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Flow Diversification

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Abstract

We measure flow diversification in mutual funds using the cross-sectional correlation of daily flows across investor clienteles. Greater flow diversification is associated with lower future flow volatility, smaller subsequent outflows, and lower cash holdings. We decompose flow correlation into predictable and unexpected components. Unexpectedly low flow correlation is associated with higher post-outflow fund returns, mitigating outflow-induced externalities on incumbent shareholders. Flow diversification also dampens the higher flow-performance sensitivity of illiquid funds, partially offsetting strategic complementarities that can generate fragility.

I. Introduction

A number of studies show that outflows force mutual funds to engage in costly trading, generating an externality for non-redeeming shareholders and contributing to fragility in underlying markets (Edelen (1999), Wermers (2000), Greene and Hodges (2002), Alexander, Cici, and Gibson (2007), Coval and Stafford (2007), Chen, Goldstein, and Jiang (2010), and Falato, Goldstein, and Hortaçsu (2021)).[1] In this article, we study whether the imperfectly correlated liquidity needs of investors can mitigate the negative externalities induced by outflows. Imperfect correlation in liquidity demands can arise from a variety of sources: investors may differ in their sensitivities to economic conditions or fundamentals; behavioral differences may lead to heterogeneity in trading patterns (Christie and Huang (1995), Chang, Cheng, and Khorana (2000), and Bessembinder, Chan, and Seguin (1996)); or geographic distance between investors and portfolio holdings might shape

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[1] In addition to performance deterioration due to trading costs, redemptions can also result in the realization of capital gains, creating a tax externality (Dickson, Shoven, and Sialm (2000), Sialm and Zhang (2020)).

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differences in liquidity demand (Ferreira, Massa, and Matos (2017)). Our central thesis is that for a mutual fund, diversification across investors with variation in such demands confers a "flow diversification" benefit that reduces the magnitude of liquidity externalities.

The channel is not simply the mechanical offsetting of investor flows; rather, it operates through a reduction in unexpected outflows. Rakowski (2010) argues that flow volatility, which proxies for unexpected outflows, causes funds to hold excess cash and trade more frequently, incurring incremental explicit and implicit (price impact) costs, all of which reduce short-horizon returns. Flow volatility is a reduced-form outcome that reflects two underlying forces: the volatility of individual investor flows and the correlation structure across those flows. Even if all investors exhibit identical flow volatilities, lower correlation across investor flows reduces net flow volatility, allowing funds to have smaller cash buffers and incur lower trading costs. In this sense, understanding the correlation in investor liquidity demands provides direct insight into the mechanism through which unexpected outflows generate liquidity externalities.[2]

Empirically identifying the effects of flow diversification is challenging for two reasons. First, investor-level daily demand is not observable, even to a fund manager; mutual fund plumbing is such that fund managers only receive notifications of net flows across all investors in a share class, which means that investor-level flow correlations are not calculable. But because share classes pool investors with similarly correlated liquidity needs, correlation in flows across share classes, which are calculable, serves as a proxy for differences in the correlation structure across investor-specific liquidity needs. The literature is consistent with this view. For example, flows of broker-sold funds are less sensitive to poor performance (Del Guercio and Reuter (2014)) and deliver lower returns relative to directly sold funds (Bergstresser, Chalmers, and Tufano (2009)); retail clients monitor their funds less extensively than institutional clients (Evans and Fahlenbrach (2012)); investors in retirement accounts exhibit inertia (Agnew, Balduzzi, and Sundén (2003)); and tax clienteles are important (Sialm and Starks (2012)). In the practitioner arena, it is well known that fee-only Registered Investment Advisors who serve as fiduciaries attempt to reduce fire-sale behavior by encouraging investors to stay invested in market downturns, whereas retail investors who do not delegate their assets do not receive such treatment. Exploiting these insights, we measure daily fund-level flow correlation (*FlowCorr*) as the scaled value-weighted average covariance of flows across share classes for over 6,500 active mutual funds over the 2007–2024 period.

