Forced Sales and Dealer Choice in OTC Markets*

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December 12, 2021

Abstract

Using novel trade-level data, we study how municipal bond mutual funds trade in response to daily flows. When forced to sell bonds to satisfy redemptions, funds pre-arrange fewer trades, sell more liquid bonds, and trade with more central dealers, who offer faster execution. Funds are especially likely to turn to more central dealers when trading lower rated bonds, when funds have low cash buffers, and when trading after periods of aggregate outflows. More central dealers charge higher markups when funds demand fast execution.

JEL classification: G11, G23

Keywords: dealers, fire sales, liquidity, municipal bonds, mutual funds, OTC markets

*We thank Adi Sunderam and participants at the Purdue Finance brown bag for helpful comments.

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1 Introduction

Fixed-income open-end mutual funds have roughly doubled in size over the 2010–2019 decade, with holdings of corporate and foreign bonds growing from \$1 trillion to \$2.3 trillion,[1] and holdings of municipal bonds growing from \$464 billion to \$831 billion.[2] Mutual funds' shares of the corporate and municipal bond markets have also grown significantly: from 9.3% to 16.3% for corporate bonds and from 12% to 21.5% for municipal bonds. Because open-end mutual funds promise their investors daily liquidity while investing in illiquid assets, many of which do not trade for days, weeks, or even months, there have been concerns about the financial stability risks posed by open-end mutual funds, fixed-income ones in particular. These concerns were highlighted most recently in March 2020 when in the midst of the COVID-19 pandemic, funds suffered large redemptions and were forced to liquidate their portfolio securities, contributing to dislocations in the bond markets. Although a number of papers has investigated how funds manage liquidity through cash buffers (Chernenko and Sunderam, 2020), interfund lending programs (Agarwal and Zhao, 2019), cross-trading among affiliated funds (Goncalves-Pinto and Schmidt, 2013), and by selling more liquid securities in order to meet redemptions (Choi et al., 2020), one aspect of funds' trading that has not received much attention is the choice of dealer to trade with and how this choice is affected by fund flows.

Many assets, including corporate and municipal bonds, syndicated loans, and many derivative securities, trade in over-the-counter (OTC) markets where investors search for and negotiate bilaterally with dealers. Dealers differ in the strength of their connections to other dealers and customers and thus in their willingness to take bonds into inventory, in how quickly they can unwind inventory, and in the markups they charge (Di Maggio, Kermani, and Song, 2017; Li and Schürhoff, 2019). Although the literature has made significant progress in modeling and documenting the structure of interdealer networks in OTC markets, there is still limited empirical evidence on how sophisticated investors such as mutual funds choose which dealer to trade with, especially when funds are forced to sell because of investor redemptions. This lack of evidence is largely due to the opacity of OTC markets and limited data that would allow one to identify both dealers and customers.[3] In this paper,

[1] https://fred.stlouisfed.org/graph/?g=tr0I

[2] https://fred.stlouisfed.org/graph/?g=tr1J

[3] One exception to this is NAIC data on the trades of insurance companies. These data have been used by O'Hara, Wang, and Zhou (2018) and Hendershott et al. (2020) among others. Although insurance companies may be forced to sell downgraded bonds (Ellul, Jotikasthira, and Lundblad, 2011) or to sell bonds in order to pay claims, the urgency to trade is usually not as strong as for open-end mutual funds that offer daily

we use novel data on the trades, including anonymized dealer identifiers, of municipal bond mutual funds to investigate how dealer choice in the municipal bond market depends on the motive and urgency to trade.

Municipal bond mutual funds provide a great laboratory in which to study how sophisticated investors choose dealers in OTC markets when forced to trade on short notice. Trading municipal bonds is costly (Green, Hollifield, and Schürhoff, 2007; Schwert, 2017) and there is significant heterogeneity in markups charged by different dealers (Li and Schürhoff, 2019). Furthermore, because most municipal bonds trade infrequently—70% of bonds do not trade in a given month—we are able to identify more than 85% of all mutual funds sales of municipal bonds in the Municipal Securities Rulemaking Board (MSRB) transaction data. These transaction data include the date, time, price, and, most importantly for our purposes, anonymized dealer identifiers. Thus, we know which bonds mutual funds sell in response to outflows, when and who they sell to, and how much it costs them.

To set the stage, we start by documenting the high-frequency response of fund sales to outflows. While the literature (Edelen, 1999) has previously related semiannual, quarterly, or monthly turnover to fund flows, our data on the timing of sales and on daily fund flows allow us to study the higher frequency dynamics of the response of sales to outflows. We show an asymmetric response with sales responding strongly to outflows but not to inflows. The immediate response to a dollar of outflows is 29 cents in sales on day t. Funds continue to sell in response to lagged outflows, with the coefficient on outflows declining from 0.12 on day $t-1$ to 0.03 on day $t-5$. The cumulative effect of outflows on days [t – 5, t] is 0.57, which is broadly similar to Edelen (1999) finding that over a six-month period a dollar of gross outflows is associated with about 70 cents in trading activity.

Given that a sizable portion of redemptions is met through immediate sales of portfolio securities, we then investigate how the choice of bonds to sell and dealer to trade with depends on whether the sale is in response to outflows. We first show that when a fund trades after experiencing outflows, it is less likely to prearrange trades, i.e., have a dealer first search for a counterparty to immediately take the other side of the trade. We then show that bonds sold in response to outflows tend to be more liquid. In particular, they have larger offering amounts, better ratings, and shorter remaining maturities.

Next, we turn to our main question—how does the choice of dealer to trade with depend on whether the sale is in response to outflows? We show that when forced to trade in order

liquidity.

to meet redemptions, funds trade with more central dealers. We measure centrality using the natural logarithm of eigenvector centrality which measures each dealer's connection to other dealers giving more weight to dealers who are themselves connected to more important dealers. The economic magnitude of the effect of fund flows on dealer centrality is large, with a one percentage point increase in outflows associated with about 10% greater dealer eigenvector centrality. Furthermore, the effect is significantly stronger when the fund has a smaller cash buffer, indicating greater urgency to trade in order to meet redemption requests.

Dealer centrality is likely to be more important when forced to trade lower rated bonds. Holding such bonds in inventory is riskier than holding higher rated bonds, and peripheral dealers, for whom it may take longer to resell the bonds, may be more reluctant to take lower rated bonds into inventory. Peripheral dealers may instead seek to prearrange trades and avoid taking on inventory risk (Schultz, 2017; Goldstein and Hotchkiss, 2020; Li and Schürhoff, 2019). Thus, when forced to sell lower rated bonds, funds may want to trade with more central dealers. This is exactly what we find. Splitting the sample into bonds rated AA and above, bonds rated A, and bonds rated BBB and below, we show that the effect of outflows on dealer centrality is strongest for lower rated bonds and is in fact not distinguishable from zero for bonds rated AA and above.[4]

Dealer centrality may also be more important when funds are forced to trade in times of aggregate market distress. Using aggregate outflows from municipal bond funds as a proxy for stressed market conditions, we show that the relationship between fund-level outflows and dealer centrality is significantly stronger during such times. Interestingly, aggregate outflows themselves are negatively associated with dealer centrality. Thus, funds not suffering outflows during stressed market conditions tend to trade with less central dealers, perhaps because the more central dealers are busy trading with funds demanding immediate execution due to outflows.

In our final analysis, we study the relationship between transaction costs and outflows. When we include fund and month fixed effects, we find that within fund variation in outflows is actually negatively associated with markups. When we decompose flows into inflows and outflows, we find that the relationship is driven by outflows: sales on days with larger outflows incur smaller markups. This negative relationship between outflows and markups is due to funds selling higher rated, more liquid securities and making larger trades in response to outflows. Once we control for bond fixed effects, credit rating, and trade size, the coefficient

[4] Out of bonds with a credit rating, about 50% are rated AA and above, 30% are rated A, and 20% are rated BBB and below.

on fund flows turns positive and statistically significant. When two funds trade the same bond, the one experiencing one percentage point larger outflows will incur about 4 basis points larger markup. This is 18% of the median markup of 22 basis points and 6% of the mean markup of 63 basis points. When we then interact fund flows with dealer centrality, we find positive coefficients on the interaction but not the direct effect of centrality. These results are consistent with funds having to pay higher markups to get faster execution from more central dealers. Overall, our analysis of markups suggests that the choice of dealer has similar significance to the choice of security to trade in response to outflows.

Our paper contributes to three separate strands of literature. First, we contribute to the literature on the vulnerability of mutual funds to outflows and on how funds manage their liquidity in order to mitigate the risks and the costs of fire sales (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017; Jiang, Li, and Wang, 2021; Chernenko and Sunderam, 2020; Choi et al., 2020; among others). We advance this literature in several important ways. To the best of our knowledge, we are the first to relate fund flows and sales at the daily frequency. We show that a dollar of outflows is associated with 29 cents in immediate sales and another 28 cents in sales over the following five days. Even funds with sizable cash buffers immediately sell about 21 cents worth of bonds for each dollar of flows. Our high frequency data also allow us to more precisely characterize the types of bonds that funds sell in response to outflows, while the previous literature has only looked at monthly or quarterly changes in portfolio holdings. Most importantly, our paper contributes to our understanding of mutual fund liquidity management by studying their trading strategies and in particular the choice of dealer when trading in response to outflows.

Second, we contribute to the literature on trading in OTC markets and on the structure of OTC networks. Since the seminal theoretical papers by Duffie, Gârleanu, and Pedersen (2005, 2007) and Lagos and Rocheteau (2007), several papers have studied different aspects of OTC markets and have documented the core-periphery structure of many OTC markets, which consist of a few well-connected dealers who trade extensively with customers and among themselves and of a large number of peripheral dealers. More central dealers tend to charge higher markups (Di Maggio, Kermani, and Song, 2017; Li and Schürhoff, 2019), presumably because customers value the execution speed they offer. While the two papers place emphasis on dealers, our main subjects of interest are their clients – mutual funds. We provide the first direct evidence on how the urgency to trade, in our case in response to outflows, causes funds to trade with more central dealers. Given that a large fraction of trading in municipal and corporate bonds happens in response to fund outflows, our results may help explain why so much trade takes place with central dealers even though these dealers charge higher markups.

Third, our paper contributes to our understanding of trading in the municipal bond market. With \$3.9 trillion in outstanding bonds issued by more than 50,000 municipalities, municipal bond market is an important source of financing for state and local governments.[5] Open-end mutual funds are the second-largest investor in this market after households: mutual funds hold about \$800 billion or 20% of the market. Funds' trading is thus likely to affect liquidity and prices in this market, and therefore the terms at which municipalities are able to raise financing. While understanding trading in the municipal bond market is important in its own right, our results on how outflows affect the choice of dealer are likely to extend to other liquidity-motivated trading in OTC markets.

2 Data

We create a novel data set of municipal bond sales by open-end mutual funds by combining fund holdings data from Morningstar Direct with municipal bond transaction data from the Municipal Securities Rulemaking Board (MSRB).

Dealers are required to report all municipal bond transactions, both customer and interdealer trades, to MSRB. Except for a limited set of transactions negotiated "away from the market," all reported transactions are made publicly available through the Electronic Municipal Market Access (EMMA) website. While publicly disseminated MSRB data do not include dealer or customer identifiers, our version of the MSRB transaction data, obtained directly from MSRB, includes anonymized dealer identifiers and covers the 2011–2016 period.

2.1 Sample

The sample of funds consists of open-end municipal bond funds in Morningstar Direct. Since a fund's trading during the incubation period may not be representative of its trading once established, we exclude funds that are less than two years old (Evans, 2010) and funds with total net assets (TNA) of less than \$10 million. To guard against potential data errors, we require the ratio of the net market value of portfolio securities to fund TNA to be in the

[5] See the MSRB's Muni Facts sheet: http://www.msrb.org/msrb1/pdfs/MSRB-Muni-Facts.pdf

[0.5, 2] interval. Such filters are common in the literature (e.g., Coval and Stafford, 2007). Funds also need to have nonmissing daily flows on days $[t-2, t]$ relative to bond sales.

The sample of bonds consists of CUSIPs in MSRB data that correspond to fixed-rate or zero-coupon bonds with original maturity of at least one year and offer amount of at least $100,000.[6] We also require bonds to have a valid credit rating at the time of the transaction.[7]

2.2 Identifying fund sales in MSRB

Almost all papers in the mutual fund literature identify sales of portfolio securities based on changes in portfolio holdings between adjacent reporting periods, which are usually quarterly or monthly. Our innovation is to match sales implied by the holdings data to actual trades in the MSRB municipal bond transactions data. We are thus able to identify the date, time, price, and dealer associated with the trade. What allows us to carry out this merge is the fact that most municipal bonds trade infrequently and that, because markups decrease in trade size (Green, Hollifield, and Schürhoff, 2007), investors avoid splitting trades. Because trading is infrequent, there are usually not that many potential matches for a given mutual fund sale. That funds avoid splitting trades helps to further narrow the set of potential matches.

Our algorithm works as follows:

1. Define implied sales as declines in par value of at least $5,000 and 5% of the fund's position last period. Smaller changes in holdings are generally due to amortization and bond calls and thus are excluded. We require the length of the reporting period, i.e., the difference between two adjacent holdings snapshots, to be no more than three months (92 days).

