Flow-Induced Trading: Evidence from the Daily Trading of Municipal Bond Mutual Funds

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Abstract

We use novel data on the daily flows, trading, and cash buffers of open-end municipal bond mutual funds to study the dynamics of trading in response to fund flows. We document a much stronger short-term reliance on cash buffers than would be suggested by monthly regressions. When trading in response to fund flows, funds also tilt their trading to slightly more liquid bonds. Propensity to sell in response to outflows is affected strongly by market conditions: it decreases with the average markup and increases with the expectations of future aggregate outflows. We use our daily data to estimate the potential effects on flow-induced sales of requiring funds to hold a 10% highly liquid assets buffer. During the early stages of the COVID-19 pandemic, cumulative aggregate sales by the sample funds would have been only 18% lower.

Keywords: fire sales, mutual fund flows, municipal bonds, liquidity management, daily trading

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1 Introduction

The high-frequency dynamics of flow-induced trading and liquidity management in open-end mutual funds remain poorly understood, despite a large literature examining monthly or quarterly changes in portfolio holdings.[1] While studies have found evidence of funds using cash buffers to accommodate fund flows, the magnitudes in typical regressions using low-frequency data are generally small.[2] Moreover, little is known about how market conditions, such as expectations of future negative shocks to aggregate fund flows or market liquidity, affect the responsiveness of trading to fund flows. This lack of understanding of high-frequency dynamics of trading and liquidity management makes it challenging to evaluate the potential effects of policies aimed at reducing the financial stability risks posed by the liquidity mismatch in open-end mutual funds, such as the SEC's proposed rule requiring funds to hold 10% of their assets in cash and highly liquid securities.[3] While current estimates from monthly or quarterly regressions suggest that such a policy would have little effect on flow-induced sales, it is possible that short-term reliance on cash buffers allows enough time for new buyers to enter the market, significantly improving dealers' ability to intermediate. Understanding these dynamics, however, requires higher frequency data than have been historically available to researchers.

We shed new light on the dynamics of trading and the use of cash buffers to accommodate fund flows by constructing novel daily data on the trading activity, fund flows, and cash buffers of municipal bond mutual funds. These daily data allow us to trace out the response of sales and purchases of portfolio securities to inflows and outflows, to more accurately estimate the role of cash buffers in accommodating fund flows, and to study how market conditions, especially expectations of future aggregate outflows, affect the responsiveness of trading to fund flows. Daily data also allow us to use COVID-19 as a case study in which to evaluate the potential effects on flow-induced sales of requiring funds to hold a 10% buffer of cash and highly liquid securities. What makes it

[1] See, for example, Edelen (1999), Coval and Stafford (2007), Chen, Goldstein, and Jiang (2010), Chernenko and Sunderam (2016), Morris, Shim, and Shin (2017), Shek, Shim, and Shin (2018), Chernenko and Sunderam (2020), Huang (2020), Jiang, Li, and Wang (2021), Li, O'Hara, and Zhou (2023), among many others.

[2] Jiang, Li, and Wang (2021), for example, report an 8 cents decline in cash holdings for each dollar of quarterly net outflows from corporate bond funds.

[3] https://www.sec.gov/files/rules/proposed/2022/33-11130.pdf

possible for us to construct this unique data set of daily trading and cash buffers is the illiquidity and infrequent trading in the municipal bond market. We develop an algorithm that takes advantage of the infrequent trading to match changes in mutual fund holdings of municipal bonds to the Municipal Securities Rulemaking Board's (MSRB) transactions data. As a result, we know the date and price of almost all mutual fund trades, and we can construct the time series of daily trading volume and daily cash buffers.

Our empirical methodology estimates regressions of daily sales and purchases on contemporaneous, lagged, and future fund inflows and outflows.[4] In our regressions of sales, the estimated coefficient on day t outflows is 0.242, indicating that a dollar of outflows is associated with 24.2 cents worth of contemporaneous sales. Since muni funds almost never hold securities other than municipal bonds and cash equivalents, we can infer that the rest of outflows is accommodated using cash buffers.[5] Funds sell additional 26.9 cents worth of bonds over the following fifteen trading days, with most of these sales (17.8 cents) happening over the following five trading days. We also find positive and statistically significant coefficients on future outflows. The sum of the estimated coefficients on outflows on days $[t+1, t+5]$ is 0.177. These results are consistent with funds having some ability to forecast future fund flows, receiving advance notice of large flows, or with flows taking a few days to settle and thus to be captured in Morningstar daily flows data.[6] Overall, a dollar of outflows is associated with 68.8 cents worth of bond sales.

The response of bond purchases to inflows is much more gradual than the response of sales to outflows. The estimated coefficient on day t inflows is 0.083, or about one-third of the estimated coefficient on day t outflows in the sales regressions. The estimated coefficient on day $t-1$ inflows is actually larger at 0.121. The sum of the coefficients on inflows over days $[t-15, t+5]$ is 0.702, similar to the sum of the coefficients on outflows in the regressions of bond sales. When we split purchases into primary versus secondary market ones, we find that they contribute equally to the

[4] Outflows are the negative of net fund flows on days with negative net flows, and zero otherwise. Inflows are net fund flows on days with positive net flows, and zero otherwise.

[5] Funds can also draw down lines of credit or interfund lending programs. In practice these are rarely utilized.

[6] Wahal and Wang (2022) for example document a spike in mutual funds' net inflows around the turn of the month, which can be attributed to monthly payment cycles experienced by mutual fund investors, particularly retirement accounts.

response of total purchases to inflows. The timing of their response, however, is different: not surprisingly, secondary market purchases respond more quickly than primary market ones. The estimated coefficients on day t and $t-1$ inflows are 0.052 and 0.073 for secondary market purchases versus 0.030 and 0.048 for primary market purchases. These results provide quantitative estimates of the speed and magnitude of the potential effects of fund flows on secondary and primary market activity in the municipal bond market.

Our data on daily flows and trading allow us to construct the time series of daily cash buffers and investigate how cash buffers modulate the response of trading to fund flows. Funds sell significantly less in response to day t outflows when they hold more cash as of the previous trading day. Funds with less than 0.5% of their total net assets (TNA) in cash sell about 50 cents worth of bonds in response to contemporaneous outflows, while funds with more than 5.0% of their TNA in cash sell less than 20 cents worth of bonds in response to contemporaneous outflows. There is no significant difference between high and low cash funds in terms of how their purchases respond to inflows, although funds with larger cash buffers on day $t-1$ on average buy more bonds on day t. Our results on the dynamics of trading and on the effects of cash buffers indicate that cash buffers are more important than would be suggested by the monthly or quarterly regressions typically estimated in the literature. Such regressions may significantly underestimate the importance of cash buffers as cash buffers may change significantly during the relevant period.

We next ask whether other fund characteristics besides cash buffers can help explain cross-sectional variation in the response of trading to fund flows. We find that larger funds sell less in response to outflows. These may be because larger funds are more likely to internalize the price pressure effects of their trading (Chernenko and Sunderam, 2020). Funds holding longer maturity bonds also sell less in response to outflows, potentially because these bonds are less liquid and have larger markups. Interfund lending programs are associated with a weaker response of sales to outflows; however, the difference is not statistically significant. We find no association between fund characteristics and the response of purchases to inflows.

Our novel data on fund transactions also allow us to analyze the characteristics of bonds bought or sold by funds. In line with the existing literature (Dötz and Weth, 2019; Choi et al., 2020; Huang et al., 2021; Jiang, Li, and Wang, 2021; Ma, Xiao, and Zeng, 2022), conditional on trading, funds sell more liquid bonds, such as higher-rated bonds and bonds with shorter maturity, in response to larger outflows. Similarly, funds that experience inflows purchase more liquid bonds, but to a lesser extent. The effects on the characteristics of traded bonds are nonetheless relatively small, indicating that selective trading is less critical than using cash buffers in liquidity management by municipal bond funds.

A major advantage of our data is that it allows us to investigate how the dynamics of flow-induced trading are affected by market conditions. Importantly, our data allow us to i) construct measures of the expected future aggregate outflows and ii) control for the effect of day $t-1$ cash buffers on the responsiveness of trading to fund flows. We find that the responsiveness of sales to outflows decreases with average markups and increases with the expectation of future aggregated outflows. These effects are large. A one standard deviation increase in average markups (31 basis points) is associated with a 0.074 increase in the sensitivity of sales to day t outflows. A one standard deviation increase in the expected aggregate net outflows over the following five trading days (5 basis points) is associated with a 0.033 increase in the sensitivity of sales to day t outflows. This is true controlling for day $t-1$ cash buffers. Thus the increase in the propensity to sell in response to outflows during periods of aggregate net outflows is not due to funds having recently drawn down their cash buffers to meet earlier redemptions, but rather due to funds selling in expectation of future aggregate outflows (Brown, Carlin, and Lobo, 2010).

A striking example of this dynamic is the start of the COVID-19 pandemic in March 2020. We show a large spike in the sensitivity of sales to outflows from close to zero just before the pandemic to 0.505 at the peak in late March. This is despite the fact that most funds continued to maintain sizable cash buffers. This spike in the sensitivity of sales to outflows is likely due to the expectation of further aggregate outflows. Once aggregate outflows subside by early April, the sensitivity of sales to outflows declines substantially.

Finally, we use COVID-19 to evaluate the potential effects of requiring funds to hold 10% of their assets in cash and highly liquid securities. We first use the pre-crisis data to estimate the relationship between sales and fund flows, along with their interactions with cash buffers, market markup, and expected aggregate outflows. After initializing all funds to have a 10% cash buffer as of March 8, we use the estimated coefficients along with the actual fund flows to estimate the path of sales and cash buffers from March 9 through April 30.[7] We find that cumulative aggregate sales through April 9 would have been only 18% smaller. This means that unless larger cash buffers have a dramatic effect on redemptions or fundamentally change how funds trade in response to fund flows, requiring cash buffers on the order of 10% is unlikely to have a significant effect on flow-induced sales during periods of market stress.

Our paper contributes to a voluminous literature on the flow-induced trading of open-end mutual funds, including, among many others, Edelen (1999); Coval and Stafford (2007); Chernenko and Sunderam (2016); Choi et al. (2020); Falato et al. (2021); Li, O'Hara, and Zhou (2023). Except for a few recent papers that use ANCerno transaction-level data for a select sample of equity mutual funds (Agarwal, Tang, and Yang, 2012; Eisele et al., 2020; Busse et al., 2021; Cicero et al., 2022; Barardehi, Da, and Warachka, 2023; Binsbergen et al., 2024), almost all papers in the literature are limited to looking at monthly or quarterly changes in portfolio holdings. We develop an algorithm to identify the exact time and price of transactions by municipal bond funds. The resulting daily time series of flows, trades, and cash buffers paint a fine-grained picture of how municipal bond funds trade in response to fund flows. Our results provide evidence of much stronger reliance on cash buffers than would be suggested by monthly or quarterly regressions. At the same time, we document sharp increases in the sensitivity of sales to outflows during periods of stressed market conditions, and show that these increases cannot be explained by funds having recently drawn down their cash buffers to satisfy earlier redemptions.

Besides informing research on the liquidity management and fragility of open-end mutual funds, our results should be of interest to practitioners and policymakers. Given real-time data on fund flows and municipal bond trades, our estimates can be used to forecast the volume of mutual fund purchases and sales of municipal bonds. Such forecasts can help dealers and other market participants better manage their risks. Our results should also be of interest to policymakers interested in reducing the potential vulnerability of open-end funds that hold illiquid securities such as municipal bonds to outflows. Our results on the increases in the sensitivity of sales to outflows during periods of aggregate fund outflows and in particular during March 2020 suggest that requiring

[7] We first check that when we use the actual cash buffers as of March 8, the predicted time series of aggregate sales by sample funds matches their actual sales. This difference is only 2.8%, or \$0.9 billion, during March 9–April 30, 2020.

funds to hold larger cash buffers may not make much difference.

The rest of the paper is organized as follows. The next section describes our data and provides an overview of our algorithm for identifying daily fund trades. Section 3 reports the results of baseline regressions that trace out the effects of inflows and outflows on sales and purchases of municipal bonds. Sections 4 and 5 investigate how cash buffers and other fund characteristics modulate the response of sales and purchases to fund flows. In Section 6, we look at which bonds funds trade in response to fund flows. Section 7 investigates how the propensity to trade in response to fund flows varies with market conditions. Section 8 conducts a case study of fund trading during the early stage of the COVID-19 pandemic and reports the results of the exercise aimed at quantifying the potential effects of requiring funds to hold 10% cash buffers. Section 9 reports the robustness of our results to alternative specifications, while Section 10 concludes.

2 Data

We construct a fund-date panel data set with daily fund flows and daily trading activity, i.e., the value of bonds purchased and sold on each trading day. Our final sample consists of open-end municipal bond funds with daily fund flows in Morningstar. Because flows and trading during incubation may not be representative of flows and trading once funds are open to the public, we require funds to be at least two years old and to have TNA of at least \$10 million (Evans, 2010). To guard against errors in the portfolio holdings data, we exclude fund-month observations with the ratio of the market value of portfolio holdings to TNA outside the $[0.5, 2]$ interval (Coval and Stafford, 2007). We exclude short-duration funds (whose Morningstar category includes the word "short"), as it is hard to draw a clear distinction between their cash buffers and portfolio holdings. Finally, because trading around fund mergers and in liquidation may not be representative of trading during other times, we exclude observations within one month of a fund merger and all observations after funds announce their liquidation.[8]

[8] Announcements of fund liquidations are collected manually from the SEC filings.

2.1 Identifying Daily Fund Trades

Almost all papers in the mutual fund literature identify trades in portfolio securities as changes in portfolio holdings between adjacent reporting periods, which are usually quarterly or monthly. Our innovation is to match changes in portfolio holdings to actual trades in the MSRB municipal securities transactions data. We thus know the date, time, and price associated with each trade. What allows us to carry out this match is the fact that most municipal bonds trade infrequently and that, because markups decrease in trade size (Harris and Piwowar, 2006; Green, Hollifield, and Schürhoff, 2007; Li and Schürhoff, 2019), investors generally avoid splitting trades. Because trading is infrequent, there are usually few potential matches for a given mutual fund trade. The rest of this section outlines our algorithm; the Internet Appendix provides the details.

Throughout most of our sample period (2009–2020), we use Morningstar as our primary source of portfolio holdings data. In October 2019 funds start reporting their quarterly portfolio holdings on the SEC form N-PORT. Whenever N-PORT data are available, we use N-PORT instead of Morningstar.

About 81% of fund holdings snapshots in the combined Morningstar/N-PORT data are monthly; 2% have a two-month lag between adjacent portfolio holdings, and 17% are quarterly. To narrow the trading window when it is longer than a month, we augment Morningstar holdings data with portfolio holdings scraped from the SEC forms N-Q and N-CSR, taking advantage of the fact that some funds report their holdings to Morningstar and the SEC on different schedules. SEC forms N-Q and N-CSR report security descriptions — issuer name, coupon, and maturity date — but not CUSIPs. As a result we have to identify CUSIPs based on the other information provided. To avoid introducing any data errors, we use scraped data only to narrow the range of dates when a fund traded a given bond.[9]

We next adjust changes in portfolio holdings for the effect of mergers and tag changes in portfolio holdings that are likely due to bond events: maturities, calls, exchanges, refunding, mandatory tenders, amortization, and distributions in default. When we cannot match a holdings-implied

[9] For example, suppose we know from Morningstar data that a fund sold a bond during months $[s, t]$. Based on N-Q and N-CSR data, however, we may know that the fund still held the bond at the end of month $s' \in [s, t)$. We can therefore narrow the trading interval to $(s', t]$.

change to MSRB, we use the dates and prices of these bond events to calculate the fund's daily cash buffers. We use the same approach to handle primary market purchases. In other words, when a fund initiates a position in a newly issued bond and we cannot match this position to a specific transaction in MSRB, we use the bond's offering date and price to calculate the fund's daily purchases and cash buffers. Municipal bond data are from Mergent Municipal Bond Securities Database (MBSD) and Bloomberg.

Before attempting to match changes in mutual fund portfolio holdings to municipal bond trades in MSRB, we first match insurance company trades in municipal bonds to MSRB. Because the National Association of Insurance Commissioners (NAIC) data on insurance company trades generally includes trade date and price, we have a fairly accurate and robust match to MSRB. This match allows us to exclude insurance company trades from the population of potential matches for mutual fund trades.

Our algorithm attempts different types of matches between changes in mutual fund portfolio holdings and MSRB trades.

1. **Single fund trades** are 1–1 matches between holdings-implied trades and MSRB trades. Most matched trades in our data are single fund trades.

2. **Single family trades** are cases where the sum of holdings-implied sales (purchases) by affiliated funds matches to a single MSRB trade. In attempting to identify cases where multiple funds coordinate their trading and place a single trade, we use alternative definitions of "family." We first use the fund's branding name from Morningstar.[10] Next, we use the information on fund portfolio managers to identify cases where multiple funds, potentially part of different families, have the same portfolio manager(s). Third, we use family information from the SEC form N-CEN.

3. **Split fund trades** are cases where a fund's holdings-implied trade matches to a combination of MSRB trades.

4. **Split family trades** are cases where the sum of holdings-implied sales (purchases) by family

[10] A limitation of this variable is that it is a header rather than historical value.

funds matches to a combination of MSRB trades.

5. **Single larger MSRB trades** are cases where we match a single fund trade or sum of family trades to a single larger MSRB trade, where there are no trades with the same par value, and where the sum of all (remaining) trades with smaller par value is smaller than the holdings-implied trade.

Between 2009 and 2020, we are able to explain over 90% of all changes in portfolio holdings with either bond events, fund mergers, or actual trades in MSRB. Internet Appendix Figure IA1 reports our success rate over time. The overall match rate trends up slightly over the sample period. It dips slightly during periods of market turmoil: late 2010, the Taper Tantrum in mid-2013, and the onset of the COVID-19 pandemic in early 2020. Increases in trading activity during these periods hamper our ability to uniquely identify mutual funds trades.

Table 1 reports the share of changes in portfolio holdings that are explained by i) bond events, ii) fund mergers, iii) securities never appearing in MSRB, and iv) different types of matched MSRB trades. Although when running the match to MSRB we include all funds holding municipal bonds, Table 1 reports the classification of changes in portfolio holdings for our final sample of open-end mutual funds with daily fund flows from Morningstar.[11] Various bond events—maturities, calls, new issues, exchanges, and default distributions—account for 31.83% of all portfolio holding changes. In par-weighted terms, bond events account for 21.10%. This is mostly due to partial calls affecting smaller par values. At the same time, new issues tend to be larger and therefore account for a larger share of all changes in par-weighted terms (9.52%) than in equal-weighted terms (6.37%). Fund mergers account for 1.43% of all changes in holdings.

Trades matched to MSRB account for 55.79% of all changes in portfolio holdings. If we exclude non-MSRB securities and focus on changes that are not due to bond events or fund mergers, trades matched to MSRB account for 85.94% of changes in portfolio holdings. About three-quarters of MSRB-matched trades are single fund trades, i.e., cases where the change in portfolio holdings matches a single trade in MSRB.

[11] The only exception to this is that Table 1 includes reporting periods affected by mergers and liquidations.

Table 1
Classification of Changes in Portfolio Holdings

This table reports the share of all changes in portfolio holdings of open-end municipal bond funds that can be explained by i) bond events, ii) fund mergers, iii) securities never appearing in MSRB, and iv) different types of matched MSRB trades. The sample consists of 610 open-ended municipal bond funds that have daily fund flows in Morningstar, TNA as of the previous reporting period of at least \$10 million, age as of the previous reporting period of at least 2 years, and ratio of the net value of portfolio holdings to TNA in the $[0.5, 2]$ range. The sample period is 2009–2020; specifically, adjacent holdings snapshots are included as long as the last snapshot falls within Jan 2009–Dec 2020. Changes in holdings of Variable Rate Demand Notes (VRDNs) and other cash equivalents as well as changes in Tender Option Bonds are excluded. Cross trades are opposite trades by affiliated funds such that none of the individual trades can be matched to MSRB. $N = 778,692$.

Type	N	Equal-weighted (%)	Par-weighted (%)
Bond events			
Maturities, calls, and redemptions	182,480	23.43	9.86
New issues and remarketing issues	49,636	6.37	9.52
Exchanges	15,497	1.99	1.68
Default distributions	324	0.04	0.04
Fund mergers	11,141	1.43	1.04
Securities never in MSRB	14,041	1.80	3.37
Matched to MSRB			
Single fund trade	325,895	41.85	42.32
Part of a single family trade	51,231	6.58	8.09
Split fund trade	25,772	3.31	5.77
Part of a split family trade	5,479	0.70	1.33
Part of a single larger MSRB trade	26,094	3.35	4.39
Not matched			
Cross trades	1,898	0.24	0.29
Others	69,204	8.89	12.29

2.2 Summary Statistics

Table 2 reports summary statistics for our sample. Panel A shows that municipal bond mutual funds trade infrequently. For a given fund, only 10.68% of all trading days have bond sales activity. Purchases are a bit more common with 15.28% of all trading days seeing some purchase activity. Primary market purchases are slightly more common than secondary market ones with funds engaging in primary market purchases on 9.28% of all trading days and in secondary market purchases on 7.58% of all trading days.[12][13] Conditional on trading, the median values of sales and purchases are 0.33% and 0.38% of TNA. The distributions are skewed however, with mean values of 0.62%

[12] This difference could be in part due to how our algorithm handles primary market purchases. When we cannot match a fund's position in a newly issued bond to a specific primary market trade, which is often the case due to a large number of similar trades at issuance, we assume that the fund purchased on the issue date at the offering price. As a result, we identify the date and price of all primary market purchases but not of all secondary market purchases.

