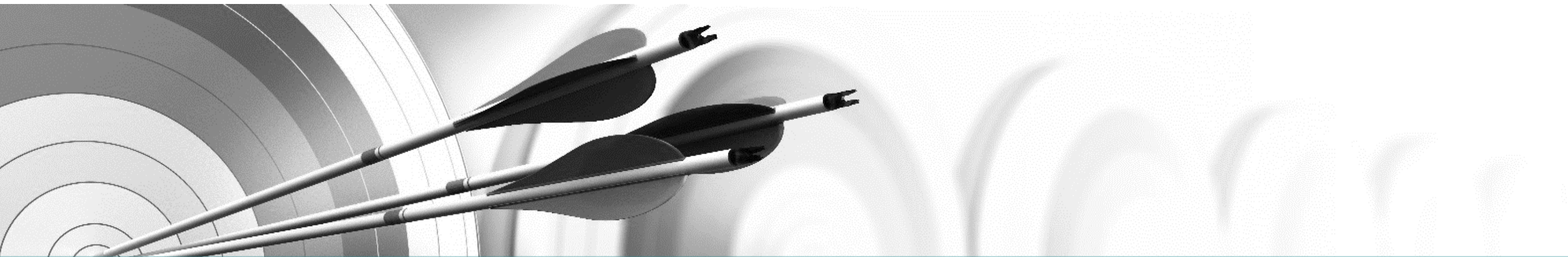

ECMI Working Paper no 13 | November 2021

# Strategic Complementarity among Investors with Overlapping Portfolios

Christof W. Stahel

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# Strategic Complementarity among Investors with Overlapping Portfolios

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## Abstract

Academics and regulators posit that mutual funds that engage in significant liquidity transformation can be systemically risky because investors in these funds redeem at the fund's net-asset-value and compete for a common fund liquidity pool, both features, they argue, can lead to run-like behavior because of strategic complementarity considerations. An alternative, more general explanation is that all investors who hold overlapping portfolios compete for finite asset market liquidity when they decide to sell assets, which can lead to investor behavior that should be observationally similar to that reported for mutual fund investors.

To test this, we analyze over the period from 2000 to 2021 a class of investors with overlapping portfolios, those that invest in separately managed accounts. Unlike mutual fund investors, these investors directly own the assets in their portfolios and receive the market price when selling them. Hence, the net-asset-value redemption and common liquidity pool channel present in mutual funds has been turned off for these investors.

The results from estimating standard flow-performance models show concave relationships for investors in overlapping portfolios that contain less liquid assets. Consistent with the main conjecture, we further find evidence that the sensitivity of outflows to past underperformance increases during periods of market illiquidity and for portfolios that are less liquid. We also find that such behavior is less accentuated for investors with large account holdings because they more likely take into account the impact of their own decisions to sell.

These results expand our understanding of the financial ecosystem and systemic risk and help design more effective regulations. Furthermore, they suggest that the behavior of investors with overlapping portfolios should serve as the benchmark to assess any systemic risk inherent in the mutual fund structure.


*JEL classification:* G01, G20, G23.

*Keywords*: Financial Fragility, Overlapping Portfolios, Separately Managed Accounts

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# 1 Introduction

Academics and regulators posit that mutual funds could be a source of systemic risk because of their inherent liquidity transformation as funds offer investors the possibly to redeem at the end of every trading day yet invest in less liquid securities.[1] For example, Goldstein, Jiang, and Ng (2017) argue that "[corporate bonds] funds present a particularly strong concern for [financial] stability due to the illiquidity of their assets." Their underlying concern is that mutual funds to meet investor redemption requests must use cash and sell assets. This, they argue, will possibly depress asset prices and reduce a fund's liquidity profile, and, in turn negatively impact the remaining shareholders. And because of this first-mover advantage, previously not redeeming shareholders are incentivized to also redeem shares, which, it is hypothesized, could result in a run on the fund leading in turn to fire sales, further depressed asset prices, and evaporated liquidity (Goldstein, Jiang, and Ng 2017).[2]

We argue that there is an alternative, more general incentive for any type of investor to sell ahead of others, reflecting the investor's concern about the impact on the market values and liquidity of the assets held when the same assets are sold by other investors with overlapping portfolios. This concern increases an investor's incentive to sell when its expectation of other investors selling increases. Then, if investors are selling after assets underperformed, a concave flow-performance relationship emerges that resembles the one presented for bond fund investors in Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017), yet this behavior is more fundamental because these direct investors neither redeem at a net-asset-value nor do they share a common liquidity pool.

Other investors could sell for a variety of reasons. For example, because bond returns can exhibit momentum as discussed in Jostova, Nikolova, Philipov, and Stahel (2013), some investors might expect further negative returns after bad performance and, hence, might want to sell. Or after

[1]See, for example, Feroli, Kashyap, Schoenholtz, and Shin (2014), Chen, Goldstein, and Jiang (2010), Goldstein, Jiang, and Ng (2017), FSOC (2019), BIS (2019), IMF (2019).

[2]See also Falato, Hortaçsu, Li, and Shin (2021) for an alternative perspective.

a valuation shock, some investors might update their beliefs about the future value of the assets and want to rebalance their portfolios. Or yet, some investors may sell these assets because they might be concerned about positive feedback traders as in De Long, Shleifer, Summers, and Waldmann (1990a), which can continue to drive prices away from fundamentals. Whatever the motive, a first investor selling an asset will sell it at the best available price before the next investor will sell at the next lower price and so on as prices drop and market liquidity is being drawn down. In other words, if there is an expectation that others will sell, it pays to sell first in a series of many investors selling the same asset. From that perspective, any acceleration in asset sales after underperformance can be related to this more general notion of investors not wanting to hold assets with prices depressed below fundamental values and low liquidity that might further deteriorate because they expect others to also sell. In this case, it can be rational to sell as well, possibly ahead of others.

These kind of events can occur even in the liquid equity market. According to the financial press, the downfall of Archegos Capital in the first quarter of 2021 led to three large prime brokers that supported trades with Archegeos to simultaneously exit common equity positions.[3] Specifically, on March 26, 2021 one of them decided to sell securities they previously used to hedge exposures to total return swaps with Archegos Capital. According to the press, over the course of that day, a first broker sold more than $10 billion of shares in Viacom CBS, Baidu Inc, and Tencent Music Entertainment Group, among others. At the same time, another prime broker offloaded $8 billion worth of shares, and a third one sold in a private deal $4 billion of shares related to similar Archegos swaps. This first wave of sell-offs significantly depressed the values of the stocks and severely reduced their market liquidity.[4] Thus, not selling immediately could have been harmful. As a matter fact, that sell-off left two other prime brokers "sprinting for the exit before it slammed shut, but by the time they decided to start selling [the following Monday], the stocks had fallen

[3]See, for example, REUTERS Financials April 2, 2021 "Timeline - Diary of a meltdown: How the Archegos Capital fire sale went down." and the Financial Times March 20, 2021 "Archegos banks discussed co-operation to head off selling frenzy".

[4]While a coordinated liquidation would have been the preferred strategy, the financial press reported that this coordination effort seemed to have been abandoned. "Representatives from its trading partners held a meeting with Archegos to discuss an orderly wind-down of troubles trades" but "some banks had begun selling [ahead of others] to stem their own losses," Financial Times March 20, 2021.

too far to avert major losses." The actions of the three prime brokers appear to have depressed the values of the liquidated stocks resulting in losses for them but even larger losses for the two brokers that waited for another day to sell.[5]

The concern for an investor is that such an impact could be long-lasting. Falling prices might not immediately rebound as in the models presented by Duffie (2010), where such patterns can reflect institutional impediments such as search costs for trading counterparties or time to raise capital by intermediaries. Similarly, De Long, Shleifer, Summers, and Waldmann (1990b) argue that noise traders chasing trends, extrapolating expectations about prices, or executing stop-loss orders can push prices away from fundamental values. For example, Coval and Stafford (2007) posit that the price impact from market participants having to sell stocks can generate returns with a long-lasting negative effect. Cai, Han, Li, and Li (2019), focusing on the corporate bond market, argue that correlated trading can lead to significant price impacts, particularly on the down side, that do not fully reverse for several quarters. Hence, a sell-off can affect other holders that have not sold yet, like the latter two prime brokers in the above stock market example, and in turn lead to selling dynamics where initially depressed values and liquidity trigger further sales. With the bond market generally being less liquid than the equity market, it is not unreasonable to expect that bond market investors exhibit even stronger incentives to sell ahead of others, and that investor behavior in this market following bad performance can resemble the pattern presented in the literature for bond fund investors (Chen, Goldstein, and Jiang 2010, Goldstein, Jiang, and Ng 2017).

The Financial Stability Board (FSB 2014) refers to the impact on other investors holding but not selling the assets as the asset liquidation or market transmission channel that gives rise to contagion and systemic risk. Generally citing the results in Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017), the FSB and other regulators and supervisory bodies repeatedly identified mutual funds holding less liquid asset as being more likely systemically risky, which they argue calls for strict regulation. However, regulated funds and by extension regulated fund investors are not the only investors holding less liquid securities. For example, US mutual funds

[5] See also the Senate Committee on Banking, Housing, and Urban Affairs inquiry on the fall out: https://www.banking.senate.gov/download/brown-letter-to-nomura_482021.

at the end of 2019 held only 17% of the US and foreign corporate bonds outstanding (Figure 1).[6] Hence, the majority of these assets were held by other market participants. Furthermore, during the sell-off of fixed-income securities in March 2020 triggered by the global pandemic, US long-term mutual funds accounted for a relatively small fraction of the sales in fixed-income securities. For example, close to 70% of the investment grade corporate bond sell volume during March 2020 were from sales by investors other than mutual funds (Figure 2). Thus, if all market participants are selling, narrowly focusing on mutual funds and their investors falls short of understanding the financial ecosystem and designing more effective regulations.

