, ESSEC Business School, Rochester Institute of Technology, Texas A&M University, University of Illinois Urbana Champaign, University of Oklahoma, Universite Paris-Dauphine, University of Tennessee and Southern Methodist University for their comments. The authors thank the Finance Industry Regulatory Authority (FINRA), and in particular, Alie Diagne, Ola Persson, Jonathan Sokobin and Chris Stone for provision of data. Anand and Venkataraman are affiliated as visiting economists with the office of chief economist at FINRA

Do buy-side institutions supply liquidity in bond markets?
Evidence from mutual funds

Abstract

We examine the role of buy-side institutions as liquidity suppliers in bond markets. Focusing on mutual funds, we classify a fund's trading style as liquidity supplying (demanding) if the fund helps absorb (strain) dealers' inventory. While mutual funds in aggregate demand liquidity, persistent cross-sectional variation exists – stable funding, family affiliation with dealers, and fund manager skill are associated with liquidity supply. Liquidity supplying trading style earns higher alpha, especially in illiquid markets. Our evidence suggests that bond market liquidity can be enhanced by removing institutional frictions that impede broad investor participation in liquidity provision.

I. Introduction

Liquidity in the corporate bond market has received considerable attention in recent years. Evidence from academic studies points to a reduction in capital commitment by corporate bond dealers between 2006 and 2016, attributable at least in part to banking regulations such as Volcker Rule (see, Bessembinder, Jacobsen, Maxwell, and Venkataraman (2017), Bao, O'Hara, and Zhao (2017), Dick-Neilsen and Rossi (2017), Schultz (2017), among others). During the same decade, the outstanding amount of corporate bonds have 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.[1]

Regulators are concerned about the consequences of these developments for the corporate bond market, including the impact of funds' rebalancing and redemption needs on the liquidity and pricing of underlying bonds.[2] The U.S. Securities and Exchange Commission (SEC) has issued 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] In contrast to the regulatory view that bond funds might further strain dealers' limited capacity, market participants appear to hold the view that buy-side institutions play a balanced role in bond markets. For example, a 2017 Greenwich Associates survey reports that 78% of credit investors describe buy-side institutions as an important source of corporate bond liquidity.[4]

In this study, we focus on unanswered questions relating to whether, and to what extent, buy-side institutions play the role of liquidity suppliers in the corporate bond market. Although this role appears similar to those played by bond dealers, the key distinctions are that (a) unlike equities, corporate bonds

---

[1] 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.
[2] "Is there a liquidity problem post-crisis?", Speech by Stanley Fischer, Vice Chairman, Federal Reserve Board, on November 10, 2015, available at "https://www.federalreserve.gov/newsevents/speech/fischer20161115a.htm."
[3] https://www.sec.gov/divisions/investment/guidance/im-guidance-2014-1.pdf
[4] "Innovations ease corporate bond trading", Greenwich Associates, Quarter 2, 2017.

trade in over-the-counter (OTC) markets, making it difficult for institutions to compete directly with dealers by posting continuous bid and ask quotes or using limit orders,[5] and (b) institutions do not necessarily incur inventory carrying costs when they assume longer-term positions that meet their investment objectives. This flexibility allows institutions to selectively profit from trading opportunities when other participants demand liquidity in an illiquid market. We focus on bond mutual funds, an important category of buy-side institutions, because they trade frequently and are more likely than other bond-focused institutions to benefit from liquidity supply.

The framework of liquidity supply that we propose hinges on the notion of trading against sustained customer imbalances. We measure imbalances using the enhanced version of the TRACE database, which, in addition to reporting all U.S. corporate bond transactions reflected in public TRACE, also includes uncapped trade size and masked dealer identifiers. Unlike the TAQ data (for equities) 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 classify 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 cumulative inventory crosses zero. Cumulative inventory is the signed, aggregate dollar inventory based on all dealers' trades with customers in the bond.

Over our sample period from 2002 to 2014, the inventory cycles that we identify are long lasting, with the average cycle length of over 70 calendar days and peak inventory of $26 million.[6] We observe a decline in the bond price when dealers build up inventory in a positive cycle followed by a reversal in the unload phase of the cycle. The former is consistent with dealers 'shading' indicative quotes to manage slow-moving inventory and the latter is consistent with price reversals that compensate liquidity suppliers

[5] Institutions rely on alternative mechanisms for supplying liquidity in bond markets. For example, "In the bigger bond market, bigger is better", *The Wall Street Journal*, June 21, 2017, reports that "instead of just calling banks for quotes on bonds, big funds often amass large stockpiles of their own and then call banks to tell them at what price they are willing to sell."

[6] In equities, the holding period of active market makers (i.e., high-frequency traders) is very short (in seconds) while in corporate bonds, Schultz (2017) estimates that half-life of individual dealer inventory position is four to five weeks.

for absorbing trade imbalances (see Kraus and Stoll (1972), Grossman and Miller (1988)). Price reversals are stronger in positive cycles than in negative cycles, which supports the evidence of buy-sell asymmetry in price impact of corporate bonds (see Cai, Han, Li and Li (2018)).

Prior research shows that changes in market-level bond illiquidity explain a significant portion of time series variation in corporate bond yield spreads (see Bao, Pan and Wang (2011)). A potential driver of market-wide illiquidity is the commonality in inventory cycles across bonds. We study how systematic price pressures vary over time based on the proportion of corporate bonds that experience an inventory cycle. Mutual fund outflows (inflows) are positively associated with commonality in positive (negative) cycles, implying that mutual funds' simultaneous sale (purchase) of bonds is material enough to generate widespread demand for liquidity. Both positive and negative cycles decline during the financial crisis, which is consistent with capital constraints faced by dealers (see Duffie, Garleanu and Pedersen (2007)).

In the cross-section of bonds, inventory cycles are less likely for smaller issue size, higher credit risk, closer to maturity and older bonds. These bond attributes are typically associated with lower secondary market liquidity. Since inventory cycles are constructed from completed transactions, these results support both the customer's desire to minimize trading in less liquid securities (see Choi, Shachar, and Shin (2017)) and the dealer's endogenous choice to build less risky positions (see Goldstein and Hotchkiss (2017)). Credit rating events are positively associated with inventory cycles that tend to reverse quickly, likely reflecting the fact that switching investor clienteles serve as a natural counterparty to offset dealer positions.

We examine whether bond mutual funds respond to signals of market imbalances as reflected in inventory cycles. We classify mutual funds' trading style as liquidity supplying when a fund helps lay off dealer risk by absorbing the inventory positions and liquidity demanding when a fund further strains the inventory positions of bond dealers. Following Da, Gao and Jagannathan (2011), we measure trades using changes in bond holdings over a fund's reporting period. In our sample obtained from Morningstar, bond funds report most often at the monthly frequency (72%), followed by quarterly reporting (25%). We overlay the change in bond holding over a reporting periods on the inventory cycle in a bond, and classify a holding change as liquidity supplying, demanding, or unclassified.[7] Aggregating the classification across all corporate bond holdings for a reporting period, we obtain a fund's composite "*LS_score*" for that period, with higher (lower) values of *LS_score* signifying a higher propensity to supply (demand) liquidity. Trading style is zero when the fund on average neither strains nor offsets dealers' inventory positions.

We use the fund trading style to answer the following questions: First, do bond funds vary in their trading styles? Second, does trading style predict risk-adjusted fund performance, and further, do market conditions affect performance? And finally, what explains the trading style? The returns attributable to trading style are distinct from the liquidity premium earned for holding illiquid bonds. Stated differently, we focus on *how* institutions implement the trades, rather than *which bonds* they hold in the portfolios.

We find that mutual funds on average exhibit a trading style that strains the inventory position of dealers; that is, in aggregate, mutual funds tend to sell (buy) a bond at the same time that other participants sell (buy) the bond, and this behavior is more pronounced during the 2007-09 financial crisis. In the cross-section, trading style varies across funds, and notably, a significant percentage of bond funds exhibit a trading style that absorbs the inventory position of dealers.

To understand whether mutual funds are rewarded for supplying liquidity, we examine 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 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? We build a panel predictive model where the dependent variable is trading style measured over a 12-month period. The key explanatory variables are the 12-month lagged

[7] That is, the change in bond holdings is classified as liquidity supplying if the fund buys the bond during an interval when dealers face sustained selling from customers. The opposite is classified as liquidity demanding. Change in bond holdings that do not overlap, or fall short of a minimum overlap threshold, with an inventory cycle are unclassified.

attributes that capture the nature of investor base, the characteristics of fund holdings, and the skill of the trading desk. The results suggest that funds with stable investor base, as evidenced by low investor flow-performance sensitivity, and lower investor outflows, are able to supply liquidity, as they are not forced into costly trading in response to investor flows (see Giannetti and Kahraman (2018)). Liquidity supplying funds exhibit a tendency to hold older and smaller bond issues, indicating that it is easier to supply liquidity in bond segments where dealer interest is lacking but also that the ability to manage an illiquid portfolio is an important skill for implementing a liquidity supplying trading style.