A second identification challenge is that persistent flow correlation is unlikely to be random across funds: to the extent that fund managers know their clientele's tendencies, they can ex ante adjust cash buffers to minimize trading costs or even adjust their clientele mix to reduce flow correlation. Because holding additional

[2]One can also view the mechanism through a market microstructure lens because a mutual fund is effectively a market maker who is required to provide end-of-day immediacy. Net flows are equivalent to order imbalance, and flow volatility corresponds to order imbalance volatility. Bogousslavsky and Collin-Dufresne (2023) show that order imbalance volatility influences price impact, even when holding the level effect of order imbalance constant, because liquidity providers face risk in offloading inventory in the future. In other words, holding net flows constant, flow volatility affects fund-level transaction costs because it is related to *unexpected* future outflows.

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cash generally involves a lower and more predictable opportunity cost than forced short-run trading, it is optimal for fund managers to adjust cash buffers ex ante rather than incur trading costs ex post.[3] In fact, we observe precisely such behavior: there is a positive relation between end-of-quarter cash buffers and average flow correlation in the quarter, and the addition of share classes is associated with both a sharp decline in flow correlation and a reduction in cash buffers. This evidence of endogenous adjustments underscores the economic importance of flow diversification.[4] But it also makes it difficult to interpret the return consequences of flow correlation from persistent cross-sectional differences alone. To sharpen inference, we decompose *FlowCorr* into an average component that represents its conditional expectation (*ExpFlowCorr*) and a deviation from the average that represents unexpected flow correlation (*UnexpFlowCorr*). Under this decomposition, predictable differences in flow correlation should be absorbed, at least partially, through managerial responses such as cash holdings; on the other hand, unexpected flow correlation captures short-run deviations in the synchronization of investor liquidity demands that are harder to manage ex ante and therefore more likely to generate variation in immediate trading needs and post-outflow returns.

Consistent with this mechanism, in daily sorts on *UnexpFlowCorr* for funds experiencing outflows, the average spread in subsequent 3-day benchmark-adjusted returns between low and high *UnexpFlowCorr* quintiles is 1.07 basis points (t-stat = 3.61). In contrast, and as expected, analogous sorts based on *ExpFlowCorr* show no such variation in returns. In regressions that control for a variety of fund characteristics as well as fund and day fixed effects, we continue to see a reliable negative relation between fund returns and *UnexpFlowCorr.* These return differences are neither transitory nor reversed: over a 20-day return horizon, the average spread in benchmark-adjusted returns is 4.13 basis points (t-stat = 3.76), and the coefficient on *UnexpFlowCorr* in regressions remains negative and statistically significant. We interpret these results as evidence on the short-run return consequences of unexpectedly synchronized liquidity needs, rather than as estimates from a fully exogenous shock to flow correlation.

These differences in returns are in the same order of magnitude as trading costs and therefore economically meaningful to investors, but there are other ways to think about economic significance. In daily data, the average benchmark-adjusted return difference between small and large outflow quintiles over the 2007–2024 period is 1.22 basis points. Thus, the return spread associated with unexpected flow diversification in sort-based tests (1.07 basis points) is an order of magnitude comparable to that of the liquidity externality itself. A second comparison is to

[3]This tradeoff is economically meaningful. Wermers (2000) estimates the return difference between equity and non-equity holdings (a measure of cash drag) to be about 0.70% per year, while Edelen, Evans, and Kadlec (2013) report trading costs of about 1.44%. Differentials between trading costs and cash drag are even bigger in small cap and value funds, where trading costs in the underlying securities are higher (see also Yan (2008) and Simutin (2014)).

[4]The economic underpinnings of flow correlation are also evident in other ways. For instance, flow correlation is related to prior market returns and investor sentiment. But most interestingly, flow correlation spikes in December and toward the last three trading days of the month, lining up with correlated trading arising from the payment cycle (Etula, Rinne, Suominen, and Vaittinen (2020)), retirement contributions, or tax-motivated trading (Sialm and Zhang (2020)).