In this paper, we fill some of this knowledge gap by investigating the behavior of another type of market participant that does not receive the net-asset-value upon redemption and does not share in a common liquidity pool: investors in separately managed accounts. A separately managed account is a portfolio of assets owned by an investor and managed by a professional investment firm on its behalf. This type of market participant offers a laboratory setting because investors in separately managed accounts following the same strategy have by design overlapping portfolios. Hence, they are exposed to the above discussed strategic complementarity at the asset market level, but most importantly, they are not affected by fund redemptions at the net-asset-value or by a shared fund liquidity pool. The reason is that these investors are the *sole owners of the assets in their portfolios* and only compete for pricing and market liquidity, first and foremost, with other investors holding the same securities when they decide to sell or purchase these assets. Hence, the fundamental distinction between these investors and investors in mutual funds is that these investors do not receive the net-asset-value upon redemption and do not share a common pool of liquidity in a collective investment vehicle like mutual fund investors do.[7]

While the total amount of assets under management in separately managed accounts is smaller than the total amount managed in the mutual fund industry, the assets under management are

[6]We exclude the holdings of funds other than US long-term mutual funds. Furthermore, mutual funds held only 7% of the amount of government securities outstanding and 22% of the US Municipal securities, where government securities exclude T-bills and other short-term government securities.

[7]Note that we do not exclude the possibility, as in the literature on mutual funds where investors in mutual funds rely on fund returns to update their assessment about fund managers' abilities, that investors in separately managed accounts gauge the ability of investment managers based on the returns of the strategies.

not insignificant. The 2021 average of reported assets in (composite) equity and fixed-income focused separately managed accounts stood at \$9.95 trillion, up from \$1.13 trillion in 2001 and split roughly two-thirds to one-third between equity and fixed-income focused strategies (see Figure 3). This is a cumulative increase of 784% over the 20 years, or 11.5% per year, possibly driven in part by a reduction in the typical minimum investment requirement and an increased demand for professionally managed investment portfolios that can, at the margin, be tailored to investors' requirements.[8] For additional institutional details on separately managed accounts, see below.

In light of the above discussion, we conjecture the main hypothesis: Investors with overlapping portfolios represented by investors in separately managed accounts following the same strategy exhibit a positive sensitivity of outflows to past underperformance of portfolio assets and that this sensitivity is stronger if the portfolio is invested in less liquid assets. Using monthly data covering more than 4,000 strategies over the period from 2000 to 2021, we find strong support for the main hypothesis: Outflows from separately managed accounts follow past underperformance and this sensitivity is stronger for portfolios invested in less liquid assets. Hence, these empirical patterns of behavior of investors with overlapping portfolios are similar to those reported for mutual fund investors.

To validate the main results supporting the conjectured underlying mechanism, we analyze for fixed-income focused managed accounts three hypotheses that derive from the main argument that such strategic complementarity reflects the competition for limited asset market liquidity when investors with overlapping portfolios decide to sell assets. First, we find that the sensitivity of outflows to past underperformance is stronger during periods of lower market-wide liquidity. Second, we show that the sensitivity increases with portfolio asset illiquidity. And third, we present evidence that the larger the size of the average account invested in a given strategy the lower is the sensitivity. The rational behind this result is that if a large account was to be liquidated, the immediate impact on the asset values will be relatively large, which the account holder will more

[8]This increase also reflects the increase in asset values over this period and likely a broader propensity to report SMA assets to the Morningstar database possibly driven by strategic considerations similar to those of hedge funds when deciding to report (Aragon and Nanda 2017).

likely internalize when deciding to sell.

The remainder of the paper is organized as follows. In the next section we present institutional background information of separately management accounts before presenting the data source and sample statistics. We then present the baseline results before validating the underlying mechanism. In the final section we conclude and discuss the implication of the results for the ongoing debate about how to identify and address systemic risk concerns.

## 2 What is a Separately Managed Account?

The US Securities and Exchange Commission (SEC) defines a "separately managed account" (SMA) as an advisory account that is *not* a pooled investment vehicle like a registered investment company, a business development company, or a private fund. SMAs are individually managed investment accounts usually offered to clients of a sponsor firm, like Morgan Stanley or Merrill Lynch, through financial consultants connected to the sponsor's platform.[9] An SMA investor chooses a specific investment strategy usually managed by an independent investment management firm for the sponsor. Depending on the relationship between the sponsor and the investment management firm, the operational functions like portfolio rebalancing, reporting, and tracking are either done by the sponsor or the investment management firm. Trading is usually done by the sponsor, but for cases where the investment management firm has a comparative advantage in the market, for example for some fixed income securities, accessing their dealer network results in better execution parameters.[10] In any of these cases, the SMA client will receive the best-execution market price prevailing when the trade order is executed. As such, an SMA can be thought of as an investment vehicle similar to a mutual fund, in which the customer pays a fixed fee to a money manager for its services managing the customer's investment. The important difference, however, is that a mutual fund investor owns shares in an investment company that in turn owns the underlying portfolio assets, whereas an SMA investor owns the assets directly.

[9]The term Separate Account is generally used only to describe accounts not offered through a sponsor. Rather the client is its own sponsor.

[10]Such trades are known as give-ups, where the sponsor gives up the trading to the investment management firm.

A sponsor firm will offer a prospective client a menu of investment strategies. For example, an investor can choose to invest in a strategy with a US large cap equity exposure. Generally, the asset allocation in the strategy is driven by an underlying portfolio selection model that the sponsor obtained from a third-party investment management firm. Beyond this, the selection of a particular investment strategy or portfolio, SMA investors can, within limits, tailor their portfolios, for example, to address tax considerations, preferences for ESG exposures, or to exclude certain investments from their portfolios. The important implication is that all investors with a sponsor that have chosen a particular investment strategy will broadly hold in their own SMA portfolios the same assets as the other investors in the same strategy. That is their portfolios are overlapping.

Imbedded in the above discussed difference of asset ownership between investing in a mutual fund or in an SMA, is the process of liquidating parts or all of the investment in a fund or an SMA. When fund investors decide to sell their shares, subject to some cutoff-time for submitting a redemption request, the investors will receive the net-asset-value of the fund struck at 16:00 of the day of the redemption requests.[11] The fund will then subsequently sell parts of the portfolio to, together with cash in the fund, meet these requests. Because a redeeming investor does generally not pay for any price impact that results from the fund subsequently liquidating assets, according to Chen, Goldstein, and Jiang (2010) other investors in the fund have an incentive to also redeem on the same day leading to an acceleration of redemptions.[12]

In the case of SMA investors, this mechanism does not play out because SMA investors are direct owners of their assets. These investors do not receive any sort of net-asset-value of the account determined on the day they decide to liquidate some or all of their accounts and they do not share a common liquidity pool that will be drawn upon. Rather, the sponsor (or investment managers) will execute the corresponding trades on behalf of the investors, generally in line with the portfolio selection model and subject to a best-execution requirement. As such, any initial

[11]Under SEC rule mutual fund investors have to receive their proceeds no later than on day T+7, but the value of the redemption is determined on day T.

[12]Under the SEC rule "Liquidity Risk Management Programs and Swing Pricing" funds could swing the NAV as a function of daily flow, but US funds have not implemented this tool. See https://www.sec.gov/rules/final/2016/33-10234.pdf.

price impact from selling assets will be born by the SMA investors and strategic complementarity considerations in the sense of Chen, Goldstein, and Jiang (2010) are absent. However, because the size of SMA accounts are likely much larger than the average size of individual investors' holding of a mutual fund, the liquidation of a limited number of accounts could already depress prices and reduce market liquidity.[13] The implication is that because all SMA investors in a given strategy effectively hold the same portfolio, they engage in a strategic game similar to the one referenced in Chen, Goldstein, and Jiang (2010) but because of market dynamics and not because of a structure similar to that of mutual funds.

# 3 Data, Sample and Empirical Measurements

## 3.1 Data

The SMA data is from Morningstar's separate account module. Investment management companies report the total net assets aggregated across all accounts in a given strategy on a voluntary basis. For example, strategies developed for a particular sponsor and sold under that sponsor's name might not be reported.[14] The information collected offers separate account information to asset managers, financial advisors, and investment consultants when analyzing alternative SMA investment opportunities for their clients.

The sample covers January 2000 to February 2021 and contains information on strategy composites, that are data aggregates of one or more *fully discretionary portfolio accounts* managed according to a common investment strategy mandate.[15]

Since we are interested in the behavior of investors when facing strategic complementarity con-

[13]The initial balance required for an investment in mutual fund retail and institutional share classes is typically less than \$5,000 and anywhere between \$500,000 and \$1 million, respectively, but the investment minimum in an SMA is often between \$100,000 and \$5 million for a retail account and between \$10 million and \$100 million for an institutional account.

[14]Investment management companies advising separately managed accounts report to the SEC information on all SMAs on Form ADV regardless. https://www.sec.gov/rules/final/2016/ia-4509.pdf.

[15]Other data available in Morningstar cover Collective Investment Trusts (comprised of a pooled group of assets of trusts operated by a bank or a trust company); Pooled Funds (Canada-domiciled funds that are separate legal entities in which clients' assets are pooled together to acquire an interest in a basket of securities); and Configured Unified Managed Accounts (model portfolios where reported returns are based on non-discretionary assets).

cerns at the asset level because of overlapping portfolios, we limit the sample to strategies with at least two accounts aggregated under each strategy. The reported total assets in a particular strategy reflect the collection of investor accounts that largely hold the same assets in their portfolios and share asset market liquidity but not a liquidity pool. We further restrict the sample to US, European, and global equity-focused strategies, and US, global and emerging market fixed income-focused strategies.[16] Returns and total assets are either reported monthly or quarterly. We keep the return (Morningstar field "Monthly Return") and total net assets ("Vehicle Assets") of a strategy in a given month only if total net assets for the strategy were also available in the prior month. Data on the number of accounts in a strategy ("Number of Strategy Accounts") are usually reported at the quarterly frequency. In this case we fill forward missing monthly observations with the most recent end of previous quarter observation.