Fund families affiliated with broker-dealers are more likely to supply liquidity, which points to informational advantages that are difficult to replicate by unaffiliated funds. Younger and smaller funds are more likely to supply liquidity, which is an unexpected result, since larger funds in OTC markets enjoy informational advantages. One implication is that smaller funds could overcome the trading cost advantage enjoyed by large funds (see O'Hara, Wang and Zhao (2017)) by being strategic about when they trade. The model that includes fund fixed effects has higher explanatory power (26%) in relation to the model with observable fund attributes (6%), suggesting that the identity of the fund contains information on trading style. Trading style may reflect the fund manager's sensitivity to trading conditions, the skill of buy-side trading desk, and the strength of the relationship with dealer community.

As further evidence of the importance of fund identity, we find that trading style is persistent over time, although the strength of the persistence declines when markets are stressed. We observe significant differences in trading style in the cross-section of funds even when they face extreme flows. Notably, liquidity supplying funds (unlike liquidity demanding funds) continue to trade in a way that does not strain dealer inventories. Evidence in Goldstein, Jiang and Ng (2017) suggest that the concave flow-performance sensitivity of bond mutual funds could be an important source of bond market fragility, as poor performance induces large outflows and triggers fire-sale feedback effects. Our results suggest that fragility concerns may not apply uniformly across all bond mutual funds – while mutual funds in aggregate tend to further strain dealers' inventory positions, significant cross-sectional variation exists, and some funds supply liquidity by absorbing market imbalances.

This study furthers our understanding of liquidity sources in fixed income markets. As noted by SEC Commissioner Michael S. Piwowar, while bond trading platforms hold much promise, the majority of venues, even in recent years, restrict the customer's request-for-quotation (RFQ) messages to participating bond dealers.[8] We show that, despite similar (and likely, larger) information frictions in our sample period, mutual funds participate in liquidity supply when other participants need it. Buy-side institutions represent an increasing share of the investor base in corporate bonds and the economic importance of this source of liquidity cannot be overstated.[9] To tap into, and further encourage, this channel of liquidity supply, trading platforms must promote trading protocols that facilitate direct participation by buy-side institutions.

This study also contributes 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 results highlight that it is important to understand *how* a fund builds portfolio positions, in addition to *which bonds* the fund holds in the portfolio. We present a methodology to classify trading style that is specifically designed for bond markets. Data limitations introduce noise in our measure of trading style as corporate bonds account for only 35% of the total fund position changes in a reporting period. Despite this limitation, trading style contains useful information about future fund performance, which comes from all of the fund's portfolio positions.

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 trading 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 managing transaction costs and capturing a portion of the returns

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

[9] According to Federal Reserve data, corporate bond holdings of banks (-$404 million) and broker/dealers (-$250M) have declined while those of insurance ($533M), retirement funds ($326M) and mutual funds ($1,456) have increased between 2007 and 2014. (https://www.fitchratings.com/web_content/images/fw/fw-chart-20141111.htm).

to liquidity provision in bond markets.

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).[10]

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. The availability of TRACE database led to a significant boost on research on liquidity in the corporate bond market. Notable findings 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 (2016)), (b) TRACE reporting leads to 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 to higher bond yields (Friewald, Jankowitsch and Subrahmanyam (2012)), and (d) electronic trading systems are increasing their market share in 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 includes 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 include information on disseminated and non-disseminated historical transactions, including those in privately-traded 144A bonds; unmasked trade sizes that are

[10] The noise measure is downloaded from http://www.mit.edu/~junpan/.

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).[11] 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.[12]

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

[11] 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.
[12] We find similar results for a sub-sample of bond funds with average corporate bond holdings of 50% or greater.

sample. The snapshots of fund holdings 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% 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.

Research on the trading behavior of buy-side institutions has largely focused on equities markets due to availability of data. Anand, Irvine, Puckett and Venkataraman (2013) classify the trading style of equity mutual funds and pension funds based on transaction data made available by Abel-Noser. A key challenge for empirical research on bond funds is that similar data on the transactions of mutual funds and pension funds are not available.[13] 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 the fund's holdings in bonds 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

[13] 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.

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 funds' holdings increase over time, from about $600 billion to $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. Attracting counterparties via "quote shading" leads to a mean-reversion in dealer inventory. Empirical support from equity markets for these theoretical predictions is presented by Hansch, Naik, and Viswanathan (1998) and Panayides (2007) using data on LSE dealers and NYSE specialists, respectively.

We construct dealer inventory cycles based on customer-to-dealer transactions to identify scenarios where dealers have accumulated large positive or negative inventory positions. 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.[14] When customer buying and selling activity that is aggregated across dealers is balanced, it does not generate an inventory cycle. This encompasses situations where a dealer acts as an agent, rather than a principal, and simply transfers the position from one customer to another (see Harris (2016) and Choi and Huh (2017)), or situations where a dealer quickly offsets a principal position with one customer with another customer. Interdealer trading offers an important channel

[14] 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.

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 that the desired dealer inventory, which is not observable, is zero. Zero inventory is intuitively appealing because inventory requires capital commitment and exposes the position to volatile prices. The cycle begins when the cumulative inventory crosses zero and ends when the cumulative inventory crosses zero again from the opposite direction. Cumulative inventory is the signed, aggregate dollar inventory based on all dealers' trades with customers in the bond.[15]

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.[16]

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 dealer buying activity to accommodate persistent sell imbalances 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.[17] The length of the loading and unloading phase of the inventory cycle is similar indicating

[15] 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. Interdealer trades are not included because they do not impact aggregate dealer positions.
[16] We find similar results when we impose a minimum inventory cycle length of 15 days.
[17] For an individual dealer, Schultz (2017) finds that inventory position is mean-reverting, and the half-life of an active

that peak 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 2 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, and abnormal return as the bond return less the benchmark index return.

For positive cycles, Panel A shows the build-up in dealer inventory during the load phase and the reduction in dealer inventory during the unload phase. The abnormal returns are negative in the load phase, which is consistent with dealers lowering their quotes to manage slow-moving inventory, and positive in the unload phase, which points to reversals in bond prices that compensate dealers for absorbing customer flow (see Kraus and Stoll (1972) and Grossman and Miller (1988)). In Panel B, we find the opposite patterns in dealer inventory and abnormal returns for negative 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 those findings, Panel A illustrates that price pressures in positive cycles (i.e., sell herding) almost entirely reverse while some component of price changes 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 cycles.[18] During the build-up (loading) phase, returns are negative for the positive cycles and positive for the 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 (2011) and Cai et al. (2018) also report that reversals exhibit significant asymmetry –

individual dealers' inventory is about a month for actively traded investment grade bonds, and about five weeks for high yield bonds. We note that our inventory cycles reflect the aggregate positions of all dealers in a bond.

[18] 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.

price reversals are on average stronger after a price reduction than a price increase. This asymmetry is consistent with Edmans, Levit, and Reilly (2017) who argue that when investors have more flexibility (buying any bond), their trades are likely to be more informed.

We next investigate the length of inventory cycles and the dollar value of peak inventory by year. Since the TRACE data begin in July 2002 and our calculation of trading style (see Section IV) 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, while still large and significant, are relatively 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 an increase in dealers playing an agency role by matching 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. The evidence on reduction in dealer capital may raise questions about the measurement of our inventory cycles. However, even as the agency role of dealers has grown, Bessembinder et al. (2017) find that principal volume remains in excess of 90% of total trading volume in bonds.

We examine the incidences of inventory cycles around a well documented bond-specific stress event - the downgrade of a bond from investment to speculative grades by at least one of the three credit rating agencies (see Figure 2, Panel C). [19] Consistent with customer selling imbalance, bond downgrades are associated with an increase in aggregate dealer inventory. In addition, about 36 percent of downgraded bonds experience a positive inventory cycle while the percentage of bonds in negative cycles significantly drops around event. 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 an inventory cycle as an empirical proxy for abnormal price pressure in a bond. Large customer imbalances could be driven by correlated trades of institutional investors in response to new information or induced by liquidity shocks, 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 commonality in inventory cycles by aggregating incidents of price pressure across bonds. In Table 3, Panel A, we study whether aggregate inventory cycles co-move with aggregate market conditions by estimating the following time-series regression:

$$PropCycle_t = \propto + \sum_{k=1}^{n} \beta_k X_{kt} + \varepsilon_t \qquad (1)$$

where $PropCycle_t$ is the proportion of sample bonds that are in a positive (column 1) or a negative (column 2) cycle for at least five days in month *t*, and X_{kt} include the average *VIX* index as a measure of market stress; the *Noise* measure constructed by Hu, Pan and Wang (2013) and the crisis dummy to capture supply of arbitrage capital; customer demand as captured by aggregate bond fund flows, and supply of bonds from the primary market as captured by aggregate corporate bond issuance. Following the literature, the crisis

[19] For a downgrade event, we use the earliest date of the downgrade from S&P, Moody's, or Fitch.

dummy equals one for the period from July 2007 to April 2009 and zero otherwise. All variables are measured contemporaneously over month *t*.

The results indicate substantial level of commonality in bond-level price pressure, and point to both supply- and demand-side explanations. 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 suggests that primary market may act as a substitute for purchasing bonds from the secondary market.