2. Exclude changes in holdings due to maturity and other redemption events. We consider a change in holdings to be due to an event affecting the bond's outstanding amount

[6] The rate on variable rate notes is often times set through an auction mechanism in which investors appear to sell and buy back bonds from dealers. This makes it difficult to identify sales of variable rate bonds.

[7] Our credit ratings data come from the public disclosures by the credit rating agencies per SEC Rules 17g-7 and 17g-2. Rule 17g-7 was adopted by the SEC on August 27, 2014 and became effective on June 15, 2015. It requires nationally recognized statistical ratings organization (NRSROs) to make publicly available all credit ratings that were outstanding as of, or initially determined on or after, June 15, 2012. Before June 15, 2012, Rule 17g-2 required public disclosure of all credit ratings initially determined on or after June 26, 2007.

if the event takes place during the fund's reporting period or within fifteen days after the reporting period.[8]

3. Attempt 1-1 match between the implied fund sales and MSRB trades. Funds differ in whether they stop reporting portfolio securities to Morningstar once the trade is executed or once it is settled. Therefore, in matching fund sales to MSRB trades, we require either the trade date or the settlement date to be within the fund's reporting period.

4. After setting aside sales used in the previous step, check if there is a unique combination of trades in MSRB data whose combined par value is equal to the fund's sale.[9]

5. Aggregate unmatched fund sales to the family level and attempt 1-1 match between family sales and MSRB trades.[10]

6. Check, if a previously unmatched fund sale can be matched to a unique MSRB trade such that a) it is the only sale in MSRB with par value that is equal to or larger than the fund's sale, and b) the combined par value of all smaller MSRB sales is less than the par value of the fund's sale. These sales correspond to cases where the fund's investment adviser combines the fund's sale with sales from other portfolios managed by the adviser.[11]

Figure 1 reports the success of our algorithm in identifying mutual fund sales in MSRB for each year during our 2011–2016 sample period. The figure plots the cumulative percentage of of all mutual funds sales that are matched to MSRB at different stages in the algorithm. The numbers on the right report cumulative match rates for 2016. Overall, we are able to match 85% of all municipal bond sales by funds in our sample. About 60% of all sales (70% of all matched sales) are cases where the fund's sale is matched to a single unique sale in MSRB. In about 15% of all sales, funds split their sales into a number of smaller trades. Finally, 10% of all sales are cases where the fund's sale is combined either with sales by other funds within the same family or with sales by other portfolios managed by the fund's

[8] Most bonds mature on either the first or fifteenth day of the month. This means that funds usually stop reporting holdings of bonds that mature during month $t+1$.

[9] To keep this problem computationally feasible, we restrict this step to sales of bonds that have at most twenty five smaller customer sales in MSRB.

[10] Fund families are defined using Morningstar's *Branding Name* variable.

[11] This could also include sales by other mutual funds managed by the investment adviser when holdings of these funds are for some reason missing from Morningstar.

investment advisor. To focus on the fund's own trading decisions, our analyses exclude sales that are combined with other funds or other portfolios managed by the fund's investment adviser. Table 11 shows that our results are robust to including sales executed as part of a larger trade.

Table 1 compares the characteristics of matched and unmatched sales. Unmatched sales tend to be larger revenue bonds with longer maturity and lower credit rating. These bonds trade more frequently making it less likely that algorithm identifies the unique trade or combination of trades that correspond to the fund's sale.

Importantly, there are no differences in average daily flows during the reporting period between matched and unmatched sales. In particular, it is not the case that funds experiencing larger outflows are less likely to have their sales matched to MSRB (because funds sell more liquid bonds in response to outflows).[12] Our analysis looks at how dealer choice is affected by fund flows within the cross-section of matched sales, controlling for bond fixed effects (which absorb cross-bond variation in the offering amount, general obligation versus revenue type, and insurance) and for time-varying bond characteristics such as bond age, rating, and maturity. Thus, even though matched sales may look different on observable characteristics from unmatched sales, differences in characteristics should not affect the internal validity of our analysis. Furthermore, considering that unmatched sales account for less than 15% of all sales, the relationship between outflows and dealer centrality would have to be negative and at least seven times as strong within unmatched sales in order to make the relationship between outflows and dealer centrality zero within the overall population of sales.

To show that our results are likely to hold for unmatched sales as well, Table 10 estimates regressions of dealer centrality on fund outflows for subsamples of larger bonds, revenue bonds, uninsured bonds, bonds with longer maturity, and larger sales, in other words for matched sales that on observable characteristics look similar to unmatched sales.

Our analysis of the relationship between the value of sales and fund flows may be biased towards zero however because we underestimate the value of daily sales. We show that our results are robust and are in fact slightly stronger when we limit the sample to fund-months observations for which we match all of the fund's sales to MSRB.

[12] Appendix Figure B1 compares the distribution of daily flows for fund-months observations with matched versus unmatched sales. The distributions look very similar. Although, given the large sample size, the Kolmogorov-Smirnov test does reject the hypothesis of the equality of the two distributions, economically the difference between the two distributions is very small. The largest absolute difference between the two empirical cumulative distribution functions is 0.0034.

2.3 Summary statistics

Table 2 reports summary statistics for our final sample of mutual fund sales of municipal bonds matched to MSRB. The sample covers 69,257 sales of 40,265 different bonds by 560 municipal bond funds. The mean (median) par traded is \$2.41 (\$1.20) million. Ninety percent of all sales have positive markup, defined as the relative difference, in basis points, between the par-weighted average price at which the dealer unwinds the position (potentially through a chain of transactions with other dealers) and the original transaction price. The mean (median) markup is 63 (22) basis points. Around 20% of our sample are prearranged trades; another 29% are unwound within the same day. Of all sales for which we can identify the chain of subsequent trades that unwind the initial sale, 35% are split into more than one subsequent sale, and 52% are resold directly to other customers without any intermediate interdealer trades. For 37% of sales, the fund sells to a new dealer that it has not traded with during the past 90 days.

We match each sale with fund and bond characteristics at the time of the transaction. For the median sale, the cumulative 1/2/3-day net outflows, scaled by previous month TNA, are 3, 7, and 11 basis points respectively. The median fund has cash-to-TNA ratio of 2%, TNA of \$636 million, and comes from a fund family with family size of \$9.35 billion.[13] Of all bond sales, 24% are on general obligation bonds, 22% on insured bonds, with the median offering amount being \$15 million. On transaction dates, bonds tend to have over 13 years until maturity, and median rating of AA-.[14]

3 Results

3.1 Daily flows and daily bond sales

To set the stage, we start by documenting the high-frequency response of fund sales to fund flows. We estimates regressions of the dollar value of daily sales, scaled by TNA as of the end of the previous month, on daily flows, also scaled by last month's TNA:

$$\frac{Sales_{f,d}}{TNA_{f,m-1}} = \alpha_f + \alpha_d + \sum_{s=-15}^{5} \beta_s \cdot \frac{Flows_{f,d+s}}{TNA_{f,m-1}} + \varepsilon_{f,d} \tag{1}$$

[13] We only consider open-end municipal bond funds within the family when calculating family TNA.

[14] Bond ratings are encoded such that AAA = 0, AA+ = 1, AA = 2, etc.

Because sales and fund flows are scaled by TNA, the coefficients can be interpreted as the dollar value of sales in response to a dollar of fund flows. We include fund, α_f, and date, α_d, fixed effects. The results are similar without these fixed effects.

Figure 2 plots the estimated coefficients on fund flows; full regression output is reported in the Appendix Table B1. Panel (a) plots the coefficients on the first five lags and leads of inflows and outflows, both expressed as positive quantities. Inflows have essentially no effect on sales, while outflows have a large positive effect. The coefficient on day t outflows is 0.26, indicating a large response of sales of portfolio securities to outflows. The coefficients on lagged outflows declines from 0.10 for day $t-1$ to 0.02 for day $t-5$.

The sum of the coefficients on day t and the first five lags of outflows is 0.50. The sum of the coefficients on the next ten lags, i.e., outflows during days $[t-15, t-6]$, is 0.08. This response of sales to outflows is broadly similar to though weaker than Edelen (1999) finding in the context of domestic equity funds that a dollar of outflows is associated with about 76 cents of additional sales over a period of six months. One reason for the difference is that because of less than perfect match to MSRB, we underestimate daily sales. When we restrict the sample to fund-months with all sales matched to MSRB, the sum of the coefficients on outflows during $[t-5, t]$ increases from 0.50 to 0.57. The other reason is that in contrast to equity funds, maturities and redemption of municipal bonds increase funds' cash balances allowing them to meet outflows without selling portfolio securities.

In Panel (b) of Figure 2 we split observations based on the fund's cash-to-assets ratio as of the end of the previous month. Consistent with cash buffers reducing the need to trade to meet redemptions, the response of sales to outflows is much stronger for funds with small cash buffers (0.35) than for funds with large cash buffers (0.21).

Given that sales respond most strongly to contemporaneous outflows but also to outflows on days $t-1$ and $t-2$, in the rest of our analyses, we will relate the choice of dealer to trade with to various measures of outflows over days $[t-2, t]$.

3.2 Flow-induced sales are less likely to be prearranged trades

How do funds respond to outflows? Which bonds do they sell? And which dealers do they trade with? In this section we look at the incidence of prearranged trades, we then study how the choices of bonds to sell and dealer to trade with depend on outflows.

We define prearranged trades as offsetting trades of the same bond by the same dealer happening within sixty seconds of each other (Li and Schürhoff, 2019; Schultz, 2017; Bessembinder et al., 2018). Table 3 reports the results of the linear probability model regressions of the prearranged trade dummy on fund outflows. All regression specifications include fund, bond, month-date, and credit rating fixed effects.

In column 1, the coefficient on time t net outflows is -0.021, statistically significant at 1%. This means that a one percentage point larger net outflow is associated with 2.1% lower probability that the sale is prearranged. This is about 10.5% of the unconditional probability of 20%. Column 2 splits net outflows into inflows and outflows. Only the coefficient on outflows is statistically significant at 5%. The coefficient on inflows is positive 0.008 and not statistically significant.

In columns 3–4 and 5–6 we look at cumulative fund flows over $[t-1, t]$ and $[t-2, t]$ respectively, and find similar results. Prearranged trades and net outflows are negatively correlated, and the effect is entirely due to outflows. The effect of flows on prearranged trades gets weaker over time. This makes sense—if a fund waits two days to trade in response to outflows, it probably has time to prearrange its sale.

Overall, the results in Table 3 show that forced sales are less likely to be prearranged, suggesting that funds demand immediate execution when forced to sell to satisfy redemptions.

3.3 Characteristics of bonds sold

Which bonds do funds sell in response to outflows? Previous literature (Chernenko and Sunderam, 2016; Choi et al., 2020) suggests that bond funds draw down their cash buffers or sell Treasury and other liquid securities to meet redemption requests. Here we provide more granular evidence relating the characteristics of sold bonds to daily fund flows. Table 4 reports the results.

In columns 1 and 2 the dependent variable is the natural log of the bond's offering amount. In column 1, the coefficient on net outflows is a highly statistically significant 0.066. Column 2 splits net outflows into inflows and outflows and shows that the effect of flows on offering amount is driven entirely by outflows. Overall the results in columns 1 and 2 indicate that compared to trading voluntarily, funds sell larger bonds when trading in response to outflows.

In columns 3 and 4 the dependent variable is the bond's credit rating, encoded so that larger values correspond to weaker credit ratings. The results in column 4 indicate that a one percentage point increase in outflows is associated with 0.23 notches better credit rating. Once again the association between flows and ratings is entirely due to outflows, with the coefficient on inflows being small and insignificant.

In columns 5 and 6, we find that outflows are associated with higher probability that the bond is insured, while in columns 7 and 8, we find a negative association between outflows and remaining maturity.

Overall, the results in Table 4 indicate that among bonds that are sold by mutual funds, larger, better rated, insured bonds with shorter remaining maturity are more likely to be sold following fund outflows. These characteristics are often associated with higher bond liquidity, implying that funds sell more liquid bonds when facing larger investor redemptions.[15]

The analysis in Table 4 compares bonds that are sold when funds experience outflows with bonds that are sold when funds experience inflows. For further insights into which of their bonds funds choose to sell, in Appendix Table B2 we ask how sold bonds compare with the rest of the fund's portfolio, and how the difference between bonds that are sold and those that are not sold depends on fund flows. For each bond sale, we define the set of bonds that could have been sold as bonds that were held by the fund at the beginning of the reporting period, that did not experience a redemption event during the reporting period, and that were not sold earlier in the reporting period. The dependent variable is an indicator equal to one if the bond is sold during the current period, and zero otherwise.[16] The main explanatory variables are bond characteristics and their interactions with daily flows. We include fund-date fixed effects so as to compare different bonds held by the same fund at the same time. Similarly to the results in Table 4, we find that funds are more likely to sell larger and higher rated bonds with shorter maturity.

Overall, our results indicate that funds tend to sell more liquid bonds, proxied by bond characteristics, and even more so when they face larger outflows.