[13] Appendix Table B1 reports additional summary statistics on the correlation between sales and purchases. Conditional on selling at least one bond, funds engage in bond purchases 32.2% of the time. Conversely, conditional on purchasing at least one bond, funds engage in bond sales 22.5% of the time.

Table 2
Summary Statistics

This table reports summary statistics for the sample of daily trading by open-end municipal bond mutual funds. Panel A reports the share of fund-date observations with positive trading activity and the distributions of bond sales and purchases conditional on positive trading activity. Panel B reports the percentiles of sold and purchased bonds relative to the fund's existing portfolio. Panel C reports summary statistics on fund flows, fund characteristics, and aggregate market conditions. Credit ratings are encoded so that AAA = 0, AA+ = 1, ..., BB+ = 10, ..., C = 20. The sample period is 2009–2020. N = 1,089,130.

Panel A: Trading Measures

		Conditional on $\neq 0$				
				Percentile		
	Share $\neq 0$ (%)	Mean	SD	25th	50th	75th
Sales (%)	10.68	0.62	0.90	0.08	0.33	0.82
Purchases (%)	15.28	0.63	0.84	0.14	0.38	0.83
Primary purchases (%)	9.28	0.68	0.84	0.19	0.44	0.89
Secondary purchases (%)	7.58	0.44	0.68	0.05	0.20	0.55

Panel B: Characteristics of Traded Bonds

			Percentile		
	Mean	SD	25th	50th	75th
Sales					
Rating percentiles	39.66	28.73	15.00	35.00	62.00
Maturity percentiles	52.95	28.88	29.00	54.00	78.00
Offering amount percentiles	57.23	26.80	36.54	59.14	80.00
Issue size percentiles	56.99	26.67	36.00	59.33	79.00
Purchases					
Rating percentiles	43.16	29.26	17.13	40.51	67.00
Maturity percentiles	61.88	27.24	42.00	66.00	86.00
Offering amount percentiles	58.08	27.17	37.00	61.00	81.16
Issue size percentiles	57.95	27.34	36.91	61.00	81.35

Panel C: Fund Flows, Fund Characteristics, and Aggregate Market Conditions

			Percentile		
	Mean	SD	25th	50th	75th
Net flows (%)	0.00	0.40	-0.06	-0.01	0.06
Outflows (%)	0.06	0.26	0.00	0.01	0.06
Inflows (%)	0.06	0.29	0.00	0.00	0.06
Daily cash (%)	3.86	4.02	1.15	2.62	5.13
Fund TNA ($m)	713.47	1,517.30	101.17	227.21	613.40
Family TNA ($m)	12,182.71	15,263.53	1,336.60	8,462.40	14,577.97
Single state fund	0.64	0.48	0.00	1.00	1.00
Interfund lending	0.41	0.49	0.00	0.00	1.00
Weighted average rating (WAR)	4.32	1.71	3.22	3.98	4.90
Weighted average maturity (WAM)	15.43	4.70	11.26	16.20	19.01
Market markup (%)	0.91	0.31	0.69	0.87	1.10
Δ Yield spread (%)	-0.00	0.12	-0.05	-0.01	0.03
VIX	19.23	8.32	13.50	16.66	22.50
Aggregate outflows (%)	-0.01	0.06	-0.05	-0.02	0.00
Expected aggregate outflows (%)	-0.02	0.05	-0.05	-0.02	0.00

and 0.63% of TNA and standard deviations of 0.90% and 0.84%.

Panel B of Table 2 looks at the characteristics of traded bonds. To examine how traded bonds compare with the rest of a fund's portfolio, we calculate the percentile rankings of traded bonds relative to bonds held as of the previous holdings snapshot. Traded bonds tend to have higher credit ratings[14] and larger size than the rest of the portfolio. This is consistent with funds trading more liquid bonds. Purchased bonds tend to have longer remaining maturity. This is due to purchases including newly issued bonds.

Panel C reports summary statistics on fund flows, fund characteristics, and aggregate market conditions. Net daily flows average to zero, with a standard deviation of 0.40%. Daily outflows are set to the magnitude of net flows on days with negative net flows and to zero otherwise. Conversely, daily inflows are set to the value of net flows on days with positive net flows and to zero otherwise. Outflows and inflows average about 6 basis points of TNA with standard deviations of 26–29 basis points.

Mean (median) daily cash buffers are 3.86% (2.62%), with a sizable standard deviation of 4.02%. The median fund has TNA of \$227 million and belongs to a fund family with TNA of \$8,462 million.[15] Single-state funds account for 64% of the sample. 41% of fund-dates in our sample are associated with an interfund lending program. Finally, the average market-wide markup is 91 basis points, but as we will show later on, the average market markup varies significantly over time and declines over the 2009–2020 period.

3 Trading in Response to Daily Flows

Table 3 and Figure 1 report the results of regressions of daily trading activity on daily flows:

$$Trading_{f,t} = \alpha_t + \sum_{s=-15}^{+5} \left(\beta_s^{out} \times Outflows_{f,t+s} + \beta_s^{in} \times Inflows_{f,t+s}\right) + \varepsilon_{f,t}, \tag{1}$$

where f indexes funds and t indexes trading days. Inflows are equal to the value of daily net flows on days with positive net flows and to zero otherwise. Outflows are equal to the magnitude of daily net flows on days with negative net flows and to zero otherwise. Trading activity and fund flows are scaled by TNA as of the end of the previous month so that the coefficients can be interpreted

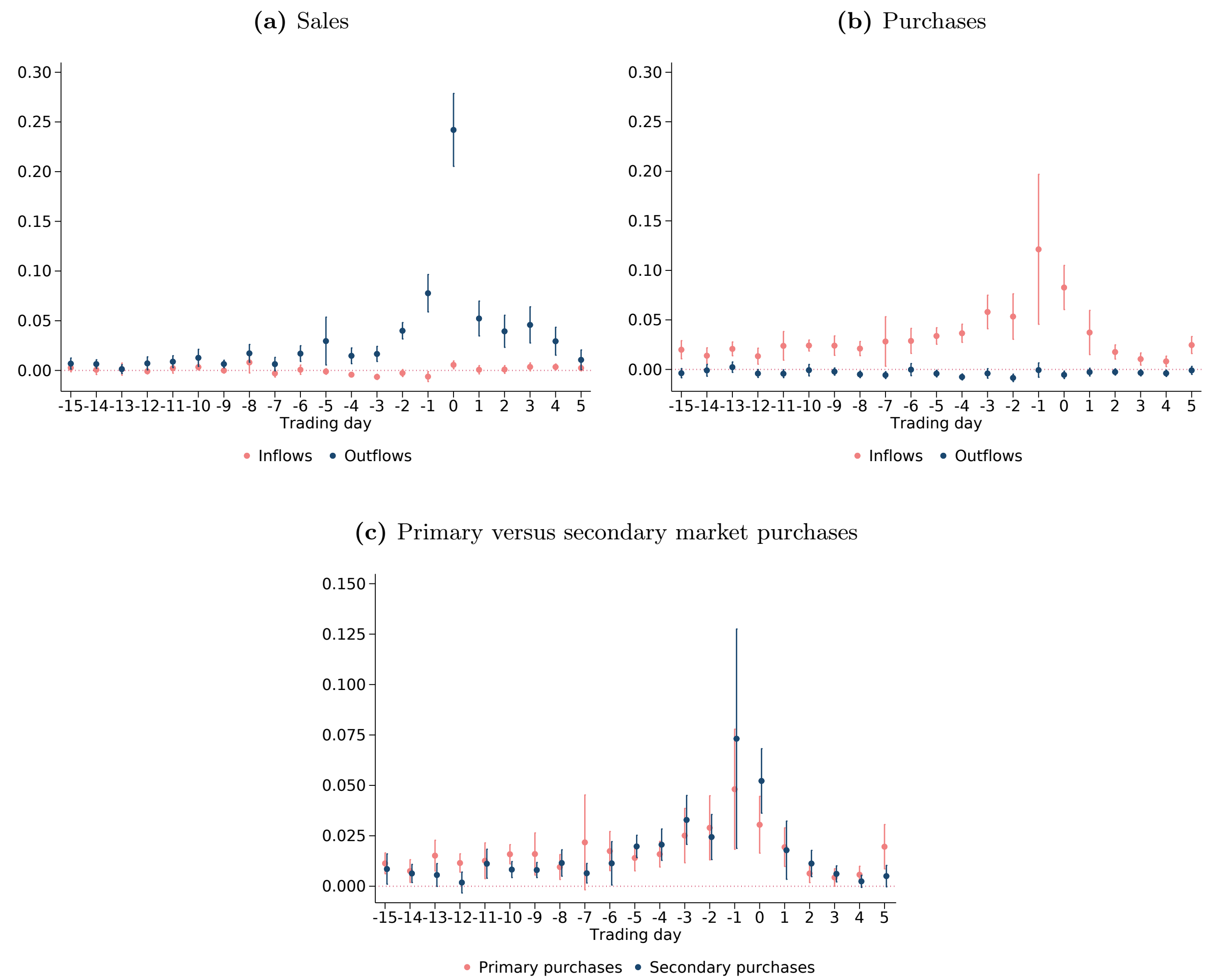
[14] Credit rating are encoded so that AAA = 0, AA+ = 1, ...

[15] Family size is calculated as the TNA of all municipal bond funds.

as the dollar value of sales and purchases in response to a dollar of inflows or outflows. Regression specifications include date fixed effects. Robustness analyses in Table 9 show that we find very similar results when using objective-date fixed effects or fund and date fixed effects. We include fifteen lags and five leads of daily inflows and outflows.[16]

Figure 1
Trading in Response to Daily Flows

This figure plots the estimated coefficients, along with their 95% confidence intervals, from the regressions of daily trading on daily fund flows. Subfigure (a) plots the estimated coefficients from the regression of daily sales in column 1 of Table 3. Subfigure (b) plots the estimated coefficients from the regression of daily purchases in column 2 of Table 3. Subfigure (c) plots the estimated coefficients on inflows from the regressions of primary and secondary market purchases in columns 3 and 4 of Table 3. All specifications include date fixed effects. Standard errors are adjusted for clustering by fund.



(a) Sales **(b)** Purchases **(c)** Primary versus secondary market purchases

[16] Appendix Table B2 shows that the coefficients on contemporaneous and lagged fund flows are not affected when we exclude future fund flows.

Table 3
Trading in Response to Daily Flows

This table reports the results of regressions of daily trading on daily flows:

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

where f indexes funds and t indexes trading days. Fund flows and trading activity are scaled by TNA 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 inflows and outflows. We report the sums of the coefficients on outflows and inflows over different windows. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. N = 1,089,130.

		Purchases			
	Sales	Total	Primary	Secondary	Net sales
	(1)	(2)	(3)	(4)	(5)
$Outflows_{f,t}$	0.242***	−0.005***	−0.002*	−0.003***	0.247***
	(0.019)	(0.002)	(0.001)	(0.001)	(0.019)
$Outflows_{f,t-1}$	0.078***	−0.001	0.000	−0.001	0.078***
	(0.010)	(0.004)	(0.002)	(0.002)	(0.010)
$Outflows_{f,t-2}$	0.040***	−0.009***	−0.005***	−0.004***	0.048***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.004)
$Outflows_{f,t-3}$	0.017***	−0.004*	−0.003***	−0.001	0.021***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.003)
$Outflows_{f,t-4}$	0.015***	−0.008***	−0.006***	−0.002**	0.022***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.005)
$Outflows_{f,t-5}$	0.030**	−0.004**	−0.001	−0.003***	0.034***
	(0.012)	(0.002)	(0.002)	(0.001)	(0.012)
$Inflows_{f,t}$	0.006***	0.083***	0.030***	0.052***	−0.077***
	(0.002)	(0.011)	(0.007)	(0.008)	(0.011)
$Inflows_{f,t-1}$	−0.006**	0.121***	0.048***	0.073***	−0.127***
	(0.003)	(0.039)	(0.015)	(0.028)	(0.038)
$Inflows_{f,t-2}$	−0.003	0.053***	0.029***	0.024***	−0.056***
	(0.002)	(0.012)	(0.008)	(0.006)	(0.011)
$Inflows_{f,t-3}$	−0.006***	0.058***	0.025***	0.033***	−0.064***
	(0.001)	(0.009)	(0.007)	(0.006)	(0.009)
$Inflows_{f,t-4}$	−0.004***	0.037***	0.016***	0.021***	−0.041***
	(0.001)	(0.005)	(0.003)	(0.004)	(0.005)
$Inflows_{f,t-5}$	−0.001	0.034***	0.014***	0.020***	−0.035***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.005)
Adjusted R^2	0.063	0.066	0.048	0.042	0.075
$\sum_{s=-5}^{-1} \beta_s^{out}$	0.178	−0.025	−0.015	−0.010	0.203
$\sum_{s=-5}^{0} \beta_s^{out}$	0.420	−0.030	−0.017	−0.014	0.451
$\sum_{s=-15}^{0} \beta_s^{out}$	0.511	−0.055	−0.027	−0.028	0.566
$\sum_{s=1}^{5} \beta_s^{out}$	0.177	−0.013	−0.009	−0.004	0.191
$\sum_{s=-15}^{5} \beta_s^{out}$	0.688	−0.068	−0.035	−0.033	0.757
$\sum_{s=-5}^{-1} \beta_s^{in}$	−0.021	0.303	0.132	0.171	−0.324
$\sum_{s=-5}^{0} \beta_s^{in}$	−0.015	0.386	0.163	0.223	−0.401
$\sum_{s=-15}^{0} \beta_s^{in}$	0.000	0.604	0.301	0.302	−0.603
$\sum_{s=1}^{5} \beta_s^{in}$	0.011	0.098	0.055	0.043	−0.087
$\sum_{s=-15}^{5} \beta_s^{in}$	0.011	0.702	0.357	0.345	−0.690
Date FEs	✓	✓	✓	✓	✓

In column 1, the dependent variable is gross sales. The immediate response of day t sales to day t outflows is 0.242. This means that out of a dollar of outflows on day t, about one quarter is accommodated through immediate sales, and three quarters is accommodated using cash buffers. The estimated coefficients on lagged outflows decline quickly in magnitude from 0.078 for day $t-1$ to 0.030 for day $t-5$. The sum of the estimated coefficients on outflows on days $[t-5, t]$ is 0.420.

We find positive and statistically significant coefficients on outflows on days $[t+1, t+5]$, suggesting that funds trade in anticipation of outflows. This can capture either statistical predictability of fund flows, advance notice from larger clients, or the fact that fund flows may take a few days to settle.[17] The sum of the estimated coefficients on outflows on days $[t+1, t+5]$ is 0.177.

The sum of the estimated coefficients on outflows over trading days $[t-15, t+5]$ is 0.688, indicating that over a month-long period about two-thirds of a dollar of outflows is accommodated through sales of portfolio securities, and one-third is accommodated using cash buffers. This result is broadly consistent with Chernenko and Sunderam (2016), who look at the liquidity management of corporate bond funds during the 2004–2012 period. They estimate regressions of changes in cash holdings on monthly flows and find that a dollar of flows during month t is associated with a 32.9 cents change in cash holdings. It is reassuring that very different approaches — regressions of daily sales on daily fund flows versus regressions of changes in cash holdings on monthly flows — deliver similar conclusions regarding accommodation of fund flows at the monthly horizon.[18] The similarity in monthly responses to fund flows between municipal and corporate bond funds also suggests that our results are likely to apply not only to municipal bond funds but also to corporate bond funds. At the same time, our daily regressions paint a fine-grained picture of the dynamics of trading in response to fund flows. In particular our results show a very strong short-term reliance on cash buffers, which help funds to spread their trading over time and to prearrange trades and thereby lower transaction costs.

[17] See Choi, Kronlund, and Oh (2022) and Wahal and Wang (2022) for discussion of the settlement of daily flows and how daily flows are captured in Morningstar data.

[18] Interestingly, our estimates of monthly response are also similar to Edelen (1999), who studies trading of equity mutual funds. He shows that over a six-month period, a dollar of outflows is associated with approximately 70 cents in trading activity. The microstructure of stock markets was, however, very different during his sample period (the second half of the 1980s) and stock mutual funds used to hold significantly larger cash buffers than in the more recent data.

In column 2 of Table 3, the dependent variable is total purchases. Purchases respond strongly to inflows and only weakly to outflows. The response of purchases to inflows is more gradual than the response of sales to outflows. The estimated coefficient on day t inflows is only 0.083, or about one-third of the 0.242 coefficient on day t outflows in the sales regression in column 1. The sum of the estimated coefficients on $[t-5, t]$ inflows is 0.386, which is very similar to the sum of the estimated coefficients on outflows (0.420) over this period in column 1. While future inflows are associated with larger purchases today, the response of purchases to inflows over $[t+1, t+5]$ is only half as strong as the response of sales to outflows: 0.098 versus 0.177. The sum of the coefficients on inflows over $[t-15, t+5]$ is 0.702, which is again very similar to the response of sales to outflows.

Columns 3 and 4 of Table 3 decompose purchases into primary versus secondary market ones. Inflows are accommodated roughly equally through primary and secondary market purchases: the sum of the coefficients on inflows over days $[t-15, t+5]$ is 0.357 for primary market purchases versus 0.345 for secondary market purchases, but their dynamics are different. Secondary market purchases respond to inflows more quickly than do primary market purchases. The coefficient on day t inflows is almost 75% larger for secondary market purchases (0.052) than for primary market purchases (0.030). Secondary market purchases also load more heavily on the first five lags of inflows. The sum of the coefficients on $[t-5, t-1]$ inflows is 0.171 for secondary market purchases versus 0.132 for primary market purchases. Interestingly, primary market purchases appear to be a bit more responsive to future inflows than are secondary market purchases.

Finally, for completeness column 5 of Table 3 reports the results for net sales, the difference between gross sales and gross purchases.

4 Cash Buffers

We next investigate how cash buffers affect the responsiveness of trading to fund flows. A major advantage of our daily flows and trading data is that they allow us to construct the time series of daily cash-to-assets ratios. We can therefore estimate how day $t-1$ cash buffers affect the response of day t trading to fund flows. Analyses using monthly or quarterly holdings data may significantly underestimate the importance of cash buffers as cash buffers may change significantly during the relevant period. This may be especially the case during periods of high volatility when funds may experience large fund flows and trade a lot. As a result, lagged cash buffers may be a poor proxy for cash buffers at the time that trading decisions are made.

Table 4 reports the results. As before, we include date fixed effects and adjust the standard errors for clustering by fund. For brevity, we report only the coefficients on day t fund flows and their interactions with cash buffers. In Panel A, we use daily cash buffers, i.e., the cash-to-assets ratio as of day $t-1$. To illustrate the importance of using daily cash buffers, in Panel B, we use monthly cash buffers, i.e., the cash-to-assets ratio as of the last monthly or quarterly holdings snapshot.

In column 1 of Table 4, the dependent variable is gross sales. The interaction of day t outflows with day $t-1$ cash buffers is negative and statistically significant. In Panel A, a one percentage point increase in the day $t-1$ cash-to-assets ratio is associated with 0.018 lower sensitivity of day t sales to day t outflows. This is about 5% of the coefficient on day t outflows. There is no interaction between inflows and cash buffers in this regression. When we use monthly cash buffers in Panel B, the estimated coefficient on the interaction of day t outflows with the lagged value of the cash-to-assets ratio is -0.008, or less than half of its magnitude in Panel A.

The results in column 1 of Panel B are consistent with the existing literature that estimates monthly or quarterly regressions. Choi et al. (2020), for example, find that in a broad sample of taxable bond funds, a one percentage point decrease in the cash-to-assets ratio is associated with 0.0055 greater sensitivity of sales of corporate bonds to fund flows.[19] The results in Table 4 thus show that monthly or quarterly regressions that use lagged cash buffers significantly underestimate the effect of cash buffers on the responsiveness of trading to fund flows. This may be especially important for understanding the use of cash buffers during stressed market conditions (Jiang, Li, and Wang, 2021). Nevertheless, our results indicate that even funds with sizable cash buffers engage in some sales in response to outflows instead of relying exclusively on their cash buffers.

Column 2 of Table 4 looks at total purchases, while columns 3 and 4 split total purchases into

[19] Choi et al. (2020) standardize the cash ratio to have zero mean and unit standard deviation. In the outflow sample in Table 6 in their paper, the coefficient on the interaction of fund flows with the lagged cash ratio is -0.069. Since the standard deviation of the cash ratio in their data is 12.54pp (Table 1), the effect of a one percentage point decrease in the cash-to-assets ratio is to increase the sensitivity of sales to fund flows by $0.069/12.54 = 0.0055$.