Aggregate inventory cycles do not have a close connection with *VIX* index and *Noise* measure of arbitrage capital. For both positive and negative cycles, the coefficient of the *crisis* dummy is negative and statistically significant suggesting that commonality in inventory cycles is associated with capital constraints faced by bond dealers after controlling for fund flows.[20]

In Table 3, Panel B, we examine the cross-sectional relationship between the probability of observing an inventory cycle in a bond and a number of bond characteristics. We report Fama-MacBeth estimates for the following monthly cross-sectional regressions:

$$BondInCycle_{i,t} = \beta_{lag} BondInCycle_{i,t-1} + \sum_{k=1}^{n} \beta_k X_{ki,t} + \sum F_i + \varepsilon_{i,t} \qquad (2)$$

where $BondInCycle_{i,t}$ equals one if bond i experiences a positive (column 1) or negative (column 2) inventory cycle for at least five days in month *i*, and equals zero otherwise. $X_{ki,t}$ include bond issue size,

[20] In unreported analysis, both VIX index and Noise measures have a negative and statistically significant (at the 1% level) effect on positive cycles when *crisis* dummy is not included in the specification, indicating that the explanatory power of these variables is subsumed by the *crisis* variable.

bond time to maturity, bond age since issue, an indicator variable that equals one for investment grade bonds and zero otherwise, and indicator variables for bonds that have been upgraded or downgraded within two months surrounding month *t*. Results indicate that inventory cycles are less likely for older bonds and those with smaller issue size, higher credit risk, and shorter maturity. Building on evidence from Edwards, Harris and Piwowar (2007), our results suggest that inventory cycles are less likely in bonds with lower trading activity and higher trading costs, which likely reflects both the customer's desire to minimize trading in less liquid securities (see Choi et al. (2017)) and the dealer's endogenous choice to avoid inventory in risky bonds (see Goldstein and Hotchkiss (2017)).[21] 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 2, Panel C, an inventory cycle is more likely when the bond experiences an upgrade or downgrade event that generates trading interest from customers.

Conditional on observing an inventory cycle, we next examine how the length of inventory cycle (in days) and the peak inventory (in $) are affected by bond attributes and market conditions. This analysis is related to the literature on dealer networks that maps highly connected dealers at the core and sparsely connected dealers at the periphery (see Li and Schurhoff (2016), DiMaggio, Kermani and Song (2016), Hollified, Neklyudov and Spatt (2017)). The literature shows that intermediation chains are shorter when a central dealer is involved, and longer when markets are stressed, or more difficult to complete trades. In comparison, inventory cycles that we examine are observed when aggregate customer flow to the dealer community is material and sustained. The higher peak inventory captures intensity and the longer cycle length potentially reflects longer dealer intermediation chains, holding all else the same.

In Table 3, Panel C, the results for both the positive and negative cycles show that the peak inventory is smaller and the length is longer for cycles in smaller and older bonds, consistent with the fact that these bonds are less frequently traded and may require a long time for the dealers to unload and go back to neutral. Longer-maturity bonds are associated with longer and deeper cycles, although the effects

[21] 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.

are economically small. Conditional on observing a positive cycle, both upgrade or downgrade credit events increase peak inventory but do not affect cycle length. A likely explanation is that new investor clienteles in different rating categories serve as natural counterparties that quickly offset dealer positions. Dealers are therefore willing to commit capital as inventory risk is lower. For negative cycles, credit events are associated with shorter cycles but do not affect peak inventory, consistent with dealer's ability to quickly locate existing owners of the bonds who may want to sell. These results highlight the importance of dealer-customer relationships – dealers track who currently owns a bond and who may be a natural clientele given a changing circumstance.

The coefficients of the *VIX* index and the crisis dummy indicate that higher market uncertainty leads to an increase in cycle length. These conditional results are broadly consistent with earlier evidence on the probability of observing a cycle. When it is harder to unload inventory, dealers are more reluctant to perform their intermediation role, making it less likely to observe inventory cycles to start with.

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) the bond holding during a positive (negative) inventory cycle. The opposite is considered liquidity demanding. Stated differently, a liquidity supplying (demanding) bond fund buys (sell) the bond during an interval when other customers in aggregate are selling the bond. The buying (selling) activity of the fund helps absorb (further strain) the dealers' inventory.

The market structure of corporate bonds offers several mechanisms for institutions to gauge liquidity conditions in a bond. Dealers "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 updated many times intra-day using automated pricing models. Buy-side institutions may also 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 (such as MarketAxess), 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.

During a positive inventory cycle, it is likely that dealers signal the larger than desired inventory by lowering the indicative quotes in the runs. In our framework, a bond fund with a trading style that is liquidity supplying will respond opportunistically by buying the bond, thus alleviating dealer inventory positions. Institutions could contact dealers, via a messaging system or by phone, 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 (see Anand et al. (2013) and Cheng et al. (2017)), or daily trade imbalance from TAQ data (see Da et al. (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; however, Da et al. (2011) find that liquidity supply is not a significant source of outperformance for equity mutual funds. 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 structure of equity and bond markets suggest that trading strategies that work in equity markets may be more difficult to implement in bond markets.

Our methodology is designed to take advantage of a fixed-income market structure where inventory positions of market makers can be measured with accuracy. Figure 3 illustrates the advantage of classifying trading style using dealer inventory cycles (IC) versus the change in dealer inventory (ΔI, i.e., customer trade imbalance from TRACE) or bond returns (R_b). The figure depicts a fund with an increase in bond holdings (ΔH) in a reporting period that coincides with positive inventory cycle (IC = +), implying the fund helps absorb the dealers' inventory. The load and the unload phase of inventory cycle encompass periods of opposite bond returns, and opposite sign changes in dealer inventory (ΔI). Thus, depending on whether the fund's reporting period overlaps with the load or unload phase of the inventory cycle, the correlation between change in fund holdings and the change in dealer inventory (ΔH, ΔI), or the correlation between change in fund holdings and bond returns (ΔH, R_b) could be either positive or negative. Using our methodology, if the correlation between the change in fund holdings and sign of the inventory cycle (ΔH, IC) is positive, 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.[22]

After classifying the change in each bond holding for a fund-reporting period as liquidity supply, or demand, we calculate the *LS_score* for the fund-reporting period, as follows:[23]

$$LS\_score = \frac{Liquidity\ supplied\ (\$) - Liquidity\ demanded\ (\$)}{Liquidity\ supplied\ (\$) + Liquidity\ demanded\ (\$) + Unclassified\ (\$)} \qquad (3)$$

In equation (3), changes in fund holdings that do not coincide or significantly overlap with an inventory cycle in a bond are marked as "unclassified." 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.[24] Finally, we eliminate changes in fund holdings that overlap with primary bond issuance, focusing only 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

[22] 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.
[23] 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.
[24] 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.

supplying; however, this is not the focus of our study (see Nagler and Ottonello (2018)).

From equation (3), the *LS_score* of a fund that is not responsive to dealer inventory "signals" is zero. While some holding changes would be randomly assigned as liquidity supplying or liquidity demanding, the expected net effect is zero, with no expectation of style persistence. For institutional reasons such as herding behavior of institutions (Cai et al. (2018)), index rebalancing (Dick-Neilsen and Rossi (2016)), and credit rating events (Ellul, Jotikasthira and Lundblad (2011)), a typical bond mutual fund is expected to sell a bond when other participants are selling the bond. Thus, we expect that *LS_score* of mutual funds on average will be less than zero. Nonetheless, bond mutual funds differ substantially in their investor clientele, investment strategy, and trading technology, and some bond funds may selectively participate in opportunities to supply liquidity when others need it based on signals about trade imbalance (i.e., quantity) or dealer quotes (i.e., price), or both. For these funds, we expect that *LS_score* of will be greater than zero.

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 a robustness check, we replicate many of our analyses for funds that hold 50% of their portfolio in corporate bonds during our sample period. The average corporate bond holdings for this sample is 78%. Another limitation is that while the majority (72%) of funds report at the monthly level, our 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.

Table 4, Panel A reports descriptive statistics for *LS_score* over our sample period. An *LS_score* of zero points to a trading style that neither absorbs nor strains 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 pooled mean and median values of *LS_score* are both -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. Thus, as expected, mutual funds in aggregate exhibit a trading style that demands liquidity from bond dealers.

The statistics in Panel A also indicate that the average *LS_score* exhibits variation over time. In comparison with the full sample mean of -0.055, *LS_score* 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, suggesting that during that time of stress, bond funds exhibit a trading style that demands liquidity from dealers. 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 needs 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.

Importantly, we observe significant cross-sectional variation in trading style, with the 25th percentile of -0.168 and the 75th percentile of 0.057. A significant percentage of bond funds exhibit a trading style that absorbs dealer inventory.[25] In Table 4, Panel B, we further explore the cross section by assigning bond funds into quintiles in each reporting period based on the 12-month rolling average *LS_score* and examining the descriptive statistics on fund attributes across the quintiles. 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 largely similar across quintiles.

[25] In a related study using TRACE data, Choi and Huh (2016) show that dealers are increasing relying in recent years on "prearranged" trades that match one customer to another customer, which points to liquidity provision by customers instead of dealers. Since TRACE data do not provide the identity of customer, Choi and Huh (2016) are unable to track participation by any individual participant. While there is an uptick in pre-arranged trades in recent years, Bessembinder et al (2017) find that it represents a small slice of the overall trading activity in corporate bonds market.