[15] We use bond characteristics instead of direct measures of liquidity because most of the latter are based on transaction data (see Schestag, Schuster, and Uhrig-Homburg (2016) for an overview of bond liquidity measures). Since municipal bonds trade infrequently, the sample of bonds with valid liquidity measures would be biased and not representative of the overall population of municipal bonds.

[16] If multiple bonds are sold on the same day, each bond that could have been sold but was not sold is included only once. Thus the sample consists of all bonds that could have been sold, with multiple bonds having the sold indicator equal to one.

3.4 Funds trade with more central dealers when facing outflows

The results in previous sections show that when trading in response to outflows, funds prearrange fewer trades and sell more liquid bonds. In this section, we investigate whether, in response to outflows, funds also trade with more central dealers, who may be able to offer faster execution (Li and Schürhoff, 2019). Table 5 reports the results of the regressions of log eigenvector centrality on cumulative fund flows over different windows around the bond sale.[17] The regression specifications include fund, bond, month-date, and rating fixed effects. We are thus asking whether the same fund trades with a more central dealer when experiencing outflows and whether out two funds selling the same bond, the fund experiencing larger outflows is likely to choose a more central dealer. The standard errors are adjusted for clustering by dealer to account for the persistence in dealer centrality and in fund-dealer relationships and by month date to account for any cross-sectional correlation at a given point in time.

In column 1, the coefficient on day t fund outflows is positive and statistically significant. A one percentage point larger net outflow is associated with about 10% increase in dealer centrality. The coefficient on the log of par traded is positive and highly statistically significant, indicating that funds choose more central dealers for larger trades, likely because central dealers are willing to take larger positions into inventory.

In column 2, we split fund flows into inflows and outflows. The estimated coefficients are similar in magnitude, with the coefficient on outflows being positive and the coefficient on inflows being negative, but only the coefficient on outflows is statistically significant at 10%.

In columns 3–4, we relate dealer centrality to cumulative fund flows over $[t-1, t]$. The coefficient on net outflows in column 3 is smaller in magnitude than in column 1 but is still significant at 5%. In column 4, we again find evidence of a more significant response to outflows than to inflows. We find similar results in columns 5–6 when we use cumulative fund flows over $[t-2, t]$.

Overall, the results in Table 5 indicate that funds choose more central dealers when trading in response to outflows.

[17] Appendix Table B3 shows that our results are robust to using six alternative definitions of centrality.

3.5 Cash buffers mitigate the effect of outflows on dealer centrality

Funds with large cash buffers may search longer for a dealer willing to transact at an attractive price and may therefore be less likely to trade with central dealers. In Table 6 we estimate regressions of dealer centrality on fund flows and their interaction with the fund's lagged cash-to-assets ratio. We again report the results for fund flows cumulated over different windows around the bond sale.

In columns 1–3, we look at fund flows on day t. In column 1, the coefficient on fund outflows is 0.161 and statistically significant at 5%. The coefficient on the interaction of flows with the fund's lagged cash-to-assets ratio is negative and significant at 5%. While outflows have a large positive effect on dealer centrality for a fund with no cash holdings, for a fund with a 5% cash buffer, the effect of fund flows is cut in half ($0.161 - 0.05 \times 1.669 = 0.078$).

Because cash holdings are measured as of the last reporting period, they may have changed due to previous outflows, portfolio transactions, interest payments, and payments on maturing and called bonds. In other words, cash holdings as of the previous period are a noisy proxy for what we are really interested in—cash holdings right before the bond sale. To reduce the magnitude of the potential measurement error, in columns 2 and 3 we restrict the sample to bond sales that happen within 30 and 15 days of the last observation of cash holdings. As we restrict the sample and reduce measurement error, the coefficient on the interaction of fund flows increases in magnitude. In column 3, where we restrict the sample to sales that happen within 15 days of the last observation of cash holdings, the interaction coefficient is -5.758, more than three times as large as in column 1. According to the estimates in column 3, for a fund with a 5% cash buffer, the effect of fund flows on dealer centrality is not distinguishable from zero ($0.330 - 0.05 \times 5.758 = 0.042$).

In columns 4–9, we use cumulative flows over $[t-1, t]$ and $[t-2, t]$. We find similar, though economically somewhat weaker results, consistent with the idea that lagged flows have a weaker effect on dealer centrality. If a fund waited two days to trade after receiving redemption requests, it almost certainly approached a number of dealers before deciding which one to trade with.

3.6 Effect of outflows on dealer centrality is stronger for lower rated bonds

How does the decision to use a central dealer depend on the riskiness of the bond the fund is trying to sell? Central dealers may have a greater advantage in trading riskier bonds. Lower rated bonds expose dealers to greater inventory risk while dealers search for a counterparty to sell the bonds to. Furthermore, given that most muni investors tend to hold highly rated bonds, lower rated bonds may be held by a more limited set of investors, making search for counterparties costlier. Consistent with this, Appendix Figure B2 shows that sales of lower rated bonds are much more likely to be prearranged with the dealer essentially acting as a broker instead of taking bonds into inventory. Therefore, we may expect funds trading lower rated bonds in response to outflows to be particularly likely to turn to more central dealers.

In Table 7 we estimate regressions of dealer centrality on fund flows for bonds with different credit ratings. Column 1 reports our benchmark regression estimated on the sample of rated bonds. The results here are similar to the full sample results in column 1 of Table 5. In column 2, we interact fund flows with the bond's credit rating, encoded so that 0 corresponds to AAA, 1 corresponds to AA+, and so on. The coefficient on the interaction of net outflows and credit rating is positive and statistically significant, indicating that the effect of net outflows on dealer centrality is stronger for lower rated bonds.

In columns 3–5, we split the sample into bonds rated AAA through AA- (about 50% of the sample), bonds rated A+ through A- (about 30% of the sample), and bonds rated BBB+ and below (about 20% of the sample). We find that the coefficient on outflows increases in magnitude and statistical significance as we move from higher to lower rated bonds. For bonds rated AA- and above, the coefficient is small and not statistically significant. As these bonds do not carry much credit risk and are usually held by diverse clientele, they are easier for dealers to unload, making the choice of dealer less important. For bonds rated BBB+ and below on the other hand, outflows have a larger positive effect on dealer centrality. For these bonds the choice of dealer depends a lot on whether or not the fund is trading in response to outflows.

3.7 Aggregate outflows exacerbate the effect of fund outflows on dealer centrality

How does the relationship between outflows and dealer centrality depend on aggregate market conditions? If many other funds had suffered outflows and had to liquidate their holdings leading up to day t, dealers may be still working on unwinding their inventories. Peripheral dealers may be especially reluctant to take additional bonds into inventory and may quote wide bid-ask spreads. Funds selling bonds in response to outflows at such times may therefore be especially likely to turn to more central dealers.

Table 8 investigates the interaction between fund-level and aggregate flows. Columns 1 and 2 split the sample based on whether aggregate flows over the previous week were negative or positive.[18] When aggregate outflows over the week leading up to the sale were positive, dealer centrality is quite sensitive to fund flows. The coefficient on net outflows is 0.168 and is statistically significant at 1%. When, on the other hand, aggregate outflows over the week leading up to the sale were negative, the coefficient on dealer centrality is smaller in magnitude and is not statistically significant.[19]

In column 3, we interact fund-level net outflows with aggregate net outflows. The direct effect of fund net outflows is smaller in magnitude (0.05) and not statistically significant, while the interaction with aggregate net outflows is positive and statistically significant at 5%. Thus, when other funds are experiencing inflows and are therefore in position to buy bonds in the secondary market, the effect of individual fund outflows on dealer centrality is attenuated.

In column 4, we split fund-level net outflows into inflows and outflows and separately interact these with aggregate net outflows. We find that only the interaction between fund outflows and aggregate fund flows is statistically significant. This is consistent with the idea that funds trade with more central dealers when they experience outflows, especially so if other funds had suffered outflows, leaving dealers with large inventories.

As an alternative to aggregate flows, we also tried proxying for market conditions using 30-day rolling market volatility, calculated from daily returns of the Bloomberg Barclays

[18] Aggregate daily flows are calculated using fund-level daily flows from Morningstar. Because not all funds report daily flows to Morningstar, aggregate flows are measured with error. Weekly flows are cumulated over seven calendar days between $t-7$ and $t-1$. Cumulating flows over $t-6$ to t yields quantitatively similar results.

[19] We cannot reject the hypothesis that the coefficients are the same.

Municipal Bond Index. Consistent with the aggregate flow results, the relation between dealer centrality and fund outflows is significantly stronger when muni market returns have been volatile. The results are not reported but are available upon request.

4 Markups and fund flows

The previous section examined how funds adjust their trading in response to outflows. We showed that funds prearrange fewer trades, trade with more central dealers, and sell more liquid bonds. In this section we ask how do transaction costs depend on fund flows? And how are transaction costs affected by the different adjustments that funds make to their trading? Following Li and Schürhoff (2019), we calculate markups as the relative difference, in basis points, between the price received by the customer selling the bond to the dealer and the value-weighted average prices in subsequent sales of that bond to other customers. Table 9 reports the results of the regressions of markups on fund flows.

In columns 1–4, we look at all sales for which we can calculate markups. In column 5-8, we limit the sample to sales that are completely unwound within 15 days. For sales that take longer to unwind, measured markups may be affected by changes in interest rates and risk and are thus likely to be a noisier proxy for transaction costs.

In column 1, we regress markups on fund flows, fund and month-date fixed effects, fund and family size. Looking at within fund variation, markups actually decrease with net outflows. A one percentage point increase in net outflows is associated with about 5.4 basis points smaller markup. Splitting net outflows into inflows and outflows in column 2, we find that the effect is driven by outflows, with the coefficient on inflows being essentially zero.

That within a fund markups are negatively related to net outflows is likely due to funds that experience outflows trading more liquid bonds that carry smaller markups.[20] To control for difference across bonds, in column 3, we add bond and credit rating fixed effects, bond age and maturity, as well as the log of par value traded. The coefficient on net outflows is now positive (3.97) and statistically significant at 5%. Thus when funds sell the same bond, flow-induced sales carry significantly larger markups than voluntary sales.

The coefficient on the log of the par value traded is negative and highly significant, con-

[20] It could also be the case that dealers are less concerned about asymmetric information when trading with funds experiencing outflows. Under this alternative explanation, we would expect the result to hold even with bond fixed effects. Column 3 however shows that this is not the case.

sistent with the prior literature documenting large economies of scales effects in transaction costs in the municipal and corporate bond markets (Harris and Piwowar, 2006; Edwards, Harris, and Piwowar, 2007). Controlling for par value traded turns the coefficient on fund size from negative and statistically significant to positive and insignificant. Thus the negative effect of fund size is due entirely to larger funds trading larger quantities.

In column 4, we interact fund flows with dealer centrality to see whether central dealers charge higher markups when funds are desperate to sell in order to meet redemption requests. We standardize dealer centrality to ease the interpretation of the interaction term and to make the coefficient on net outflows comparable across columns 3 and 4. The coefficient on the interaction of net outflows with dealer centrality is positive (3.95) and statistically significant at 10%. The direct effect of net outflows is reduced slightly from 3.965 in column 3 to 3.708 in column 4. Centrality itself does not affect markups.[21]

To reduce measurement error in our measure of markups, in columns 5–8, we limit the sample to sales that are completely unwound within 15 days. This subsample accounts for about 84–87% of the overall sample. We find stronger results within this subsample. Comparing the results in columns 8 and 4, we see that the interaction between net outflows and centrality is about 20% larger (4.85 vs. 3.95) and is statistically significant at 1%. The direct effect of flows in column 8 is smaller (2.868 vs. 3.708) and is statistically significant at 10%. The direct effect of centrality is smaller and not statistically significant. Overall, the results in column 8 suggest that fund outflows affect markups because funds suffering outflows tend to trade with more central dealers who charge a premium for their ability to offer immediate execution.

The economic magnitudes are fairly large. For a fund trading with a dealer that is one standard deviation about the mean, the effect of a one percentage point net outflow is $2.868 + 1.00 \times 4.852 = 7.72$ basis points. This is more than a third of the median markup of 22 basis points. Contrast this with trading with a dealer that is one standard deviation below the mean of centrality. When trading with such a dealer, the effect of net outflows is negative and not statistically significant ($2.868 - 1.00 \times 4.852 = -1.98$ basis points).

[21] Li and Schürhoff (2019) find that central dealers charge higher markups. There are a few important differences between the specifications in Table 9 and their paper. First, we include bond fixed effects thereby asking how markups on the same bond vary with dealer centrality. Second, we study trading by mutual funds, a group of sophisticated investors, whereas Li and Schürhoff (2019) look at all municipal bond trades. Finally, the coefficient on centrality in column 4 measures the effect of centrality on markups for a fund with zero net outflows. Because most sales in our data are in fact flow-induced, if we did not control for fund flows, the coefficient on centrality would be larger.

We can gain further insights into the importance of dealer centrality by examining variation in markups across bonds with different credit ratings. Median markup increases from 9.5 basis points for AAA rated bonds to 18, 24, and 27 basis points for AA, A, and BBB rated bonds, respectively. Thus, when facing one percentage point net outflows, the effect on markups of trading with a dealer that is one standard deviation above the mean is roughly comparable in magnitude to selling AA instead of A rated bonds. Note that according to the results in Table 4, a one percentage point increase in outflows is associated with 0.23 notches better credit rating.