Table 4
Cash Buffers

The table reports the results of regressions of daily trading on daily fund flows interacted with the cash-to-assets ratio:

$$\begin{aligned} Trading_{f,t} &= \alpha_t + \gamma_0^{out} \cdot Outflows_{f,t} \times Cash_{f,t-1} + \gamma_0^{in} \cdot Inflows_{f,t} \times Cash_{f,t-1} \\ &+ \sum_{s=-15}^{5} \left(\beta_s^{out} Outflows_{f,t+s} + \beta_s^{in} Inflows_{f,t+s} \right) + \varepsilon_{f,t}, \end{aligned}$$

where f indexes funds and t indexes trading days. In Panel A, cash buffers are as of day $t-1$; in Panel B, cash buffers are as of the last monthly or quarterly holdings snapshot. Flows variables over $[t-15, t+5]$ are included but omitted for brevity. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. N = 1,089,130.

Panel A: Daily Cash Buffers

		Purchases			
	Sales	Total	Primary	Secondary	Net sales
	(1)	(2)	(3)	(4)	(5)
Outflows$_{f,t}$	0.383***	−0.004	−0.002	−0.002	0.386***
	(0.035)	(0.003)	(0.002)	(0.002)	(0.037)
Outflows$_{f,t}\times$ Cash$_{f,t-1}$	−0.018***	−0.000	−0.000	−0.000	−0.018***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.004)
Inflows$_{f,t}$	0.003	0.071***	0.027*	0.044***	−0.068***
	(0.003)	(0.017)	(0.014)	(0.011)	(0.017)
Inflows$_{f,t}\times$ Cash$_{f,t-1}$	0.001	0.002	0.001	0.001	−0.001
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
Cash$_{f,t-1}$	0.002**	0.007***	0.006***	0.002***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Adjusted R^2	0.071	0.071	0.052	0.044	0.081
Date FEs	✓	✓	✓	✓	✓

Panel B: Monthly/Quarterly Cash Buffers

		Purchases			
	Sales	Total	Primary	Secondary	Net sales
	(1)	(2)	(3)	(4)	(5)
Outflows$_{f,t}$	0.282***	−0.008***	−0.004*	−0.004**	0.290***
	(0.031)	(0.003)	(0.002)	(0.001)	(0.031)
Outflows$_{f,t}\times$ Cash$_{f,m-1}$	−0.008**	0.000	0.000	0.000	−0.008**
	(0.004)	(0.000)	(0.000)	(0.000)	(0.004)
Inflows$_{f,t}$	0.002	0.079***	0.017***	0.062***	−0.077***
	(0.003)	(0.012)	(0.005)	(0.012)	(0.012)
Inflows$_{f,t}\times$ Cash$_{f,m-1}$	0.000	0.000	0.001	−0.001	0.000
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Cash$_{f,m-1}$	0.003***	0.006***	0.004***	0.002***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Adjusted R^2	0.065	0.069	0.050	0.043	0.076
Date FEs	✓	✓	✓	✓	✓

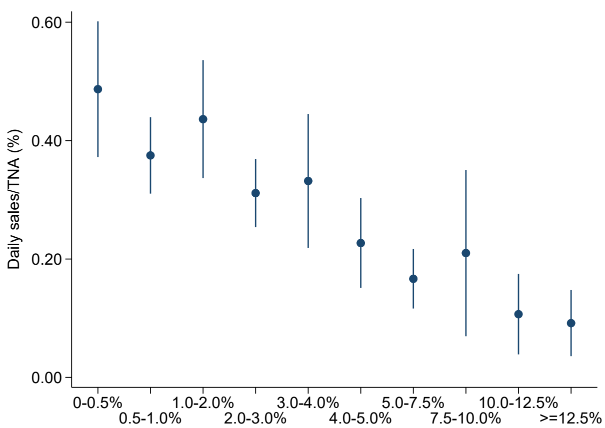
primary versus secondary market ones. There is no significant interaction between fund flows and cash buffers in these regressions. But larger cash buffers at $t-1$ are associated with more purchases, especially primary ones, at t regardless of fund flows.

Figure 2 investigates potential nonlinearities in the relationship between cash buffers and how trading responds to fund flows. We estimate similar regressions as before, but instead of interacting day t fund flows with the level of cash buffers at $t-1$, we create dummies for ranges of the cash-to-assets ratio. We plot the coefficient on day t outflows (inflows) for each range of the cash-to-assets ratio. Subfigure (a) reports the results for sales, while subfigure (b) reports the results for purchases.

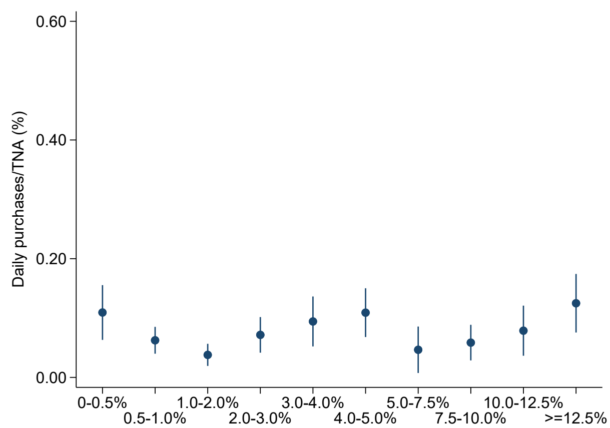
Figure 2
Cash Buffers and Trading in Response to Fund Flows

This figure presents the results of regressions of daily trading on daily fund flows interacted with dummy variables for ranges of the cash-to-assets ratio. Only day t flows are interacted with day $t-1$ cash-to-assets ratio.

(a) Sales



(b) Purchases



For funds with small cash buffers in the 0–2% range, the contemporaneous response of sales to outflows is almost 0.5 or double the average response of 0.242 estimated in Table 3. The coefficient on day t outflows declines for funds with larger cash buffers, with the relationship flattening out around 5% cash-to-assets ratio. For larger values of the cash-to-assets ratio, there is much less variation in the contemporaneous sensitivity of sales to outflows.

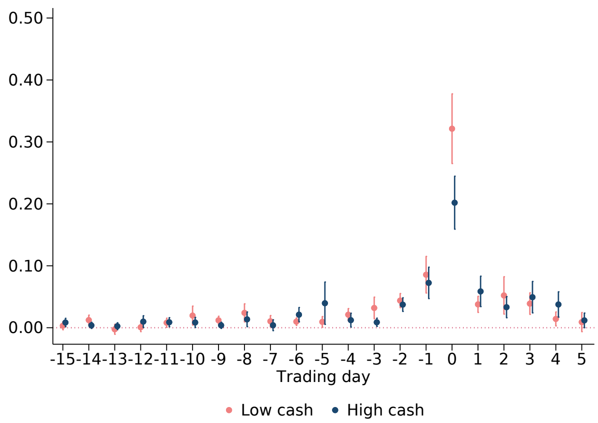
Subfigure (b) of Figure 2 shows no clear pattern in how the relationship between day t purchases and day t inflows varies across funds with different values of the cash-to-assets ratio.

So far we have looked only at how day $t-1$ cash buffers modulate the response of day t trading to day t fund flows. To look at how cash buffers may affect the dynamics of trading over time, we split funds into those with large versus small cash buffers on day $t-16$, and we trace out their trading over time. Figure 3 and Appendix Table B3 report the results.

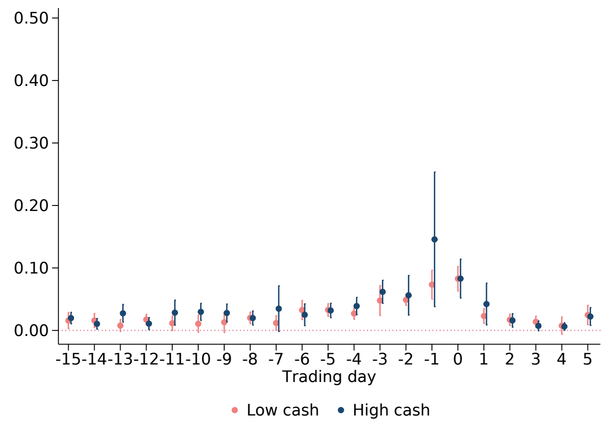
Figure 3
Daily Flows and Daily Trading: Low versus High Cash Funds

This figure plots the estimated coefficients, along with their 95% confidence intervals, from the regressions of daily trading on daily fund flows. Subfigure (a) plots the coefficients on outflows from the regression of daily sales in columns 1–2 of Appendix Table B3. Subfigure (b) plots the coefficients on inflows from the regression of daily purchases in columns 3–4 of Appendix Table B3. All specifications include date fixed effects. Standard errors are adjusted for clustering by fund.

(a) Sales



(b) Purchases



Most of the difference between sales of low and high cash funds is in how they respond to day t outflows. The coefficient on day t outflows is 0.321 for low cash funds versus 0.202 for high cash funds. The other coefficients in the sales regressions are broadly similar. The sum of the coefficients on $[t-5, t-1]$ outflows is 0.192 for low cash funds versus 0.170 for high cash funds. High cash funds have a slightly stronger response to outflows over $[t+1, t+5]$. The sum of the coefficients on future outflows is 0.190 for high cash funds versus 0.152 for low cash funds. There is some evidence that sales of low cash funds respond negatively to inflows while sales of high cash funds are not sensitive to inflows. The sum of the coefficients on inflows over $[t-15, t]$ is -0.050 for low cash funds versus 0.020 for high cash funds.

Turning to the analysis of purchases in subfigure (b) of Figure 3 and in columns 3–4 of Appendix Table B3, we find that while low and high cash funds respond similarly to day t inflows, high cash funds respond more strongly to lagged flows. The sum of the coefficients on $[t-15, t+5]$ inflows is 0.746 for high cash funds but only 0.555 for low cash funds. Most of this difference is due to the loading on day $t-1$ inflows. These results are consistent with low cash funds using inflows to rebuild their cash buffers, and high cash funds using more of the inflows to purchase portfolio securities.

The results in this section underscore the role of cash buffers as a liquidity management tool and suggest that studies that estimate monthly or quarterly regressions may significantly underestimate the effect of cash buffers on the responsiveness of trading to fund flows. This has important implications for policy and for understanding how cash buffers, as well as other liquidity management tools, may affect trading during stressed market conditions, a question we examine in Section 7.

5 Cross-Sectional Differences in Flow-Induced Trading

Are there other cross-sectional differences in how funds trade in response to flows? To answer this question, Table 5 reports the results of regressions of daily trading on daily flows over $[t-15, t+5]$, with day t flows interacted with various fund characteristics: cash-to-assets ratio, fund size, family size, single-state fund dummy, interfund lending dummy, weighted average rating (WAR), and weighted average maturity (WAM). To make their economic magnitudes easier to compare, all continuous fund characteristics are standardized to have zero mean and unit standard deviation.

In column 1 of Table 5, the dependent variable is gross sales. As we saw in Table 4, sales of funds with larger cash buffers respond less to outflows.[20] Larger funds sell significantly less in response to outflows. This may be because larger funds are more likely to internalize the price impact of their trading (Chernenko and Sunderam, 2020). It is also possible that larger funds are better able to predict their flows and thus trade in anticipation of future flows. Appendix Figure B1 presents evidence consistent with this idea. Family size, measured as the aggregate TNA of municipal bond mutual funds in the fund family, does not seem to affect the responsiveness of sales to fund flows.

Funds with interfund lending programs sell less in response to outflows, but the estimated coefficient is not statistically significant.Funds holding longer maturity bonds sell less in response to outflows, potentially because longer maturity bonds may be less liquid and costlier to trade. The average rating does not seem to affect the responsiveness of sales to outflows.

[20] The difference in the coefficient relative to Table 4 is primarily due to Table 5 using standardized value of the cash-to-assets ratio.

Table 5
Cross-Sectional Variation in Flow-Induced Trading

This table reports the results of regressions of daily trading on day t fund flows interacted with various fund characteristics. All fund characteristics are standardized to have zero mean and standard deviation of one. Flows variables over $[t-15, t+5]$ are included but omitted for brevity. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. N = 1,089,130.

		Purchases		
	Sales	Total	Primary	Secondary
	(1)	(2)	(3)	(4)
Outflows$_{f,t}$	0.310***	−0.003	0.001	−0.004
	(0.031)	(0.005)	(0.003)	(0.003)
Outflows$_{f,t}\times$ Cash$_{f,t-1}$	−0.073***	−0.002	−0.002*	−0.001
	(0.015)	(0.001)	(0.001)	(0.001)
Outflows$_{f,t}\times$ Ln(Fund TNA)$_{f,m-1}$	−0.054***	0.003	−0.000	0.003
	(0.013)	(0.002)	(0.002)	(0.002)
Outflows$_{f,t}\times$ Ln(Family TNA)$_{f,m-1}$	0.016	−0.002	0.000	−0.002
	(0.016)	(0.003)	(0.002)	(0.002)
Outflows$_{f,t}\times$ Single state$_{f}$	−0.016	−0.000	−0.004	0.004
	(0.036)	(0.004)	(0.003)	(0.003)
Outflows$_{f,t}\times$ Interfund lending$_{f,m}$	−0.035	−0.002	−0.002	−0.000
	(0.026)	(0.005)	(0.003)	(0.003)
Outflows$_{f,t}\times$ WAR$_{f,m-1}$	0.008	−0.001	−0.000	−0.001
	(0.013)	(0.003)	(0.002)	(0.001)
Outflows$_{f,t}\times$ WAM$_{f,m-1}$	−0.038**	0.003	0.002	0.001
	(0.018)	(0.002)	(0.001)	(0.001)
Inflows$_{f,t}$	0.002	0.088***	0.031***	0.057**
	(0.006)	(0.028)	(0.011)	(0.023)
Inflows$_{f,t}\times$ Cash$_{f,t-1}$	0.005***	0.007	0.002	0.005
	(0.002)	(0.009)	(0.007)	(0.007)
Inflows$_{f,t}\times$ Ln(Fund TNA)$_{f,m-1}$	0.004	0.013	−0.005	0.017
	(0.004)	(0.014)	(0.007)	(0.011)
Inflows$_{f,t}\times$ Ln(Family TNA)$_{f,m-1}$	−0.002	−0.002	0.004	−0.006
	(0.002)	(0.006)	(0.005)	(0.006)
Inflows$_{f,t}\times$ Single state$_{f}$	0.009*	−0.002	−0.018*	0.016
	(0.005)	(0.020)	(0.010)	(0.016)
Inflows$_{f,t}\times$ Interfund lending$_{f,m}$	0.005	−0.011	0.001	−0.013
	(0.005)	(0.016)	(0.010)	(0.015)
Inflows$_{f,t}\times$ WAR$_{f,m-1}$	0.001	0.011	0.004	0.007
	(0.003)	(0.009)	(0.006)	(0.010)
Inflows$_{f,t}\times$ WAM$_{f,m-1}$	0.004	0.003	0.001	0.002
	(0.003)	(0.007)	(0.006)	(0.006)
Cash$_{f,t-1}$	0.005	0.029***	0.021***	0.007***
	(0.003)	(0.004)	(0.003)	(0.001)
Ln(Fund TNA)$_{f,m-1}$	0.004	−0.001	−0.003	0.002
	(0.003)	(0.003)	(0.002)	(0.001)
Ln(Family TNA)$_{f,m-1}$	−0.007**	−0.003	0.001	−0.005***
	(0.003)	(0.002)	(0.002)	(0.001)
Single state$_{f}$	−0.030***	−0.022***	−0.020***	−0.001
	(0.006)	(0.006)	(0.004)	(0.003)
Interfund lending$_{f,m}$	0.008**	0.011***	0.008***	0.004**
	(0.004)	(0.004)	(0.003)	(0.002)
WAR$_{f,m-1}$	−0.014***	−0.012***	−0.011***	−0.001
	(0.004)	(0.004)	(0.003)	(0.001)
WAM$_{f,m-1}$	0.012***	0.012***	0.010***	0.002
	(0.003)	(0.003)	(0.002)	(0.001)
Adjusted R^2	0.076	0.073	0.054	0.045
Date FEs	✓	✓	✓	✓

Turning to the direct effects of fund characteristics, the strongest effect is that single-state funds sell less on average. This may be because national funds have more opportunities to rebalance their portfolios across bonds from different states. Funds holding low-rated bonds (i.e., the ones with higher WAR) also sell less on average. This is consistent with lower-rated bonds being less liquid. It may also be consistent with funds viewing low-rated bonds as being undervalued and holding on to such bonds, while selling bonds that had been upgraded. Funds holding bonds with longer remaining maturity sell more on average.

In column 2 of Table 5, the dependent variable is total purchases, while columns 3 and 4 split total purchases into primary versus secondary market ones. We do not find any meaningful cross-sectional variation in how purchases respond to contemporaneous inflows. Recall, however, from Figure 1 that the contemporaneous response of purchases to inflows is much weaker than the contemporaneous response of sales to outflows and that purchases load more strongly on day $t-1$ inflows than on day t inflows. We do find other differences across funds. Funds with larger cash buffers buy more bonds. A one standard deviation increase in the cash-to-assets ratio is associated with 0.029 larger bond purchases. This is 4.3% of the mean value of gross purchases scaled by TNA. Column 3 shows that this effect is driven primarily by primary market purchases. Single-state funds and those holding lower-rated bonds have smaller purchases on average. Funds with interfund lending and funds holding longer maturity bonds have larger purchases on average. These results are similar to the sales results in column 1 and suggest that certain funds have greater portfolio turnover on average.

In addition to studying cross-sectional differences in the responsiveness of trading to contemporaneous flows, we examined how the dynamics of trading vary with fund characteristics. We estimate regressions of trading on daily fund flows while interacting all lags and leads of fund flows with fund characteristics as of $t-16$. We summarize the results visually in Figures B1 and B2 in the Appendix by plotting the dynamics of trading for different funds. Each subfigure shows the dynamics for two different sets of funds. For example, subfigure (a) of Figure B1 shows the dynamics of sales for small versus large funds. The results indicate that most of the cross-sectional variation is in the responsiveness of sales to day t outflows and purchases to day $t-1$ inflows. The other differences are generally much smaller and less significant. The main exception is that sales of national funds are more sensitive to future outflows than are sales of single-state funds.

6 Characteristics of Traded Bonds

Besides using cash buffers, funds may respond to fund flows by trading more liquid securities (Dötz and Weth, 2019; Choi et al., 2020; Huang et al., 2021; Jiang, Li, and Wang, 2021; Ma, Xiao, and Zeng, 2022). An important advantage of our daily data is that we can see which exact bonds are traded in response to daily outflows and inflows. Most papers in the literature are limited to looking at all bonds that are traded during a given month or quarter. To measure how sold and purchased bonds compare to the rest of a fund's portfolio, we calculate the percentiles of traded bonds relative to the fund's portfolio holdings as of the last holdings snapshot. We then estimate regressions of bond characteristic percentiles on inflows and outflows as well as date and fund fixed effects. The characteristics we look at are credit rating, remaining maturity, bond size (offering amount), and issue size. We do not look directly at transaction-based measures of liquidity because most municipal bonds trade rarely and thus have missing values of most liquidity measures.

To account for the effect of large outliers in daily flows, we winsorize fund inflows and outflows at the 99th percentile. While the 99th percentile of daily outflows is 0.74%, the maximum is 47.66%. The relationship between the characteristics of traded bonds is unlikely to be linear and monotonic over the whole range of outflows. In particular, when selling in response to very large outflows, the characteristics of sold bonds almost have to resemble the characteristics of the portfolio.

Table 6 reports the results with the characteristic percentiles of sold bonds in columns 1–4 and of purchased bonds in columns 5–8. Regression specifications include flows on days $[t-1, t+1]$; further lags and leads of fund flows are generally not significant.