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Rakowski (2010), who reports that funds in the lowest quartile of daily flow volatility outperform those in the highest quartile by 0.89 basis points per day. Again, the mitigation due to flow diversification is comparable to this benchmark. It is also instructive to see how practitioners consider liquidity management in similar contexts. Through a "real-life example," Cheng, Fabozzi, Harlow, Lee, and Zhang (2024) describe the liquidity management techniques used by a particular fund to mitigate trading costs when facing a small, unexpected outflow of comparable magnitude—emblematic of the lengths to which portfolio managers go to avoid trading costs.

Given these results, we consider the effects of flow diversification on shareholder runs. Chen, Goldstein, and Jiang (2010) argue that the expectation that some investors will exit a fund and impose a cost on others generates a multiplier effect. Their approach to studying such payoff complementarities is to determine if flow-performance sensitivity is higher in funds with illiquid assets, leveraging the idea that redemptions impose higher costs on non-redeeming shareholders in illiquid funds (see also Goldstein, Jiang, and Ng (2017), Falato, Hortaçsu, Li, and Shin (2021), and Jiang, Li, Sun, and Wang (2022)). We reproduce their monthly regressions with daily data and then ask whether flow-performance sensitivities vary with flow diversification, even in the presence of higher flow-performance sensitivities for illiquid funds. This is indeed the case: independent of asset liquidity, lower levels of flow diversification are associated with higher flow-performance sensitivities. We then assess whether flow diversification mitigates higher flow-performance sensitivities in illiquid funds subject to outflows, essentially asking whether flow diversification can partially offset strategic complementarities. Consistent with this idea, we find that flow-performance sensitivity in illiquid funds is higher in funds when flow diversification is low and attenuated when flow diversification is high.

Our tests imply that liquidity management in delegated asset management involves not only the liquidity of portfolio holdings (Pástor, Stambaugh, and Taylor (2020)) but also the liquidity demands of the investor base. Similar diversification-based mechanisms arise in other financial settings, including banking, where inter-regional claims insure against local liquidity shocks (Allen and Gale (2000)); loan contracting, where customer concentration affects interest rate spreads (Campello and Gao (2017)); mortgage-backed securities, where heterogeneous prepayment risk affects pricing (Johnson (2004)); funds of funds, where diversification provides insurance against temporary liquidity shocks (Bhattacharya, Lee, and Pool (2013)); and money market funds, where client-base diversification shapes risk-taking and run incentives (Kacperczyk and Schnabl (2013), Schmidt, Timmermann, and Wermers (2016)). At the family level, Massa (2003) argues that investor heterogeneity motivates fund families to expand product offerings, albeit with negative effects on performance.

Market participants have developed alternative mechanisms to mitigate mutual fund liquidity externalities, including swing pricing, which shifts trading costs to redeeming shareholders (Jin, Kacperczyk, Kahraman, and Suntheim (2022)); redemption-in-kind, which allows funds to meet redemptions by transferring securities rather than selling them (Agarwal, Ren, Shen, and Zhao (2023)); and ETF (exchange traded fund) structures, which use secondary-market trading and in-kind redemption processes to reduce trading and tax externalities (Du, Starks, and Xiaolan (2023)). Given these structural advantages, it is perhaps unsurprising

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that mutual fund assets have increasingly shifted toward ETFs over the last decade (ICI Factbook (2024)) and that prominent asset managers have explored dual mutual fund–ETF share-class structures.

II. Institutional Details

Investors who submit trades before market close on day (t) receive the NAV (net asset value) struck at the close on the same day. Portfolio managers typically observe aggregated share-class flows late on day (t) or early on day ($t + 1$), depending on the trading platform. Because redemption-induced trading needs not occur entirely on day ($t + 1$) and may be spread over several days, we measure post-flow performance primarily over days ($t + 1$) to ($t + 3$).