Overall, the results in Table 9 show that the relationship between outflows and markups is affected by two opposing forces. On the one hand, when forced to sell to meet redemptions, funds sell more liquid securities with smaller markups. On the other hand, in order to sell quickly, funds trade with more central dealers who use their position in the network and their bargaining power to charge higher markups.

5 Robustness

5.1 Do results apply to unmatched bonds?

One concern with the results is their external validity. As indicated in Table 1, mutual fund sales that are matched to MSRB transaction data look different on observable characteristics from unmatched sales. In particular, unmatched sales tend to involve larger uninsured revenue bonds with longer maturity, lower ratings, and higher trading volume.

Since most of our analyses look in the cross-section of matched sales and control for both fixed and time-varying bond characteristics, differences in observable characteristics between matched and unmatched sales should not affect the internal validity of our analyses. It is possible however that our results do not apply to the types of bonds that our algorithm fails to match to MSRB transactions data.

To help alleviate concerns about the external validity of our results, we pursue three approaches. First, in Table 10 we estimate regressions of dealer centrality on fund flows on subsamples of bonds that look similar on observable characteristics to the unmatched sales. Second, in the Appendix Table B4 we interact fund flows with the lagged value of bond turnover. The interaction is small and not statistically significant, suggesting again that our results continue to hold for sales of bonds with high turnover that are less likely to match to MSRB. Finally, we estimate a Heckman two-step selection model as another approach to account for differences between matched and unmatched sales. Because inclusion of fixed effects in the first-stage probit regressions would potentially lead to inconsistent estimators, we estimate the model with fixed effects included only in the second-stage regressions. We report the results in the Internet Appendix and interpret them with an abundance of caution.

Table 10 reports the results of regressions of dealer centrality on fund flows on subsamples that look similar on observable characteristics to the unmatched sales. Column 1 reports the results for the full sample. Column 2 restrict the sample to sales of bonds with offer amount of at least \$91 million. This corresponds to the median of the distribution of offer amount within the sample of unmatched sales. Except for weaker statistical significance due to the sample size being cut by more than three-fourths, the coefficient on net outflows (0.126) in column 2 is actually larger than the full sample coefficient (0.100) in column 1. We find similar results in columns 3 and 4 when we restrict the sample to uninsured and revenue bonds respectively.

In column 5, we restrict the sample to sales of bonds with remaining maturity of at least 22.6 years. This corresponds to the median of the distribution of maturity within the sample of unmatched sales. Here the results are more than three times as strong as in the full sample (0.307 versus 0.100). This is consistent with longer maturity bonds having greater exposure to interest rate and credit risk and thus posing greater inventory risk for dealers.

Finally, column 6 restricts the sample to sales of at least \$1.52 million in par value. This corresponds to the median of the distribution of par traded within the sample of unmatched sales. Once again we find similar results with the coefficient on net outflows of 0.149 versus 0.100 in the full sample.

5.2 Robustness

Table 11 reports a number of additional robustness checks and sample splits. Each row corresponds to a different alternative specification or sample split. We report the coefficient on cumulative fund flows. Row 1 reports the baseline regression in column 1 of Table 5. In row 2, we include bond-month fixed effects. We are thus comparing two funds selling the same bond during the same month. Despite the sample size being cut by about 60%, with the exception of the day t flows, the coefficients on net outflows retain their magnitude and statistical significance.

Row 3 includes combined sales, i.e., cases where the fund's sale is combined with sales by the fund's affiliates. The results here are somewhat weaker, which is not surprising given that combined sales are likely to be affected by factors other than the fund's outflows. In row 4, we exclude split sales from the baseline sample and find somewhat stronger results. Row 5 excludes sales of bonds issued by Puerto Rico and other US territories. Because of the Puerto Rican government-debt crisis, trading of these bonds may have been affected by unique considerations. Our results are not driven by the sales of these bonds and are robust to their exclusion.

Rows 6–11 report the results of a number of sample splits that may help shed further light on the relationship between fund flows and dealer centrality. Rows 6 and 7 split the sample period with row 6 reporting the results for the 2011–2013 subperiod and row 7 reporting the results for the 2014–2016 subperiod. We find stronger results for the 2011–2013 period, which included most of the instances of aggregate outflows. These results are therefore consistent with the evidence on stressed market conditions in Table 8.

Rows 8–9 and 10–11 split the sample into young versus old funds and into small versus large fund families. We find stronger results for younger funds and smaller fund families. These results are potentially consistent with older funds and larger fund families having stronger bargaining power vis-a-vis dealers and/or access to alternative liquidity management tools such as interfund lending programs and cross-trading opportunities.

6 Conclusion

This paper uses novel data on municipal bond sales by open-end mutual funds to study how funds' trading decisions, in particular the choice of dealer to trade with, are affected by fund flows. We show that when trading to meet redemptions, mutual funds prearrange fewer trades, sell more liquid bonds, and trade with more central dealers. This is especially the case when funds have small cash buffers, when trading lower rated bonds, and when trading after aggregate outflows from municipal bond funds. We also show that central dealers use their ability to quickly execute trades and their bargaining power to charge higher markups to funds trading in response to outflows.

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Appendix A: Variable Definitions

Table A1
Variable Definitions

Variable	Definition
Trade characteristics	
Par traded	Par value of the amount traded, in $ millions.
Trade price	Dollar price per hundred dollars of par value.
Dealer markup	The difference between the par-weighted average price of the sales to customers that completely unwind the dealer(s) position and the price paid when purchasing from the customer. Our algorithm for identifying chains of trades from the original sale by a customer to a dealer to sales to other customers builds on Li and Schürhoff (2019) and allows for the original par value to be split into smaller trades at any step in the intermediation chain. Markup is expressed in basis points of the par-weighted average price of sales to customers. Markup is winsorized at 1st and 99th percentiles.
Prearranged trade	Indicator variable equal to one if there is an offsetting trade by the same dealer within sixty seconds.
Same-day unwind	Indicator variable equal to one if the sale is unwound on the same day.
Days to unwind	Number of days until the last trade that unwinds the original sale by customer to dealer.
Split trade	Indicator variable equal to one if the sale is unwound by selling to more than one customer.
Customer unwind	Indicator variable equal to one if the intermediation chain does not include any interdealer trades.
New dealer	Indicator variable equal to one if the fund has not sold to or bought bonds from the dealer during the previous 90 days. Because most purchases take place in the primary market where trades are bunched together, the match rate for identifying bond purchases in MSRB transaction data is significantly lower than for the match rate for identifying bond sales.
Dealer centrality	Log of eigenvector centrality of the interdealer network, weighted by the dollar value of the amount traded. Network centrality is calculated using semi-annual snapshots of the interdealer network.
Relative centrality	Difference between dealer centrality and the average centrality of all dealers that, over the previous three months, trade with the fund.
Dealer volume	Dollar value of dealer's trades with customers during the semi-annual period, in $ millions. The calculation uses fixed rate or zero-coupon bonds with original maturity of at least one year and offering amount of at least $100,000.
Dealer share	Dealer's share of the dollar value of all trades with customers over the semi-annual period.

Table A1—*Continued*

Variable	Definition
Fund characteristics	
Net outflows	The negative of daily fund flows from Morningstar. Fund flows are scaled by previous month TNA and expressed in percentage points. Fund flows are winsorized at 1st and 99th percentiles.
Cash/TNA	The ratio of cash & cash equivalents to fund's TNA as of the last reporting date before the bond sale. The value of cash & cash equivalents is calculated from the position-level data from Morningstar. Cash equivalents include holdings of money market mutual funds, repo, commercial paper, T-Bills, agency and municipal debt securities with original maturity of less than one year, and variable rate demand notes. Cash ratios are winsorized at the 99th percentile.
Fund TNA	Fund TNA as of the end of the last reporting date before the bond sale. Expressed in $ millions.
Family TNA	Aggregate TNA of all open-end municipal bond funds within a family, defined using Morningstar's *Branding Name*. Expressed in $ millions.
Fund age	Number of years since the inception date of the fund's oldest share class.
Bond characteristics	
GO bond	Indicator variable equal to one if the bond is general obligation.
Insured	Indicator variable equal to one if the bond is insured.
Bond age	Number of years since the bond's offering date.
Maturity	Number of years until the bond's maturity date.
Offer amount	Par value of the bond's offering amount, in $ millions.
Rating	The median of Moody's, S&P, and Fitch ratings when all are available, lower rating otherwise. Ratings are from credit rating disclosures per SEC Rule 17g-7 after June 2012 and from disclosures per SEC Rule 17g-2 before June 2012. Ratings are coded such that AAA = 0, AA+ = 1, AA = 2, etc.
Market conditions	
Aggregate net outflows	Total net outflows from all open-end municipal bond funds during the seven days leading up to the transaction date, not including the transaction date. We first calculate aggregate net outflows on each day and scale these by aggregate TNA (of funds with valid flow data) as of the previous month. We then calculate cumulative outflows over the previous seven days.

Figure 1
Match Rate Over Time

This figure reports the percentage of Morningstar holding-implied sales of municipal bonds that are matched with MSRB transactions. Numbers on the right report cumulative match rates for 2016.

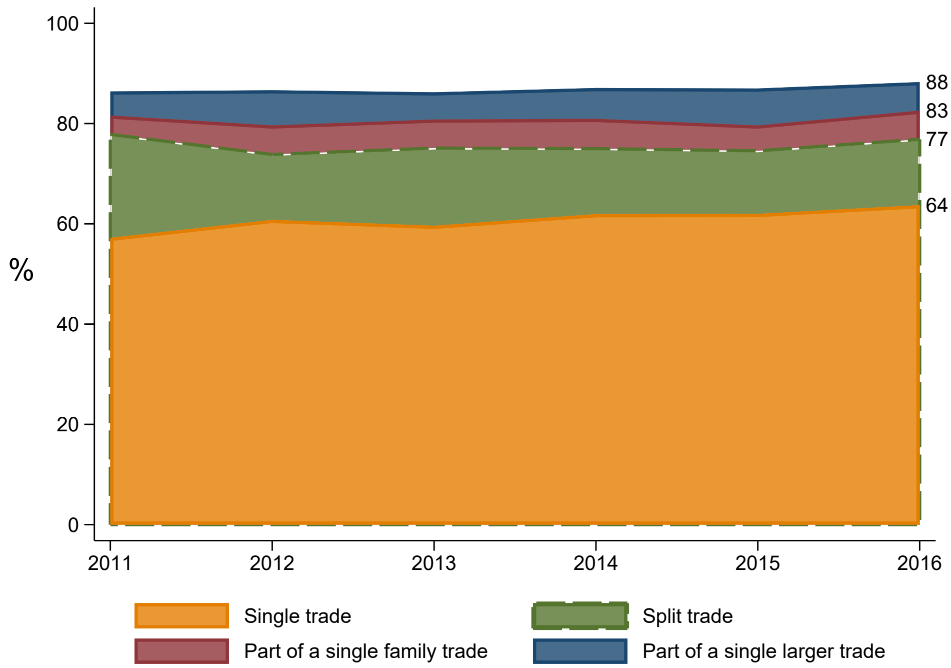
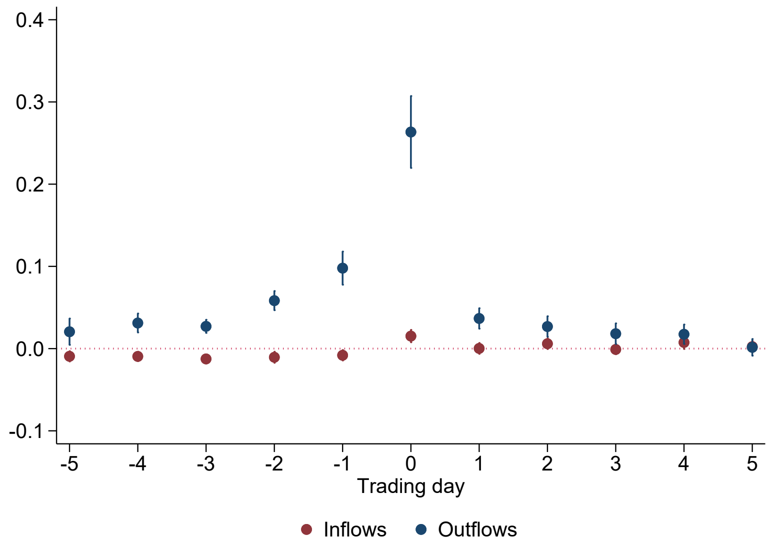


Figure 2
Daily Flows and Sales

This figure plots the estimated coefficients, along with their 95% confidence intervals, from the regressions of daily sales on daily fund flows. Panel (a) plots the estimated coefficients on inflows and outflows that correspond to the regressions in column 1 of Appendix Table B1. Panel (b) plots the estimated coefficients on outflows for funds with low versus high cash-to-assets ratio as of the previous month (columns 2 and 3 of the Appendix Table B1). Fund and date fixed effects are included in all specifications. Standard errors are adjusted for clustering by month-date.