## 3.2 Sample

Panel A of Table 1 presents sample statistics for 2020 grouped by investment category. For each strategy, the assets under management and the number of accounts are first averaged across the available monthly observations in 2020.[17] The column titled "Strategies in Category" is the average number of strategies in a category, "Accounts per Strategy" is the average of the average number of accounts in a strategy in the category, "Median Assets per Strategy" is the median aggregate assets of the strategies in the category, "Median Assets per Account" is the median of the average assets per account in a strategy in the category, and "Total Assets in Category" is the aggregate assets across all accounts in the category.

The total number of equity-focused strategies (2,757) is more than twice the number of fixed-income focused strategies (1,253), but the average number of accounts per strategy is significantly larger in fixed-income-focused strategies (259) compared to the equity strategies (167). Similar

[16]The equity-focused strategies in the sample are US Equity Large Cap Blend, US Equity Large Cap Growth, US Equity Large Cap Value, US Equity Mid Cap, US Equity Small Cap; Europe Equity Large Cap; Global Equity Large Cap, Global Equity Mid/Small Cap, and Global Emerging Markets Equity. The fixed income-focused strategies are US Fixed Income, US Municipal Fixed Income; Global Fixed Income, and Emerging Markets Fixed Income.

[17]Averaging information across 2020, accounts for missing information during some months in 2020.

pictures arise in terms of median assets per strategy with \$214 million in equity focused strategies and \$424 millions in fixed-income-focused strategies. And finally, the median account size with \$12 million in equity focused strategies is a bit larger than half the median account size in fixed-income-focused strategies of \$20 million.[18] While mutual fund total net assets are larger compared to reported total assets in SMAs, the SMA account levels are sizable.[19] In aggregate, total net assets across all composite equity focused strategies are \$6.30 trillion and \$3.8 trillion in composite fixed-income focused strategies.[20]

### 3.3 Measurement of flow and performance

The two key variables in the empirical analyses are strategy flows and strategy performance. We follow standard practice and compute the net flows from current and last month's total net assets and the return over the month. Specifically, the flow for strategy $S$ during month $t$ is:

$$\text{Flow}_{S,t} = \frac{\text{Assets}_{S,t} - \text{Assets}_{S,t-1} \times (1 + r_{S,t})}{\text{Assets}_{S,t-1}}, \tag{1}$$

where $\text{Assets}_{S,t}$ are the aggregate assets in strategy $S$, and $r_{S,t}$ is the return of the strategy over month $t$. We exclude observations with absolute flows larger than 100% to remove outliers.

To measure performance, we follow Goldstein, Jiang, and Ng (2017) and estimate for each strategy and month the lagged average alpha over the past year by running a 12-month rolling window time-series regression of excess strategy returns on excess returns of the bond market and the stock market and take the intercept as the average alpha. We use the Vanguard Total Bond Market Index Fund returns to proxy for the aggregate bond market and the CRSP value-weighted market returns for the aggregate stock market. As a robustness test, we also present results using the raw strategy returns in excess of the risk-free rates. Panel B of Table 1 presents sample statistics

[18]Note that some strategies contain average accounts that are significant lager than the medians reported here.

[19]According to ICI's 2021 Investment Company Factbook (Investment Company Institute, Washington, DC 2021), at the end of 2020 about \$12.7 trillion were held in equity mutual funds and about \$5.2 trillion in bond mutual funds.

[20]While we do not have position information for every SMA strategy portfolio, in a sample of the 20 largest fixed-income strategy portfolios on average only about 3% of portfolio assets were held in mutual funds.

of these two model variables.

## 3.4 Measurement of Market and Portfolio Liquidity

Under our hypothesis, investors with overlapping portfolios, here SMA investors in the same strategy, will be more concerned about the impact on asset values and liquidity if other investors liquidate parts or all of their accounts when market liquidity is low or when the portfolio underlying the strategy is less liquid. To analyze these implications, we compute several market and portfolio liquidity measures.

### 3.4.1 Market Liquidity

We use four time-series measures of aggregate corporate bond market liquidity to capture periods when liquidity in the corporate bond market evaporates and hence could increase the concern of investors about the negative externality arising from the decisions of other investors with overlapping portfolios to sell (the same) assets. First, we use two aggregate corporate bond market liquidity measures estimated from data in TRACE (Trade Reporting and Compliance Engine). The first, HOW, is the aggregate effective bid-ask spread proposed by Hong and Warga (2000), and the second, DFL, is the index of aggregate corporate bond market illiquidity proposed by Dick-Nielsen, Feldhütter, and Lando (2012). Second, Bao, Pan, and Wang (2011) show that an increase in aggregate stock market volatility reduces the liquidity of the corporate bond market. Following Goldstein, Jiang, and Ng (2017), we use the VIX index (from the Chicago Board Options Exchange (CBOE)) as another measure of aggregate corporate bond market illiquidity. Finally, Brunnermeier and Pedersen (2009) argue that market liquidity is related to funding liquidity because the latter affects the supply liquidity to asset markets from financial institutions. To proxy for funding liquidity, we use the TED spread, the difference between the three-month London Interbank Offered Rate (LIBOR) and the three-month Treasury-bill interest rate, from the St. Louis Fed data.

Past studies on the flow performance-relationship using these proxies have generally divided the sample into periods based on the mean of a variable computed over the full sample. Following this methodology, however, creates a problem when facing a variable that exhibits a time-trend because it would simply split the sample into an earlier-half and later-half. For example, HOW has been trending down over the last 20 years as shown in Figure 4. To address this concern, we proceed as follows. First, we compute the monthly average value of each macro variable. Then, we detrend each variable by subtracting its lagged past five-month rolling average resulting in monthly observations that are free from the trend concerns. We then divide the sample based on whether a detrended macro variable is above or below its time-series average. Panel B of Table 1 presents sample statistics of these four model variables.

### 3.4.2 Portfolio Liquidity

Beyond information about the investment strategy, we have no details on the portfolio composition to compute a position-by-position based measure of portfolio liquidity as, for example, Goldstein, Jiang, and Ng (2017) had. However, according to Getmansky, Lo, and Makarov (2004), the first-order autocorrelation in hedge fund returns is increasing in the illiquidity of a hedge funds's portfolio, and Khandani and Lo (2011) show that this is also the case for mutual fund and other portfolios. Following their arguments, we compute for each strategy time-varying first-order autocorrelations $\rho_{S,t}$ using rolling 10- and 12-month windows. We then divide the sample every month into two groups based on whether a strategy is above or below the cross-sectional average of that month. Panel B of Table 1 presents sample statistics of these two model variables.

# 4 Results

## 4.1 Flow-Performance Relationship for Equity and Fixed-Income Focused Strategies

In this subsection, we present the baseline results showing that flows are sensitive to past performance, and that the flow-performance relationship is concave for fixed-income focused strategies but not for equity-focused strategies, a result that mirrors the evidence presented in Table 2 of

Goldstein, Jiang, and Ng (2017) for mutual funds. The results are based on the baseline regression separately estimated for equity and fixed-income SMAs:

$$\begin{aligned}\text{Flow}_{S,t} = \beta_1 \text{Alpha}_{S,t-12\to t-1} + \beta_2 \text{Alpha}_{S,t-12\to t-1} \times \text{I}(\text{Alpha}_{S,t-12\to t-1} < 0) \\ + \beta_3 \text{I}(\text{Alpha}_{S,t-12\to t-1} < 0) + \gamma\, \text{Controls}_{S,t} + \alpha + \eta_{S,t}\end{aligned} \tag{2}$$

where $\text{Flow}_{S,t}$ is the strategy $S$ net flow in month $t$ and $\text{Alpha}_{S,t-12\to t-1}$ is the strategy $S$ alpha estimated as the intercept from a regression of excess strategy returns on excess aggregate bond market and aggregate stock market returns over the past one year. $\text{Controls}_{S,t}$ include a number of strategy characteristics: the lagged flow ($\text{Flow}_{-1}$), the natural log of the strategy's aggregate account assets (log(Asset)), and the natural log of the strategy's age (log(Age)). Following Goldstein, Jiang, and Ng (2017), we include monthly fixed effects and cluster the errors at the strategy level.

We present in Table 2 the estimation results of equation (2). The main baseline results in columns one and four present strong evidence that the flow-performance relationship is positive, and that this relationship is concave for fixed-income focused strategies but linear for equity-focused strategies. The slope coefficient $\beta_1$ for Performance for fixed-income focused strategies is 0.1044 and the slope coefficient $\beta_2$ for Alpha interacted with the negative performance dummy $\text{I}(\text{Alpha}_{S,t-12\to t-1} < 0)$ is 0.7139 and statistically significant. In other words, the sensitivity of outflows to negative Alpha is 0.8183 (= 0.1044 + 0.7139), which is significant at the 1% level. For equity focused strategies, the slope coefficient $\beta_1$ for Performance is 0.3329 and significant, which implies that flows are sensitive to past performance but the insignificant coefficient $\beta_2$ suggests that this relationship is linear without any display of concavity.