V. Trading style and fund performance

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

$$R_{i,t} - R_{ft} = \alpha_i + \beta_{i,STK} STK_t + \beta_{i,BOND} BOND_t + \beta_{i,DEF} DEF_t + \beta_{i,OPTION} OPTION_t + \varepsilon_{i,t} \quad (4)$$

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 calculated as the return spread between the GNMA mortgage-backed security index, which contains prepayment options, 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:

$$\propto_{i,t+1} = \beta_1 LS\_score_{i,[t-11,t]} + \beta_2 LS\_score_{i,[t-11,t]} * MktLiq_{t+1} + \sum_{k=1}^{n} \beta_k X_{ki,t} + \sum T_{t+1} + \sum FC_i + \varepsilon_{i,t+1} \quad (5)$$

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 the interaction between trading style and measures of market stress, including the *VIX* Index, the *crisis* dummy, 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 affiliation indicator that equals one if the fund family is affiliated with a broker-dealer and zero otherwise, maximum percentage rear load fees, proportion of assets held 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. The averages are all value weighted. These variables are designed to capture general fund attributes such as its age and size, as well as characteristics of the fund's assets and liabilities. 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.

The results in Table 5 provide 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. The coefficient on *LS_score* is positive and significant at the 5% level. 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 a lower future monthly alpha of 2.1 basis points (relative to funds in the middle quintiles). 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 a relatively higher future monthly fund alphas of 3.0 basis points.

Models (3) to (5) examine how the effects of trading style on fund performance vary across periods with differing levels of market stress. 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 rewards to liquidity supply are larger in the crisis period. We introduce the interactions of *LS_score* with *Noise* in model (4) and *VIX* index in model (5). In these models, the impact of *crisis* variable is subsumed by other market illiquidity variables, whose interactions with *LS_score* have significant and positive coefficients. Funds with a liquidity supplying style earn higher compensation when markets are stressed and illiquid. This evidence complements the findings of several studies that illiquidity factor is an important determinant of asset returns (Bao, Pan, and Wang (2011), Nagel (2012), Friewald, Jankowitsch, and Subrahmanyam (2012), among others). Acharya and Pedersen (2005) show that security characteristics could serve as an illiquidity hedge in a fund's portfolio. Our results suggest in contrast to the assets' illiquidity, which tends to be associated with high but pro-cyclical returns, a fund's trading style that is liquidity supplying might help partially offset the decline in fund performance when markets are stressed.

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 (Q5) *LS_score* quintiles is 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. Model (4) presents the economic impact of market conditions on performance of trading style. When *Noise* 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. When *Noise* 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. To put this number in perspective, the average monthly gross alpha of our sample funds is 3.40 basis points. Overall, we conclude that trading style has an economically material impact on fund performance.

Model (6) confirms that the relation between trading style and fund performance is robust to the inclusion of fund attributes and portfolio characteristics. The coefficient estimates of low (Q1) and high (Q5) *LS_score* quintiles in models (2) and (6) are similar in magnitude. In models (7) and (8), 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. While the Q5-Q1 difference in coefficient estimates is statistically significant in both columns, the economic magnitude of the difference is larger for the non-investment grade sample than the investment grade sample.

In model (9), we examine a sample of bond funds with an allocation to corporate bonds over our sample period that exceed 50 percent. For these bond funds, which hold about 78% of their portfolios in corporate bonds, trading style can be estimated more precisely due to higher overlap between the fund's position changes and the inventory cycles of corporate bonds in the TRACE database. The Q5-Q1 monthly difference in alphas is 6.5 basis points, marginally larger than that 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 and that trading style exhibits significant variation across funds. What explains trading style, and further given the impact on fund performance, why do other funds not mimic the liquidity supplying style? In this section, we consider several explanations. A mutual fund's ability to opportunistically respond to dealer inventory shocks may depend on the flexibility afforded by its investment strategy (asset side) and the behavior of fund investors (liability side). To the extent that the fund holds cash or liquid bonds, or a large number of bonds in the portfolio, it might have greater ability to purchase bonds in a positive cycle, or sell bonds in a negative cycle. Alternatively, the investment strategy of a liquidity supplying fund could tilt its portfolio towards bonds that tend to be less liquid and have a greater opportunity to supply liquidity when others need it. On the funding side, flexibility to engage in liquidity supply could also come from positive investor fund flows, or from flows that are stable and less sensitive to the fund's past performance.

Another potential explanation for variation in trading style is trading relationships – 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.[26] Hendershott, Li, Livdan, and Schurhoff (2016) develop a model on costs and benefits of

[26] Green, Hollifield and Schurhoff (2007) develop a model where fragmentation and lack of transparency in the bond market create opportunities for dealers to exploit monopoly power over customers.

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*:

$$LS\_score_{i,[t+1,t+12]} = \sum_{k=1}^{n} \beta_k X_{ki,t} + \sum T_t + \sum F_i + \varepsilon_{i,t} \quad (6)$$

All models include time fixed effects, and in addition, models (5)-(6) includes fund family and fund fixed effects, respectively. Standard errors are double-clustered by fund family and reporting period.

In model (1), we study the impact of fund investors on trading style. The coefficient on lagged fund flows is positive and statistically significant, implying that investor redemptions hurt the fund's ability to supply liquidity. Further, we find that bond funds with higher 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's response to fund performance. However, the results in model (1) indicate that these fund features convey no incremental information beyond the flow-performance sensitivity, which may act as a sufficient statistic for many explicit and implicit design features. Consistent with Giannetti and Kahraman (2018)'s findings on equity fire sales, our results suggest that funds with a stable investor base are more likely to 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 has information on future trading style. Funds that hold older and smaller bonds have a higher propensity to supply liquidity, suggesting that bond funds supply liquidity in segments of the market where dealer interest is lacking. The number of bond holdings or the percentage of portfolio held as cash do not explain trading style.[27] Trading style shows a negative association with bond duration and credit risk. Thus, bond funds with a trading style that supplies liquidity have lower exposures to interest rate and credit risk, but higher exposures to bond illiquidity. In model (3), we find a positive and statistically significant coefficient on the broker affiliation indicator, which points to informational advantage of being affiliated with a broker-dealer firm. Perhaps surprisingly, liquidity supplying funds tend to be younger and smaller in terms of TNA. With the exception of fund age, which loses statistical significance, the results are similar when we combine all the variables in model (4), with a corresponding increase in explanatory power to 6%.

We observe a significant increase in the explanatory power when we include fund-family fixed effects in model (5) (15.3%), relative to model (4) (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 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.

The results are broadly similar when we separately examine investment grade and non-investment grade bond funds. Notable differences are that the percentage of portfolio held as cash impacts trading style for non-investment grade funds while broker affiliation and fund size are not significant for investment-grade funds. In model (9), the results for bond funds with average corporate bond allocations that exceed 50 percent are broadly similar to those for the full sample in model (4), confirming that our findings are not driven by noise in measuring trading styles for funds with smaller corporate bond allocations.

[27] Cash holding is positive and significant at the 10% level when it is included alone. It is, however, negatively correlated with portfolio duration and when both variables are included, cash holding becomes insignificant.

VII. Persistence in trading style

The results in Table 6 indicate that trading style is largely a fund attribute. If so, it should be persistent over time. We examine this conjecture in Table 7. In Panel A, we report a transition matrix for funds assigned into quintiles based on the 12-month rolling average trading style. The transitions are from months [*t-11, t*] to non-overlapping future months [*t+1, t+12*] and [*t+13, t+24*]. If past trading style contains no information for future trading style, then funds should randomly sort on trading style in future periods. Under this null, funds have an equal (20%) probability of being assigned to an *LS_score* quintile in future periods. The results in Panel A strongly reject the null. 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 that 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 remaining in the same quintile. The Pearson's chi-square test statistically rejects the null that past trading style contains no information for future trading style.[28]

To further investigate the persistence, we use a regression framework that builds on specifications in Table 6. Table 7, Panel B reports OLS estimates for panel predictive regressions of funds' average *LS_score* on funds' past average *LS_score* and its interaction with various aggregate market conditions. Average *LS_score* is calculated over the period from months [*t+1, t+12*] while past average *LS_score* is calculated over the period from months [*t-11, t*]. All models include the explanatory variables and the time fixed effects as in model (4) of Table 6. For the full sample (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 coefficients on lagged *LS_score* are positive and highly significant, implying that the fund's past trading style contains relevant information about future trading style. In models (2)-(4), the coefficients on interaction between lagged *LS_score* and market stress are negative, indicating that it is challenging for bond funds to maintain trading style in periods of market stress. In model (5), we interact

[28] We also find that the difference in *LS_score* between Q1 and Q5 funds is significant in future months [*t+1, t+12*] and [*t+13, t+24*].

LS_score with aggregate investor flow to bond mutual funds, a measure of market funding conditions. The results suggest that aggregate fund flows do not impact persistence in trading style; however, when we interact lagged *LS_score* with investor flows to each individual fund, the coefficient on interaction term is positive and statistically significant at the 10% level. The result suggests that fund flows may reinforce the ability of funds to maintain trading style in future periods.