(a) Inflows versus outflows



(b) High versus low cash funds

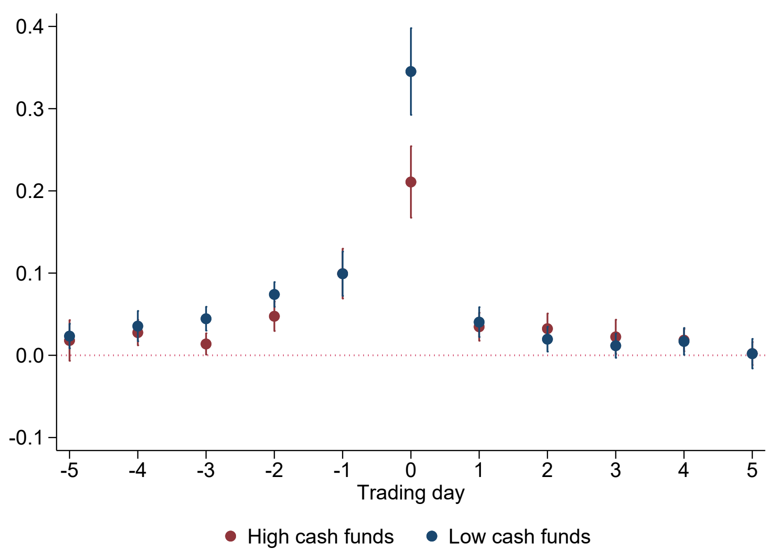


Table 1
Characteristics of Matched and Unmatched Sales

This table reports the characteristics of matched and unmatched sales of municipal bonds. Δ is the difference in means between unmatched and matched sales. t-statistics for the difference in means are adjusted for clustering by fund and bond. Credit ratings are encoded so that AAA = 0, AA+ = 1, ..., BB+ = 10, ..., C = 20. The sample period is 2011–2016.

	Matched sales			Unmatched sales				
	N	Mean	Median	N	Mean	Median	Δ	t-stat
Sale amount ($m)	113,916	3.26	1.61	17,250	4.03	1.52	-0.77	-2.75
GO bond	113,916	0.23	0.00	17,250	0.14	0.00	0.09	8.98
Insured	113,916	0.20	0.00	17,250	0.13	0.00	0.08	8.20
Bond age (years)	113,916	4.06	2.70	17,250	3.49	2.21	0.57	5.66
Maturity (years)	113,916	14.58	13.73	17,250	21.01	22.60	-6.43	-21.14
Offer amount ($m)	113,916	56.84	16.34	17,250	226.08	91.16	-169.25	-8.15
Rating	103,239	4.12	3.00	16,083	5.97	5.00	-1.85	-10.75
Turnover (%)	113,916	13.09	1.62	17,250	31.69	18.59	-18.59	-16.50
Average daily flow (%)	90,530	-0.03	-0.03	13,369	-0.02	-0.02	-0.01	-1.33
TNA ($m)	113,916	2,200.47	790.21	17,250	2,003.34	716.69	197.14	1.00
Fund age (years)	113,916	21.36	22.42	17,250	22.56	24.17	-1.20	-3.14

Table 2
Summary Statistics

This table reports summary statistics for the sample of municipal bond sales by open-end mutual funds matched to MSRB transaction data. Only single fund and split trades are included. Sales that are combined with sales by affiliates of the fund are excluded. The sample period is 2011–2016.

				Percentile		
	N	Mean	SD	25th	50th	75th
Par traded ($m)	69,257	2.41	3.77	0.50	1.20	3.00
Trade price ($)	69,257	104.99	14.24	100.42	106.01	113.12
Dealer markup (bps)	50,725	62.74	95.84	4.91	22.20	98.96
Prearranged trade	69,257	0.20	0.40	0.00	0.00	0.00
Same-day unwind	69,257	0.29	0.45	0.00	0.00	1.00
Days to unwind	50,725	7.00	17.25	0.00	0.00	6.00
Split trade	50,725	0.35	0.48	0.00	0.00	1.00
Customer unwind	50,725	0.52	0.50	0.00	1.00	1.00
Eigenvector centrality	69,252	0.09	0.20	0.00	0.01	0.04
Centrality	69,252	-4.52	2.31	-5.94	-4.39	-3.16
New dealer	64,142	0.37	0.48	0.00	0.00	1.00
1-day outflow (%)	69,257	0.10	0.38	-0.04	0.03	0.15
2-day outflow (%)	69,257	0.17	0.57	-0.07	0.07	0.30
3-day outflow (%)	69,257	0.22	0.74	-0.10	0.11	0.44
Cash/TNA	69,257	0.03	0.04	0.00	0.02	0.04
Fund TNA ($m)	69,257	1,502.83	2,058.58	207.32	636.17	2,076.67
Family TNA ($m)	69,257	12,201.88	12,962.69	1,771.28	9,352.73	14,217.60
Fund age (years)	69,257	20.06	10.55	12.75	21.00	26.83
GO bond	69,257	0.24	0.43	0.00	0.00	0.00
Insured	69,257	0.22	0.42	0.00	0.00	0.00
Bond age (years)	69,257	3.91	4.04	0.78	2.38	6.29
Maturity (years)	69,257	13.98	9.10	6.56	12.76	20.55
Offer amount ($m)	69,257	55.09	131.39	4.64	14.94	48.25
Rating	69,257	4.08	3.25	2.00	3.00	6.00
Bond turnover (%)	69,257	13.11	26.02	0.00	1.74	12.92
# trading days	69,257	8.01	12.41	0.00	3.00	10.00

Table 3
Prearranged Trades

This table shows that flow-induced sales are less likely to be prearranged. The table reports the results of the linear probability model regressions of the prearranged trade dummy on net outflows:

$$I(\mathit{Prearranged\ trade})_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta \cdot \mathit{Flows}_{f,t} + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. A sale is considered to be prearranged if the same dealer resells the bond within sixty seconds. The sample consists of mutual fund sales for which we can construct the sequence of trades resulting in the complete unwind of the initial trade by the dealer(s). *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Cumulative fund flows over					
	$[t, t]$		$[t-1, t]$		$[t-2, t]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Net outflows$_{f,t}$	−0.021***		−0.019***		−0.009*	
	(0.008)		(0.006)		(0.005)	
Inflows$_{f,t}$		0.008		0.013		−0.001
		(0.025)		(0.019)		(0.014)
Outflows$_{f,t}$		−0.026**		−0.021**		−0.013**
		(0.012)		(0.008)		(0.006)
Ln(Par traded)$_{b,d,f,t}$	−0.036**	−0.036**	−0.036**	−0.036**	−0.036**	−0.036**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Ln(Fund TNA)$_{f,t-1}$	−0.000	−0.000	0.000	0.000	0.001	0.001
	(0.026)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Ln(Family TNA)$_{f,t-1}$	0.075	0.074	0.076	0.075	0.075	0.072
	(0.057)	(0.056)	(0.057)	(0.056)	(0.057)	(0.054)
Ln(Bond age)$_{b,t}$	−0.019*	−0.019*	−0.019*	−0.019*	−0.019*	−0.019*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Ln(Maturity)$_{b,t}$	−0.019	−0.018	−0.019	−0.019	−0.019	−0.019
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
N	24,978					
Adjusted R^2	0.28	0.28	0.28	0.28	0.28	0.28
Fund FEs	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓

Table 4
Bond Characteristics

This table reports the results of regressions of bond characteristics on fund flows:

$$Bond\ chars_{b,d,f,t} = \alpha_f + \alpha_t + \beta \cdot Flows_{f,t} + \gamma' X_{f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Standard errors are adjusted for clustering by bond and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Ln(Offer amount)		Rating		Insured		Ln(Maturity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net outflows$_{f,t}$	0.066***		−0.165***		0.009*		−0.081***	
	(0.019)		(0.040)		(0.005)		(0.014)	
Inflows$_{f,t}$		−0.066		−0.034		0.001		0.044
		(0.052)		(0.106)		(0.012)		(0.028)
Outflows$_{f,t}$		0.066***		−0.225***		0.013**		−0.093***
		(0.022)		(0.048)		(0.005)		(0.019)
Ln(Fund TNA)$_{f,t-1}$	0.159***	0.159***	−0.379***	−0.381***	−0.014	−0.014	0.047*	0.047*
	(0.050)	(0.050)	(0.119)	(0.119)	(0.010)	(0.010)	(0.025)	(0.024)
Ln(Family TNA)$_{f,t-1}$	−0.049	−0.049	0.249*	0.236*	0.047**	0.048**	−0.037	−0.040
	(0.065)	(0.066)	(0.129)	(0.129)	(0.018)	(0.018)	(0.036)	(0.036)
N	69,248							
Adjusted R^2	0.26	0.26	0.32	0.32	0.14	0.14	0.42	0.42
Fund FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table 5
Dealer Centrality

This table shows that mutual funds trade with more central dealers when selling in response to outflows. The table reports the results of regressions of dealer's log eigenvector centrality on fund flows:

$$Centrality_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta \cdot Flows_{f,t} + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Cumulative fund flows over					
	$[t, t]$		$[t-1, t]$		$[t-2, t]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Net outflows$_{f,t}$	0.100**		0.083**		0.086***	
	(0.047)		(0.033)		(0.030)	
Inflows$_{f,t}$		−0.107		−0.056		−0.058
		(0.107)		(0.080)		(0.063)
Outflows$_{f,t}$		0.098*		0.095**		0.099***
		(0.057)		(0.039)		(0.036)
Ln(Par traded)$_{b,d,f,t}$	0.387***	0.387***	0.387***	0.387***	0.386***	0.386***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Prearranged trade$_{b,d,f,t}$	1.161*	1.161*	1.161*	1.161*	1.160*	1.160*
	(0.649)	(0.649)	(0.649)	(0.649)	(0.649)	(0.649)
Ln(Fund TNA)$_{f,t-1}$	0.003	0.003	0.001	0.001	0.001	0.001
	(0.068)	(0.068)	(0.069)	(0.069)	(0.068)	(0.069)
Ln(Family TNA)$_{f,t-1}$	0.250	0.250	0.248	0.250	0.240	0.243
	(0.219)	(0.219)	(0.218)	(0.218)	(0.217)	(0.217)
Ln(Bond age)$_{b,t}$	−0.080**	−0.080**	−0.081**	−0.081**	−0.081**	−0.081**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Ln(Maturity)$_{b,t}$	−0.183*	−0.183*	−0.182*	−0.182*	−0.181*	−0.182*
	(0.098)	(0.098)	(0.097)	(0.097)	(0.098)	(0.098)
N	40,475					
Adjusted R^2	0.45	0.45	0.45	0.45	0.45	0.45
Fund FEs	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓

Table 6
Cash Buffers and Dealer Centrality

This table shows that the effect of fund flows on dealer centrality is significantly stronger for funds with smaller cash buffers. The table reports the results of regressions of dealer's log eigenvector centrality on fund flows interacted with the cash-to-assets ratio:

$$Centrality_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_0 \cdot Flows_{f,t} + \beta_1 \cdot Flows_{f,t} \times \frac{Cash}{TNA}_{f,t-1} + \beta_2 \cdot \frac{Cash}{TNA}_{f,t-1} + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Cumulative fund flows over								
	$[t,t]$			$[t-1,t]$			$[t-2,t]$		
		Days since last cash observation			Days since last cash observation			Days since last cash observation	
		≤ 30	≤ 15		≤ 30	≤ 15		≤ 30	≤ 15
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net outflows$_{f,t}$	0.161**	0.221***	0.330***	0.132***	0.182***	0.253***	0.130***	0.173***	0.250***
	(0.061)	(0.060)	(0.088)	(0.040)	(0.042)	(0.057)	(0.036)	(0.043)	(0.049)
Net outflows$_{f,t}\times$ Cash/TNA$_{f,t-1}$	−1.669**	−2.279**	−5.758***	−1.417***	−1.954***	−4.025***	−1.112***	−1.539***	−2.969***
	(0.746)	(0.878)	(2.087)	(0.386)	(0.523)	(1.055)	(0.299)	(0.426)	(0.842)
Cash/TNA$_{f,t-1}$	0.215	−0.242	−1.519	0.230	−0.243	−1.619	0.261	−0.210	−1.626
	(0.468)	(0.675)	(1.090)	(0.477)	(0.669)	(1.070)	(0.479)	(0.667)	(1.055)
Ln(Par traded)$_{b,d,f,t}$	0.347***	0.323***	0.306***	0.346***	0.322***	0.304***	0.345***	0.321***	0.302***
	(0.109)	(0.106)	(0.098)	(0.109)	(0.106)	(0.097)	(0.109)	(0.106)	(0.097)
Ln(Fund TNA)$_{f,t-1}$	0.004	0.093	−0.021	−0.004	0.086	−0.027	−0.005	0.085	−0.026
	(0.060)	(0.067)	(0.158)	(0.061)	(0.068)	(0.157)	(0.061)	(0.068)	(0.155)
Ln(Family TNA)$_{f,t-1}$	0.297	0.277	0.352	0.301	0.281	0.366	0.296	0.273	0.348
	(0.214)	(0.208)	(0.307)	(0.214)	(0.208)	(0.308)	(0.213)	(0.207)	(0.308)
Ln(Bond age)$_{b,t}$	−0.098**	−0.078*	−0.049	−0.099**	−0.078*	−0.050	−0.099**	−0.079*	−0.053
	(0.045)	(0.043)	(0.061)	(0.045)	(0.043)	(0.061)	(0.045)	(0.043)	(0.060)
Ln(Maturity)$_{b,t}$	−0.204*	−0.167	−0.337***	−0.203*	−0.164	−0.333***	−0.203*	−0.165	−0.332***
	(0.108)	(0.109)	(0.104)	(0.108)	(0.108)	(0.103)	(0.108)	(0.108)	(0.105)
N	40,475	30,166	12,321	40,475	30,166	12,321	40,475	30,166	12,321
Adjusted R^2	0.42	0.43	0.49	0.42	0.43	0.50	0.42	0.43	0.50
Fund FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 7
Credit Ratings