In the models in column two and five, we use flows winsorized at the 1% and 99% level, and in models three and six we use raw returns in excess of the risk-free rate. The results consistently show that investors in separately managed account with a fixed-income focus, those who generally hold less liquid assets, exhibit a behavior observationally equivalent to investors in mutual funds. However, these SMA investors neither redeem at a net-asset-value nor share a common fund liquidity pool. As such, the results are consistent with the conjecture that SMA investors are concerned about strategic complementarity at the asset level.[21]

## 4.2 Drivers of Strategic Complementarity among Investors with Overlapping Portfolios

### 4.2.1 Bond Market-wide Liquidity

We argued above that investors with overlapping portfolios, here specifically SMA investors, are concerned about other investors' behavior since they hold similar portfolios. When an SMA investor decides to liquidate some or all of her account, the price and liquidity impact will depend on the liquidity of the bond market at large and hence can be of concern for investors with overlapping portfolios. When the market is less liquid, investors selling assets from their SMA accounts will have a larger negative price and liquidity impact on portfolios of investors who remain in the same strategy but do not sell. Hence, during periods of market-wide illiquidity, the flow-performance relationship should be more pronounced. To test this hypothesis, we run the following regression:

$$\begin{aligned}\text{Flow}_{S,t} = {} & \beta_1 \text{Alpha}_{S,t-12\rightarrow t-1} + \beta_2 \text{Alpha}_{S,t-12\rightarrow t-1} \times \text{I(Market Illiquidity}_t) \\ & + \beta_3 \text{I(Market Illiquidity}_t) + \gamma \, \text{Controls}_{S,t} + \alpha + \eta_{S,t}, \\ & \forall \text{Alpha}_{S,t-12\rightarrow t-1} < 0,\end{aligned} \tag{3}$$

where $\text{Flow}_{S,t}$ is the strategy $S$ net flow in month $t$ and $\text{Alpha}_{S,t-12\rightarrow t-1}$ is the strategy $S$ alpha estimated as the intercept from a regression of excess strategy returns on excess aggregate bond market and aggregate stock market returns over the past one year, and $\text{Market Illiquidity}_t$ is an indicator variable that equals to one if the particular illiquidity proxy is in this period above the sample mean and zero otherwise, and $\text{Controls}_{S,t}$ remain the same as before. We use four proxies to capture periods of bond market-wide illquidity based on the VIX, the DFL and HOW bond market

[21] In unreported results, consistent with the argument that asset liquidity when selling assets is the fundamental concern of direct investors, the sensitivity of flows to past performance is unrelated to the amount of cash held in an SMA portfolio.

illiquidity indices, and the TED spread. Following Goldstein, Jiang, and Ng (2017), we estimate the regressions of fixed-income focused strategies using only strategy-month observations with negative $\text{Alpha}_{S,-1}$.

Table 3 presents the results from estimating equation (3). It shows that the sensitivity of investor liquidations following a strategy's underperformance significantly accelerates during periods when the corporate bond market is more illiquid as measured by the four proxies. For example, during periods with low VIX, the sensitivity 0.6128 of flows to past performance is less than half the sensitivity 1.2823 (= 0.6128 + 0.6695) during periods of high VIX identifying bond market illiquidity. Economically the impacts are significant as well; a 1% decrease in past performance is associated with incremental outflows of 0.67%. Similarly, during illiquid periods as identified by a high DFL or HOW index or a high TED spread, the sensitivity of investor liquidations to strategy underperformance strongly accelerates. A 1% decrease in past performance is associated with incremental outflows of 0.94%, 0.83%, and 0.60%, respectively. The differences in the sensitivities of flows to lagged alpha between high and low liquidity periods are statistically significant in all four proxies.

#### 4.2.2 Portfolio Liquidity

Besides time-varying market-wide liquidity affecting the strategic complementarity concerns among investors with overlapping portfolios, the liquidity of the portfolio itself affects investors behavior. Investors who hold securities directly in less liquid portfolio assets will be more sensitive to past negative performance because asset sales will have a larger negative price and liquidity impact on the portfolios of investors who remain in the strategy. To test this hypothesis, we perform the following regression:

$$\begin{aligned}
\text{Flow}_{S,t} = {} & \beta_1 \text{Alpha}_{S,t-12\to t-1} + \beta_2 \text{Alpha}_{S,t-12\to t-1} \times \text{I}(\text{Portfolio Illiquidity}_{S,t-1}) \\
& + \beta_3 \text{I}(\text{Portfolio Illiquidity}_{S,t-1}) + \gamma \, \text{Controls}_{S,t} + \alpha + \eta_{S,t} \qquad (4) \\
& \forall \text{Alpha}_{S,t-12\to t-1} < 0,
\end{aligned}$$

where $\text{Flow}_{S,t}$ is the strategy $S$ net flow in month $t$ and $\text{Alpha}_{S,t-12\to t-1}$ is the strategy $S$ alpha estimated as the intercept from a regression of excess strategy returns on excess aggregate bond market and aggregate stock market returns over the past one year, and Portfolio $\text{Illiquidity}_{S,t}$ is an indicator variable that equals one if the portfolio in period $t$ above the cross-sectional sample mean and zero otherwise, and $\text{Controls}_{S,t}$ remain the same as before. We use two proxies to capture periods of portfolio illiquidity, the time-varying first-order autocorrelation by strategy computed over a rolling 10- or 12-month window. The regression results are again based on fixed-income focused strategies using only strategy-month observations with negative $\text{Alpha}_{S,-1}$.

The estimation results of equation (4) in the first two columns of Table 4 present evidence that investors in less liquid SMA strategy portfolios indeed show a higher sensitivity than investors in more liquid portfolios. For example, for illiquid portfolios, the sensitivity of flows to past performance is about twice as large (1.4301 = 0.6330 + 0.7971 or 1.4046 = 0.7042 + 0.7004) as for portfolios that are more liquid (0.6331 or 0.7042), supporting the hypothesis that investors are concerned about strategic complementarity at the asset market level.

We showed above that during periods of high aggregate bond market illiquidity, the sensitivity of flows to past negative performance increased. To test whether Portfolio $\text{Illiquidity}_{S,t}$ simply proxies for Market $\text{Illiquidity}_t$, we include the DFL-based market-wide liquidity indicator variable in regression (4) as an additional interaction term. The results in the last two columns of Table 4 provide evidence that portfolio liquidity, while varying across strategy portfolios and time, is not merely a proxy for market-wide illiquidity. This is not surprising given that the time-series correlation between the DFL measure of market illiquidity and the time-series of monthly average portfolio illiquidity is between 6% and 12% for the two portfolio illiquidity proxies. The fact that the interaction term $\text{I}(\text{Portfolio Illiquidity}_{S,t-1}) \times \text{I}(\text{Market Illiquidity}_{t-1})$ is insignificant might reflect that investment management companies that generate the strategy portfolios are able to reduce portfolio illiquidity specifically during times of market-wide illiquidity by, for example, tilting the portfolio towards assets that remain at the same level of liquid during a spell of lower market-wide liquidity. An indication supporting this possibility is the fact that the correlations between the two liquidity measures turns negative during times when aggregate market liquidly deteriorates $\mathrm{I}(\text{Market Illiquidity}_t) = 1$.

### 4.2.3 Account Size

We showed above that investors with overlapping portfolios in fixed-income focused SMA strategies exhibit a sensitivity of flows that was larger for negative past performance than for positive past performance. We argued that this result supports the main hypothesis that investors exhibit behavior consistent with strategic complementarity at the asset market level. The concern of these investors is that if another investor in the same strategy liquidates part or all of their account the selling pressure in the overlapping assets will negatively impact non-liquidating investors.

However, because SMA investors own their assets, the larger the size of an account in a strategy, the more likely the account holder will consider the impact of its own decision to liquidate an account on the sales proceeds, which in turn should dampen the incentive to sell when expecting others to sell. This could especially be the case for institutional SMAs, where the initial investment requirement is often between \$10 million and \$100 million and account balances can be significant.

To investigate this point, we proceed in two ways. First, we attempt to directly assess whether strategies containing larger accounts exhibit lower sensitivity. While we do not have information on individual accounts, total assets in a strategy, $\text{Assets}_t$, can be written in terms of the number of accounts times the average size of the accounts $\text{Assets}_t = \sum_{i \in S} \text{Assets}_{i,t} = \mathrm{N}_{S,t} \times \overline{\text{Assets}_{S,t}}$, where $\mathrm{N}_{S,t}$ is the number of accounts in strategy $S$ at time $t$ and $\overline{\text{Assets}_{S,t}}$ is the average account size in strategy $S$. We then interact separately $\log(\mathrm{N}_{S,t})$ and $\overline{\log(\text{Assets}_{S,t})}$ with past performance in equation (4). Second, we follow the approach of Goldstein, Jiang, and Ng (2017) and estimate model (2) separately for strategies that have been reported to focus on retail investors, institutional investors, or both. The argument is that investors in institutional focused strategies likely hold larger account balances, not least because the minimum initial investment is significantly larger for these accounts, and hence these investors are less likely to liquidate when expecting other investors in the same strategy to liquidate because they more likely internalize the negative externality generated by their own liquidation.

We estimate equation (2) for fixed-income focused strategies using only strategy-month observations where $\text{Alpha}_{S,-1}$ is negative. In column one of Table 5 we presents the results where $\log(\text{Assets}_S)$ is replaced with $\log(\text{N}_S)$ and $\overline{\log(\text{Assets}_S)}$. The coefficient on $\text{Alpha}_{S,-1}$ (0.8004) in the first column is similar in magnitude to the sum of the coefficients $\text{Alpha}_{S,-1}$ and $\text{Alpha}_{S,-1} \times \text{I}(\text{Alpha}_{S,-1})$ (0.8183 = 0.1044 + 0.7139) reported in column four of Table 2. The second column of Table 5 reports the estimation result for equation (2) with the interaction terms $\log(\text{N}_S)$ and $\overline{\log(\text{Assets}_i)}$. The coefficient on the interaction term of past performance with $\overline{\log(\text{Assets}_i)}$ is negative and significant implying that for strategies with larger average accounts, the sensitivity of flows to past performance is lower. The mean and standard deviation of $\overline{\log(\text{Assets}_{i\in S})}$ in Panel B of Table 3.2 are 16.63 and 2.70, respectively. These statistics, together with the coefficient estimate, imply that a one standard deviation increase in the average log assets decreases the sensitivity by almost half from 1.2040 to 0.6329.[22]

The models in column three through five report results for model (2) by investor type. Consistent with the results reported in Goldstein, Jiang, and Ng (2017), the strategies with an institutional focus exhibit a lower sensitivity (0.4936) to past performance than do strategies focused on retail investors (1.1971), albeit neither of the coefficients is significant. The coefficient on past performance for strategies with both types of investors (0.7885) is significant and between the coefficients for institutional and retail investors.