Finally, we conduct an additional analysis to test whether funds' trading style remains robust in periods of extreme flows. Goldstein et al. (2017) argue that the concave flow-performance sensitivity of bond mutual funds may be an important source of bond market fragility, as poor performance induces large outflows and triggers fire-sale feedback effects. If liquidity supplying funds still trade in the manner that avoids straining dealers' risk bearing capacity, such fragility concern may not apply uniformly across all funds and may be somewhat mitigated. In the spirit of Coval and Stafford (2007), we identify periods when funds face large inflows and outflows. These large flows are plausibly exogenous events that force fund trading. We then examine whether liquidity supplying and demanding funds trade differently in response to these shocks. Table 8, Panel A provides a description of the events. We sort funds into quintiles based on a 12-month moving average of flows. Funds in the lowest quintile experience large monthly outflows of -8.6% of TNA. To meet this redemptions, these funds reduce their cash, sell government bonds, and importantly for our analysis, sell some of their corporate bond holdings (column 4). Columns (5) and (6) show that the proportion of value associated with bonds sold exceed that of bonds purchased for these funds. At the opposite end, funds in the highest flow quintile receive inflows of 17.11% of TNA, and as a result are net buyers of corporate bonds.

Table 8, Panel B re-examines (as in Table 7) how the ex-ante trading style of a fund is associated with the fund's trading style in the face of large inflows (Flow Q5, models 4-6) and outflows (Flow Q1, models 1-3). We present the results of the following estimation:

$$LS\_score_{i,buy\ or\ sell,[t+1,t+12]} = \beta_{LS} LS\_score_{i,[t-11,t]} + \sum_{k=1}^{n} \beta_k X_{ki,t} + \sum T_t + \varepsilon_{ibuy\ or\ sell,,t} \quad (7)$$

where $LS\_score_{i,buy\ or\ sell,[t+1,t+12]}$ is based on fund i's trading style associated only with *selling* in the large outflow quintile, and with *buying* in the large inflow quintile. $LS\_score_{i,[t-11,t]}$ is based on funds' overall trading in the 12-month period ending in month *t*. The model includes time fixed effects and control variables similar to those in Tables 6 and 7.

We find that funds with a higher *LS_score* are relatively more liquidity supplying even when facing large flow shocks. That is, a fund's trading style persists even when the fund is forced to buy or sell due to extreme investor flows. Comparing the coefficients in models (1) and (4) shows that the magnitude of the effect is larger when funds are buying in response to inflows than when they sell due to outflows. The asymmetry is consistent with selling being more constrained than buying since funds are restricted in only selling the bonds that they hold. We find similar results when we use Q1 and Q5 dummies instead of the continuous *LS_score* variable (models 2 and 5). The differences between Q1 and Q5 funds are statistically significant, confirming that liquidity demanding funds are more likely than liquidity supplying funds to demand liquidity in their flow-induced trading. The addition of controls yields similar inferences for buying when funds have large inflows but weakens the results for selling during outflows. Overall, these results show that fund-specific skills and preferences play an important role in mitigating or reinforcing the destabilizing effects of flow-induced trades.

VIII. Conclusions

Regulators and market participants are concerned that the growth in corporate bond issuance activity and the reduction in dealer capital point to a liquidity problem in bond markets. A related concern is whether the liquidity transformation and periodic rebalancing needs of investment funds, including both exchange traded funds and open-end mutual funds, could further strain the risk bearing capacity of bond dealers. Against this backdrop, the general perception among bond investors, according to 2017 Greenwich Associates survey, is that buy-side institutions, including mutual funds, represent an important liquidity source. This role of institutions is relatively unstudied. Our paper attempts to fills this gap in the literature.

We focus on mutual funds, an important category of bond-focused buy-side institutions. We develop a methodology to classify a fund's trading style into liquidity demanding versus supplying. Our methodology is specifically designed for bond markets to take advantage of a market structure where liquidity suppliers (dealers) are clearly identified. We find that mutual funds in aggregate sell (buy) a bond when other participants are also selling (buying), thus further straining dealer capacity. However, trading styles vary across funds. We identify a significant percentage of funds that respond to a trade imbalance signal by absorbing the dealers' inventory, even when they face extreme investor flows. These funds are associated with a higher alpha, and the impact is more pronounced when markets are stressed. Among the drivers of trading style, stable funding, family affiliation with broker-dealer, and trading desk skill influence the fund's ability to take advantage of the ebb and flow of markets. The fund's identity plays an important role, which points to the fund manager's ability to build the investment process around liquidity cues.

This study furthers the understanding of liquidity sources in bond markets. 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."[29] We find that some mutual funds exhibit a persistent strategy of absorbing customer trade imbalances, even though the bond market structure during our sample period inserted the bond dealer in virtually all transactions between buyers and sellers. Recent years have witnessed a growth in "all-in-all" trading platforms that allow select buy-side institutions to participate (e.g., Market Axess' Open Trading platform). However, survey evidence indicates that market participants expect request-for-quote (RFQ) platforms based on traditional bond dealers to dominate in the future.[30]

Our results have important policy implications. For designers of trading systems, our results imply that trading platforms can expand the liquidity pool of counterparties, and also improve risk sharing for bond dealers, by developing trading protocols that facilitate direct access to buy-side institutions. For regulators, our evidence suggests that bond market liquidity can be enhanced by removing institutional frictions that impede broad investor participation in liquidity provision.

---

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

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

References

Acharya, V. and L. H. Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics,* 77, 375-410.

Amihud, Y. and H. Mendelson, 1980, Dealership market: Market making with inventory, *Journal of Financial Economics* 8, 31–53.

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs. *Review of Financial Studies*, Vol. 2 (25), 557-598.

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman, 2013, Institutional Trading and Stock Resiliency: Evidence from the 2007-09 financial crisis. *Journal of Financial Economics*, 108, 773-797.

Asquith, P., A. S. Au, P. Covert, P. A. Pathak, 2013, The market for borrowing corporate bonds. *Journal of Financial Economics*, 107, 155-182.

Bao, J., M. O'Hara, and X. Zhou, 2017, The Volcker Rule and market-making in times of stress, *Journal of Financial Economics*, Forthcoming.

Bao, J., J. Pan, and J. Wang, 2011, The illiquidity of corporate bonds, *Journal of Finance*, 66, 911-946

Bessembinder, H., W. Maxwell, and K. Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics, 82*(2), 251.

Bessembinder, H., S., Jacobsen, W. Maxwell, and K. Venkataraman, 2017, Capital commitment and illiquidity in corporate bonds, *Journal of Finance*, Forthcoming.

Cai, F., S. Han, D. Li, and Y. Li, 2018, Institutional herding and its price impact: Evidence from the corporate bond market, *Journal of Financial Economics,* forthcoming.

Cheng, S., A. Hameed, A. Subrahmanyam and S. Titman, 2017, Short-term reversals: The effects of past returns and institutional exits, *Journal of Financial and Quantitative Analysis, 52*, 143-173.

Chen Y., and N. Qin, 2017, The behavior of investor flows in corporate bond mutual funds, *Management Science,* 63, 1365–1381.

Chernenko, S, and A. V. Sunderam. Liquidity transformation in asset Management: Evidence from the cash holdings of mutual funds, working paper, Harvard Business School.

Choi, J., and Y. Huh, 2017, Customer liquidity provision: Implications for corporate bond transaction costs, working paper, University of Illinois.

Choi, J., O. Shachar, and S. S. Shin, 2017, Dealer Liquidity Provision and the Breakdown of the Law of One Price: Evidence from the CDS-Bond Basis, *Management Science*, forthcoming.

Cici, G., and S. Gibson, 2012, The performance of corporate bond mutual funds: Evidence based on security-level holdings, *Journal of Financial and Quantitative Analysis*, 47, 159-178.

Coval, J., and E. Stafford, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics*, 86, 479-512.

Da, Z., P. Gao, and R. Jagannathan, 2011, Impatient Trading, liquidity provision, and stock selection by mutual funds, *Review of Financial Studies*, 24, 675-720

Dick-Nielsen, J. and M. Rossi., 2017, Dealer inventory and the cost of immediacy, working paper, Copenhagen Business School and Texas A&M University.

Di Maggio, M., A. Kermani, Z. Song, 2016, The value of trading relationships in turbulent times, *Journal of Financial Economics,* Forthcoming.

Duffie, D., N. Gârleanu, and L. H. Pedersen, 2007, Valuation in over-the-counter markets, *Review of Financial Studies*, 20(5), 1865-1900.

Ederington, L. H., W. Guan, and P. K. Yadav, 2015, Dealer spreads in the corporate bond market: Agent versus market-making roles, working paper, University of Oklahoma.

Edmans, A., D. Levit, and D. Reilly, 2017, The Effect of Diversification on Price Informativeness and Governance, working paper, London Business School.

Edwards, A., L. Harris, and M. Piwowar, 2007, Corporate bond market transaction costs and transparency, *Journal of Finance*, v63i3, 1421-1451

Ellul, A., C. Jotikasthira, and C. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics*, 101, 596-620.

Friewald, N., R. Jankowitsch, and M. Subrahmanyam, 2012, Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises, *Journal of Financial Economics*, 105, 18-36.

Friewald, N. and F. Nagler, 2016, Dealer inventory and the cross-section of corporate bond returns, working paper.

Giannetti, M., and B. Kahraman, 2018, Open-end organizational structures and limits to arbitrage, *Review of Financial Studies*, 31, 773-810.