In column 1 of Table 6, the dependent variable is the rating of sold bonds. Sold bonds tend to be more highly rated (have lower WAR) than the rest of the portfolio. The average WAR percentile of sold bonds is 40. Funds may sell higher-rated bonds either because these bonds are more liquid or because funds believe these bonds are relatively undervalued. Bonds sold in response to outflows are even more highly rated. The coefficient on day t outflows is -5.443, indicating that bonds sold

Table 6
Characteristics of Traded Bonds

This table reports the results of regressions of traded bonds' characteristic percentiles on daily flows:

$$\textit{Characteristic percentiles}_{f,t} = \alpha_f + \alpha_t + \sum_{s=-1}^{1} \left(\beta_s^{out} \cdot \textit{Outflows}_{f,t+s} + \beta_s^{in} \cdot \textit{Inflows}_{f,t+s} \right) + \varepsilon_{f,t},$$

where f indexes funds and t indexes trading days. For each characteristic, we compare the bond sold or purchase with the distribution of that characteristic across the fund's portfolio holdings as of the last holdings snapshot. Higher percentiles mean the bond is lower-rated, have longer maturity, larger offering amount, and larger issue size relative to portfolio bonds held by the fund. Daily characteristic percentiles are value-weighted across all bonds sold or purchased by the fund on a given day. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Sales				Purchases			
	Rating	Maturity	Bond size	Issue size	Rating	Maturity	Bond size	Issue size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Outflows}_{f,t}$	-5.443^{***}	-6.875^{***}	0.448	2.296^{***}	0.913	1.473^{*}	-1.875^{**}	-2.297^{***}
	(0.553)	(0.561)	(0.512)	(0.505)	(0.902)	(0.781)	(0.767)	(0.778)
$\text{Outflows}_{f,t-1}$	-1.304^{**}	-1.806^{***}	0.359	0.140	1.675^{*}	0.539	-0.468	-0.670
	(0.636)	(0.632)	(0.579)	(0.579)	(0.903)	(0.786)	(0.776)	(0.778)
$\text{Outflows}_{f,t+1}$	-1.119^{*}	0.159	1.739^{***}	1.960^{***}	0.138	0.068	-0.216	-0.623
	(0.672)	(0.661)	(0.609)	(0.604)	(0.871)	(0.763)	(0.756)	(0.757)
$\text{Inflows}_{f,t}$	-0.744	0.181	-1.510^{**}	-1.238^{*}	-3.108^{***}	-2.016^{***}	-0.292	1.494^{***}
	(0.849)	(0.797)	(0.749)	(0.750)	(0.591)	(0.527)	(0.521)	(0.517)
$\text{Inflows}_{f,t-1}$	0.362	1.941^{**}	-0.769	-0.625	-4.214^{***}	-3.025^{***}	-1.824^{***}	0.356
	(0.850)	(0.788)	(0.738)	(0.738)	(0.591)	(0.529)	(0.522)	(0.524)
$\text{Inflows}_{f,t+1}$	-2.197^{***}	1.091	-0.720	0.006	-2.361^{***}	-1.071^{*}	-2.047^{***}	-1.769^{***}
	(0.812)	(0.758)	(0.699)	(0.700)	(0.620)	(0.552)	(0.538)	(0.541)
N	109,781	120,105	120,105	120,105	129,187	147,670	147,670	147,670
Adjusted R^2	0.06	0.08	0.07	0.07	0.08	0.09	0.10	0.10
μ_y	39.67	52.96	57.23	56.98	43.08	61.83	58.08	57.95
Fund FEs	✓	✓	✓	✓	✓	✓	✓	✓
Date FEs	✓	✓	✓	✓	✓	✓	✓	✓

in response to 1% outflows tend to have more than 5 percentiles lower WAR. The coefficient on day $t-1$ outflows is also statistically significant, but its magnitude is about one-quarter of the effect of day t outflows.

In column 2 of Table 6, the dependent variable is the remaining maturity of sold bonds. The average maturity percentile of sold bonds is 53, indicating that they are broadly similar to the rest of the portfolio. Bonds sold in response to outflows have significantly shorter maturity. The coefficients on day t and $t-1$ outflows are -6.875 and -1.806. Columns 3 and 4 of Table 6 find weaker results for bond and issue size. While there is evidence that in response to outflows, funds sell larger bonds and bonds that are part of larger issues, these effects of outflows on bond and issue size are economically smaller than the effects on rating and remaining maturity.

Columns 5–8 of Table 6 look at the characteristics of bond purchases. Columns 5 and 6 show that flow-induced purchases tend to have stronger credit ratings (lower WAR) and shorter maturity. This is consistent with funds purchasing more liquid bonds when trading in response to inflows. Columns 7 and 8 find mixed results in terms of the effect of fund flows on bond and issue size. While some of the coefficients are statistically significant, they tend to be relatively small economically.

Overall, Table 6 shows that while municipal bond mutual funds tilt the characteristics of traded bonds in response to fund flows, with the exception of credit rating and maturity, these effects are relatively small. It seems that, at least in the context of municipal bond funds, most of the adjustment is borne through the use of cash buffers rather than selective trading of portfolio bonds. This may be because there is less cross-sectional variation in the liquidity of municipal bonds than across various categories of securities—Treasuries, agencies, ABS, and corporate bonds—held by taxable bond funds.

7 Flow-Induced Trading and Market Conditions

We next take advantage of our daily flows and trading data to ask how the propensity to trade in response to fund flows varies with market conditions. Our daily data are ideally suited to study this question because they give us more statistical power and allow us to control for the most recent value of the fund's cash buffer. Doing so is especially important when trying to document the effect of the expected future shocks to fund flows or liquidity.

Our first measure is the overall market liquidity as measured by the par-weighted average of dealer markups. All else equal, we expect the sensitivity of sales to outflows to decrease as markups increase. Second, following (Jiang, Li, and Wang, 2021), we use CBOE Volatility Index (VIX) as our measure of aggregate uncertainty.

Our third measure of market conditions is the change in the tax-adjusted yield spread between the Bloomberg Municipal 10-year Benchmark and 10-year Treasuries. The tax-adjusted yield spread measures the relative value of municipal bonds compared to Treasuries. When the tax-adjusted yield spread is high, municipal bonds have low prices and high expected returns. All else equal, mutual funds should be reluctant to sell municipal bonds when this is the case. We use the change in the tax-adjusted yield spread rather than the level because the level may not be stationary and may change over time due to changes in tax rates and other structural changes in the municipal bond market.

Fourth, we look at how flow-induced trading is affected by the expected aggregate fund flows. When funds expect future aggregate fund flows to be negative, they may want to sell today to make sure that they do not have to liquidate at even worse prices in the future (Brown, Carlin, and Lobo, 2010). We estimate expected aggregate net outflows over $[t+1, t+5]$ by running a rolling window regression of aggregate net outflows over $[t+1, t+5]$ on lagged outflows, the level and change in market markup, the level and change in the tax-adjusted yield spread relative to Treasuries, log of customer trading volume, and dealer imbalance—the difference between customer sale volume and purchase volume, scaled by total customer trading volume. Table B4 in the Appendix reports the results of these regressions estimated over the whole sample period. Aggregate fund flows are fairly predictable, with adjusted R^2 of around 0.37. Nevertheless, because funds may use more sophisticated models to forecast aggregate fund flows, our estimates of the expected aggregate fund flows may be noisy proxies for fund expectations. As a result, the estimated coefficients on the interactions of fund outflows with the expected aggregate net outflows may be biased towards zero.

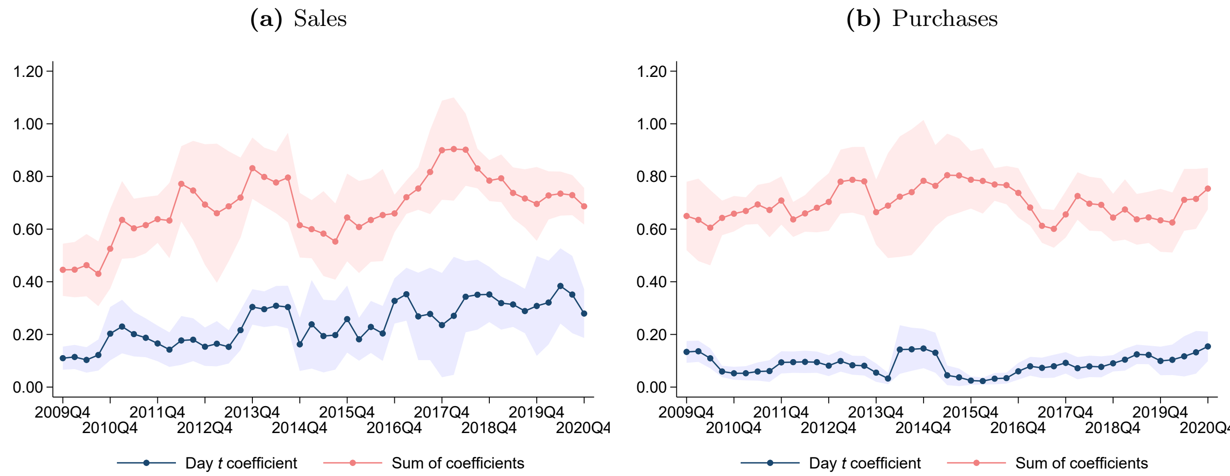
In our analyses, we estimate these regressions using a $[t-267, t-16]$ rolling window, which serves three purposes. First, the rolling window uses only historical data and avoids any possibility of a forward-looking bias. Second, the rolling window does not overlap with fund-level flows over $[t-15, t]$ included in the main regressions. Third, by using a rolling window instead of all historical data up to say $t-16$, we allow the predictability of aggregate fund flows to change over time.

We start by reporting in Figure 4 how the propensity to trade in response to fund flows has changed over time. We estimate four-quarter rolling window regressions of sales and purchases on fund inflows and outflows, and we report the day t coefficient as well as the sum of the coefficients on days $[t-15, t+5]$. Subfigure (a) reports the results for sales, while subfigure (b) reports the results for purchases.

Subfigure (a) of Figure 4 shows that the coefficient on day t outflows has more than doubled

Figure 4
Time Series of Flow-Induced Trading

This figure plots the estimated coefficients, along with their 95% confidence intervals, from the four-quarter rolling regressions of daily trading on daily fund flows. Subfigure (a) plots the coefficient on day t outflows and the sum of outflow coefficients on days $[t-15, t+5]$ from the regression of daily sales in column 1 of Table 3. Subfigure (b) plots the coefficient on day t inflows and the sum of inflow coefficients on days $[t-15, t+5]$ from the regression of daily purchases in column 2 of Table 3. All specifications include date fixed effects. Standard errors are adjusted for clustering by fund.



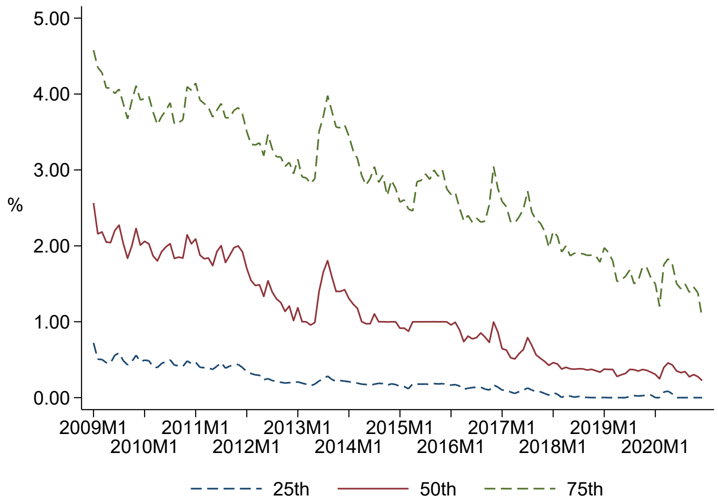
over time from 0.110 in 2009Q4 to 0.279 in 2020Q4. The sum of the coefficients on outflows over days $[t-15, t+5]$ has increased from 0.445 to 0.687. The increase in the coefficient on day t outflows accounts for almost 70% of the increase in the sum of the coefficients. This increase in the propensity to sell in response to fund flows is not due to changes in cash buffers, as there is no time trend in cash buffers over this period. Thus, it is not the case that funds traded little in response to outflows during 2009–2010 because, coming out of the financial crisis, funds were sitting on large cash buffers.

The increase in the propensity to sell in response to outflows is likely due to the decrease in markups documented in Figure 5. We plot the 25th, 50th, and 75th percentiles of markups on all customer trades, excluding sales of VRDNs. The median markup declines from 257 bps in January 2009 to 23 bps in December 2020. We hypothesize that as markups decline, funds are more likely to sell in response to outflows.

Subfigure (b) of Figure 4 looks at the changes in the responsiveness of purchases to inflows. There is no noticeable time trend in the propensity to buy in response to day t inflows. There is an

Figure 5
Time Series of Dealer Markup

This figure plots the distribution of the dealer markup on all municipal bond non-prearranged trades, excluding VRDN trades, for each month between January 2009 and December 2020.



overall upward trend in the sum of the coefficients on inflows over days $[t-15, t+5]$. It trends up from 0.650 in 2009Q4 to 0.754 in 2020Q4.

We now turn in Table 7 to a formal analysis of how market conditions affect flow-induced trading. For brevity and because purchases are significantly less responsive to contemporaneous fund flows to begin with, Table 7 looks only at daily sales. We control for fund inflows and outflows on each day over $[t-15, t+5]$ but report only the coefficients on day t flows. We also control for, but do not report, the interaction of day t inflows and outflows with dummies for 18 bins of the cash-to-assets ratio. These interactions are meant to allow for the possibility of non-linear effects of cash buffers on the propensity to sell in response to outflows. Finally, we include date fixed effects, which absorb the direct effect of the market conditions variables. Standard errors are adjusted for clustering by date.

There are several noteworthy results in Table 7. First, the average market markup is associated with a significantly lower sensitivity of sales to outflows. The par-weighted average markup declines from 1.48% in January 2009 to 0.46% by the end of December 2020. A one percentage point decline in markups is associated with about 0.22–0.24 increase in the sensitivity of day t sales to day t

Table 7
Flow-Induced Sales and Market Conditions

This table reports the results of the regressions of daily sales on day t fund flows interacted with measures of market conditions: i) the par-weighted average market markup on non-prearranged customer trades, ii) the change in tax-adjusted 10-year municipal bond yield spread over 10-year Treasury yield, iii) CBOE Volatility Index (VIX), iv) 5-day average aggregate net outflows over $[t-4, t]$, and v) the realized and expected future aggregate net outflows over $[t+1, t+5]$. Expected aggregate net outflows are the prediction from a rolling window regression of future aggregate net outflows on contemporaneous and lagged aggregate net outflows, the level and change in market markup, the level and change in the tax-adjusted yield spread to Treasuries, log customer trading volume, and dealer imbalance. We use a 252-day rolling estimation window $[t-267, t-16]$. Flows variables over $[t-15, t+5]$ are included but omitted for brevity. All columns include the interactions of inflows and outflows on day t with dummies for 18 bins of the cash-to-assets ratio: [0, 0], (0, 0.5%), [0.5%, 1.0%), ..., [4.5%, 5.0%), [5.0%, 6.0%), [6.0%, 7.0%), ..., [9.0%, 10.0%), [10.0%, 12.5%), [12.5%, 100%). Standard errors are adjusted for clustering by date. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. N = 1,089,130.

	(1)	(2)	(3)	(4)
$\text{Outflows}_{f,t}$	0.519***	0.510***	0.514***	0.514***
	(0.073)	(0.070)	(0.070)	(0.070)
$\text{Outflows}_{f,t}\times$ Market markup_t	−0.218***	−0.242***	−0.240***	−0.238***
	(0.035)	(0.035)	(0.036)	(0.036)
$\text{Outflows}_{f,t}\times$ Δ Yield spread_t	−0.110	−0.109*	−0.130**	−0.133**
	(0.070)	(0.059)	(0.064)	(0.064)
$\text{Outflows}_{f,t}\times$ VIX_t	−0.001	0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Outflows}_{f,t}\times$ Aggregate net outflows_t				0.083
				(0.228)
$\text{Outflows}_{f,t}\times$ Realized aggregate net outflows_{t+1}	0.556***		0.187	0.157
	(0.156)		(0.197)	(0.233)
$\text{Outflows}_{f,t}\times$ Expected aggregate net outflows_{t+1}		0.856***	0.712**	0.655**
		(0.228)	(0.296)	(0.292)
$\text{Inflows}_{f,t}$	0.018*	0.018*	0.018*	0.018*
	(0.011)	(0.011)	(0.011)	(0.011)
$\text{Inflows}_{f,t}\times$ Market markup_t	0.001	−0.001	−0.000	−0.001
	(0.006)	(0.006)	(0.006)	(0.006)
$\text{Inflows}_{f,t}\times$ Δ Yield spread_t	0.007	0.009	0.006	0.003
	(0.023)	(0.022)	(0.022)	(0.025)
$\text{Inflows}_{f,t}\times$ VIX_t	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Inflows}_{f,t}\times$ Aggregate net outflows_t				−0.022
				(0.052)
$\text{Inflows}_{f,t}\times$ Realized aggregate net outflows_{t+1}	0.087**		0.042	0.055
	(0.043)		(0.048)	(0.061)
$\text{Inflows}_{f,t}\times$ Expected aggregate net outflows_{t+1}		0.114*	0.081	0.089
		(0.063)	(0.077)	(0.077)
Adjusted R^2	0.080	0.080	0.080	0.080
Cash × Flows interactions	✓	✓	✓	✓
Date FEs	✓	✓	✓	✓

outflows.

Second, increases in the tax-adjusted yield spread relative to Treasuries are associated with a somewhat lower sensitivity of sales to outflows. A one standard deviation increase in the change in the tax-adjusted yield spread of 12 basis points is associated with about 0.016 lower sensitivity of sales to outflows. This is about 7% of the average sensitivity of 0.242.

Third, column 1 of Table 7 includes the realized value of aggregate net outflows over $[t+1, t+5]$. The interaction with outflows is positive and highly statistically significant 0.556. This means that a one standard deviation increase in the realized aggregate net outflows of 6 basis points is associated with a 0.033 increase in the sensitivity of sales to outflows. Column 2 replaces realized aggregate net outflows with our measure of the expected aggregate net outflows. The estimated coefficient on the interaction with fund outflows is 0.856.

Column 3 interacts fund outflows with both realized and expected aggregate net outflows. We find a larger and more highly statistically significant coefficient of 0.712 on the interaction with the expected aggregate net outflows than on the interaction with the realized aggregate net outflows, which is not statistically significant. This means that future aggregate fund flows matter only to the extent that they are predictable. Once we control for the expectation of aggregate fund flows, the effect of actual future fund flows is cut by two-thirds and completely loses its statistical significance. It is interesting that in column 4, where we control for the average aggregate net outflows over $[t-4, t]$, neither past nor actual future aggregate outflows are statistically significant. The measure that is significant is the expectation of future aggregate net outflows. When funds anticipate future aggregate outflows and likely deterioration in liquidity, they are more aggressive in selling in response to outflows today. This is consistent with the theoretical predictions of Brown, Carlin, and Lobo (2010).

7.1 Alternative Horizons

To shed more light on how flow-induced sales are affected by expectations of future aggregate fund flows and liquidity, Table 8 uses expectations of aggregate net outflows over alternative horizons, which corresponds to the following four weeks of trading: $[t+1, t+5]$, $[t+6, t+10]$, $[t+11, t+15]$, and $[t+16, t+20]$. We find that the estimated interaction is the largest at 0.715 when using the expectation of aggregate net outflows over the following week, i.e., $[t+1, t+5]$. The coefficient on the interaction term declines to 0.585 but remains statistically significant at 1% for $[t+6, t+10]$. In column 3, which uses the expected aggregate net outflows over the third

Table 8
Flow-Induced Sales and Expected Aggregate Outflows: Alternative Horizons

This table reports the results of regressions of daily sales on day t fund flows interacted with the expected daily aggregate net outflows over each of the following four trading weeks: $[t+1, t+5]$, $[t+6, t+10]$, $[t+11, t+15]$, and $[t+16, t+20]$. Expected aggregate net outflows are the prediction from a rolling window regression of future aggregate net outflows on contemporaneous and lagged aggregate net outflows, the level and change in market markup, the level and change in the tax-adjusted yield spread to Treasuries, log customer trading volume, and dealer imbalance. We use a 252-day rolling estimation window $[t-267, t-16]$. Fund inflows and outflows over $[t-15, t-1]$ are included but omitted for brevity. Standard errors are adjusted for clustering by date. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. N = 1,089,130.

	Horizon of expected aggregate outflows			
	$[t+1, t+5]$ (1)	$[t+6, t+10]$ (2)	$[t+11, t+15]$ (3)	$[t+16, t+20]$ (4)
Outflows$_{f,t}$	0.511***	0.510***	0.506***	0.506***
	(0.070)	(0.070)	(0.071)	(0.071)
Outflows$_{f,t}\times$ Market markup$_t$	−0.239***	−0.237***	−0.226***	−0.223***
	(0.035)	(0.036)	(0.035)	(0.035)
Outflows$_{f,t}\times$ Δ Yield spread$_t$	−0.120**	−0.090	−0.100*	−0.109*
	(0.061)	(0.057)	(0.059)	(0.066)
Outflows$_{f,t}\times$ VIX$_t$	0.000	0.000	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Outflows$_{f,t}\times$ Aggregate net outflows$_t$	0.146	0.236	0.408***	0.533***
	(0.189)	(0.159)	(0.144)	(0.156)
Outflows$_{f,t}\times$ Expected aggregate net outflows$_{t+1}$	0.715***	0.585***	0.274	0.075
	(0.273)	(0.217)	(0.205)	(0.136)
Inflows$_{f,t}$	0.018*	0.016	0.016	0.016
	(0.011)	(0.011)	(0.010)	(0.010)
Inflows$_{f,t}\times$ Market markup$_t$	−0.001	0.000	0.001	−0.000
	(0.006)	(0.006)	(0.006)	(0.006)
Inflows$_{f,t}\times$ Δ Yield spread$_t$	0.007	0.010	0.010	−0.002
	(0.024)	(0.022)	(0.024)	(0.029)
Inflows$_{f,t}\times$ VIX$_t$	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Inflows$_{f,t}\times$ Aggregate net outflows$_t$	0.006	0.010	0.044	0.066
	(0.041)	(0.037)	(0.037)	(0.041)
Inflows$_{f,t}\times$ Expected aggregate net outflows$_{t+1}$	0.109	0.102**	0.046	0.044
	(0.072)	(0.051)	(0.050)	(0.034)
Adjusted R^2	0.080	0.080	0.080	0.080
Cash × Flows interactions	✓	✓	✓	✓
Date FEs	✓	✓	✓	✓

week, i.e., $[t+11, t+15]$, the coefficient on the interaction term is cut in half to 0.274 and loses its statistical significance. When we look even further out at the expected aggregate net outflows over $[t+16, t+20]$, the coefficient on the interaction term declines to 0.075. As we move from the first two weeks in columns 1–2 to weeks three and four in columns 3–4, the coefficient on the recent aggregate net outflows over $[t-4, t]$ increases in magnitudes from 0.146 in column 1 to 0.533 in column 4 and becomes statistically significant in columns 3–4. This pattern of results is consistent with recent aggregate flows being a strong predictor of the near-term expected aggregate flows over the next couple of weeks. When the expected aggregate net outflows over weeks one and two are included in columns 1–2, the interaction of fund outflows with aggregate net outflows over $[t-4,t]$ is small and not statistically significant. But when we use the expected aggregate net outflows over weeks three and four, which are noisier and potentially less relevant for fund's trading decisions, aggregate net outflows over $[t-4,t]$ become statistically significant. Overall, the results in Table 8 highlight the advantage of using daily data to study how expectations of market conditions affect mutual fund trading behavior.