This table shows that funds are especially likely to turn to more central dealers when selling lower rated bonds in response to outflows. The table reports the results of regressions of dealer's log eigenvector centrality on fund flows, splitting the sample into bonds with different credit ratings:

$$Centrality_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta \cdot Flows_{f,t} + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	All rated bonds		By credit ratings		
			≥AA-	A+/A/A-	≤BBB+
	(1)	(2)	(3)	(4)	(5)
Net outflows$_{f,t}$	0.106**	−0.046	−0.035	0.172**	0.226**
	(0.051)	(0.070)	(0.069)	(0.082)	(0.109)
Net outflows$_{f,t}$× Rating$_{b,t}$		0.030**			
		(0.014)			
Ln(Par traded)$_{b,d,f,t}$	0.347***	0.347***	0.310***	0.288***	0.387***
	(0.109)	(0.109)	(0.084)	(0.106)	(0.137)
Ln(Fund TNA)$_{f,t-1}$	0.020	0.018	0.097	−0.099	−0.101
	(0.058)	(0.059)	(0.146)	(0.109)	(0.171)
Ln(Family TNA)$_{f,t-1}$	0.280	0.272	0.287	0.352	0.131
	(0.212)	(0.210)	(0.326)	(0.272)	(0.284)
Ln(Bond age)$_{b,t}$	−0.098**	−0.096**	−0.087**	−0.085	−0.065
	(0.044)	(0.044)	(0.040)	(0.073)	(0.052)
Ln(Maturity)$_{b,t}$	−0.201*	−0.202*	−0.110	−0.258	−0.047
	(0.109)	(0.109)	(0.121)	(0.175)	(0.199)
N	40,414	40,414	17,889	11,501	9,964
Adjusted R^2	0.42	0.42	0.46	0.43	0.44
Bond FEs	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓

Table 8
Fund Flows and Dealer Choice during Stressed Market Conditions

This table shows that the effect of fund flows on dealer centrality is stronger during stressed market conditions. The table reports the results of regressions of dealer's log eigenvector centrality on fund flows interacted with aggregate flows into all municipal bond mutual funds:

$$Centrality_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_0 \cdot Flows_{f,t} + \beta_1 \cdot Flows_{f,t} \times Agg.\ flows_{t-1} + \beta_2 \cdot Agg.\ flows_t + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. *Aggregate outflows* is the total outflow of all open-end muni funds over one week before the transaction. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Aggregate outflows			
	>0	≤ 0		
	(1)	(2)	(3)	(4)
Net outflows$_{f,t}$	0.168***	0.084	0.052	
	(0.059)	(0.080)	(0.054)	
Net outflows$_{f,t}\times$ Agg. outflows$_{t-1}$			0.261**	
			(0.117)	
Inflows$_{f,t}$				−0.159*
				(0.094)
Inflows$_{f,t}\times$ Agg. outflows$_{t-1}$				0.310
				(0.336)
Outflows$_{f,t}$				−0.029
				(0.075)
Outflows$_{f,t}\times$ Agg. outflows$_{t-1}$				0.450***
				(0.108)
Aggregate outflows$_{t-1}$			−0.177*	−0.235***
			(0.096)	(0.088)
Ln(Par traded)$_{b,d,f,t}$	0.281**	0.371***	0.344***	0.345***
	(0.105)	(0.105)	(0.108)	(0.108)
Ln(Fund TNA)$_{f,t-1}$	0.098	0.152**	0.067	0.065
	(0.135)	(0.067)	(0.072)	(0.072)
Ln(Family TNA)$_{f,t-1}$	0.175	−0.099	0.191	0.188
	(0.277)	(0.185)	(0.173)	(0.173)
Ln(Bond age)$_{b,t}$	−0.194*	−0.038	−0.091	−0.092
	(0.108)	(0.095)	(0.096)	(0.096)
Ln(Maturity)$_{b,t}$	−0.183	0.021	−0.170**	−0.171**
	(0.117)	(0.144)	(0.084)	(0.084)
N	17,625	16,062	40,475	40,475
Adjusted R^2	0.45	0.45	0.39	0.39
Fund FEs	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓

Table 9
Markups and Fund Flows

This table reports the results of regressions of markups on fund flows:

$$Markup\ (bps)_{b,f,d,t} = \alpha_f + \alpha_b + \alpha_t + \beta_0 \times Flows_{f,t} + \beta_1 \times Centrality_{d,t} \times Flows_{f,t} + \gamma' X_{b,f,t} + \varepsilon_{b,f,d,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. *Centrality* is standardized so that the coefficient on *Net outflows* represents the effect at mean centrality and the coefficient on the interaction of *Net outflows* and *Centrality* can be interpreted as the change in the sensitivity to *Net outflows* associated with a one standard deviation change in centrality. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	All sales				Sales unwound within 15 days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net outflows$_{f,t}$	−5.425***		3.965**	3.708**	−6.651***		3.094*	2.868*
	(1.360)		(1.845)	(1.858)	(1.223)		(1.828)	(1.559)
Net outflows$_{f,t}\times$ Centrality$_{d,t-1}$				3.954*				4.852***
				(2.097)				(1.582)
Inflows$_{f,t}$		−0.012				−1.198		
		(2.875)				(2.708)		
Outflows$_{f,t}$		−7.089***				−9.036***		
		(1.675)				(1.565)		
Centrality$_{d,t-1}$				1.548				0.809
				(1.066)				(1.178)
Ln(Par traded)$_{b,d,f,t}$			−17.806***	−18.071***			−18.333***	−18.484***
			(1.031)	(1.088)			(1.234)	(1.293)
Prearranged trade$_{b,d,f,t}$			−1.828	−2.610			−3.539*	−3.999*
			(2.779)	(2.890)			(2.002)	(2.182)
Split trade$_{b,d,f,t}$			51.702***	51.526***			50.166***	50.125***
			(2.742)	(2.722)			(2.919)	(2.914)
Ln(Fund TNA)$_{f,t-1}$	−8.646***	−8.693***	3.993	4.082	−8.133***	−8.213***	8.441**	8.529**
	(2.579)	(2.571)	(3.979)	(3.966)	(2.415)	(2.399)	(3.911)	(3.898)
Ln(Family TNA)$_{f,t-1}$	0.769	0.321	−5.654	−5.537	1.159	0.488	−7.402	−7.076
	(4.914)	(4.765)	(4.913)	(4.830)	(5.152)	(4.945)	(4.628)	(4.578)
Ln(Bond age)$_{b,t}$			8.822***	8.881***			6.431***	6.461***
			(1.319)	(1.332)			(1.289)	(1.286)
Ln(Maturity)$_{b,t}$			−10.237***	−10.172***			−4.792***	−4.754***
			(1.897)	(1.885)			(1.791)	(1.764)
N	50,717	50,717	24,978	24,977	44,044	44,044	21,083	21,082
Adjusted R^2	0.23	0.23	0.56	0.56	0.24	0.24	0.61	0.61
Fund FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓	✓	✓
Bond FEs			✓	✓			✓	✓
Rating FEs			✓	✓			✓	✓

Table 10
Selection: Subsample Analyses

This table shows that the relationship between fund flows and dealer centrality holds in subsamples of sales that look more similar on observable characteristics to the unmatched sales. The table reports the results of regressions of dealer's log eigenvector centrality on fund flows:

$$Centrality_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta \cdot Flows_{f,t} + \beta' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Column 2 restricts the sample to sales of bonds with offer amount of at least \$91.16 million; this corresponds to the median offer amount for unmatched sales. Columns 3 and 4 restrict the sample to sales of uninsured and revenue bonds respectively; sales of these bonds are less likely to be matched to MSRB. Column 5 restricts the sample to sales of bonds with remaining maturity of least 22.6 years; this corresponds to the median maturity for unmatched sales. Column 6 restricts the sample to sales of at least \$1.52 million in par value. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Full sample	Offer amount ≥ 91.16	Uninsured	Revenue	Maturity ≥ 22.60	Par traded ≥ 1.52
	(1)	(2)	(3)	(4)	(5)	(6)
Net outflows$_{f,t}$	0.100**	0.126*	0.112*	0.117**	0.307***	0.149**
	(0.047)	(0.073)	(0.059)	(0.058)	(0.102)	(0.070)
Ln(Par traded)$_{b,d,f,t}$	0.387***	0.492***	0.373***	0.416***	0.460***	0.396***
	(0.109)	(0.116)	(0.108)	(0.117)	(0.115)	(0.053)
Prearranged trade$_{b,d,f,t}$	1.161*	1.381**	1.283*	1.150*	1.227*	1.806***
	(0.649)	(0.675)	(0.646)	(0.669)	(0.678)	(0.677)
Ln(Fund TNA)$_{f,t-1}$	0.003	−0.056	−0.022	0.007	−0.005	0.096
	(0.068)	(0.110)	(0.070)	(0.072)	(0.114)	(0.095)
Ln(Family TNA)$_{f,t-1}$	0.250	0.353*	0.260	0.286	0.264*	0.177
	(0.219)	(0.190)	(0.211)	(0.230)	(0.150)	(0.228)
Ln(Bond age)$_{b,t}$	−0.080**	−0.026	−0.073**	−0.084**	−0.077*	−0.049
	(0.036)	(0.054)	(0.032)	(0.038)	(0.042)	(0.046)
Ln(Maturity)$_{b,t}$	−0.183*	−0.183	−0.111	−0.201*	5.313	−0.200
	(0.098)	(0.171)	(0.113)	(0.109)	(8.009)	(0.144)
N	40,475	9,315	32,661	32,235	11,727	14,641
Adjusted R^2	0.45	0.34	0.44	0.44	0.44	0.39
Fund FEs	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓

Table 11
Robustness

This table shows the robustness of the results in Table 5 on the association between fund flows and dealer centrality to alternative specifications. Model (2) uses fund and bond–month fixed effects. Model (3) uses all matched sales, i.e., including sales that are executed as part of larger trades by the fund family or the fund's investment adviser. Model (4) excludes split trades, focusing on bond sales that are executed through a single trade. Model (5) excludes bonds issued by Puerto Rico and other U.S. territories. Models (6) and (7) split the sample period into the 2011–2013 and 2014–2016 subperiod. Models (8) and (9) split the sample of funds into young versus old funds. Models (10) and (11) split the sample into small versus large fund families. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

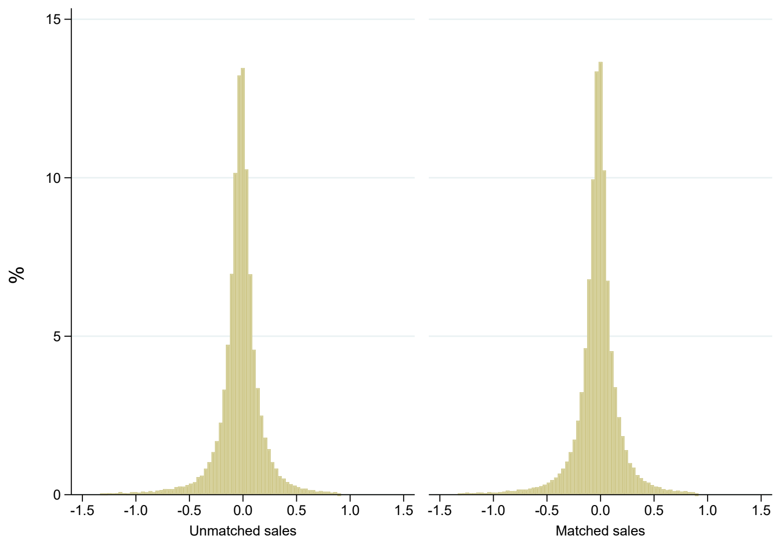
	Cumulative fund flows over								
	$[t,t]$			$[t-1,t]$			$[t-2,t]$		
	N	β	R^2	N	β	R^2	N	β	R^2
(1) Baseline	40,441	0.099**	0.453	40,441	0.082**	0.453	40,441	0.085***	0.453
		(0.047)			(0.033)			(0.030)	
(2) CUSIP-month FEs	15,935	0.068	0.700	15,935	0.102***	0.700	15,935	0.104***	0.700
		(0.051)			(0.035)			(0.032)	
(3) Include combined sales	50,367	0.075*	0.468	50,367	0.066**	0.468	50,367	0.070***	0.468
		(0.040)			(0.027)			(0.024)	
(4) Exclude split sales	25,970	0.119**	0.376	25,970	0.080**	0.376	25,970	0.086**	0.376
		(0.053)			(0.035)			(0.034)	
(5) Exclude U.S. territories	37,903	0.100*	0.467	37,903	0.087**	0.467	37,903	0.086***	0.467
		(0.052)			(0.035)			(0.031)	
(6) 2011–2013	21,056	0.183***	0.497	21,056	0.143***	0.497	21,056	0.136***	0.497
		(0.064)			(0.040)			(0.034)	
(7) 2014–2016	15,280	0.041	0.467	15,280	0.027	0.467	15,280	0.034	0.467
		(0.048)			(0.031)			(0.027)	
(8) Young funds	18,675	0.140***	0.493	18,675	0.106***	0.493	18,675	0.102***	0.493
		(0.052)			(0.032)			(0.031)	
(9) Old funds	16,090	0.048	0.495	16,090	0.060	0.495	16,090	0.076	0.495
		(0.073)			(0.060)			(0.051)	
(10) Small fund families	17,762	0.140**	0.471	17,762	0.127***	0.472	17,762	0.115***	0.472
		(0.059)			(0.048)			(0.041)	
(11) Large fund families	17,106	0.070	0.510	17,106	0.069*	0.510	17,106	0.075**	0.510
		(0.057)			(0.041)			(0.036)	

Appendix B: Additional Results

Figure B1
Daily Flow Distribution

This figure plots the distributions of daily fund flows during months with matched versus unmatched sales. Panel (a) shows the histogram of daily fund flows. Panel (b) shows the empirical cumulative distribution function.