Green, R., B. Hollifield, and N. Schürhoff, 2007, Financial Intermediation and the Costs of Trading in an Opaque Market, *Review of Financial Studies*, 20, 275-314.

Grossman, S.J., and M.H. Miller, 1988, Liquidity and market structure, *Journal of Finance*, 43 (3), 617-633.

Goldstein, I., H. Jiang, and D. Ng, 2017, Investor flows and fragility in corporate bond funds, *Journal of Financial Economics*, Forthcoming.

Goldstein, M., E. Hotchkiss, and E. Sirri, 2007, Transparency and liquidity: A controlled experiment on corporate bonds, *Review of Financial Studies*, 20, 235-273.

Goldstein, M., and E. Hotchkiss, 2017, Providing liquidity in an illiquid market: Dealer behavior in U.S. corporate bonds, working paper, Babson College.

Hansch, O., N. Y. Naik, and S. Viswanathan, 1998, Do inventories matter in dealership markets? Evidence from the London Stock Exchange, *Journal of Finance*, 53, 1623-1656.

Harris, L., 2016, Transaction costs, trade throughs, and riskless principal trading in corporate bond markets, working paper, University of Southern California.

Hendershott, T., D. Livdan, D. Li, and N. Schürhoff, 2016, Relationship trading in OTC markets, working paper, UC Berkeley.

Hendershott, T. and A. Madhavan, 2015, Click or call? Auction versus search in the over-the-counter market, *Journal of Finance*, 70, 419-447.

Hollified, B., A. Neklyudov, and C. Spatt, 2017, Bid-Ask spreads, trading networks, and the pricing of securitization, *Review of Financial Studies,* forthcoming.

Hu, G.X., J. Pan, and J. Wang, 2013, Noise as information for illiquidity, *Journal of Finance*, 68, 2341-2382.

Kraus, A., and H. Stoll, 1972, Price impact of block trading on the New York Stock Exchange, *Journal of Finance*, 27 (3), 569-88.

Li, D., and N. Schürhoff, 2018, Dealer networks, *Journal of Finance,* forthcoming.

Massa, M., A. Yasuda, and L. Zhang, 2013, Supply uncertainty of the bond investor base and the leverage of the firm, *Journal of Financial Economics*, 110, 185-214.

Nagel, S., 2012, Evaporating liquidity, *Review of Financial Studies*, 25, 2005-2039.

Nagler, F., and G. Ottonello, 2018, Structural changes in corporate bond underpricing, working paper, Bocconi University.

O'Hara, M., Y. Wang, and X. Zhou, 2017, Best execution of corporate bonds, *Journal of Financial Economics*, forthcoming.

Panayides, M., 2007, Affirmative obligations and market making with inventory, *Journal of Financial Economics*, 86, 513-542.

Puckett, A., and S. Yan. 2011. The interim trading skills of institutional investors. *Journal of Finance,* 66, 601–633.

Schultz, P., 2001, Corporate bond trading costs: A peek behind the curtain, *Journal of Finance*, 56, 677-698.

Schultz, P., 2017, Inventory management by corporate bond dealers, working paper, University of Notre Dame.

Stoll, H.R., 1978, The supply of dealer services in securities markets, *Journal of Finance*, 33 (4), 1133-1151.

Appendix 1: Inventory cycles

We refer to a cycle during which aggregate dealer 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. 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.

Simply accumulating inventory over time is prone to several issues: potential reporting errors that may compound infinitely;[31] our inability to separate proprietary positions from market making;[32] and the lack of information on inventory that dealers hold from primary market operations. To minimize the impact of these issues, we make an adjustment when the cycle length exceeds three calendar months (63 trading days). 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 discussed in Duffie (2013) and Schultz (2017) for an active, individual dealer.

In the first 63 trading days, we accumulate the dealer imbalances from the beginning of the cycle, which reflects the accumulation of daily customer imbalance absorbed by the dealer community. The dealer inventory is set equal to the cumulative dealer imbalance. Example 1 provides the simplest case, in which the cycle ends within the first 63 trading days as a result of new trades pushing the inventory across zero. Examples 2-4 represent the cases where a cycle becomes longer than 63 trading days as the inventory does not revert to zero during this period. For these cases, we drop the daily dealer imbalance that occurs 63 trading days ago ("older") from the cumulative dealer imbalance calculation. Dropping the older imbalance can cause a new inventory cycle to begin in the opposite direction.[33] We make an adjustment to the starting

[31] 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.

[32] The inventory positions of dealers are typically mean-reverting suggesting that the trade is motivated by liquidity provision. Proprietary positions that are motivated by information are unlikely to show similar patterns. Given that trade motivation is not reported, it is not possible to separate the two types of dealer positions.

[33] As robustness, we construct a simple 63-day cumulative inventory measure (discussed later) and find similar results.

inventory to counteract the mechanical effect, which is best explained using a few different scenarios.

In example 2, we consider an inventory cycle that ends on a day without any reported transactions in the bond. That is, the inventory is pushed across zero due to the older daily imbalance being dropped. In this case, we reset the starting inventory of the new cycle to zero. In example 3, a cycle ends on a day with reported transactions in the bond but also and older imbalance being dropped on that same day. The older imbalance is sufficient to push the inventory across zero. In this case, the starting inventory of the new cycle is the reported transactions on the day. In example 4, it is the combination of older imbalance dropping out and the new trades that cause the inventory to cross zero. In this case, the starting inventory of the new cycle is the residual of the new trades that is in excess of zero after offsetting the previous day inventory.

Example 1: Short cycles

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. Column 2 presents the count of the days that the bond is in an inventory cycle. Column 3 presents the (signed) daily aggregate dealer imbalance, which is the opposite of customer imbalance and represents the incremental inventory taken on by dealers on that day. Column 4 presents the cumulative imbalance from start of the cycle. Column 5 presents the 63-trading day rolling sum of daily imbalances. In example 1, the bond starts trading for the first time on trading day 1; therefore cumulative imbalance and the rolling sum imbalance until day 63 are identical. Column 6 presents our "inventory" measure. 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. Column 8 reports the cycle length.

We highlight the inventory measure in bold and italics. The column where the inventory is drawn from (either cumulative imbalance in column 4 or rolling sum imbalance 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 drawn from the cumulative imbalance.

	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 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 cumulative imbalance 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 days, 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 increase positions 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 that ends on a day when older imbalance drops 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 imbalances are dropped from inventory. As discussed earlier, when a cycle becomes longer than 63 trading days, we switch the inventory measure from cumulative imbalance to the 63-trading day rolling sum imbalance.

Here, a positive cycle starts on day 1 with the $12 million imbalance. The dealers increase their positions on days 2, 19, and 20, resulting in the peak inventory of $48 million which lasts until day 63. On day 64, we switch the inventory measure to the rolling sum imbalance, and therefore the inventory decreases to $36 million despite no trading. Notice that while the cumulative imbalance remains at $48 million, the rolling sum imbalance 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 $20 million, further reducing their inventory to $4 million. On day 82, the cycle ends as the $12 million imbalance on day 19 is dropped, pushing the inventory across the zero line. Since there is no imbalance on day 82, we do not begin a new cycle on the day. Following our convention, the long positive cycle lasts 81 days, and peaks at $48 million.

Once the cycle ends, we reset the cumulative imbalance to zero on day 82, ignoring all trades that are part of the completed inventory cycle, and the inventory equals the cumulative imbalance of zero. In contrast, the rolling sum imbalance on day 82 is -$8 million, which reflects that the $12 million imbalance 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 $12 million imbalance on day 20 is dropped. Notice here that the rolling sum is never reset, and may span across cycles.

Example 3: Long cycle that ends on a day when old trades drop out and new trades occur

Example 3 is a minor variation of Example 2. The key difference is that Example 3 reports an imbalance of $12 million whereas Example 2 reports no imbalance on day 82. In both examples, dropping the older imbalance on day 19 is sufficient to push inventory to cross zero.

	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

Once the cycle ends, we reset the cumulative imbalance on day 82 to zero, and inventory equals the cumulative imbalance of zero. In example 3, we begin a new negative inventory cycle on day 82 to reflect the daily imbalance of -$12 million.

Example 4: Long cycle that ends on a day when old trades drop out and new trades occur

Example 4 is a minor variation of example 3. The key difference is that example 4 reports a daily imbalance of $8 million on day 66, whereas example 3 reports a daily imbalance of $20 million on day 66. Until day 65, example 3 and 4 are the same. On day 66, the sale of $8 million in example 4 is smaller than $20 million in example 3, and therefore decreases the inventory to $16 million. On day 82, due to $12 million older imbalance on day 19 being dropped, the 63-day rolling imbalance decreases from $16 million to $4 million.

	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

In contrast to example 3, the dropping of older imbalance from day 19 does not end the inventory cycle. Here, the 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, -$8 million, as the starting inventory.

Robustness: Rolling Sum as Alternative Inventory Measure

As a robustness analysis, we construct inventory cycle using the rolling sum of imbalances (column 5) over 63 trading days. The rolling sum is easier to understand, and the cycles are similar in length and peak inventory to the main approach. The main results are similar to those reported in the paper. A disadvantage of the rolling sum imbalance is that dropping an older imbalance could start a new cycle in the opposite direction. As an illustration, in example 2, the 63-day rolling sum imbalance would start a new negative cycle on day 82. Such a mechanical cycle is dropped in the main approach.