# 5 Conclusion

Academics and regulators posit that mutual funds could be a source of systemic risk because of their inherent liquidity transformation where funds offer investors the possibility to redeem at the end of every trading day yet invest in less liquid securities. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) present evidence that mutual funds that invest in illiquid assets exhibit concave flow-performance relationships, which they argue is because first-mover

[22] 1.2040 = 4.7212 - 0.2115 · 16.63 and 0.6329 = 4.7212 - 0.2115 · (16.63 + 2.70).

advantage considerations incentivize fund investors to redeem when they think other fund investors are redeeming as well. We are argue in this paper that a concave flow-performance relationship can be viewed as more fundamental, arising because investors who hold the assets directly will be concerned about other investors with overlapping portfolios negatively impacting the market values and liquidity of the assets when they liquidate parts or all of their portfolios.

To investigate this conjecture, we analyze separately managed account data for the period 2000 to 2021. These data are especially suitable because investors in these accounts are the direct owners of the assets and have overlapping portfolios. If investors decide to liquidate parts or all of their accounts, they are getting the market price when the assets are sold on their behalf and not a net-asset-value as a mutual fund investor does. However, when investors sell assets, especially large quantities, limited market liquidity can lead to depressed prices beyond their fundamental values and to lower market liquidity, potentially for an extended period. This decline can incentivize others with overlapping portfolios to try to sell ahead, which can lead to a selling dynamic where initially depressed values and liquidity will trigger further sales. With the bond market being generally less liquid than the equity market, it is not unreasonable to expect that direct investors in the bond market are more likely to exhibit such behavior, especially if they expect other investors to sell significant quantities of the assets they hold themselves. In the end, we will observe a sales-past performance relationship that resembles the one presented for bond fund investors in Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017), yet it is driven by direct investors that neither redeem at a net-asset-value nor share a common liquidity pool.

Supporting the conjecture, the estimation results of standard flow-performance models show a concave flow-performance relationship for separately managed account strategies that invest in less liquid assets. We further present evidence that the sensitivity of outflows to past underperformance increases, as expected, in periods of market illiquidity and for portfolios that are less liquid. And finally consistent with the conjecture, we show that strategic complementarity considerations are less accentuated for investors that are more likely to internalize the negative externality generated by their own decisions to sell large quantities.

Hence, these findings are consistent with the argument that investors are concerned that other investors with overlapping portfolios will attempt to sell ahead of them, depress asset prices, and reduce market liquidity, which in turn can lead to behavior that is observationally equivalent to the behavior of bond mutual fund investors presented in Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017). Hence, this observational equivalence challenges the first-mover hypothesis arguments for mutual funds as posited by academics and deployed by regulators. The evidence, in particular, raises the question of how to correctly benchmark the risk that mutual funds might experience large outflows during a period of market stress because of their particular structure. The results presented suggest that the behavior of investors with overlapping portfolios but without the mutual fund structure that offers redemptions at the net-asset-value and a shared liquidity pool ought to be the benchmark to isolate any risk driven solely by the structure of the mutual fund vehicle.

Overall, the analysis furthers our understanding of the financial ecosystem, thus helping to design more effective regulations. In particular, if the observed concave flow-performance relationship is not unique to mutual funds, but a more general reflection of the behavior of investors investing in less liquid assets, mutual fund regulation prescribing, for example, redemption restrictions would miss the point. Moreover, such requirements would render the mutual fund industry less competitive and in turn drive investors into investment vehicles that are possible outside the scope of regulation.

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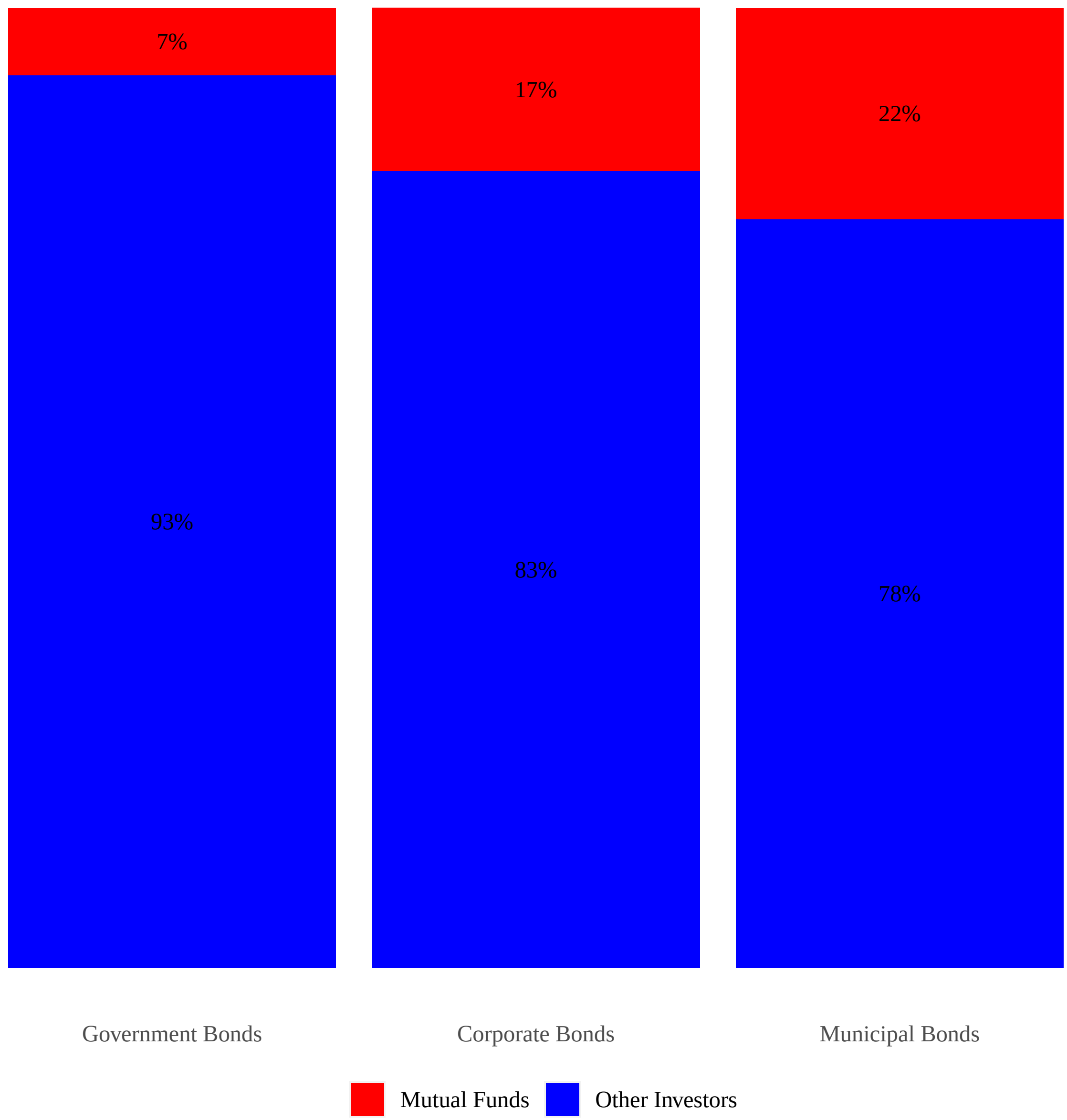


**Figure 1. Share of Total Fixed-Income Markets Holdings End of 2019**
Figure shows the long-term mutual fund share of the total market as of year-end 2019. Long-term mutual fund share is calculated by dividing the total dollar holdings of all long-term mutual funds, as reported to the Investment Company Institute, by the total amount outstanding reported by the Federal Reserve Board in the quarterly flow of funds report. Note that Government Bonds are treasury and agency bonds excluding T-bills and other short-term government securities.