8 Case Study: COVID-19

Our daily data on flows, trading, and cash buffers also allow us to zoom in on mutual funds' trading activity during the onset of the COVID-19 pandemic in early 2020. This period saw large investor redemptions from fixed income open-end funds and dislocations in capital markets (see, for example, Falato, Goldstein, and Hortaçsu, 2021; Haddad, Moreira, and Muir, 2021; Vissing-Jorgensen, 2021; Ma, Xiao, and Zeng, 2022; Li, O'Hara, and Zhou, 2023). We contribute to this literature by tracing out the dynamics of daily trading during this period and documenting large increases in the responsiveness of sales to outflows despite most funds continuing to maintain sizable cash buffers. Expectations of future aggregate outflows likely explain funds' reluctance to drawn down their cash buffers. Our results thus point to funds' limited use of cash buffers as an important contributor to fire sales in March 2020.

To set the stage, subfigure (a) of Figure 6 plots daily aggregate net flows into open-end municipal bond funds during the first half of 2020. Dotted vertical lines indicate the start of the crisis period and the dates of key interventions in the municipal bond market. First, following Li, O'Hara, and Zhou (2023), we use March 9 as the start of the crisis period. On March 23, the Federal Reserve expanded the Money Market Fund Liquidity Facility (MMLF) to include Variable Rate Demand Notes and the Commercial Paper Funding Facility (CPFF) to include tax-exempt commercial paper.[21] Finally, on April 9, the Federal Reserve established the Municipal Liquidity Facility (MLF) to directly purchase newly issued short-term securities from eligible municipalities.[22] Although these

[21] https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm.

[22] https://www.federalreserve.gov/monetarypolicy/muni.htm.

interventions did not directly address secondary market liquidity, they may have helped to stem outflows from municipal bond funds. Subfigure (a) of Figure 6 shows that during the two-week period from March 9 to March 20, open-end municipal bond funds experienced large outflows, losing 3.72% of their net assets.[23] Outflows began to subside in the week starting March 23, in line with the findings of several studies examining the effectiveness of the Federal Reserve's interventions in stabilizing the municipal bond market (see, for example, Li and Lu, 2020; Haughwout, Hyman, and Shachar, 2021; Bi and Marsh, 2022; Bordo and Duca, 2023; Li, O'Hara, and Zhou, 2023).

Subfigure (b) of Figure 6 plots the coefficient on day t outflows from the 5-day rolling window regressions of sales on day t outflows and inflows. Because rolling regressions have small sample sizes with most fund-day observations having no sales, these regressions are potentially vulnerable to outliers. To prevent outliers from unduly influencing the estimated coefficients, we exclude observations with DFBETA influence statistic greater than 0.25 in magnitude. DFBETA of a given observation is the difference in the estimated coefficient when this observation is included versus excluded, scaled by the estimated standard error of the coefficient. In a typical cross-section, this screen excludes about 7 out of 1,739 observations.

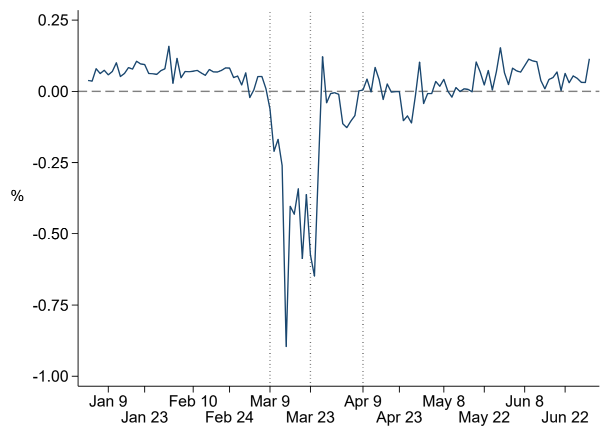
Although there are temporary spikes that are estimated with wide confidence intervals, until the first week of March 2020, the estimated coefficient on day t outflows is generally small and not statistically significant. On March 10, the coefficient jumps from -0.006 to 0.343. It continues to increase over the subsequent days and peaks at 0.505 on March 26. It means that at this point in the crisis, funds were immediately selling 50 cents of municipal bonds for each dollar of outflows. The coefficient on day t outflows experiences its first sharp drop on March 31. It then drops again on Monday, April 13, the first trading day after the establishment of the Municipal Liquidity Facility on Thursday, April 9 (with markets closed on Friday, April 10 in observance of Good Friday). The estimated coefficient on day t outflows increases again in mid-May, reaching 0.386 on May 12; but the estimates in May are much noisier. This spike in the coefficient on day t outflows during March 2020 is a striking example of the result in Table 7 that expectations of aggregate outflows are associated with large increases in the responsiveness of sales to outflows.

[23] Our measure is limited to funds that report daily flows to Morningstar. As a result, our measure underestimates aggregate fund flows. Table 5 in Vissing-Jorgensen (2021) reports aggregate outflows of $42 billion or 4.9% during the whole of March 2020.

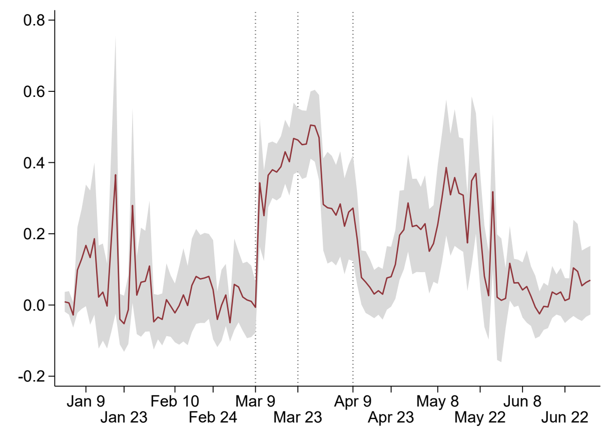
Figure 6
Flow-Induced Sales Around the Start of COVID-19 Pandemic

Subfigure (a) plots aggregate fund flows during the first half of 2020. Subfigure (b) plots the estimated coefficients on day t outflows from the 5-trading-days rolling window regressions of daily sales on day t outflows and inflows. To prevent outliers from unduly influencing the estimated coefficients, we exclude observations with DFBETA influence statistic greater than 0.25 in magnitude. DFBETA is the difference in the estimated coefficient when the ith observation is included and excluded, scaled by the estimated standard error of the coefficient. 95% confidence intervals are calculated using robust standard errors. Subfigure (c) plots the distribution of daily cash buffers. Dotted vertical lines indicate i) March 9—the start of the crisis period; ii) March 23—Federal Reserve expands the Money Market Fund Liquidity Facility and the Commercial Paper Funding Facility to include Variable Rate Demand Notes and tax-exempt commercial paper; and iii) April 9—Federal Reserve establishes the Municipal Liquidity Facility.

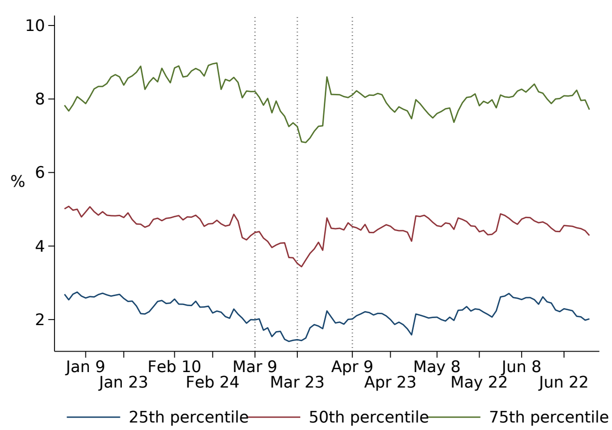
(a) Aggregate fund flows (%)



(b) Coefficient on day t outflows



(c) Cash-to-assets ratio (%)



Subfigure (c) of Figure 6 plots the 25th, 50th, and 75th percentiles of the estimated daily cash buffers held by the municipal bond funds throughout the first six months of 2020. The median cash-to-assets ratio declined from 4.37% on March 9 to 3.54% on March 24. Although this is a large decline, it is less than a quarter of aggregate fund flows during this period (3.72%). It appears that even though most funds could have relied more heavily on their cash buffers to meet redemptions, most funds chose not to. This may be because they wanted to preserve cash buffers in case investors continued to withdraw and to make sure that heavy reliance on cash buffers in the short term did not lead to even more withdrawals due to strategic complementarities (Zeng, 2017). With large aggregate outflows stopping around March 23, most funds quickly rebuilt their cash buffers over the following two weeks. Interestingly there is no indication that following the events of March 2020, funds chose to increase their cash buffers. Funds' decision not to increase cash buffers and thereby reduce vulnerability to outflows may help to explain Li, O'Hara, and Zhou (2023)'s finding that yield spreads of bonds held by mutual funds remain elevated after the muni crisis.

8.1 Estimating the Effect of Larger Cash Buffers

Our data on daily flows, trading, and cash buffers allow us to estimate the likely effect on aggregate flow-induced sales by open-end mutual funds of requiring funds to hold a 10% buffer of cash and highly liquid securities.[24][25] To conduct this exercise we first use data through February 2020 to estimate the relationship between sales and fund flows:

$$\begin{aligned} Sales_{f,t} &= \alpha_t + \sum_{s=0}^{15} \left(\beta_s^{out} Outflows_{f,t-s} + \beta_s^{in} Inflows_{f,t-s}\right) \\ &+ Outflows_{f,t} \times (\gamma_1 Cash_{f,t-1} + \gamma_2 \mathit{Expected\ agg.\ outflows}_t + \gamma_3 \mathit{Market\ markup}_t) + \varepsilon_{f,t}, \end{aligned} \tag{2}$$

where sales, fund flows and cash buffers are scaled by TNA as of the end of the previous month. To better match aggregate sales, observations are weighted by log TNA as of month $m-1$.

We initialize each fund's cash buffer as of March 8, 2020 to 10%. For each trading day between March 9 and April 30, we use the estimated coefficients along with the fund's lagged cash buffer, realized fund flows, expected aggregate outflows and market markup to predict each fund's sales on

[24] See the SEC's proposed rule on "Open-End Fund Liquidity Risk Management Programs and Swing Pricing."

[25] We do not consider the swing pricing aspect of the proposed rule or its potential interaction with the highly liquid investments minimum.

day t. We then update the cash buffer according to

$$Cash_{f,t} = Cash_{f,t-1} + Net\ flows_{f,t} + Net\ sales_{f,t-2} + Principal\ payments_{f,t} + Interest\ payments_{f,t} \tag{3}$$

Because municipal bond trades generally settle $t+2$, net sales affect the cash buffer with a two day lag. If predicted net sales are such that meeting the rest of net outflows with cash would result in a negative cash buffer, we revise the predicted value of sales so that the fund would have a zero cash buffer at the end of day t.

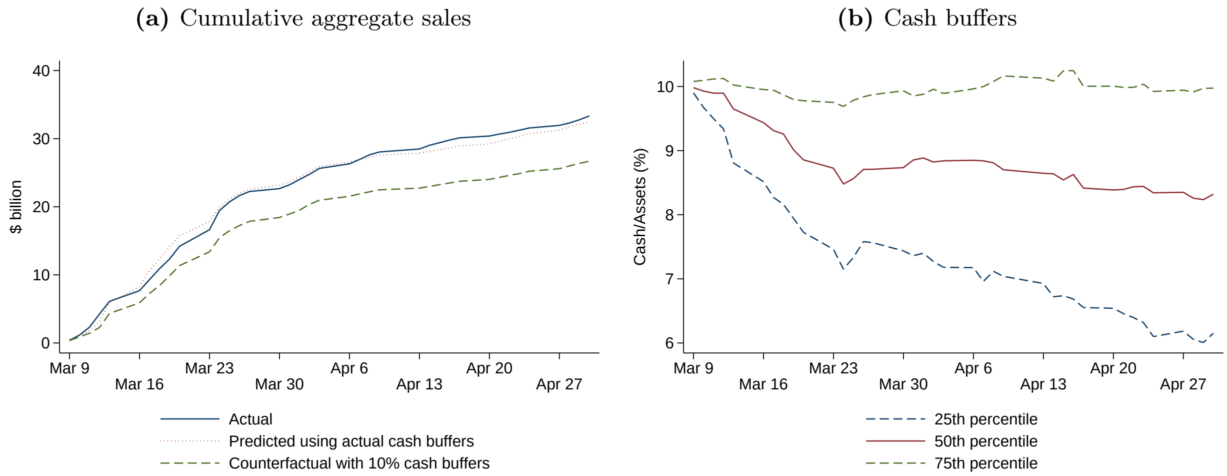
By allowing cash buffers to fall all the way to zero, our analysis is meant to establish an upper bound on the effect of cash buffers on flow-induced sales. In practice funds may not fully utilize their cash buffers or may quickly rebuild their cash buffers.[26] In this case the reduction in cumulative aggregate flow-induced sales is likely to be significantly smaller than the upper bound that we estimate.

Our analysis accounts for the effect of larger initial cash buffers on sales, but does not account for the possibility that larger cash buffers may reduce redemptions by weakening strategic interactions among fund investors (Goldstein, Jiang, and Ng, 2017; Zeng, 2017). Appendix Table B5 estimates regressions of cumulative net outflows during March 9–23, 2020 on the lagged cash-to-assets ratio and fund characteristics. The estimated coefficient on cash is small and not statistically significant, suggesting that, at least during COVID-19, larger cash buffers are unlikely to have reduced outflows. Similarly, the counterfactual exercise holds the expected aggregate outflows and market markups constant at their actual values. If cash buffers do reduce redemptions, then smaller expected aggregate outflows would result in smaller net sales in response to outflows. On the other hand, with smaller net sales by open-end funds, the average market markup should decline, which according to Equation 2 would result in somewhat larger sales in response to outflows. Although the model does not capture all of the potential effects of larger cash buffers and is subject to the Lucas critique (Lucas, 1976), we view it as a useful first step in understanding how larger cash buffers may work in practice and in quantifying the different mechanisms.

[26] For example, funds with an established highly liquid investment minimum are required to file Form N-RN when their highly liquid investments fall below the minimum for seven consecutive calendar days.

Figure 7
Counterfactual Flow-Induced Sales During COVID-19

This figure plots counterfactual sales and cash buffers under alternative initial values of the cash-to-assets ratio. Subfigure (a) plots the actual sales, sales predicted by Equation 2 when using actual initial cash buffers, and counterfactual sales predicted by Equation 2 when all funds start with a 10% cash buffer. Subfigure (b) plots the evolution of the 25th, 50th, and 75th percentiles of the distribution of the cash-to-assets ratio when funds start with a 10% cash buffer.



We report the results in Figure 7. Subfigure (a) plots cumulative aggregate sales starting on March 9, 2020. The solid blue line plots the actual sales by funds in our data. The dotted red line plots sales predicted by Equation 2 when we use each fund's actual initial cash buffer and update the cash buffer according to Equation 3. Predicted sales closely track actual sales, though initially Equation 2 slightly overestimate aggregate sales. The dashed green line plots cumulative aggregate sales under the counterfactual of all funds starting with a 10% cash buffer. Counterfactual sales are lower than actual sales or sales predicted using actual initial cash buffers, but the difference is relatively small. By April 9, the difference in cumulative sales is only 18%. Having said that, larger buffer cash seem to matter more during the first two weeks of the pandemic. Counterfactual sales through March 17 are 32% lower than predicted sales using the actual initial cash buffers. Lower initial sales may give more time for additional buyers to come in and for dealers to intermediate flow-induced sales.

Subfigure (b) plots the 25th, 50th, and 75th percentiles of the cash-to-assets ratio. Over the first two weeks, the median fund draws down a bit more than one percentage point of its cash buffer.

Cash buffers then stabilize at around 9% until mid April, when they start declining again. The 25th percentile drops to about 7.5% by March 23 and then continues to trend down to end April at around 6.2%.

Overall, the results of our analysis suggest that unless larger cash buffers stem outflows by reducing strategic complementarities in investor withdrawal decisions (Goldstein, Jiang, and Ng, 2017; Zeng, 2017) or fundamentally change how funds use cash buffers, a policy of requiring large cash buffers is unlikely to have large effects on flow-induced sales during stressed market conditions.

9 Robustness

Finally, we examine in Table 9 the robustness of our main results to alternative specifications. For each specification, we report the coefficients on day t inflows and outflows and the sums of the coefficients on inflows and outflows over days $[t-15, t+5]$. Specification (1) reports our baseline results Table 3.

Specification (2) does not include any fixed effects. The results are very similar to the baseline specification with date fixed effects. In the regression of daily sales, for example, the coefficient on day t outflows is 0.244 (versus 0.242 in the baseline specification); the sum of the coefficients on outflows is 0.714 (versus 0.688).

Specification (3) uses objective-date fixed effects and again finds virtually identical results as the baseline specification with date fixed effects. Specification (4) uses fund and date fixed effects. The results for sales are once again very similar to the baseline specification. For purchase regressions, however, we estimate somewhat smaller coefficients on inflows. In the regression of total purchases, the sum of the coefficients on inflows over days $[t-15, t+5]$ is 0.593 versus 0.702 in the baseline regression. This result appears to be driven by primary purchases, suggesting that the baseline results are driven somewhat by certain funds experiencing persistent inflows and tilting their purchases towards the primary market.

Specification (5) estimates regressions weighted by fund TNA to give more weight to larger funds that may contribute more to aggregate trading activity and to potential market instability.

Table 9
Robustness

This table shows that the results in Table 3 on the association between fund flows and trading are robust to using alternative specifications. The coefficients on day t outflows (inflows) and the sum of outflows (inflows) coefficients on days $[t-15, t+5]$ are reported. Row (2) includes no fixed effects. Row (3) replaces date fixed effects with objective-date fixed effects. Row (4) replaces date fixed effects with fund and date fixed effects. Row (5) reports value-weighted regressions with fund size as weights. Row (6) reports value-weighted regressions with absolute daily flows as weights. Row (7) controls for daily fund returns over days $[t-15, t]$. Row (8) limits the sample to fund-months with 100% of changes in holdings are explained by bond events or MSRB trades. Rows (9)–(10) split the sample period into the 2009–2014 and 2015–2020 subperiods. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

				Purchases					
		Sales		Total		Primary		Secondary	
		Day t (1)	$[-15, +5]$ (2)	Day t (3)	$[-15, +5]$ (4)	Day t (5)	$[-15, +5]$ (6)	Day t (7)	$[-15, +5]$ (8)
(1) Baseline	*Outflows*	0.242	0.688	−0.005	−0.068	−0.002	−0.035	−0.003	−0.033
	Inflows	0.006	0.011	0.083	0.702	0.030	0.357	0.052	0.345
(2) Without FEs	*Outflows*	0.244	0.714	−0.004	−0.068	−0.002	−0.066	−0.002	−0.002
	Inflows	0.005	0.006	0.082	0.700	0.030	0.358	0.052	0.342
(3) Objective-date FEs	*Outflows*	0.242	0.682	−0.005	−0.076	−0.002	−0.038	−0.003	−0.038
	Inflows	0.005	−0.006	0.082	0.679	0.030	0.343	0.052	0.337
(4) Fund & Date FEs	*Outflows*	0.239	0.635	−0.008	−0.118	−0.004	−0.079	−0.004	−0.039
	Inflows	0.002	−0.062	0.077	0.593	0.027	0.279	0.051	0.314
(5) Weighted by TNA	*Outflows*	0.192	0.622	−0.007	−0.084	−0.002	−0.048	−0.006	−0.036
	Inflows	0.006	0.090	0.100	0.761	0.029	0.358	0.071	0.403
(6) Weighted by absolute flows	*Outflows*	0.193	1.054	−0.008	−0.078	−0.003	−0.018	−0.005	−0.059
	Inflows	0.002	−0.099	0.078	0.716	0.033	0.330	0.044	0.385
(7) Daily returns controlled	*Outflows*	0.229	0.673	−0.005	−0.071	−0.001	−0.034	−0.004	−0.038
	Inflows	0.004	0.021	0.078	0.727	0.025	0.371	0.053	0.356
(8) Sample with 100% match rate	*Outflows*	0.298	0.750	−0.002	−0.098	−0.001	−0.065	−0.001	−0.033
	Inflows	0.003	−0.061	0.085	0.622	0.033	0.325	0.052	0.297
(9) 2009–2014	*Outflows*	0.187	0.644	−0.003	−0.022	−0.001	−0.001	−0.002	−0.021
	Inflows	0.006	0.016	0.112	0.682	0.046	0.322	0.066	0.360
(10) 2015–2020	*Outflows*	0.295	0.734	−0.008	−0.113	−0.003	−0.067	−0.005	−0.046
	Inflows	0.005	0.008	0.063	0.722	0.020	0.394	0.043	0.327

Consistent with the negative interaction between outflows and fund size in the sales regressions in Table 5, the coefficients on outflows in the sales regression are somewhat smaller than in the equal-weighted regression. The coefficient on day t outflows is 0.192 versus 0.242 in the equal-weighted regression, or about one-fifth smaller. The sum of the coefficients on outflows is 0.622 versus 0.688 in the equal-weighted regression or about one-tenth smaller. At the same time, we find somewhat stronger response of purchases to inflows.