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*

Cont'd next page

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. Panel C reports OLS estimates for regressions of cycle characteristics on various market variables and bond characteristics. Observations are inventory cycles. The dependent variables in columns (1) and (3) are ln(Peak inventory) and in columns (2) and (4) are ln(Cycle length). 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 (1)	Fraction of Bonds in ***Negative*** Cycle (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 bond issuance)	0.0089***	-0.0138***
	(0.003)	(0.003)
ln(Total bond issuance) *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

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

Dependent Variable:	Dummy for Being in ***Positive*** Cycle (1)	Dummy for Being in ***Negative*** Cycle (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)
Months	137	137
Observations	1,603,701	1,603,701
R-squared	0.589	0.626

Table 3 -*continued*

Panel C: Cycle Characteristics

Sample:	Positive Cycles		Negative Cycles	
Dependent Variable:	ln(Peak Inventory)	ln(Cycle Length)	ln(Peak Inventory)	ln(Cycle Length)
	(1)	(2)	(3)	(4)
NOISE	0.004	-0.002*	-0.002	-0.002
	(0.009)	(0.001)	(0.013)	(0.001)
VIX	-0.005	0.000	-0.005	0.001*
	(0.003)	(0.000)	(0.004)	(0.000)
Crisis	-0.054	0.017***	0.041	0.029***
	(0.051)	(0.003)	(0.045)	(0.003)
ln(Bond maturity)	0.011	0.012***	0.086***	0.004***
	(0.010)	(0.001)	(0.010)	(0.001)
ln(Bond issue size)	0.275***	-0.033***	0.319***	-0.046***
	(0.012)	(0.002)	(0.016)	(0.002)
ln(Bond age)	-0.399***	0.013***	-0.384***	0.011***
	(0.016)	(0.002)	(0.018)	(0.002)
Upgrade [*t*-2, *t*+2]	0.205***	0.004	0.058	-0.020**
	(0.060)	(0.005)	(0.077)	(0.007)
Downgrade [*t*-2, *t*+2]	0.204***	0.003	0.057	-0.027***
	(0.038)	(0.008)	(0.047)	(0.007)
Issuer fixed effects	YES	YES	YES	YES
Observations	85,028	85,028	67,626	67,626
R-squared	0.148	0.108	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:

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

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-reporting period (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)

Cont'd next page

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 transition matrices of funds' liquidity supply, as measured by *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 first (last) five columns then 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). The reported chi-square statistics are for the test of null hypothesis that the probability for being in each *LS_score* quintile in the future period (months *t*+1 to *t*+12 or 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 of funds' average *LS_score* on funds' past average *LS_score* and its interaction with various market and funding variables. Observations are fund-reporting period (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: Transition Matrix of LS_score

LS_score Quintile	Percentage in *LS_score* [*t*+1, *t*+12] Quintile					Percentage in *LS_score* [*t*+13, *t*+24] Quintile				
	1 (Low)	2	3	4	5 (High)	1 (Low)	2	3	4	5 (High)
1 (Low)	29.77	21.00	17.87	16.15	15.21	28.65	20.72	17.81	16.08	16.74
2	21.45	23.39	22.18	19.30	13.69	20.24	23.25	21.36	19.15	16.00
3	16.81	22.25	22.00	21.91	17.03	17.23	21.63	22.45	21.21	17.49
4	16.05	18.76	22.33	22.46	20.40	15.93	18.62	21.75	23.40	20.30
5 (High)	15.42	15.17	16.35	20.57	32.50	17.51	16.08	17.41	20.17	28.84
5 - 1	H0: Rows and Columns are Independent					H0: Rows and Columns are Independent				
Std. Error	$\chi^2 > 1{,}400$***					$\chi^2 = 744.64$***				

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

Table 8

Position Changes and Liquidity Supply in Periods of Extreme Flows

Panel A presents average position changes for fund-periods sorted into quintiles by fund flows. Observations are fund-month or coarser (unbalanced), depending on each fund's reporting frequencies. Average changes in allocation to cash and cash equivalents, government bonds, and corporate bonds (as classified by Morningstar) are reported. In the last two columns, sell and buy fractions are calculated for each observation as the sums of par amounts of corporate bond positions that are decreased and increased, respectively, over the reporting period. 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. Panel B reports OLS estimates for panel predictive regressions of funds' average *LS_score* on funds' past average *LS_score* for the subsamples of observations in flow quintiles 1 (columns (1)-(3)) and 5 (columns (4)-(6)). Average *LS_score* is calculated over the period from months *t*+1 to *t*+12 for only (forced) sale (columns (1)-(3)) and (forced) buy (columns (4)-(6)) transactions. Past average *LS_score* is calculated over the period from months *t*-11 to *t*, using both buy and sale transactions. All models include month fixed effects. Models in columns (3) and (6) also include control variables as in column (4) of Table 6 (omitted here for brevity). Standard errors, two-way clustered by fund family and month, are in parentheses. In columns (2), (3), (5), and (6), F-statistics are reported for the test of null hypothesis that the coefficients of *LS_score* Q1 and *LS_score* Q5 dummies are equal. ∗, ∗∗, and ∗∗∗ refer to statistical significance at 10%, 5%, and 1% levels.

Panel A: Funds' Position Changes Conditional on Flows

Flow Quintile	Obs.	Flow (%)	ΔCash (%)	ΔGov (%)	ΔCorp (%)	Corp. Sell Fraction	Corp. Buy Fraction
1 (Low)	6,505	-8.559	-0.048	-0.225	-0.971	0.076	0.066
2	6,541	-2.114	0.020	-0.047	0.068	0.065	0.072
3	6,556	0.771	0.170	0.185	0.951	0.058	0.076
4	6,591	4.719	0.411	0.538	2.053	0.055	0.091
5 (High)	6,746	17.114	0.774	0.897	4.258	0.052	0.126
5 - 1		25.674***	0.822***	1.122***	5.229***	-0.025***	0.060***
Std. Error		(0.005)	(0.109)	(0.107)	(0.321)	(0.004)	(0.007)

Table 8 -*continued*

Panel B: Regressions of Future LS_score on Past LS_score for Forced Sales and Purchases

	Flow Q1 Sample Y = LS-score (t+1 to t+12, sales only)			Flow Q5 Sample Y = LS-score (t+1 to t+12, buys only)		
	(1)	(2)	(3)	(4)	(5)	(6)
LS-score [t-11, t]	0.113**			0.140**		
	(0.056)			(0.055)		
LS-score [t-11, t] Q1		-0.004	-0.000		-0.010	-0.005
		(0.016)	(0.015)		(0.011)	(0.011)
LS-score [t-11, t] Q5		0.023**	0.025		0.032***	0.024***
		(0.011)	(0.014)		(0.009)	(0.009)
Controls as in Table 6	NO	NO	YES	NO	NO	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
H_0: LS-score Q1 = LS-score Q5	NA	F(1, 3894) = 3.77*	F(1, 3894) = 0.96	NA	F(1, 4138) = 9.85***	F(1, 4138) = 4.74**
Observations	6,934	6,934	6,934	6,972	6,972	6,972
R-squared (total)	0.126	0.127	0.154	0.210	0.212	0.248

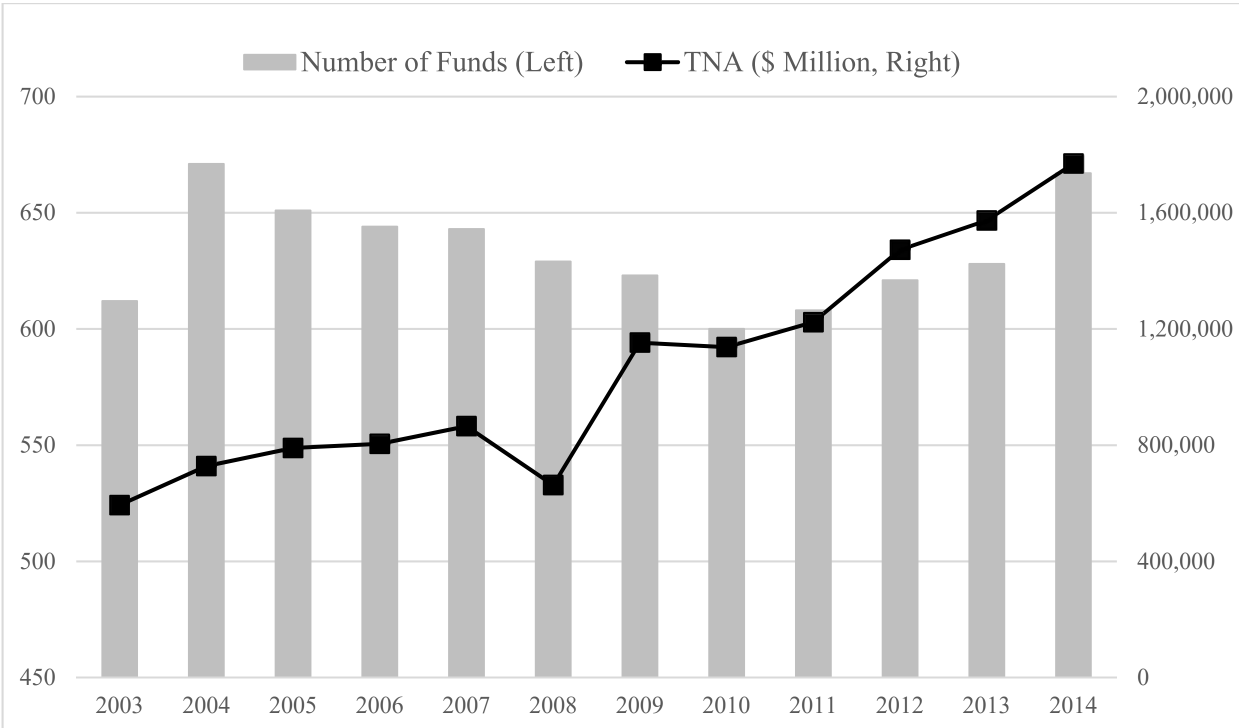


Figure 1. Taxable bond mutual funds over time. This figure presents the total net assets (TNA, in $ Million) of taxable bond funds and the numbers of these funds, as reported by Morningstar, over the sample period from 2003 to 2014. The sample includes only open-ended funds in the following Morningstar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