(a) Histogram



(b) Cumulative distribution
(largest difference = 0.0034)

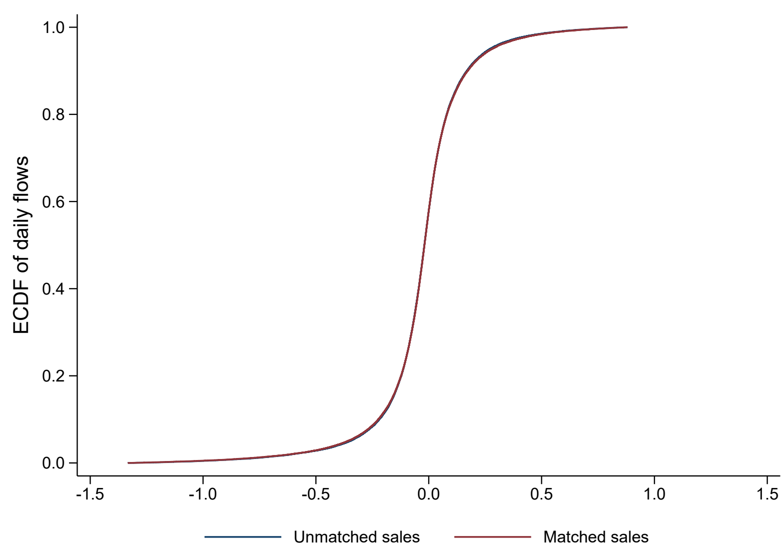


Figure B2
Prearranged Sales by Credit Rating

This figure shows that sales of lower rated bonds are more likely to be prearranged. A sale is considered to be prearranged if the same dealer resells the bond within sixty seconds. Sales of speculative-grade bonds are aggregated into a single category because they account for 5.4% of the sample. Each investment-grade rating accounts for at least 4% of the sample.

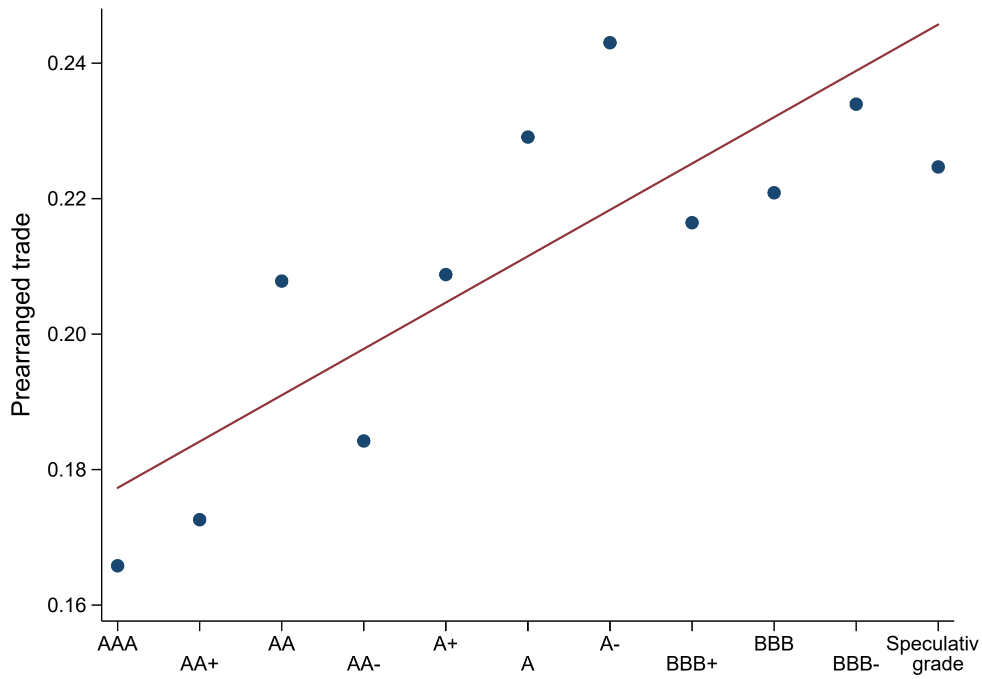


Table B1
Fund Flows and Bond Sales

This table reports the results of regressions of daily bond sales on daily flows:

$$Sales_{f,t} = \alpha_f + \alpha_t + \sum_{s=-15}^{+5} \left(\beta_s^{out} \cdot Outflows_{f,t+s} + \beta_s^{in} \cdot Inflows_{f,t+s}\right) + \varepsilon_{f,t},$$

where f indexes funds and t indexes trading days. Sales and fund flows are scaled by TNA as of the end of the previous month. In columns 4–6 the sample is limited to fund-month observations for which our algorithm matches all sales implied by changes in portfolio holdings to MSRB transaction data. Columns 2–3 and 5–6 split the sample based on the fund's cash-to-assets ratio as of the end of the previous month. For brevity we separately report only the coefficients on the contemporaneous value and the first five lags of outflows. We report the sums, and the associated standard errors, of the coefficients on outflows and inflows over different windows. Standard errors are adjusted for clustering by month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Full sample			Fund-months with all sales matched to MSRB		
		High cash	Low cash		High cash	Low cash
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Outflows}_{f,t}$	0.263***	0.211***	0.345***	0.287***	0.213***	0.385***
	(0.022)	(0.022)	(0.026)	(0.028)	(0.031)	(0.031)
$\text{Outflows}_{f,t-1}$	0.098***	0.099***	0.099***	0.121***	0.126***	0.114***
	(0.010)	(0.015)	(0.014)	(0.016)	(0.025)	(0.018)
$\text{Outflows}_{f,t-2}$	0.058***	0.047***	0.074***	0.067***	0.058***	0.078***
	(0.006)	(0.009)	(0.008)	(0.008)	(0.013)	(0.011)
$\text{Outflows}_{f,t-3}$	0.027***	0.014**	0.044***	0.031***	0.015*	0.051***
	(0.004)	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)
$\text{Outflows}_{f,t-4}$	0.031***	0.028***	0.036***	0.035***	0.027**	0.045***
	(0.006)	(0.008)	(0.009)	(0.009)	(0.010)	(0.014)
$\text{Outflows}_{f,t-5}$	0.021**	0.018	0.023***	0.028**	0.025	0.029***
	(0.008)	(0.012)	(0.007)	(0.012)	(0.019)	(0.010)
$\sum_{s=-5}^{0} \beta_s^{out}$	0.498	0.417	0.622	0.570	0.465	0.702
	(0.025)	(0.030)	(0.033)	(0.036)	(0.048)	(0.045)
$\sum_{s=-5}^{0} \beta_s^{in}$	−0.035	−0.039	−0.032	−0.041	−0.050	−0.033
	(0.006)	(0.008)	(0.012)	(0.008)	(0.012)	(0.011)
$\sum_{s=-15}^{-6} \beta_s^{out}$	0.081	0.068	0.081	0.055	0.036	0.053
	(0.018)	(0.032)	(0.018)	(0.020)	(0.031)	(0.026)
$\sum_{s=-15}^{-6} \beta_s^{in}$	−0.027	−0.025	−0.027	−0.039	−0.039	−0.037
	(0.009)	(0.012)	(0.023)	(0.012)	(0.016)	(0.015)
$\sum_{s=+1}^{+5} \beta_s^{out}$	0.101	0.110	0.091	0.074	0.077	0.062
	(0.017)	(0.024)	(0.022)	(0.017)	(0.022)	(0.026)
$\sum_{s=+1}^{+5} \beta_s^{in}$	0.015	0.006	0.035	0.009	0.007	0.012
	(0.008)	(0.009)	(0.019)	(0.008)	(0.010)	(0.011)
N	623,386	310,304	308,967	344,665	167,768	176,897
Adjusted R^2	0.06	0.06	0.06	0.05	0.04	0.06
Fund FEs	✓	✓	✓	✓	✓	✓
Date FEs	✓	✓	✓	✓	✓	✓

Table B2
Characteristics of Sold versus Unsold Bonds

This table reports the results of linear probability model regressions of position sale dummy on the interaction of bond characteristics with net outflows:

$$I(Sale)_{b,f,t} = \alpha_{f,t} + \beta_0 \cdot Bond\ chars_{b,f,t} + \beta_1 \cdot Bond\ chars_{b,f,t} \times Net\ outflows_{f,t} + \varepsilon_{b,f,t},$$

where b indexes bonds, f indexes funds, and t indexes time in days. For each actual sale in the data, the sample consists of the sale itself and all of bonds that were held by the fund at the beginning of the reporting period, that did not experience a redemption event during the reporting period, and that were not sold earlier in the reporting period. The dependent variable is scaled to have value of either 0 or 100. *Net outflows* is the negative of daily net flows reported by Morningstar. Standard errors are adjusted for clustering by bond and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Offer amt)$_{b,t}$	0.007	0.002						
	(0.006)	(0.005)						
Ln(Offer amt)$_b \times$ Net outflows$_{f,t}$		0.087***						
		(0.017)						
Rating$_{b,t}$			−0.049***	−0.046***				
			(0.004)	(0.003)				
Rating$_{b,t} \times$ Net outflows$_{f,t}$				−0.055***				
				(0.007)				
Insured$_b$					−0.038**	−0.037**		
					(0.018)	(0.018)		
Insured$_b \times$ Net outflows$_{f,t}$						−0.022		
						(0.035)		
Ln(Maturity)$_{b,t}$							−0.084***	−0.074***
							(0.014)	(0.014)
Ln(Maturity)$_{b,t} \times$ Net outflows$_{f,t}$								−0.284***
								(0.030)
N				8,682,263				
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Fund×Date FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table B3
Alternative Definitions of Dealer Centrality

This table shows that the results in Table 5 on the association between fund flows and dealer centrality are robust to using alternative measures of centrality: (1) baseline centrality (log of eigenvector centrality); (2) state-specific centrality, calculated using the network of dealers trading bonds issued by municipalities in a given state; (3) relative centrality, the difference between dealer centrality and average centrality of dealers trading with the fund in the last three months; (4) eigenvector centrality; (5) degree centrality; (6) PCA centrality (Li and Schürhoff, 2019), the first principal component extracted from value-weighted in and out degree centrality and eigenvector centrality measures; and (7) dealer's share of the aggregate trading volume with customers. All centrality measures are based on semi-annual snapshots of the trading network. To make coefficient estimates comparable across specifications, all measures are standardized residuals from the regressions of centrality measures on fund, month-date, bond, and rating fixed effects. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Cumulative fund flows over								
	$[t, t]$			$[t-1, t]$			$[t-2, t]$		
	N	β	R^2	N	β	R^2	N	β	R^2
(1) Baseline	40,475	0.065**	0.453	40,475	0.054**	0.453	40,475	0.056***	0.454
		(0.031)			(0.022)			(0.020)	
(2) State-specific centrality	39,915	0.081**	0.416	39,915	0.058**	0.416	39,915	0.051**	0.416
		(0.033)			(0.024)			(0.021)	
(3) Relative centrality	34,370	0.059*	0.411	34,370	0.059***	0.411	34,370	0.055***	0.412
		(0.034)			(0.023)			(0.020)	
(4) Eigenvector centrality	40,475	0.089**	0.300	40,475	0.063**	0.300	40,475	0.057**	0.300
		(0.039)			(0.029)			(0.029)	
(5) Degree centrality	40,475	0.082*	0.392	40,475	0.062*	0.392	40,475	0.058**	0.392
		(0.042)			(0.032)			(0.028)	
(6) PCA centrality	40,475	0.085**	0.328	40,475	0.062**	0.328	40,475	0.058*	0.329
		(0.041)			(0.031)			(0.030)	
(7) Dealer share	40,480	0.059*	0.400	40,480	0.051**	0.400	40,480	0.053**	0.400
		(0.034)			(0.025)			(0.022)	