Specification (6) estimates regressions weighted by the absolute value of day t net flows. In the regression of sales, the coefficient on day t outflows is smaller than in the baseline specification (0.193 versus 0.242), but the sum of the coefficients on outflows is larger at 1.054 (versus 0.688). These results likely capture the fact that for very large outflows, funds have essentially no choice but to sell portfolio securities.

Specification (7) controls for daily returns. These may be correlated with fund flows and may capture changes in the value of portfolio securities which may prompt funds to rebalance their portfolios. Thus some of the estimated effect of fund flows may be due to portfolio rebalancing rather than flow-induced trading. Controlling for daily returns, however, has little effect on the estimated coefficients. In the sales regressions, for example, the coefficient on day t outflows is 0.229 versus 0.242 in the baseline specification.

Specification (8) limits the sample to fund-month periods for which we can identify all portfolio transactions. Limiting the sample to 100% match rate results in larger coefficients on outflows in the sales regression but somewhat smaller coefficients on inflows in the purchases regressions. The coefficient on day t outflows in the sales regression is 0.298 versus 0.242 in the baseline regression. The sum of the estimated coefficients on outflows on days $[t-15, t+5]$ is 0.750 versus 0.688, or about 10% larger. Thus restricting the sample makes more difference for the immediate response than for estimates of the overall trading response to outflows. There are two reasons why the estimated coefficients are larger. The first one is that with less than a perfect match rate, we slightly underestimate the value of sales. The second one is that the sample with a 100% match rate is tilted towards smaller funds which tend to trade more aggressively in response to day t outflows.

Finally, specifications (9) and (10) split the sample period into 2009–2014 and 2015-2020. Consistent with the results in Figure 4, the estimated coefficients on outflows in the sales regression are larger during the second half.

Overall, the results in Table 9 show that our results are robust to a wide range of alternative specifications.[27]

10 Conclusion

We show how researchers can combine standard data sets of mutual fund portfolio holdings with MSRB's municipal securities transactions data to study the daily trading of municipal bond funds. In this paper, we use these data to study how open-end funds trade in response to daily fund flows. We trace out the dynamic response of sales and purchases to inflows and outflows and document strong short-term reliance on cash buffers. Over the $[t-15, t+5]$ trading days period, funds sell 68.8 cents of portfolio bonds for every dollar of outflows and buy 70.2 cents of bonds for every dollar of inflows. The rest is presumably accommodated through cash buffers. While sales and purchases respond similarly over a month-long period, their dynamics are different. The response of sales to outflows is much more immediate than the response of purchases to inflows. The coefficient on day t outflows in the sales regressions is almost three times larger than the coefficient on day t inflows in the purchases regressions.

Our data on daily flows and trading allow us to construct an accurate measure of daily cash buffers. We show that cash buffers have a much stronger effect on the responsiveness of sales to outflows than suggested by the existing literature that looks at monthly or quarterly changes in portfolio holdings and uses cash buffers as of the previous reporting period. Because these cash buffers are a noisy proxy for cash buffers at the time trading decision are made, the effect of cash buffers can be significantly underestimated.

Our data also allow us to ask how flow-induced trading is affected by aggregate market conditions. As markups decreased over the 2009–2020 period, the responsiveness of sales to outflows,

[27] Appendix Table B2 shows that our results are also robust to excluding future flows from the regressions.

especially to day t outflows increased significantly. We also show that expectations of future aggregate outflows are associated with a much stronger responsiveness of sales to outflows. A stark example of this dynamic was the onset of the COVID-19 pandemic in March 2020. The sensitivity of sales to outflows spiked dramatically even though most funds continued to maintain sizable cash buffers.

Finally, we use COVID-19 to estimate the potential effects on flow-induced sales of requiring funds to hold a 10% buffer of cash and highly liquid securities. Holding fixed the realized fund flows and expectations of aggregate fund flows, aggregate sales would have been only 18% smaller. Thus, unless larger cash buffers reduce outflows or fundamentally change how funds trade in response to outflows, requiring funds to hold significantly larger cash buffers may have little effect of flow-induced sales during stressed market events like COVID-19.

Our approach to measuring daily trading and cash buffers of fixed-income open-end funds should be useful for studying other questions about mutual fund trading behavior. Examples of such questions include how funds choose which dealers to trade with (Chernenko and Doan, 2022a) and how to measure mutual fund liquidity creation (Chernenko and Doan, 2022b).

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Appendix A: Variable Definitions

Table A1
Variable Definitions

Variable	Definition
Trading measures	
Sales	The aggregate amount of all sales by the fund on the same trade date, scaled by previous month TNA. Expressed in percentage points.
Purchases	The aggregate amount of all purchases by the fund on the same trade date, scaled by previous month TNA. Expressed in percentage points.
Primary purchases	The aggregate amount of all purchases by the fund on the same trade date, scaled by previous month TNA. Limited to purchases on the bonds' offering dates or purchases whose either *when_issued_indicator* or *offer_price_takedown_indicator* is 'Y' in MSRB. Expressed in percentage points.
Secondary purchases	The aggregate amount of all secondary market purchases by the fund on the same trade date, scaled by previous month TNA. Expressed in percentage points.
Characteristic percentiles	We compare the characteristics of the bond sold or purchased with the distribution of characteristics across the fund's portfolio holdings as of the last reporting date. We calculate percentile measures in terms of numeric rating, maturity, offering amount, and issue size.
Fund characteristics	
Net flows	Daily fund flows from Morningstar, scaled by previous month TNA. Expressed in percentage points.
Outflows	The absolute value of daily fund flows from Morningstar if negative and zero otherwise, scaled by previous month TNA. Expressed in percentage points.
Inflows	Daily fund flows from Morningstar if positive and zero otherwise, scaled by previous month TNA. Expressed in percentage points.
Cash	Daily cash holdings, imputed from fund transactions, fund flows, and payment schedules of portfolio bonds, and scaled by previous month TNA. Detailed construction is provided in the Internet Appendix. Expressed in percentage points.
Fund TNA	Total Net Assets as of the previous month. Expressed in $ millions.
Family TNA	Aggregate TNA as of the previous month of all open-end municipal bond funds within a family, defined using Morningstar's *Branding Name*. Expressed in $ millions.
Single state fund	Whether the fund's *Morningstar Category* indicates that the fund invests in securities of a single state.
Interfund lending	Whether the fund participates in interfund lending programs. We use the timing of the SEC exemptive relief orders allowing fund sponsors to set up interfund lending programs: `https://www.sec.gov/rules/icreleases.shtml#interfundlending`. We assume that all funds sharing the Central Index Key (CIK) numbers associated with the interfund lending application on the SEC From 40-APP participate in the program once it is approved by the SEC.
WAR	Weighted average rating across all bonds in the fund's portfolio as of the last reporting date. A bond's rating is the median of Moody's, S&P, and Fitch ratings when all are available, or lower rating otherwise. Ratings are from Mergent. Ratings are coded such that AAA = 0, AA+ = 1, AA = 2, etc.
WAM	Weighted average maturity across all bonds in the fund's portfolio as of the last reporting date. Expressed in years.
Market conditions	
Market markup	The par-weighted average dealer markup across all non-prearranged customer trades on a day, excluding trades on VRDNs. For each customer purchase, dealer markup is the relative difference between the trade price and the average price of interdealer trades for the same bond and on the same day. For each customer sale, dealer markup is the relative difference between the average price of interdealer trades for the same bond and on the same day and the trade price. Expressed in percentage points.

(Continued)

Table A1—*continued*

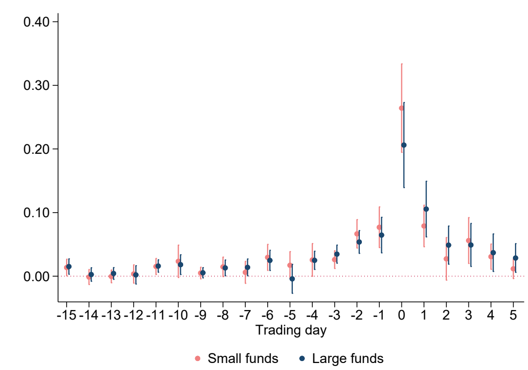
Variable	Definition
Δ Market markup	The difference between day t market markup and the 5-day average market markup over $[t-5, t-1]$. Expressed in percentage points.
Yield spread	The difference between the Bloomberg Municipal 10-year Benchmark Yield, adjusted for 37% federal income tax and 3.8% Medicare investment tax, and the 10-year Treasury yield. Expressed in percentage points.
Δ Yield spread	The difference between day t yield spread and the 5-day average yield spread over $[t-5, t-1]$. Expressed in percentage points.
VIX	Daily Chicago Board Options Exchange's CBOE Volatility Index.
Customer trading volume	The total customer sale volume and customer purchase volume, excluding VRDN trades and prearranged trades. Measured over $[t-5, t-1]$.
Dealer imbalance	The difference between customer sale volume and customer purchase volume, scaled by total customer trading volume. VRDN trades and prearranged trades are excluded. Measured over $[t-5, t-1]$.
Aggregate outflows	The 5-day average of the sum of net outflows of all open-end municipal bond mutual funds over days $[t-4, t]$, scaled by their aggregate TNA as of the previous month. Expressed in percentage points.
Expected agg. outflows	The predicted value obtained from the 252-day rolling window regression of the 5-day average aggregate outflows over $[t+1, t+5]$ on day t aggregate outflows and its five lags, day t market markup and the change in market markup, day t tax-adjusted muni yield spread and the change in tax-adjusted muni yield spread, dealer imbalance and log of customer trading volume over $[t-5, t-1]$, and indicators for day of the week and day of the month. For each day, we use i) day t information and ii) the coefficients estimated from days $[t-267, t-16]$ to predict future aggregate outflows. Expressed in percentage points.

Appendix B: Additional Results

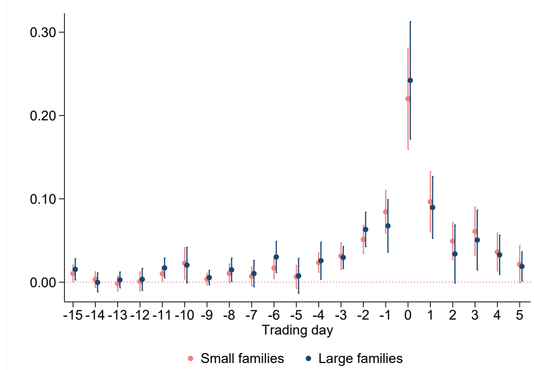
Figure B1
Cross-Sectional Variation in the Dynamics of Selling in Response to Outflows

This figure plots dynamics of sales in response to outflows for different types of funds. Standard errors are adjusted for clustering by fund.

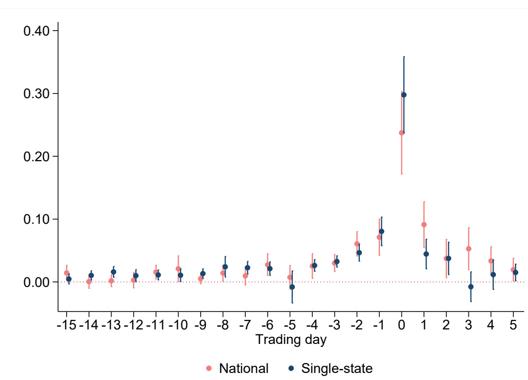
(a) Fund size



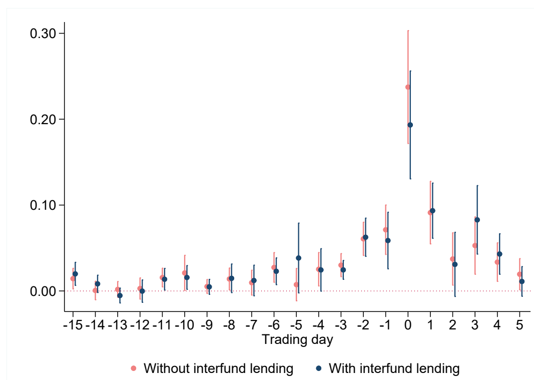
(b) Family size



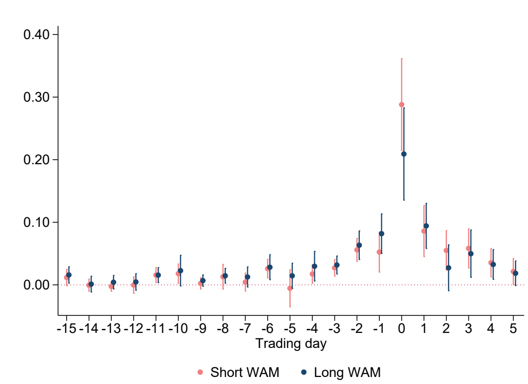
(c) National vs. single-state



(d) Interfund lending



(e) Maturity



(f) Rating

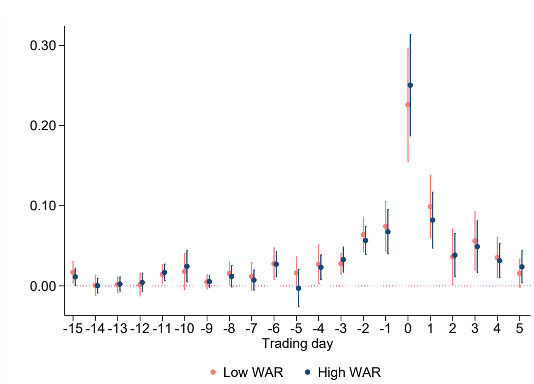
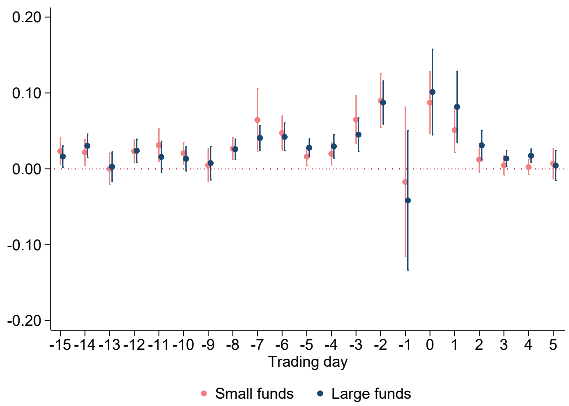


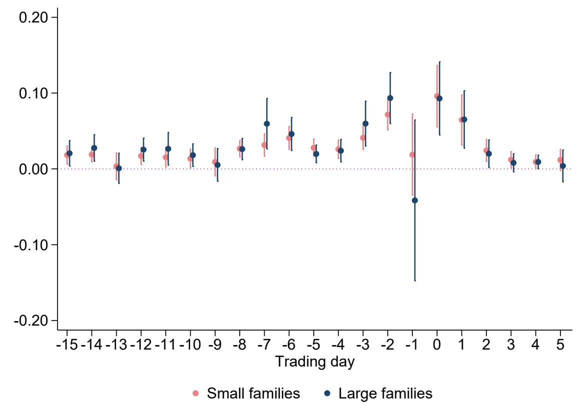
Figure B2
Cross-Sectional Variation in the Dynamics of Purchases in Response to Inflows

This figure plots dynamics of purchases in response to inflows for different types of funds. Standard errors are adjusted for clustering by fund.

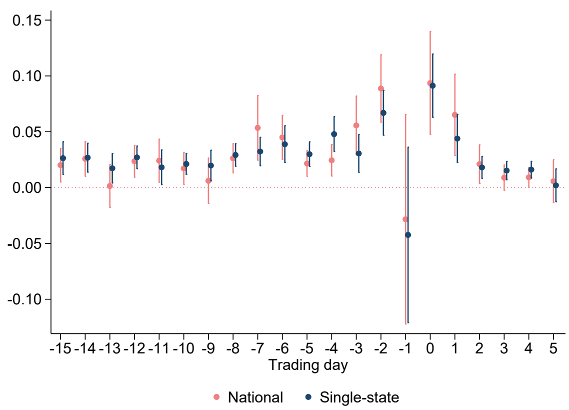
(a) Fund size



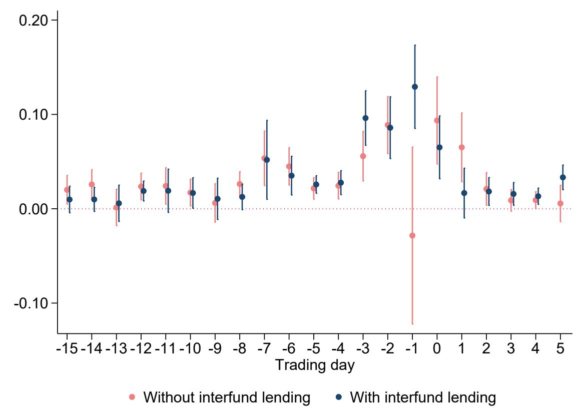
(b) Family size



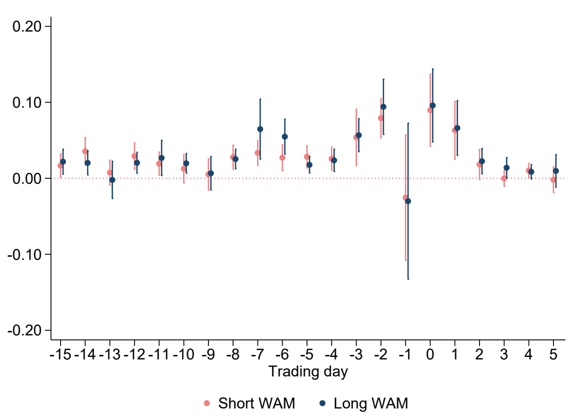
(c) National vs. single-state



(d) Interfund lending



(e) Maturity



(f) Rating

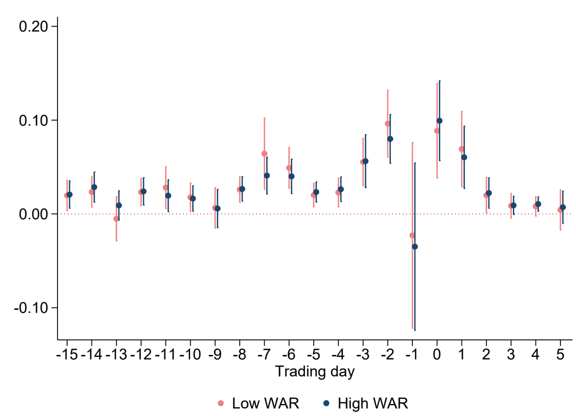


Table B1
Number of Observations with Sales or Purchases

This table reports the the number of fund-date observations with sales and purchases.

	With sales	Without sales	Total	
With purchases	37,472	128,933	166,405	#
	22.52%	77.48%	100%	% of row
	32.24%	13.25%	15.28%	% of column
Without purchases	78,770	843,955	922,725	#
	8.54%	91.46%	100%	% of row
	67.76%	86.75%	84.72%	% of column
Total	116,242	972,888	1,089,130	#
	10.67%	89.33%		% of row
	100%	100%		% of column

Table B2
Trading in Response to Daily Flows: With versus Without Future Flows

This table reports the results of regressions of daily trading on daily flows:

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

where f indexes funds and t indexes trading days. Odd-numbered columns report the baseline results in Table 3 while even-numbered columns report the results without future flows included. Fund flows and trading activity are scaled by TNA 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 inflows and outflows. We report the sums of the coefficients on outflows and inflows over different windows. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. N = 1,089,130.