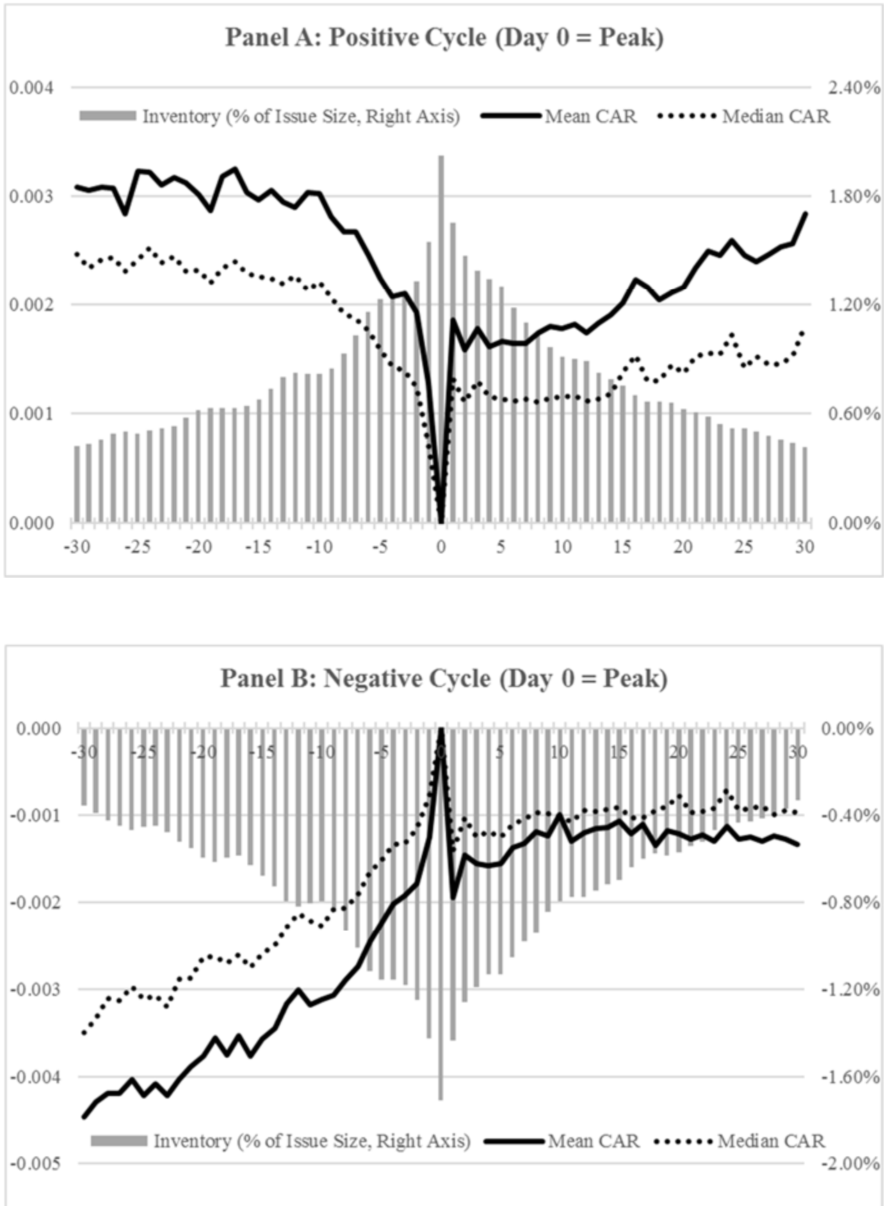


Figure 2. Dealer inventory and cumulative abnormal returns during positive and negative cycles and around bond rating downgrades. This figure presents average dealer inventory, as a percentage of bond's issue size, and mean/median cumulative abnormal returns, normalized to zero on the event day, during 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.

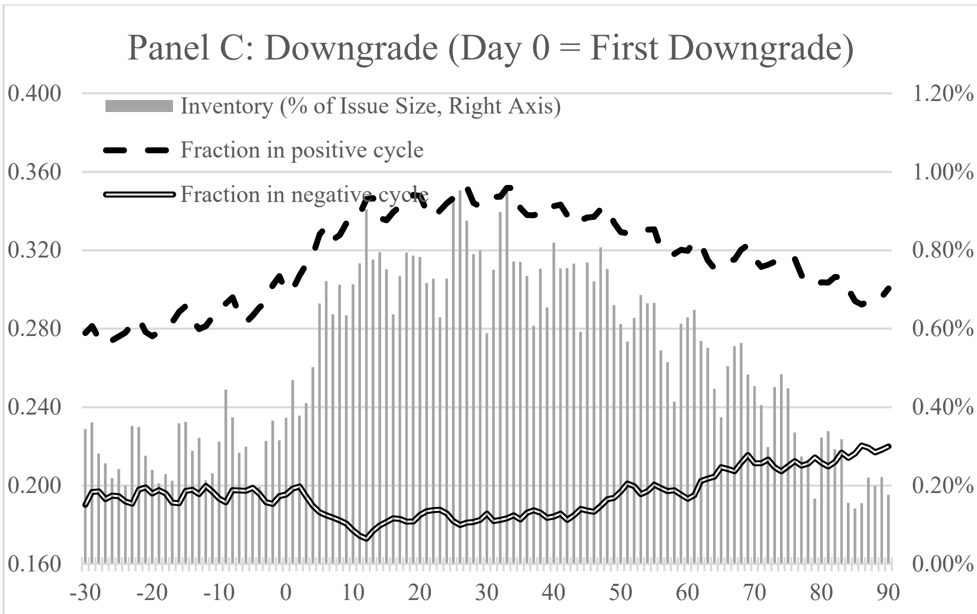
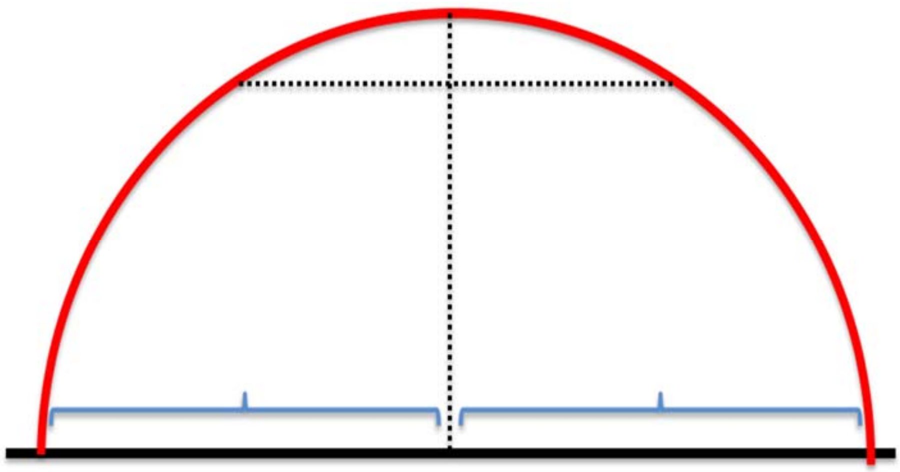


Figure 2 *-continued.*



<table>
<tr><th></th><th>Load Phase</th><th>Unload Phase</th></tr>
<tr><td>Change in dealer inventory (ΔI)</td><td>+</td><td>-</td></tr>
<tr><td>Bond return (r)</td><td>-</td><td>+</td></tr>
<tr><td>Inventory cycle (IC)</td><td colspan="2">+</td></tr>
<tr><td>Change in fund holdings (ΔH)</td><td colspan="2">+</td></tr>
<tr><td>Correlation(ΔH,ΔI)</td><td>+</td><td>-</td></tr>
<tr><td>Correlation(ΔH,r)</td><td>-</td><td>+</td></tr>
<tr><td>Correlation(ΔH,IC)</td><td>+</td><td>+</td></tr>
<tr><td>Trading style</td><td>Liquidity supply</td><td>Liquidity supply</td></tr>
</table>

Figure 3. Classifying change in fund holdings during in a positive inventory cycle.