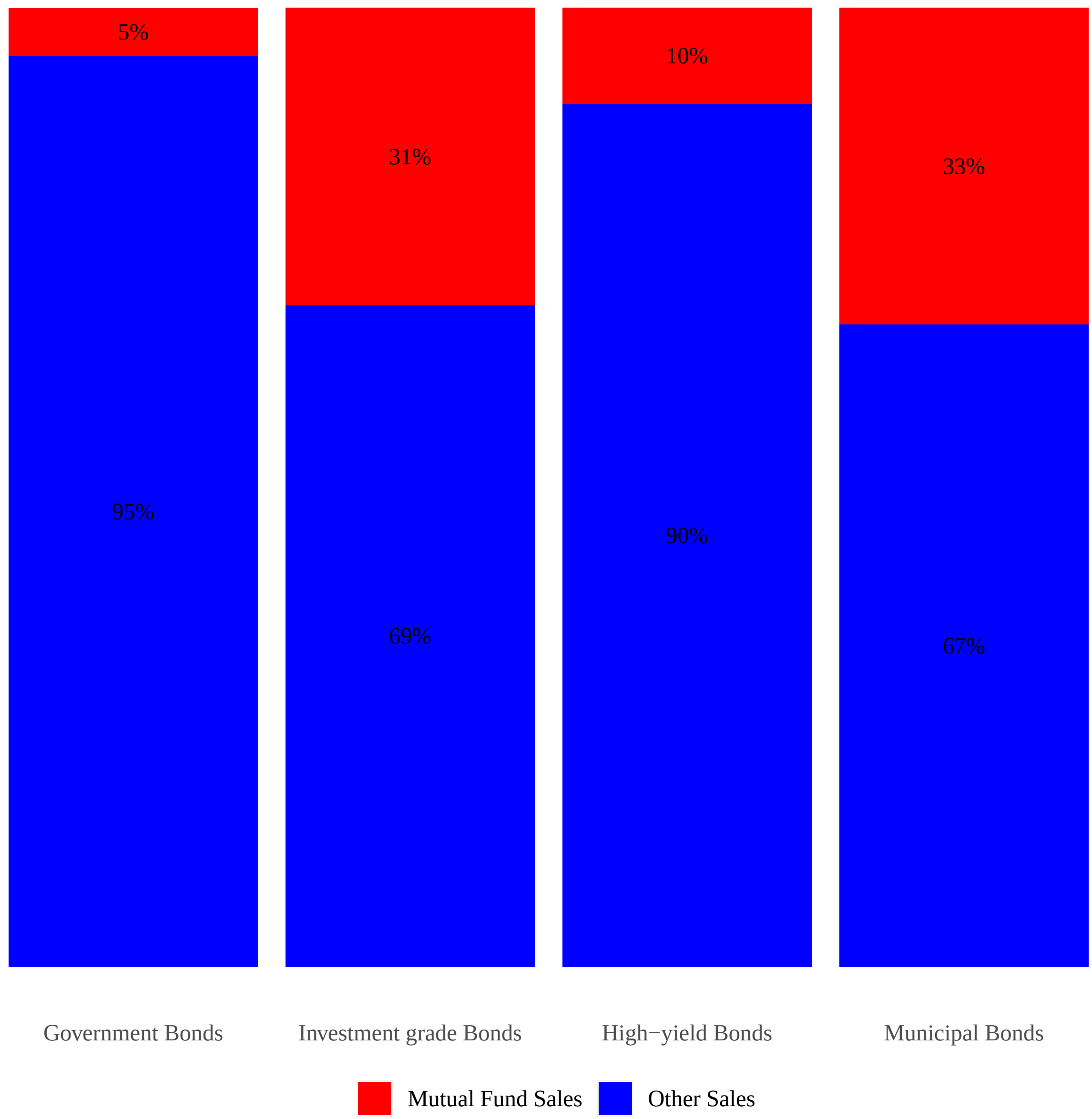


**Figure 2. Share of Fixed-Income Sale Volume During 2020 Crisis**

Figure shows the long-term mutual fund share of total sale volume in March 2020. Long-term mutual fund share is calculated by dividing the total dollar sales of all long-term mutual funds, as reported to the Investment Company Institute, by half of the total trading volume reported by FINRA TRACE for high-yield, investment grade, and municipal bonds and SIFMA for government bonds. Note that Government Bonds are treasury and agency bonds excluding T-bills and other short-term government securities, and High-yield Bonds and Investment grade Bonds contain only corporate bonds.

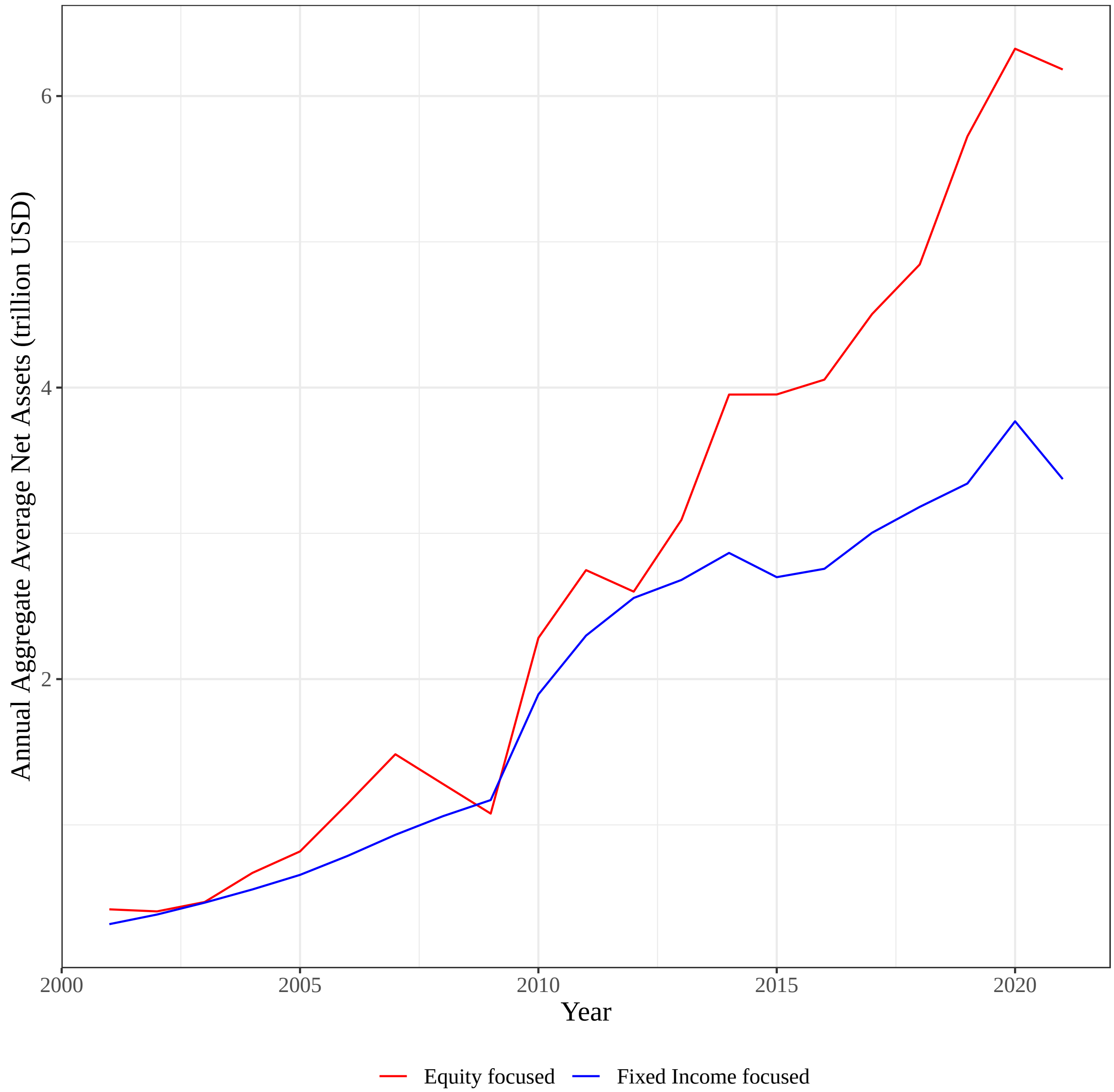


**Figure 3. Equity and Fixed-Income focused Separately Managed Account Aggregated Net Assets**

Figure shows from 2001 to 2021 aggregate assets of equity and fixed-income focused separately managed account composite strategies from Morningstar's separate account module. The sample covers US, European, and global equity focused strategies, and US, global and emerging market fixed income focused strategies. The equity focused strategies are US Equity Large Cap Blend, US Equity Large Cap Growth, US Equity Large Cap Value, US Equity Mid Cap, US Equity Small Cap; Europe Equity Large Cap; Global Equity Large Cap, Global Equity Mid/Small Cap, and Global Emerging Markets Equity. The fixed income focused strategies are US Fixed Income, US Municipal Fixed Income, Global Fixed Income, and Emerging Markets Fixed Income.

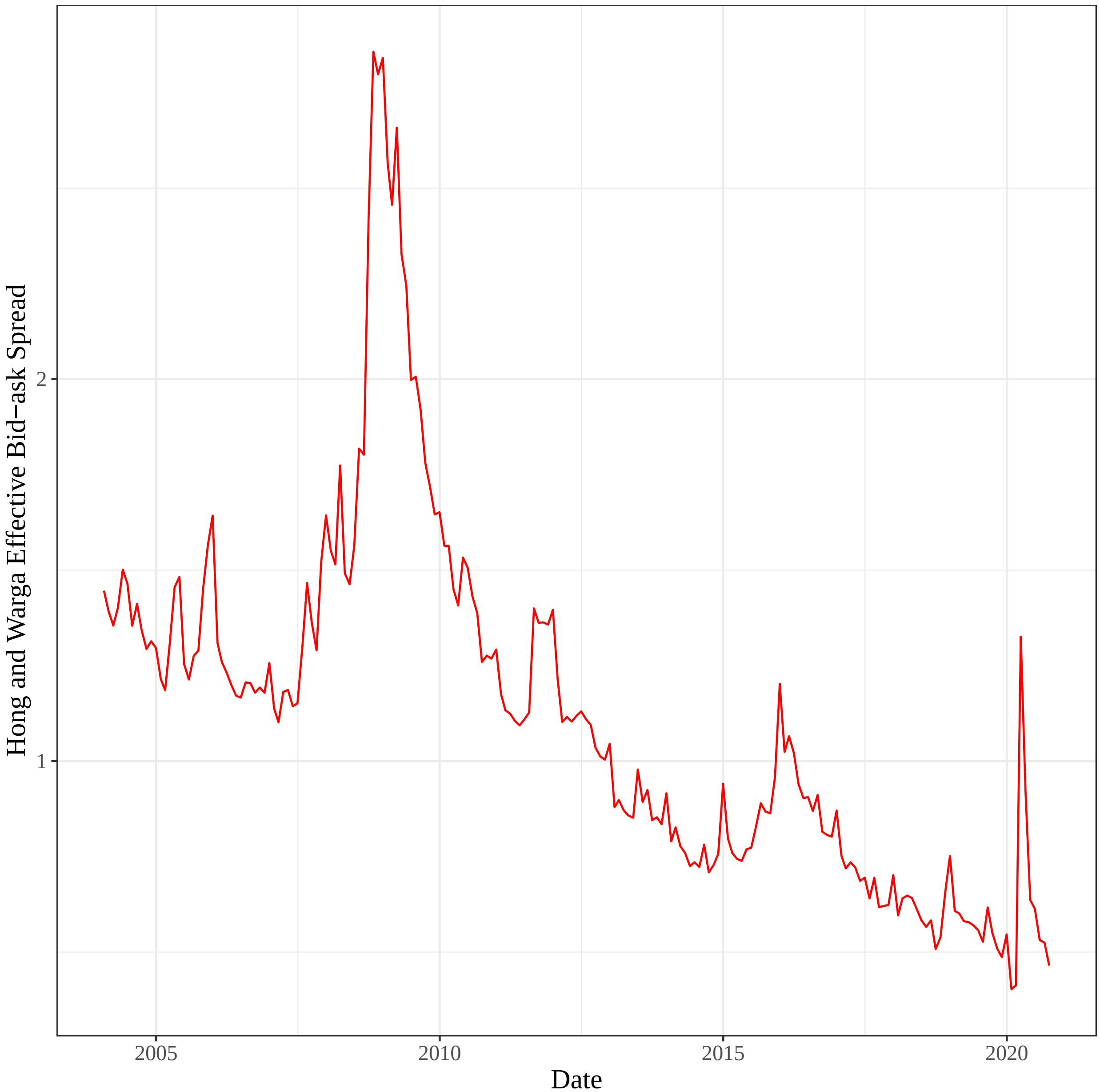


**Figure 4. Aggregate US Corporate Bond Market Liquidity**
Figures show the aggregate effective bid–ask spread from Hong and Warga (2000) computed using TRACE from 2005 through March 2021.