			Purchases							
	Sales		Total		Primary		Secondary		Net sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\text{Outflows}_{f,t}$	0.242***	0.249***	−0.005***	−0.005***	−0.002*	−0.002	−0.003***	−0.003***	0.247***	0.254***
	(0.019)	(0.018)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.019)	(0.019)
$\text{Outflows}_{f,t-1}$	0.078***	0.084***	−0.001	−0.001	0.000	0.000	−0.001	−0.001	0.078***	0.085***
	(0.010)	(0.010)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)
$\text{Outflows}_{f,t-2}$	0.040***	0.045***	−0.009***	−0.009***	−0.005***	−0.005***	−0.004***	−0.004***	0.048***	0.054***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
$\text{Outflows}_{f,t-3}$	0.017***	0.022***	−0.004*	−0.004*	−0.003***	−0.003***	−0.001	−0.001	0.021***	0.026***
	(0.004)	(0.004)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
$\text{Outflows}_{f,t-4}$	0.015***	0.019***	−0.008***	−0.008***	−0.006***	−0.006***	−0.002**	−0.002**	0.022***	0.027***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)
$\text{Outflows}_{f,t-5}$	0.030**	0.033***	−0.004**	−0.004**	−0.001	−0.002	−0.003***	−0.003***	0.034***	0.038***
	(0.012)	(0.012)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.012)	(0.012)
$\text{Inflows}_{f,t}$	0.006***	0.007***	0.083***	0.089***	0.030***	0.034***	0.052***	0.055***	−0.077***	−0.082***
	(0.002)	(0.002)	(0.011)	(0.012)	(0.007)	(0.008)	(0.008)	(0.009)	(0.011)	(0.012)
$\text{Inflows}_{f,t-1}$	−0.006**	−0.006**	0.121***	0.126***	0.048***	0.051***	0.073***	0.075***	−0.127***	−0.132***
	(0.003)	(0.003)	(0.039)	(0.038)	(0.015)	(0.015)	(0.028)	(0.028)	(0.038)	(0.038)
$\text{Inflows}_{f,t-2}$	−0.003	−0.002	0.053***	0.057***	0.029***	0.031***	0.024***	0.026***	−0.056***	−0.059***
	(0.002)	(0.002)	(0.012)	(0.012)	(0.008)	(0.008)	(0.006)	(0.006)	(0.011)	(0.011)
$\text{Inflows}_{f,t-3}$	−0.006***	−0.006***	0.058***	0.061***	0.025***	0.027***	0.033***	0.034***	−0.064***	−0.067***
	(0.001)	(0.001)	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)
$\text{Inflows}_{f,t-4}$	−0.004***	−0.004***	0.037***	0.040***	0.016***	0.018***	0.021***	0.022***	−0.041***	−0.044***
	(0.001)	(0.001)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
$\text{Inflows}_{f,t-5}$	−0.001	−0.001	0.034***	0.037***	0.014***	0.016***	0.020***	0.021***	−0.035***	−0.038***
	(0.001)	(0.001)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Adjusted R^2	0.063	0.059	0.066	0.065	0.048	0.047	0.042	0.041	0.075	0.071

(Continued)

Table B2—*continued*

	Sales		Purchases						Net sales	
			Total		Primary		Secondary			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\sum_{s=-5}^{-1} \beta_s^{out}$	0.178	0.203	−0.025	−0.026	−0.015	−0.016	−0.010	−0.011	0.203	0.230
$\sum_{s=-5}^{0} \beta_s^{out}$	0.420	0.452	−0.030	−0.032	−0.017	−0.018	−0.014	−0.014	0.451	0.484
$\sum_{s=-15}^{0} \beta_s^{out}$	0.511	0.576	−0.055	−0.057	−0.027	−0.028	−0.028	−0.029	0.566	0.633
$\sum_{s=1}^{5} \beta_s^{out}$	0.177	.	−0.013	.	−0.009	.	−0.004	.	0.191	.
$\sum_{s=-15}^{5} \beta_s^{out}$	0.688	.	−0.068	.	−0.035	.	−0.033	.	0.757	.
$\sum_{s=-5}^{-1} \beta_s^{in}$	−0.021	−0.019	0.303	0.321	0.132	0.142	0.171	0.179	−0.324	−0.340
$\sum_{s=-5}^{0} \beta_s^{in}$	−0.015	−0.012	0.386	0.410	0.163	0.176	0.223	0.234	−0.401	−0.422
$\sum_{s=-15}^{0} \beta_s^{in}$	0.000	0.009	0.604	0.655	0.301	0.330	0.302	0.325	−0.603	−0.646
$\sum_{s=1}^{5} \beta_s^{in}$	0.011	.	0.098	.	0.055	.	0.043	.	−0.087	.
$\sum_{s=-15}^{5} \beta_s^{in}$	0.011	.	0.702	.	0.357	.	0.345	.	−0.690	.
Date FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table B3
Trading in Response to Daily Flows: Low versus High Cash Funds

This table reports the results of regressions of daily trading on daily flows:

$$Trading_{f,t} = \alpha_{obj\times t} + \sum_{s=-15}^{5} \left(\beta_s^{out} \cdot Outflows_{f,t+s} + \beta_s^{in} \cdot Inflows_{f,t+s}\right) + \varepsilon_{f,t},$$

where f indexes funds and t indexes trading days. The sample is split based on the cash-to-assets as of trading day $t-16$. For brevity we separately report only the coefficients on the contemporaneous value and the first five lags of inflows and outflows. We report the sums of the coefficients on outflows and inflows over different windows. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N =$ 1,089,130.

	Sales		Purchases	
	Low cash	High cash	Low cash	High cash
	(1)	(2)	(3)	(4)
$\text{Outflows}_{f,t}$	0.321***	0.202***	−0.008***	−0.004*
	(0.029)	(0.022)	(0.002)	(0.002)
$\text{Outflows}_{f,t-1}$	0.086***	0.072***	−0.002	0.000
	(0.015)	(0.013)	(0.004)	(0.004)
$\text{Outflows}_{f,t-2}$	0.044***	0.037***	−0.009***	−0.008***
	(0.006)	(0.006)	(0.003)	(0.002)
$\text{Outflows}_{f,t-3}$	0.032***	0.009***	−0.004*	−0.004
	(0.009)	(0.003)	(0.003)	(0.003)
$\text{Outflows}_{f,t-4}$	0.021***	0.012**	−0.009***	−0.007***
	(0.005)	(0.006)	(0.002)	(0.002)
$\text{Outflows}_{f,t-5}$	0.009**	0.040**	−0.006**	−0.004*
	(0.004)	(0.017)	(0.002)	(0.002)
$\text{Inflows}_{f,t}$	0.009***	0.004**	0.083***	0.083***
	(0.003)	(0.002)	(0.010)	(0.016)
$\text{Inflows}_{f,t-1}$	−0.016***	−0.002	0.073***	0.146***
	(0.006)	(0.003)	(0.012)	(0.055)
$\text{Inflows}_{f,t-2}$	−0.007**	−0.000	0.049***	0.056***
	(0.003)	(0.002)	(0.004)	(0.016)
$\text{Inflows}_{f,t-3}$	−0.009***	−0.006***	0.048***	0.062***
	(0.003)	(0.001)	(0.012)	(0.009)
$\text{Inflows}_{f,t-4}$	−0.008***	−0.003***	0.027***	0.039***
	(0.002)	(0.001)	(0.005)	(0.007)
$\text{Inflows}_{f,t-5}$	−0.003*	−0.000	0.033***	0.032***
	(0.002)	(0.002)	(0.005)	(0.006)
Adjusted R^2	0.074	0.060	0.050	0.075
$\sum_{s=-5}^{-1} \beta_s^{out}$	0.192	0.170	−0.031	−0.024
$\sum_{s=-5}^{0} \beta_s^{out}$	0.513	0.372	−0.039	−0.027
$\sum_{s=-15}^{0} \beta_s^{out}$	0.611	0.456	−0.061	−0.057
$\sum_{s=1}^{5} \beta_s^{out}$	0.152	0.190	−0.018	−0.012
$\sum_{s=-15}^{5} \beta_s^{out}$	0.763	0.647	−0.080	−0.068
$\sum_{s=-5}^{-1} \beta_s^{in}$	−0.044	−0.011	0.230	0.335
$\sum_{s=-5}^{0} \beta_s^{in}$	−0.035	−0.007	0.312	0.418
$\sum_{s=-15}^{0} \beta_s^{in}$	−0.050	0.020	0.469	0.652
$\sum_{s=1}^{5} \beta_s^{in}$	0.008	0.011	0.086	0.094
$\sum_{s=-15}^{5} \beta_s^{in}$	−0.042	0.031	0.555	0.746
Date FEs	✓	✓	✓	✓

Table B4
Predictability of Aggregate Outflows

This table reports the results of regressions of the average aggregate outflows over days $[t+1, t+5]$ on i) day t aggregate outflows and its five lags, ii) day t average market markup and the difference between day t markup and the average over $[t-5, t-1]$, iii) day t tax-adjusted yield spread and the difference between day t tax-adjusted yield spread and the average over $[t-5, t-1]$, iv) log of customer trading volume over $[t-5, t-1]$, and v) dealer imbalance—the difference between customer sale volume and purchase volume, scaled by total customer trading volume—over $[t-5, t-1]$. Log of customer trading volume and dealer imbalance are standardized to have zero mean and standard deviation of one. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. The sample period is 2008–2020. N = 3,252.

	(1)	(2)
Aggregate net outflows$_t$	0.132**	0.098*
	(0.064)	(0.053)
Aggregate net outflows$_{t-1}$	0.125**	0.097**
	(0.059)	(0.049)
Aggregate net outflows$_{t-2}$	0.087*	0.073*
	(0.045)	(0.039)
Aggregate net outflows$_{t-3}$	0.078**	0.070*
	(0.040)	(0.037)
Aggregate net outflows$_{t-4}$	0.075**	0.069**
	(0.035)	(0.032)
Aggregate net outflows$_{t-5}$	0.075***	0.069***
	(0.028)	(0.026)
Market markup$_t$		0.018**
		(0.008)
Δ Market markup$_t$		−0.008
		(0.008)
Yield spread$_t$		0.001
		(0.002)
Δ Yield spread$_t$		0.096***
		(0.018)
Ln(Customer trading volume)$_{t-1}$		0.009***
		(0.002)
Dealer imbalance$_{t-1}$		0.005***
		(0.001)
Adjusted R^2	0.316	0.367
Day of week FEs	✓	✓
Day of month FEs	✓	✓

Table B5
Fund Flows and Cash Buffers Around the Start of the COVID-19 Pandemic

The table reports the results of regressions of cumulative net outflows during March 9–23, 2020 on the lagged cash-to-assets ratio and fund characteristics:

$$Net\ outflows\ (\%)_f = \alpha_{obj} + \beta \cdot Cash_f + \gamma' X_f + \varepsilon_f,$$

The unit of observations is a fund. Cash-to-assets ratio and other portfolio-based characteristics are measured as of the last holdings snapshot before March 9, 2020. Lagged *Net outflows* and *Return* are cumulated over February 9–March 8, 2020. *Flow volatility* and *Return volatility* are the standard deviations of daily flows and returns over March 9, 2019–March 8, 2020. All continuous explanatory variables are standardized to have zero mean and unit standard deviation. Columns 4–6 use log of fund TNA, as of February 2020, as weights. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 326$.

	Equal-weighted			Value-weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash_f	0.131	0.062	−0.171	0.091	0.032	−0.197
	(0.184)	(0.191)	(0.169)	(0.186)	(0.185)	(0.177)
Net outflows_f			−0.054			−0.115
			(0.304)			(0.319)
Return_f			-0.555^{***}			-0.448^{***}
			(0.169)			(0.149)
Flow volatility_f			1.113^{**}			1.182^{**}
			(0.487)			(0.481)
Return volatility_f			−0.010			0.038
			(0.280)			(0.296)
Expense ratio_f		0.247	0.171		0.243	0.190
		(0.239)	(0.216)		(0.236)	(0.223)
Ln(Fund TNA)_f		−0.018	0.381		0.086	0.455
		(0.379)	(0.314)		(0.364)	(0.310)
Ln(Family TNA)_f		0.731^{**}	0.619^{**}		0.754^{**}	0.629^{**}
		(0.319)	(0.281)		(0.317)	(0.279)
Ln(Fund age)_f		−0.126	0.158		−0.208	0.079
		(0.280)	(0.283)		(0.266)	(0.273)
Share class HHI_f		−0.303	−0.088		−0.309	−0.096
		(0.288)	(0.308)		(0.281)	(0.294)
Share of institutional share classes_f		0.074	0.125		0.184	0.178
		(0.220)	(0.210)		(0.213)	(0.203)
Share of retirement share classes_f		-0.354^{***}	-0.281^{**}		-0.381^{***}	-0.315^{**}
		(0.106)	(0.133)		(0.097)	(0.126)
Share of deferred load share classes_f		−0.037	0.083		0.025	0.111
		(0.193)	(0.196)		(0.207)	(0.210)
WAR_f		0.254	0.216		0.232	0.265
		(0.376)	(0.383)		(0.381)	(0.392)
WAM_f		−0.308	−0.106		−0.304	−0.202
		(0.284)	(0.315)		(0.298)	(0.317)
Adjusted R^2	0.195	0.241	0.352	0.230	0.287	0.384
Fund objective FEs	✓	✓	✓	✓	✓	✓

Internet Appendix

for

Flow-Induced Trading: Evidence from the Daily Trading of Municipal Bond Mutual Funds

This Internet Appendix provides the details of our algorithms for identifying a) mutual fund and b) insurance company trades in MSRB transactions data, and c) explains how we construct the time series of daily cash buffers.

A. Mutual Fund Trades

Portfolio Holdings

Our primary source of portfolio holdings data is Morningstar. We supplement these data with quarterly portfolio holdings reported on the SEC Form N-PORT starting in September 2019. Combining holdings data from Morningstar and N-PORT creates more holdings snapshots and, thus, shorter periods between snapshots as some funds report their holdings to Morningstar and the SEC on different schedules.[1] For example, Vanguard Intermediate-Term Tax-Exempt Fund, which as of the end of our sample period in 2020 was the largest municipal bond fund with $81.84 billion in TNA, reports its holdings to Morningstar in March, June, September, and December and to the SEC in January, April, July, and October.

Tender Option Bonds

Many municipal bond mutual funds invest in the residual or inverse floater securities issued by Tender Option Bond (TOB) trusts. These special purpose trusts acquire high-quality municipal bonds and issue two types of securities. The first type are puttable floating-rate securities (floaters)

[1] Whenever holdings data are available in both N-PORT and Morningstar, we use N-PORT.

that are usually purchased by tax-exempt money market mutual funds. The second type are the residual interest securities or inverse securities whose stream of cash flows is equal to payments on the underlying bonds net of the payments to floaters and of the fees incurred by the trust. Inverse floaters thus create leveraged exposure to the underlying bonds.[2]

There is variation across and within funds in how inverse floaters are accounted for and reported to Morningstar and the SEC. When reporting to the SEC, funds tend to account for inverse floaters as secured borrowings. This means that funds report the underlying municipal bonds as part of their portfolio and floaters issued by the TOB trusts as a liability. When reporting to Morningstar, however, funds tend to report only the inverse floaters.

To properly and consistently capture the economics of fund exposure to the underlying securities and to make sure that how changes in holdings of inverse floaters are reported does not result in seeming changes in portfolio holdings, we replace holdings of inverse floaters with the underlying bonds. We first use Mergent Municipal Bond Securities Database (MBSD) to assemble a list of TOB securities. We then use security description from Bloomberg (`MUNI_ISSUER_DES_2ND_LINE` field) to assign individual TOB securities to separate trusts and to classify TOB securities into floaters versus inverse floaters/residuals.[3] Finally, we get information on the underlying bonds (related securities) from EMMA.

We replace holdings of inverse floaters with underlying municipal bonds only when the following conditions are met. First, the trust that issued the inverse floater must have a single underlying bond. This is the case for most trusts. Second, we must have issue size information for all securities issued by the trust. Third, the trust's gearing, the ratio of the floater value to the inverse floater value, must be at most four. Larger values of the gearing ratio may be due to data errors.

When the above conditions are satisfied, we replace the inverse floater CUSIP with the underlying CUSIP. We update the par value to reflect the trust's leverage. Finally, we set the gross market

[2] Nuveen funds provide more details on tender option bonds and their use by municipal bond funds: https://documents.nuveen.com/Documents/Nuveen/Default.aspx?uniqueId=92c28f28-7c58-4819-b819-6415fbf93e5e.

[3] Common names for floaters are Puttable Tax-Exempt Receipts (PUTTERs), Short Puttable Exempt Adjustable Receipts (SPEARs), Puttable Floating Option Tax-Exempts Receipts (P-FLOATs). Common names for inverse floaters are Derivative Inverse Tax-Exempt Receipts (DRIVERs), Long Inverse Floating Exempt Receipts (LIFERS), Residual Interest Tax-Exempt Securities Receipts (RITES).

value of the position to the sum of the reported market value of the inverse floater and the par value of the floater.

Changes in Holdings

Using the combined Morningstar and N-PORT holdings data, we calculate the change in par value between adjacent holdings snapshots. Some of the resulting holdings-implied trades are due to errors in the Morningstar holdings data and changes in how TOBs are reported. The most obvious cases are when the reported par value is larger than the bond's offering amount[4] or when the implied trade happens after the fund is acquired or liquidated.[5]

We use CRSP Mutual Fund database and portfolio holdings scraped from the quarterly and annual reports filed on the SEC Forms N-Q and N-CSR(S) to narrow down the range of dates for changes in portfolio holdings calculated using Morningstar and N-PORT data. We do not add full snapshots from CRSP and N-Q/N-CSR(S) because these are subject to data errors. CRSP appears to sometimes report wrong CUSIPs for municipal bond holdings. Given the complexity and cost of parsing N-Q/N-CSR(S) filings, we parse only filings by the American, American Century, Franklin Templeton, Invesco, T. Rowe Price, Vanguard, and Western municipal bond funds. These seven large fund families have a large number of N-Q/N-CSR(S) filings on dates not included by Morningstar. Because N-Q/N-CSR(S) filings do not report security CUSIPs, we identify CUSIPs based on the security description: issuer name and state, coupon, maturity, and, when available, series information and project name.[6] To avoid introducing any data errors, we use scraped data

[4] For zero-coupon and capital appreciation bonds, the reported offering amount in Mergent MBSD is the par value at issuance rather than maturity. We compare the reported holdings of such bonds with the maximum of the offering amount and the compound accreted value (CAV) at maturity, as reported by Mergent MBSD. Because not all zero-coupon bonds have CAV information in Mergent MSBD, we further check whether the reported par value is larger than the par value of the bond's largest trade in MSRB.

[5] We use the greatest value of Morningstar's obsolete date across the fund's share classes, assuming that all share classes are obsolete.

[6] We first match a given position in N-Q/N-CSR(S) with all bonds in Mergent MBSD with the same state, coupon, and maturity date. We then apply a number of screens to the set of potential matches. First, if series information is reported and there is at least one CUSIP with the same series, we discard all CUSIPs whose series information does not match. Second, matched CUSIPs must have been outstanding at the time of the N-Q/N-CSR(S) report and their offering amount must be at least as large as a) the fund's reported holdings amount and b) the sum of the reported holdings amounts across all funds in the same fund family. After applying these screens, we use the bigram method and Jaccard index to calculate the similarity between issuer and project names in N-Q/N-CSR(S) and Mergent MBSD. Matches whose overall similarity score, the minimum of similarity scores for issuer and project

in only two narrow sets of circumstances.

1. There is a 1–1 match between a position in N-Q/N-CSR(S) and CUSIP. Furthermore, the scraped position is within two months of a position in that CUSIP in Morningstar data. Thus the scraped data either i) narrow down when a position is initiated[7] or ii) or reflect a change in between two snapshots in Morningstar.[8]

2. The match to CUSIP is not 1–1 but par value matches a position in Morningstar that is within two months of the N-Q/N-CSR(S) filing.

Bond Events

We next use Mergent MBSD and Bloomberg to determine whether changes in portfolio holdings are due to newly issued bonds or are passive changes due to bond events: remarketing, maturities, calls, mandatory tenders, amortizations, refunding, distributions in default, and exchanges. If we cannot match a change in portfolio holdings to MSRB, we assume that the implied transaction takes places on the event date at the event price. For example, when bonds are purchased in the primary market, we often times cannot determine the exact trade that corresponds to a given fund's purchase because there are many same-size trades executing on the same day. Therefore if we cannot match an initial purchase to an exact MSRB trade, we assume that it was executed at the offering price on the bond's dated date.[9]

A decline in holdings is classified as being due to bond maturity if the maturity date falls within the reporting period or within 15 days of the end of the reporting period. The latter condition

names, is less than 0.75 are discarded.

[7] For example, according to Morningstar, Vanguard Intermediate-Term Tax-Exempt fund initiates a $10.225 million position in 66285WPM2 during January–March 2017. N-Q filing from January 2017 indicates that this position was initiated in January 2017.

[8] For example, according to Morningstar, Vanguard Intermediate-Term Tax-Exempt Fund held $168.36 million of 888808DG4 in December 2017 and $133.66 million in March 2018. N-Q filing from January 2018 shows holdings of $158.46 million. Using scraped data, therefore, allows us to infer that the fund sold $9.9 million during January 2018 and $24.8 million between February and March 2018.

[9] Dated date must be within the reporting period or in the month right after the reporting period. This accounts for the fact that funds may start reporting bonds on their balance once they commit to purchasing them but before bonds are actually issued and settled.

accounts for the fact that some funds stop reporting matured bonds early.

Similarly, a decline in holdings is classified as being due to a bond call if the call date falls within the reporting period or within 15 days of the end of the reporting period. The proportional change in holdings has to match the call rate. For example, a 50% decline in holdings matches only with a bond call after which the bond's outstanding amount decreases by half.