Table B4
Dealer Centrality, Fund Outflows, and Bond Turnover

This table reports the results of regressions of dealer's log eigenvector centrality on net outflows interacted with bond turnover:

$$Centrality_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_0 \cdot Flows_{f,t} + \beta_1 \cdot Flows_{f,t} \times Turnover_{b,t} + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. *Net outflows* is the negative of daily net flows reported by Morningstar. *Inflows* is Morningstar net flows if positive, and zero otherwise. *Outflows* is the absolute value of Morningstar net flows if negative, and zero otherwise. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Cumulative fund flows over					
	$[t,t]$		$[t-1,t]$		$[t-2,t]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Net outflows$_{f,t}$	0.106**		0.093***		0.077***	
	(0.051)		(0.034)		(0.029)	
Net outflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$	−0.003		−0.005		0.005	
	(0.012)		(0.006)		(0.007)	
Inflows$_{f,t}$		−0.157		−0.070		−0.019
		(0.143)		(0.100)		(0.069)
Inflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$		0.024		0.007		−0.019
		(0.045)		(0.027)		(0.020)
Outflows$_{f,t}$		0.090		0.100**		0.103**
		(0.055)		(0.046)		(0.039)
Outflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$		0.004		−0.003		−0.002
		(0.020)		(0.017)		(0.016)
Ln(Bond turnover)$_{b,t-1}$	−0.001	−0.003	−0.000	−0.001	−0.001	0.004
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Ln(Par traded)$_{b,d,f,t}$	0.387***	0.387***	0.387***	0.387***	0.386***	0.386***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Prearranged trade$_{b,d,f,t}$	1.161*	1.161*	1.161*	1.161*	1.160*	1.160*
	(0.649)	(0.649)	(0.649)	(0.649)	(0.649)	(0.649)
Ln(Fund TNA)$_{f,t-1}$	0.003	0.003	0.001	0.001	0.000	−0.001
	(0.068)	(0.067)	(0.068)	(0.068)	(0.068)	(0.068)
Ln(Family TNA)$_{f,t-1}$	0.250	0.248	0.248	0.249	0.241	0.247
	(0.219)	(0.219)	(0.218)	(0.218)	(0.217)	(0.217)
Ln(Bond age)$_{b,t}$	−0.080**	−0.080**	−0.081**	−0.081**	−0.081**	−0.081**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Ln(Maturity)$_{b,t}$	−0.184*	−0.184*	−0.183*	−0.183*	−0.182*	−0.182*
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
N			40,475			
Adjusted R^2	0.45	0.45	0.45	0.45	0.45	0.45
Fund FEs	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓

Internet Appendix for
"Forced Sales and Dealer Choice in OTC Markets"

This internet appendix reports the following additional results.

1. Table IA1 reports the results of the Heckman correction model.
2. Tables IA2 and IA3 estimate regressions of prearranged trades and bond characteristics on fund flows interacted with bond turnover to show that the results in Tables 3 and 4 in the paper are likely to apply to unmatched trades as well.

Table IA1
Selection: Heckman Correction

Panel A reports the results of probit regression of sale matching indicator on bond characteristics:

$$I(Matched)_{b,d,f,t} = \Phi(\beta' X_{b,f,t} + \varepsilon_{b,d,f,t}),$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. Standard errors are adjusted for clustering by bond. Panel B reports results of Table 5 and Panel C reports results of Table 4, both corrected for unmatched holding-implied sales using Heckman two-stage sample selection model. λ indicates inverse Mills ratio from the first stage regression. Due to the estimation of λ, estimated standard errors may not be correct. Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

Panel A: First stage probit

	Raw estimates	Marginal effects
	(1)	(2)
Ln(Offer amt)$_{b,t}$	-0.296^{***}	-0.061^{***}
	(0.006)	(0.001)
A rated$_{b,t}$	-0.107^{***}	-0.022^{***}
	(0.020)	(0.004)
$\leq$ BBB rated$_{b,t}$	-0.290^{***}	-0.060^{***}
	(0.023)	(0.005)
Insured$_{b}$	-0.078^{***}	-0.016^{***}
	(0.025)	(0.005)
General obligation bond$_{b}$	0.010	0.002
	(0.021)	(0.004)
Ln(Bond age)$_{b,t}$	0.058^{***}	0.012^{***}
	(0.007)	(0.001)
Ln(Maturity)$_{b,t}$	-0.134^{***}	-0.028^{***}
	(0.010)	(0.002)
Ln(Bond turnover)$_{b,t-1}$	-0.218^{***}	-0.045^{***}
	(0.005)	(0.001)
Constant	2.823^{***}	
	(0.034)	
N	84,748	
Pseudo R^2	0.23	

Panel B: Dealer centrality and fund flows

	$[t,t]$		$[t-1,t]$		$[t-2,t]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Net outflows$_{f,t}$	0.099**	0.099**	0.082**	0.083**	0.085***	0.085***
	(0.047)	(0.047)	(0.033)	(0.033)	(0.030)	(0.030)
Ln(Par traded)$_{b,d,f,t}$	0.387***	0.387***	0.387***	0.387***	0.386***	0.386***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Prearranged trade$_{b,d,f,t}$	1.160*	1.160*	1.160*	1.160*	1.159*	1.159*
	(0.649)	(0.649)	(0.649)	(0.649)	(0.649)	(0.649)
Ln(Fund TNA)$_{f,t-1}$	0.001	0.002	−0.001	0.001	−0.001	0.000
	(0.069)	(0.067)	(0.069)	(0.068)	(0.068)	(0.067)
Ln(Family TNA)$_{f,t-1}$	0.251	0.251	0.249	0.249	0.242	0.241
	(0.219)	(0.218)	(0.218)	(0.218)	(0.217)	(0.217)
Ln(Bond age)$_{b,t}$	−0.081**	−0.079**	−0.081**	−0.080**	−0.082**	−0.081**
	(0.036)	(0.035)	(0.036)	(0.035)	(0.036)	(0.035)
Ln(Maturity)$_{b,t}$	−0.183*	−0.182*	−0.182*	−0.182*	−0.181*	−0.181*
	(0.098)	(0.097)	(0.097)	(0.097)	(0.098)	(0.097)
$\lambda_{b,d,f,t}$		0.070		0.073		0.078
		(0.150)		(0.150)		(0.151)
N			40,448			
Adjusted R^2	0.45	0.45	0.45	0.45	0.45	0.45
Fund FEs	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓

Panel C: Bond characteristics and fund flows

	Ln(Offer amount)		Rating		Insured		Ln(Maturity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net outflows$_{f,t}$	0.065***	0.109***	−0.168***	−0.143***	0.009*	0.007	−0.081***	−0.070***
	(0.019)	(0.012)	(0.040)	(0.040)	(0.005)	(0.005)	(0.014)	(0.014)
Ln(Fund TNA)$_{f,t-1}$	0.149***	0.066**	−0.383***	−0.429***	−0.015	−0.011	0.047*	0.027
	(0.050)	(0.033)	(0.119)	(0.127)	(0.010)	(0.009)	(0.025)	(0.024)
Ln(Family TNA)$_{f,t-1}$	−0.039	−0.061	0.251*	0.239*	0.049***	0.050***	−0.039	−0.044
	(0.065)	(0.045)	(0.129)	(0.131)	(0.018)	(0.018)	(0.036)	(0.035)
$\lambda_{b,d,f,t}$		5.071***		2.869***		−0.237***		1.205***
		(0.049)		(0.192)		(0.014)		(0.031)
N					68,763			
Adjusted R^2	0.26	0.69	0.32	0.36	0.14	0.16	0.42	0.48
Fund FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA2
Prearranged Trades, Fund Outflows, and Bond Turnover

This table reports the results of the linear probability model regressions of the prearranged trade dummy on net outflows interacted with bond turnover:

$$I(Prearranged\ trade)_{b,d,f,t} = \alpha_f + \alpha_b + \alpha_t + \beta_0 \cdot Flows_{f,t} + \beta_1 \cdot Flows_{f,t} \times Turnover_{b,t} + \gamma' X_{b,f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. A sale is considered to be prearranged if the same dealer resells the bond within sixty seconds. The sample consists of mutual fund sales for which we can construct the sequence of trades resulting in the complete unwind of the initial trade by the dealer(s). Standard errors are adjusted for clustering by dealer and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Cumulative fund flows over					
	$[t,t]$		$[t-1,t]$		$[t-2,t]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Net outflows$_{f,t}$	-0.035^{***}		-0.029^{***}		-0.015^{**}	
	(0.012)		(0.008)		(0.007)	
Net outflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$	0.008^{*}		0.006		0.004	
	(0.005)		(0.004)		(0.003)	
Inflows$_{f,t}$		0.027		0.029		0.004
		(0.026)		(0.020)		(0.014)
Inflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$		-0.009		-0.008		-0.003
		(0.010)		(0.008)		(0.005)
Outflows$_{f,t}$		-0.038^{**}		-0.028^{**}		-0.020^{*}
		(0.016)		(0.013)		(0.011)
Outflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$		0.007		0.004		0.004
		(0.006)		(0.005)		(0.004)
Ln(Bond turnover)$_{b,t-1}$	0.001	0.001	0.001	0.001	0.001	0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Ln(Par traded)$_{b,d,f,t}$	-0.036^{**}	-0.036^{**}	-0.036^{**}	-0.036^{**}	-0.036^{**}	-0.036^{**}
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Ln(Fund TNA)$_{f,t-1}$	-0.000	-0.000	0.000	0.000	0.001	0.001
	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)	(0.027)
Ln(Family TNA)$_{f,t-1}$	0.076	0.075	0.076	0.075	0.075	0.072
	(0.057)	(0.056)	(0.057)	(0.055)	(0.057)	(0.054)
Ln(Bond age)$_{b,t}$	-0.019^{*}	-0.019^{*}	-0.019^{*}	-0.019^{*}	-0.019^{*}	-0.019^{*}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Ln(Maturity)$_{b,t}$	-0.018	-0.018	-0.018	-0.018	-0.018	-0.018
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
N	24,978					
Adjusted R^2	0.28	0.28	0.28	0.28	0.28	0.28
Fund FEs	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓
Bond FEs	✓	✓	✓	✓	✓	✓
Rating FEs	✓	✓	✓	✓	✓	✓

Table IA3
Bond Characteristics, Fund Outflows, and Bond Turnover

This table reports the results of regressions of bond characteristics on net outflows interacted with bond turnover:

$$Bond\ chars_{b,d,f,t} = \alpha_f + \alpha_t + \beta_0 \cdot Flows_{f,t} + \beta_1 \cdot Flows_{f,t} \times Turnover_{b,t} + \gamma' X_{f,t} + \varepsilon_{b,d,f,t},$$

where b indexes bonds, d indexes dealers, f indexes funds, and t indexes time in months. Standard errors are adjusted for clustering by bond and month-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Ln(Offer amount)		Rating		Insured		Ln(Maturity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Net outflows$_{f,t}$	0.019		−0.164***		0.016**		−0.095***	
	(0.021)		(0.045)		(0.007)		(0.018)	
Net outflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$	0.050***		0.001		−0.005*		0.013**	
	(0.010)		(0.020)		(0.003)		(0.006)	
Inflows$_{f,t}$		0.003		0.191		−0.011		0.092***
		(0.071)		(0.143)		(0.016)		(0.034)
Inflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$		−0.070**		−0.147***		0.009		−0.036***
		(0.030)		(0.049)		(0.006)		(0.012)
Outflows$_{f,t}$		0.027		−0.142***		0.016**		−0.094***
		(0.024)		(0.050)		(0.007)		(0.022)
Outflows$_{f,t}\times$ Ln(Turnover)$_{b,t-1}$		0.042***		−0.060*		−0.004		0.004
		(0.011)		(0.031)		(0.004)		(0.006)
Ln(Bond turnover)$_{b,t-1}$	0.286***	0.288***	0.026*	0.044***	−0.015***	−0.015***	0.052***	0.055***
	(0.008)	(0.008)	(0.015)	(0.016)	(0.002)	(0.002)	(0.003)	(0.003)
Ln(Fund TNA)$_{f,t-1}$	0.133***	0.133***	−0.381***	−0.384***	−0.013	−0.013	0.042*	0.042*
	(0.042)	(0.042)	(0.119)	(0.118)	(0.010)	(0.010)	(0.024)	(0.024)
Ln(Family TNA)$_{f,t-1}$	−0.037	−0.037	0.251*	0.236*	0.047**	0.048**	−0.035	−0.038
	(0.063)	(0.063)	(0.130)	(0.129)	(0.018)	(0.018)	(0.036)	(0.037)
N	69,248							
Adjusted R^2	0.33	0.33	0.32	0.32	0.14	0.14	0.43	0.43
Fund FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month-date FEs	✓	✓	✓	✓	✓	✓	✓	✓