**Table 1. Sample Statistics**

Panel A presents sample statistics for the year 2020 averages of monthly or quarterly data by strategy. The sample is from Morningstar and covers the period from January 2000 to February 2021. "Strategies" is the average number of strategies in a category, "Accounts per Strategy" is the average number of accounts in a strategy in the category, "Median Assets per Strategy" is the median assets per strategy in the category, "Median Assets per Account" is the median assets per account in a strategy in the category, and "Total Assets in Category" is the aggregate assets in the category. Panel B reports summary statistics of the regression model variables. EQ and FI refers to equity-focused and fixed-income focused strategy Flows and Alphas, respectively. VIX, DFL, HOW, and TED are the detrended bond market liquidity indices. $ACF_{10}$ and $ACF_{12}$ are first-order autocorrelations, Average Number and Average Size are the log of the corresponding variables. See Section 3.2 for further information on the variables.

Panel A: Sample Overview

| Category | Strategies in Category | Accounts per Strategy | Median Assets per Strategy | Median Assets per Account | Total Assets in Category |
|---|---|---|---|---|---|
| Europe Equity Large Cap | 17 | 33 | 180 | 72 | 16,993 |
| Global Emerging Markets Equity | 150 | 27 | 916 | 100 | 419,878 |
| Global Equity Large Cap | 574 | 124 | 376 | 37 | 1,741,929 |
| Global Equity Mid/Small Cap | 83 | 22 | 466 | 70 | 102,725 |
| US Equity Large Cap Blend | 445 | 254 | 108 | 2 | 1,157,447 |
| US Equity Large Cap Growth | 358 | 277 | 215 | 5 | 1,419,596 |
| US Equity Large Cap Value | 315 | 358 | 134 | 3 | 535,571 |
| US Equity Mid Cap | 369 | 100 | 166 | 6 | 573,841 |
| US Equity Small Cap | 446 | 47 | 212 | 18 | 356,645 |
| *Equity Total* | 2,757 | 167 | 214 | 12 | 6,324,625 |
| Emerging Markets Fixed Income | 59 | 27 | 769 | 67 | 109,630 |
| Global Fixed Income | 73 | 64 | 738 | 68 | 191,303 |
| US Fixed Income | 887 | 241 | 432 | 29 | 3,236,593 |
| US Municipal Fixed Income | 234 | 448 | 285 | 2 | 231,346 |
| *Fixed Income Total* | 1,253 | 259 | 424 | 20 | 3,768,871 |
| **TOTAL** | 4,010 | 196 | 278 | 15 | 10,093,496 |

Panel B: Model Variables Statistics

| | EQ Flow | EQ Alpha | FI Flow | FI Alpha | VIX | DFL | HOW | TED | $ACF_{10}$ | $ACF_{12}$ | Average Number | Average Size |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Average | -0.0041 | -0.0009 | -0.0000 | 0.0005 | 0.0006 | -0.0001 | -0.0002 | -0.0109 | 0.0527 | 0.0595 | 3.0236 | 16.6302 |
| Median | -0.0018 | -0.0008 | -0.0004 | 0.0005 | -0.0084 | -0.0001 | -0.0004 | 0.0036 | 0.0313 | 0.0399 | 2.7726 | 17.1736 |
| Standard Deviation | 0.1047 | 0.0084 | 0.1047 | 0.0039 | 0.0669 | 0.0003 | 0.0016 | 0.2362 | 0.2710 | 0.2508 | 1.6855 | 2.6972 |

**Table 2. Flow Performance Relations**

Table presents results of the flow-performance relationship regression:

$$\text{Flow}_{S,t} = \beta_1 \text{Performance}_{S,-1} + \beta_2 \text{Performance}_{S,-1} \times \text{I}(\text{Performance}_{S,-1} < 0) + \beta_3 \text{I}(\text{Performance}_{S,-1} < 0) + \gamma\, \text{Controls}_{S,t} + \alpha + \eta_{S,t}$$

where $\text{Flow}_{S,t}$ is the strategy $S$ net flow in month $t$ and $\text{Performance}_{S,-1}$ is the strategy $S$ one-month lagged performance measure. The main performance measure $\text{Alpha}_{S,t-12\to t-1}$ is the strategy $S$' alpha estimated as the intercept from a regression of excess strategy returns on excess aggregate bond market and aggregate stock market returns over the past one year. Excess $\text{Return}_{-1}$ is strategy $S$' lagged return in excess of the risk free rate. $\text{Controls}_{S,t}$ include lagged flow ($\text{Flow}_{-1}$), natural log of the strategy's aggregate assets (log(Asset)), and natural log of the strategy's age (log(Age)). Regressions include month fixed effects and standard errors are clustered at the strategy.

| | Equity Focused | | | Fixed Income Focused | | |
|---|---|---|---|---|---|---|
| | $\text{Alpha}_{S,-1}$ | $\text{Alpha}_{S,-1}$ | Excess $\text{Return}_{S,-1}$ | $\text{Alpha}_{S,-1}$ | $\text{Alpha}_{S,-1}$ | Excess $\text{Return}_{S,-1}$ |
| $\text{Performance}_{S,-1}$ | $0.3329^{***}$ | $0.3272^{***}$ | $0.0073$ | $0.1044$ | $0.1304$ | $-0.1150^{***}$ |
| | $(0.0594)$ | $(0.0540)$ | $(0.0083)$ | $(0.1564)$ | $(0.1431)$ | $(0.0347)$ |
| $\text{Performance}_{S,-1} \times \text{I}(\text{Performance}_{S,-1} < 0)$ | $0.1056$ | $0.0776$ | $0.0141$ | $0.7139^{***}$ | $0.6330^{***}$ | $0.2964^{***}$ |
| | $(0.0799)$ | $(0.0727)$ | $(0.0125)$ | $(0.2460)$ | $(0.2263)$ | $(0.0539)$ |
| $\text{I}(\text{Performance}_{S,-1} < 0)$ | $-0.0043^{***}$ | $-0.0039^{***}$ | $-0.0013^{**}$ | $-0.0030^{***}$ | $-0.0026^{***}$ | $-0.0027^{***}$ |
| | $(0.0006)$ | $(0.0005)$ | $(0.0006)$ | $(0.0009)$ | $(0.0008)$ | $(0.0007)$ |
| $\text{Flow}_{S,-1}$ | $0.0206^{***}$ | $0.0384^{***}$ | $0.0228^{***}$ | $-0.0118^{*}$ | $-0.0007$ | $-0.0115^{*}$ |
| | $(0.0050)$ | $(0.0061)$ | $(0.0050)$ | $(0.0066)$ | $(0.0080)$ | $(0.0066)$ |
| $\log(\text{Asset})_S$ | $0.0027^{***}$ | $0.0023^{***}$ | $0.0028^{***}$ | $0.0031^{***}$ | $0.0027^{***}$ | $0.0032^{***}$ |
| | $(0.0001)$ | $(0.0001)$ | $(0.0001)$ | $(0.0002)$ | $(0.0002)$ | $(0.0002)$ |
| $\log(\text{Age})_S$ | $-0.0149^{***}$ | $-0.0134^{***}$ | $-0.0154^{***}$ | $-0.0117^{***}$ | $-0.0106^{***}$ | $-0.0118^{***}$ |
| | $(0.0005)$ | $(0.0005)$ | $(0.0005)$ | $(0.0008)$ | $(0.0007)$ | $(0.0008)$ |
| Winsorized Flows | NO | YES | NO | NO | YES | NO |
| Monthly FE | YES | YES | YES | YES | YES | YES |
| Strategy Cluster | YES | YES | YES | YES | YES | YES |
| Adj. $R^2$ | 0.0143 | 0.0172 | 0.0121 | 0.0082 | 0.0088 | 0.0078 |
| Num. obs. | 327026 | 327026 | 327026 | 147339 | 147339 | 147339 |
| N Clusters | 4599 | 4599 | 4599 | 1894 | 1894 | 1894 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