We do the same for amortizations and mandatory tenders. Mandatory tenders are identified with the condition that Mergent's `put_or_tender_type` = J. Mandatory tender dates are available in Mergent. We construct the amortization schedule for bonds with monthly interest frequency (Mergent's `interest_frequency` = U) and classified as one of the following types: mortgage loans (`security_code` = R), tobacco agreements (`security_code` = O), or single- or multi-family housing (`use_of_proceeds` = MFHG, SFHG, or SMHG).

Exchanges are identified as instances where a CUSIP is exchanged for another CUSIP, with corresponding position changes in a fund portfolio offsetting each other. These are mostly cases of advance refunding where an existing CUSIP is exchanged into a refunded and unrefunded CUSIPs. We track exchanges using Mergent MBSD's `prior_cusip` field and check whether the sum of changes in the related CUSIPs between two adjacent holdings snapshots is zero.

Finally, we use continuing disclosures in EMMA to manually collect data on distributions in default. We identify declines in holdings as being potentially due to distributions in default if a) the last implied price in holdings data was less than 50% and b) there are no trades in MSRB during or after the reporting period. From the continuing disclosures in EMMA, we record the distribution dates and rates.

Fund Mergers

We identify increases in holdings as being due to fund mergers by checking whether during the reporting period the fund acquired another fund that held a position equal to the increase in the acquiring fund's holdings. Target fund's last holdings snapshot must be within three months of the merger date.

Match to MSRB

Our algorithm for matching changes in mutual fund portfolio holdings to MSRB trades is designed to account for two complications. First, holdings data are not always consistent in whether changes in portfolio holdings are reported when a trade is executed or when it is settled. Our algorithm therefore checks for both trade date and settlement date that fall within the reporting period. Second, funds can hire external subadvisers (Chen et al., 2013; Chuprinin, Massa, and Schumacher, 2015) who may coordinate trades on behalf of multiple mutual funds and other clients. Historical subadviser data unfortunately are not standardized. We use subadviser data from the SEC Form N-CEN, which funds started filing in June 2018. We also use portfolio manager information from Morningstar.

Our algorithm is as follows:

1. Attempt a 1–1 match between changes in mutual fund portfolio holdings and MSRB. At this stage, we require that all funds within a family (defined using Morningstar's branding name variable) that buy (sell) the same CUSIP during the same reporting period have a valid match. If some funds within a family do not have a valid match in MSRB, we discard all matches. We do this to guard against false positives, specifically to avoid incorrectly matching one of the funds to its own trade when in fact all affiliated funds place a single trade.

2. Check if changes in holdings of funds that belong to the same fund family or that share a subadviser or portfolio manager can be matched to a single MSRB trade. We alternatively aggregate trades across i) funds with the same branding name in Morningstar, ii) funds that have the same portfolio manager(s), and iii) funds that have the same subadviser according to the SEC Form N-CEN; and we check whether the aggregated trade can be matched to a unique MSRB trade. To account for potential variation in fund reporting periods, we run the algorithm three times. We first require all funds to have the same adjacent holdings snapshots. We then require funds to have the same ending but not necessarily the same starting snapshot. Finally, we require funds to have the same starting but not necessarily the same ending snapshot.

3. Check if changes in holdings of funds that belong to the same fund family or that share a subadviser or portfolio manager can be matched to a combination of MSRB trades. To keep this problem computationally feasible, we restrict this step to trades of bonds that have at most 25 smaller (remaining) customer sales (purchases) in MSRB data during the relevant period, and we consider combinations of at most 5 trades. There cannot be any customer sales (purchases) in MSRB data with the same or larger par value. Similarly to step #2 above, we alternatively aggregate changes in holdings across i) funds with the same branding name in Morningstar, ii) funds that have the same portfolio manager(s), and iii) funds that have the same subadviser according to the SEC Form N-CEN. However, in contrast to step #2 above, we always require all funds to have the same adjacent holdings snapshots.

4. Attempt a 1–1 match between changes in mutual fund portfolio holdings and MSRB. In contrast to step #1, we no longer require all funds within a family to have a valid match in MSRB. Furthermore, if all potential MSRB matches are executed on the same day, we randomly pick one of the MSRB trades.

5. Check if a given change in mutual fund portfolio holdings can be matched to the sum of all (remaining) MSRB trades.

6. Check if a given change in mutual fund portfolio holdings can be matched to a combination of MSRB trades. Similarly to step #3, we restrict this step to trades of bonds that have at most 25 smaller (remaining) customer sales (purchases) in MSRB data during the relevant period, and we consider combinations of at most 5 trades. There cannot be any customer sales (purchases) in MSRB data with the same or larger par value. We run two versions of this algorithm. The first version considers all possible combinations of MSRB trades. In 51.0% of the matching combinations, all MSRB trades are executed within a span of three trading days. This suggests that when funds decide to split their trades, they tend to execute all trades within a relatively short period of time. Thus, the second version of our algorithm considers combinations of trades that happen over at most three consecutive trading days.

7. We repeat steps 1–6 three times to allow the algorithm to identify additional matches as earlier runs reduce the set of potential matches in MSRB.

8. Check if a given change in mutual fund portfolio holdings can be matched to a partial combination of MSRB trades. Partial combinations are cases where we know that certain MSRB trades must be part of any feasible combination of trades, but we are not sure about all of the constituent trades. Similarly to steps #3 and #6, we restrict this step to trades of bonds that have at most 25 smaller (remaining) customer sales (purchases) in MSRB data during the relevant period, and we consider combinations of at most 5 trades. There cannot be any customer sales (purchases) in MSRB data with the same or larger par value.

9. Finally, check if changes in fund holdings can be matched to a single larger MSRB trade. There cannot be any (remaining) MSRB trades with the same par value as the change in fund holdings. Furthermore, the sum of all (remaining) MSRB trades with smaller par value must be smaller than the change in fund holdings and thus not enough to explain it. All changes in holdings that match to a single larger MSRB trade have to be from a) funds in the same family, b) funds with the same subadviser according to the SEC Form N-CEN, or c) funds with the same portfolio managers.

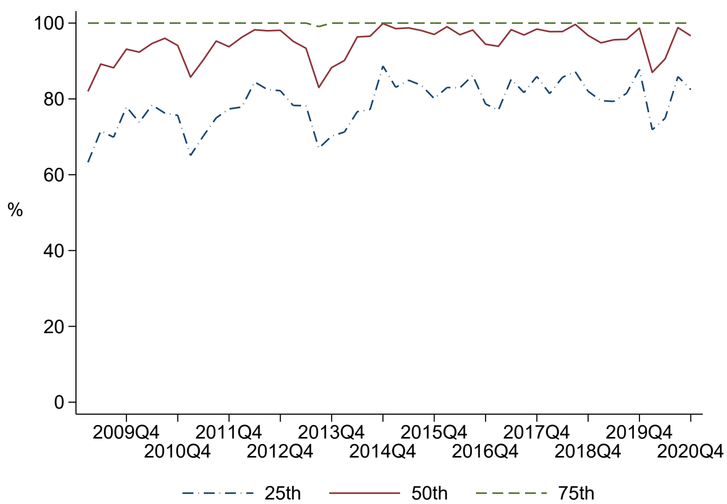
Table 1 in the paper reports the classification of changes in portfolio holdings as being due to bond events, fund mergers, and different types of matches in MSRB. The table reports the share of i) single fund trades, ii) single family trades, iii) split fund trades, iv) split family trades, and v) larger MSRB trades. The vast majority of matches (41.9% of all holdings-implied trades, or 75.0% of those matched to MSRB) are single fund trades.

To evaluate the performance of our algorithm, we calculate the share of each fund's transactions during a given reporting period that we can date either thanks to a match to MSRB or bond events. Figure IA1 plots the 25th, 50th, and 75th percentiles of the distribution of matched share during each quarter.[10] In any given quarter, the median match rate is at least 82.0%; on average it is 94.7%. The 25th percentile is generally around 80%. Thus our algorithm is able to precisely date the vast majority of trades for most funds most of the time.

[10] Each quarterly cross-section includes all partially overlapping reporting periods. In other words, a given reporting period can be included in summary statistics for multiple quarters with which it overlaps.

Figure IA1
Share of Changes in Portfolio Holdings with Exact Date

This figure plots the share of changes in portfolio holdings that we can precisely date thanks to either a match to MSRB or bond events. The unit of observation is fund-reporting period. Each quarterly cross-section includes all overlapping reporting periods.



B. Insurance Company Trades

Although we are not interested here in trading by insurance companies themselves, we want to limit MSRB transactions data to only those trades that are valid potential matches for changes in mutual fund holdings. Therefore, before attempting to match changes in mutual fund holdings of municipal bonds to MSRB, we match insurance company trades in municipal bonds to MSRB. Trades in portfolio securities are reported on Part 3 of Schedule D of insurance company filings with the National Association of Insurance Commissioners (NAIC). We obtain NAIC transactions data from S&P Capital IQ Pro. Since insurance companies generally report the date and price of their trades, we have a reliable match to MSRB. Insurance companies also report vendor's (dealer's) name, but our version of MSRB has anonymized dealer identifiers, preventing us from using dealer information to further refine our match.

There are three issues with NAIC transactions data that we need to address before matching to MSRB. First, while quarterly reports for the first three quarters disclose securities acquired and sold during the quarter, annual reports disclose securities acquired and sold during the whole year. To account for this, we subtract the value of previous sales (purchases) during the first three quarters, as long as this difference is positive. If it is negative, we keep the raw value, assuming that it refers to fourth quarter trades. We also drop a small number of cases where insurance companies report offsetting trades in the same bond on the same day with the same vendor.

Second, mergers between insurance companies can result in the double-counting of trades. The same trade will be reported by the target before it was acquired and by acquirer in its annual report that includes the target. To avoid such double-counting, we collect data on the identities of targets and acquirers and remove from acquirer's annual report trades that were placed and already reported by the target.

Third, we use counterparty information to drop trades that correspond to various bond events: maturities, calls, redemptions, exchanges, tender offers, etc. Because in some cases, insurance companies list broker-dealers as counterparties in calls and other bond events, we check if a trade's price and date match a bond action event in Mergent MBSD.[11]

Our match algorithm outlined below is designed to be conservative and to address three data issues. First, the reported date in NAIC transactions data can correspond to either trade or settlement date. In some cases it can also be off by a couple of days relative to what is reported in MSRB. Second, a single transaction reported in NAIC may represent a series of trades, potentially executed on different days. In such cases the reported date generally corresponds to the last trade and the reported par and market values are aggregates over all trades. Third, reported trades may be part of larger trades placed by either an insurance company's ultimate parent or an external investment adviser trading on behalf of multiple insurance and non-insurance clients.

1. Attempt 1–1 match between insurance company transactions and trades in MSRB with the same par value, trade date, and reported price within one basis point. At this stage, we require that all insurance companies that have the same ultimate parent and that buy (sell) the same CUSIP during the same quarter have a valid match. If some insurance companies owned by a given ultimate parent do not have a valid match in MSRB, we discard all matches. We do this to guard against false positives, specifically to avoid incorrectly matching one of the affiliated

[11] Trades that are reported to take place on Saturday or Sunday are moved to the following Monday.

insurance companies to its own trade when in fact all affiliated insurance companies place a single trade.

2. Check if each insurance company trade can be matched to the sum of all trades in MSRB on that trade date. The par-weighted price of MSRB trades must be within one basis point of the price reported in NAIC.

3. Check if each insurance company trade can be matched to the sum of all quarter-to-date MSRB trades with smaller par value. Make sure that there are no MSRB trades with same or larger par value, price within one basis point, and either trade or settlement date matching the data reported in NAIC.

4. Check if each insurance company trade is part of a single trade placed by companies affiliated through common ownership or sharing the same investment adviser. Many insurance companies hire external investment advisers such as BlackRock and PIMCO, who may trade on behalf of multiple clients at the same time in order to economize on transaction costs in OTC markets. We sequentially use two alternative definitions of affiliation through either common ownership or external advisers to aggregate all purchases (sales) of a given CUSIP by affiliated insurance companies and attempt a 1–1 match between this composite trade and MSRB.

   Our first definition is based on the NAIC group code that is shared by affiliated insurance companies. Our second definition is based on insurance companies having the same investment adviser. Insurance companies report information on their investment advisers in Part 1 - Common Interrogatories of their quarterly and annual reports.[12] We check whether all insurance companies that sell (buy) a given CUSIP on the same date and at the same price share a unique subadviser. If so, we aggregate transactions across insurance companies with the same subadviser and attempt 1–1 match between this composite trade and MSRB.

5. Check if the sum of same-day sales (purchases) across insurance companies with the same ultimate parent matches to a combination of trades in MSRB. To make this computationally

[12] We use the Central Registration Depository (CRD) number as our primary identifier. If CRD is missing (banks for example are generally exempt from the Investment Advisers Act of 1940), we identify advisers based on name. In some cases, insurance companies report advisers at the individual level but not the firm level. In such cases, we manually match individual CRDs with firm CRDs and use the latter instead.

feasible, we consider only combinations of at most 5 trades and limit to cases where there are at most 30 trades in MSRB that have not been used up by previous steps. We restrict the set of potential MSRB trades to par values that are at least 5% of the overall trade amount. In other words, we assume that insurance companies are unlikely to split a single transaction into trades that are smaller than 5% of the total. If any of the MSRB trades that are part of a combination trade match to transactions by different insurance companies, the whole combination is discarded as invalid.

We attempt two versions of this match. We first require all MSRB trades to have the same trade date as the insurance company transaction. We then relax the same date restriction and consider all quarter-to-date MSRB trades.

The implied price for the combo trade has to match the implied price in the insurance company transactions data.

6. Attempt 1–1 match between insurance company trades and MSRB. This is the same match as in step #1 except that we no longer require all companies owned by the same ultimate parent to have a valid match.

7. Repeat the above steps using MSRB settlement date instead of trade date.

8. Check if there is a 1–1 match on price but not date. The set of potential matches in MSRB consists of trades placed between the start of the current quarter and 3 days after the date reported in NAIC. For there to be a valid match, there cannot be any MSRB trades at all in the same direction as the NAIC trade and with either trade or settlement date matching the date of the NAIC trade.

   We consider two versions of this match. First, we attempt it using insurance company transactions. Second, we aggregate trades across insurance companies with the same ultimate parent.

9. Check if the sum of all NAIC trades with same date and price matches to a unique MSRB trade. This step is meant to capture cases where gaps in adviser data keep us from identifying coordinated trades.

10. Check if the sum of all NAIC trades with the same ultimate parent or subadviser matches to a unique larger trade in MSRB. The sum of MSRB trades with equal or smaller par value must be smaller than the par value of the aggregated NAIC trade. This step is meant to capture cases where ultimate parents or subadvisers place coordinated trades on behalf of both insurance companies as well as other clients. To minimize the rate of false positives we require the composite NAIC trade to account for at least 50% of the larger MSRB trade.

    We subtract the value of the composite NAIC trade from the MSRB trade and keep this difference as a potential match for mutual fund trades.

Table IA1 reports the share of different trade types for insurance company trades matched to MSRB. Trades not matched to MSRB account for 29.2% of all trades. There are a few reasons we are not able to match all insurance company trades. First, most of the unmatched trades (72.4%) are purchases, mostly primary market ones. We are unable to match these to unique trades in MSRB because of multiple trades being placed on the offering date at the offering price. Similarly, some of the unmatched sales are variable rate demand notes and auction rate securities that are sold regularly by many investors at par. Second, our algorithm is meant to be conservative. To avoid false positives, we require a tight match on the reported price. Third, many of the unmatched trades are direct trades and intercompany transfers that are not intermediated by broker-dealers.

The majority of matched trades (58.1%) are single trades by individual companies. About 17.8% are cases where trades by multiple insurance companies that are affiliated through common ownership or management or that share an investment adviser match to a single trade in MSRB. Split trades by a single insurance firm account for 7.7%. In 4.0% of cases, multiple insurance companies coordinate their trades but split them into multiple transactions. Finally, 12.4% of trades are matched to a larger MSRB trade. In par-weighted terms, the composition is broadly similar but tilted more heavily towards single company trades (64.9%) at the expense of split trades and larger MSRB trades.

Table IA1
Insurance Company Trade Match Types

This table reports the share of different match types of insurance company trades. The sample period is 2009–2020. $N = 635,949$.

Type	N	Equal-weighted (%)	Par-weighted (%)
Single company trade	369,631	58.12	64.94
Parts of a single family trade	113,296	17.82	18.19
Split company trade	48,852	7.68	4.78
Part of a split family trade	25,400	3.99	3.58
Part of a single larger MSRB trade	78,770	12.39	8.51

C. Daily Cash Holdings

This section describes the algorithm to measure daily cash holdings by open-end municipal bond funds. Daily cash is defined as the end-of-day cash level, accounting for all transactions, flows, as well as principal and interest payments occurring during the day. Our algorithm relies on the following data:

- Mutual funds' monthly (quarterly) cash level, estimated from their reported holdings. Holdings data are from Morningstar.
- Mutual funds' transactions on municipal bonds, identified using the algorithm described in the section above. This allows us to identify the exact trade date, settlement date, and the price at which each transaction takes place.
- Daily fund flows from Morningstar.
- Bond characteristics from Mergent MBSD, used to estimate the payment schedules for all portfolio bonds.

Our algorithm works as follows:

1. Measure the dollar value of transactions by the fund, assuming that the fund's cash holding change takes place on the settlement date of each transaction. Since MSRB reports clean prices, we adjust MSRB prices for accrued interests.
2. Based on reported holdings and fund transactions, identify the daily par holding amounts

for all bonds held by the fund, including bonds that are newly purchased between the two adjacent holdings snapshots.

3. Construct a schedule of principal and interest payments for each bond in the fund's portfolio. Such a schedule is based on the bond's coupon information, offering date, maturity date, and if applicable, all the scheduled full redemption and partial redemption dates.

4. Based on the bond's scheduled payments and daily holding par amount by the fund, estimate the dollar value of bond payments that the fund receives each day between the two reporting dates.

5. Impute the daily cash holding from trade amounts, interest and principal payments, and daily flows. That is, assuming that the fund reports its monthly holdings, we calculate the "unadjusted" dollar cash level on calendar day t in month m as the reported cash level as of the end of the previous month plus the cumulative cash change up to day t:

$$Cash_t = Reported\ cash_{m-1} + \sum_{d}^{1 \to t} \Big(Net\ sale\ amounts_d + Bond\ payments_d + Net\ flows_d \Big) \quad (4)$$

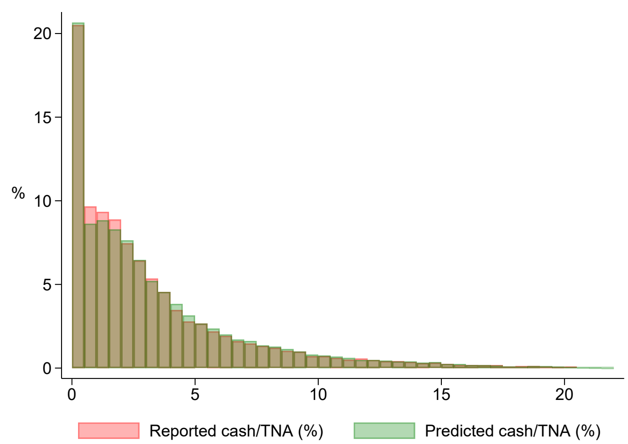
6. The unadjusted cash level on the last calendar day of month m may be different from the month-m reported cash level. We divide such a difference by the number of days in month t and add the quotient to every day during the month in order to smooth the estimates. Finally, any negative cash level is set as zero, providing us with the final "adjusted" dollar cash level.

Figure IA2 reports the distributions of the predicted cash versus the reported cash level, both scaled by the fund's TNA, on the last day of each reporting period between 2009 and 2020. The median of the difference (absolute difference) is 0 (0.30%) of fund size, and the correlation between the two cash measures is 0.93.

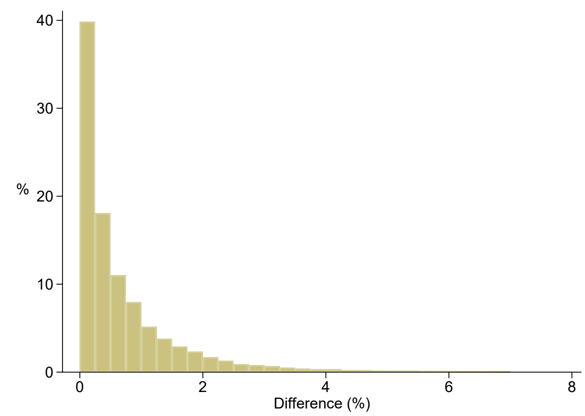
Figure IA2
Daily Cash Distribution

This figure plots the historgram of daily cash holdings, estimated using the algorithm described in the Internet Appendix. Subfigure (a) plots the distributions of end-of-month predicted cash-to-assets ratio versus reported cash-to-assets ratio. Subfigure (b) plots the distribution of the absolute difference between predicted and reported cash-to-assets ratio.

(a) Reported cash versus predicted cash



(b) Difference



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