**Table 3. Market Liquidity**

Table presents results of the flow-performance relationship regression for fixed-income focused strategies

$$\begin{aligned}\text{Flow}_{S,t} = &\beta_1 \text{Alpha}_{S,t-12\to t-1} + \beta_2 \text{Alpha}_{S,t-12\to t-1} \times \text{I}(\text{Market Illiquidity}_t) \\ &+ \beta_3 \text{I}(\text{Market Illiquidity}_t) + \gamma\, \text{Controls}_{S,t} + \alpha + \eta_{S,t}, \\ &\forall \text{Alpha}_{S,t-12\to t-1} < 0,\end{aligned}$$

where $\text{Flow}_{S,t}$ is the strategy $S$ net flow in month $t$ and $\text{Alpha}_{S,t-12\to t-1}$ is the strategy $S$ alpha estimated as the intercept from a regression of excess strategy returns on excess aggregate bond market and aggregate stock market returns over the past one year, and $\text{Market Illiquidity}_t$ is an indicator variable that equals to one if the particular illiquidity proxy in this period is above the sample mean and zero otherwise, and $\text{Controls}_{S,t}$ remain the same as before. The four proxies that capture periods of bond market-wide illquidity are based on the VIX, the DFL and HOW illiquidity indices, and the TED spread. For further details about the bond market-wide illquidity proxies, see section 3.4.1. Following Goldstein, Jiang, and Ng (2017), the regression is based on a sample of strategy-month observations with negative $\text{Alpha}_{S,-1}$.

| | $\text{Alpha}_{S,-1} < 0$ | | | |
|---|---|---|---|---|
| | VIX | DFL | HOW | TED |
| $\text{Alpha}_{S,-1}$ | $0.6128^{***}$ | $0.4942^{*}$ | $0.6177^{***}$ | $0.6837^{***}$ |
| | $(0.2240)$ | $(0.2700)$ | $(0.2223)$ | $(0.2238)$ |
| $\text{Alpha}_{S,-1} \times \text{I}(\text{Market Illiquidity}_t)$ | $0.6695^{**}$ | $0.9443^{***}$ | $0.8287^{**}$ | $0.5599^{**}$ |
| | $(0.2992)$ | $(0.3486)$ | $(0.3485)$ | $(0.2802)$ |
| $\text{I}(\text{Market Illiquidity}_t)$ | $-0.0028^{**}$ | $-0.0026^{*}$ | $-0.0027^{**}$ | $-0.0036^{***}$ |
| | $(0.0013)$ | $(0.0014)$ | $(0.0014)$ | $(0.0012)$ |
| $\text{Flow}_{S,-1}$ | $-0.0117$ | $-0.0184^{*}$ | $-0.0187^{*}$ | $-0.0118$ |
| | $(0.0104)$ | $(0.0102)$ | $(0.0102)$ | $(0.0104)$ |
| $\log(\text{Asset})_S$ | $0.0032^{***}$ | $0.0032^{***}$ | $0.0033^{***}$ | $0.0032^{***}$ |
| | $(0.0003)$ | $(0.0003)$ | $(0.0003)$ | $(0.0003)$ |
| $\log(\text{Age})_S$ | $-0.0114^{***}$ | $-0.0122^{***}$ | $-0.0123^{***}$ | $-0.0115^{***}$ |
| | $(0.0010)$ | $(0.0010)$ | $(0.0010)$ | $(0.0010)$ |
| Monthly FE | YES | YES | YES | YES |
| Strategy Cluster | YES | YES | YES | YES |
| Adj. $R^2$ | 0.0082 | 0.0091 | 0.0089 | 0.0082 |
| Num. obs. | 48367 | 43764 | 43764 | 48367 |
| N Clusters | 1674 | 1645 | 1645 | 1674 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

## Table 4. SMA Portfolio Liquidity

Table presents results of the flow-performance relationship regression for fixed-income focused strategies

$$\text{Flow}_{S,t} = \beta_1 \text{Alpha}_{S,t-12\to t-1} + \beta_2 \text{Alpha}_{S,t-12\to t-1} \times \text{I(Portfolio Illiquidity}_{S,t-1}) \\ + \beta_3 \text{I(Portfolio Illiquidity}_{S,t-1}) + \gamma\,\text{Controls}_{S,t} + \alpha + \eta_{S,t}, \quad \forall \text{Alpha}_{S,t-12\to t-1} < 0,$$

where $\text{Flow}_{S,t}$ is the strategy $S$ net flow in month $t$ and $\text{Alpha}_{S,t-12\to t-1}$ is the strategy $S$ alpha estimated as the intercept from a regression of excess strategy returns on excess aggregate bond market and aggregate stock market returns over the past one year, and $\text{Portfolio Illiquidity}_{S,t-1}$ is an indicator variable that equals to one if the particular portfolio illiquidity proxy in this period is above the sample mean and zero otherwise, and $\text{Controls}_{S,t}$ remain the same as before. Following Khandani and Lo (2011), the portfolio illiquidity proxies are the first order autocorrelations estimated over rolling 10-month or 12-month windows. The sample contains only strategy-month observations with negative $\text{Alpha}_{S,-1}$.

| | $\text{Alpha}_{S,-1} < 0$ | | | |
|---|---|---|---|---|
| | 10-month window | 12-month window | 10-month window | 12-month window |
| $\text{Alpha}_{S,-1}$ | 0.6331*** | 0.7042*** | 0.3520 | 0.3791 |
| | (0.2225) | (0.2222) | (0.3200) | (0.3208) |
| $\text{Alpha}_{S,-1} \times \text{I(Portfolio Illiquidity}_{S,t-1})$ | 0.7971** | 0.7004** | 1.1526** | 1.2344** |
| | (0.3199) | (0.3264) | (0.5737) | (0.5710) |
| $\text{Alpha}_{S,-1} \times \text{I(Market Illiquidity}_{t})$ | | | 0.8063* | 0.9358** |
| | | | (0.4349) | (0.4266) |
| $\text{Alpha}_{S,-1} \times \text{I(Portfolio Illiquidity}_{S,t-1}) \times \text{I(Market Illiquidity}_{t})$ | | | −0.5856 | −0.9585 |
| | | | (0.7216) | (0.7275) |
| $\text{I(Portfolio Illiquidity}_{S,t-1})$ | −0.0019 | −0.0015 | −0.0018 | −0.0007 |
| | (0.0014) | (0.0014) | (0.0019) | (0.0020) |
| $\text{I(Market Illiquidity}_{t})$ | | | −0.0025 | −0.0020 |
| | | | (0.0016) | (0.0016) |
| $\text{I(Portfolio Illiquidity}_{S,t-1}) \times \text{I(Market Illiquidity}_{t})$ | | | −0.0000 | −0.0014 |
| | | | (0.0027) | (0.0027) |
| $\text{Flow}_{S,-1}$ | −0.0122 | −0.0132 | −0.0187* | −0.0194* |
| | (0.0106) | (0.0108) | (0.0104) | (0.0106) |
| $\log(\text{Asset})_S$ | 0.0033*** | 0.0034*** | 0.0032*** | 0.0033*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| $\log(\text{Age})_S$ | −0.0103*** | −0.0101*** | −0.0107*** | −0.0107*** |
| | (0.0011) | (0.0011) | (0.0011) | (0.0012) |
| Monthly FE | YES | YES | YES | YES |
| Strategy Cluster | YES | YES | YES | YES |
| Adj. $R^2$ | 0.0079 | 0.0079 | 0.0088 | 0.0088 |
| Num. obs. | 42980 | 41960 | 39192 | 38330 |
| N Clusters | 1475 | 1444 | 1452 | 1417 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

**Table 5. Account Size**

Table presents estimation results of the flow-performance relationship in equation (2) for fixed-income focused strategies, where $\log(\text{Asset}_S)$ is replaced with $\log(\text{N}_S)$ and $\overline{\log(\text{Assets}_i)}$. The sample contains only strategy-month observations with negative $\text{Alpha}_{S,-1}$. The models "Institutional", "Retail", and "Both" contain observations of strategies that have been reported to focus only on institutional investors, retail investors, or both. The sample contains only strategy-month observations with negative $\text{Alpha}_{S,-1}$.

| | $\text{Alpha}_{-1} < 0$ | | | | |
|---|---|---|---|---|---|
| | All | All | Institutional | Retail | Both |
| $\text{Alpha}_{S,-1}$ | $0.8004^{***}$ | $4.7212^{***}$ | $0.4936$ | $1.1971$ | $0.7885^{***}$ |
| | $(0.1822)$ | $(1.7478)$ | $(0.3375)$ | $(0.7093)$ | $(0.2072)$ |
| $\text{Alpha}_{S,-1} \times \log(\text{Average account size})$ | | $-0.2115^{**}$ | | | |
| | | $(0.0829)$ | | | |
| $\text{Alpha}_{S,-1} \times \log(\text{Number of accounts})$ | | $-0.1108$ | | | |
| | | $(0.1473)$ | | | |
| $\text{Flow}_{S,-1}$ | $-0.0110$ | $-0.0112$ | $-0.0243$ | $-0.0147$ | $-0.0050$ |
| | $(0.0104)$ | $(0.0104)$ | $(0.0151)$ | $(0.0314)$ | $(0.0149)$ |
| $\log(\text{Average account size})$ | $0.0031^{***}$ | $0.0026^{***}$ | $0.0061^{***}$ | $0.0036^{**}$ | $0.0029^{***}$ |
| | $(0.0003)$ | $(0.0004)$ | $(0.0007)$ | $(0.0015)$ | $(0.0004)$ |
| $\log(\text{Number of accounts})$ | $0.0038^{***}$ | $0.0035^{***}$ | $0.0055^{***}$ | $0.0023^{**}$ | $0.0034^{***}$ |
| | $(0.0004)$ | $(0.0005)$ | $(0.0009)$ | $(0.0010)$ | $(0.0006)$ |
| $\log(\text{Age})_S$ | $-0.0115^{***}$ | $-0.0114^{***}$ | $-0.0110^{***}$ | $-0.0148^{***}$ | $-0.0104^{***}$ |
| | $(0.0010)$ | $(0.0010)$ | $(0.0015)$ | $(0.0028)$ | $(0.0014)$ |
| Monthly FE | YES | YES | YES | YES | YES |
| Strategy Cluster | YES | YES | YES | YES | YES |
| Adj. $R^2$ | 0.0078 | 0.0080 | 0.0116 | 0.0094 | 0.0065 |
| Num. obs. | 48552 | 48552 | 15930 | 5798 | 26824 |
| N Clusters | 1674 | 1674 | 539 | 235 | 909 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

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