Investor redemptions must ultimately be met with either cash balances or asset sales. Cash balances allow stock sales to be deferred, but they are not a complete solution because daily redemptions are difficult to predict and may exceed available liquidity when investor liquidity needs become unexpectedly synchronized.[5] Remaining shareholders bear the implicit and explicit costs associated with redemptions, including market impact, commissions, stamp duties, ticket charges, and deviations from target portfolio weights. These costs reduce the fund's NAV and therefore lower subsequent fund returns. Market participants recognize these externalities: data providers report fund flows; investment committees and fiduciaries monitor outflows from funds they own (Bailey and Richards (2017), Illan (2018)); and industry observers have linked the shift toward ETFs to mutual funds' liquidity and tax externalities (Britton (2019), Rekenthaler (2021), and Balchunas and Weber (2023)).

III. Measurement Issues and Sample Construction

A. Measuring Flow Diversification

Because investor-level daily flows are unavailable, we use share-class flows to proxy for co-movement in investor liquidity demands. This approach relies on the fact that share classes segment investors by distribution channel and account type, and prior work documents systematic differences across retail, retirement, broker-sold, and institutional investors.[6] We exploit this systematic variation in liquidity demands across share classes in measuring flow diversification. We first define flows for share class k in fund i at time t as

$$Flows_{i,k,t} = TNA_{i,k,t} - TNA_{i,k,t-1} \times (1 + r_{i,k,t}), \tag{1}$$

[5]The median autocorrelation in daily net flows is only 0.03, implying very limited predictability. We also compute the ratio of average daily outflows to beginning-of-quarter cash and find that a significant fraction of funds may not have adequate cash buffers to meet daily redemption requirements.

[6]The literature is vast, and in addition to the papers cited in the introduction, see Ben-Rephael and Israelsen (2018), Barber, Huang, and Odean (2016), Christoffersen and Musto (2002), Chalmers and Reuter (2010), Del Guercio, Genc, and Tran (2018), Del Guercio and Tkac (2002), James and Karceski (2006), Schmidt et al. (2016), and Beggs (2022).

where *TNA* represents total net assets and *r* is the net return after fees.[7] Aggregating flows across all *k* share classes yields net flows for fund *i* at time *t*:

$$Flows_{i,t} = \sum_{k=1}^{K} Flows_{i,k,t}. \tag{2}$$

Our measure of flow diversification, *FlowCorr*, is based on the covariance of flows across share classes. Intuitively, *FlowCorr* captures the extent to which liquidity demands across investor groups move together, conditional on a given level of fund net flows. We compute *FlowCorr* as the average pairwise cross-product of value-weighted deviations of class-level flows from fund-level net flows, scaled by the average squared value-weighted deviation across all share classes. This ensures that *FlowCorr* is comparable across funds with different numbers of share classes:

$$\begin{aligned} FlowCorr_{i,t} &= \frac{\sum_{k \neq l} cov\left(flows_{i,k,t}, flows_{i,l,t}\right)}{var\left(flows_{i,k,t}\right)} \\ &= \frac{\frac{2}{K(K-1)} \sum_{k=1}^{K-1} \sum_{j=k+1}^{K} \left[w_{k,t-1}\left(Flows_{i,k,t} - Flows_{i,t}\right) \times w_{j,t-1}\left(Flows_{i,j,t} - Flows_{i,t}\right)\right]}{\frac{1}{K} \sum_{k=1}^{K} w_{k,t-1}^2 \left(Flows_{i,k,t} - Flows_{i,t}\right)^2}, \end{aligned} \tag{3}$$

where $w_{k,t-1} = \frac{TNA_{i,k,t-1}}{TNA_{i,t-1}}$ is the weight of share class *k* in fund *i* at time $t-1$. *FlowCorr* is bounded between -1 and $+1$, and positive (negative) values indicate positively (negatively) correlated flows across share classes.

FlowCorr reflects both a clientele effect, the correlation in liquidity needs across types of investors segmented by share classes, and a client effect, which captures idiosyncratic, uncorrelated liquidity demands across individual investors. Clientele effects are likely endogenous because fund managers understand the typical liquidity needs of investors in different share classes, such as periodic retirement contributions and distributions, 401(k) rebalancing, and advance notice from institutional clients. These predictable features generate a slow-moving component in *FlowCorr* that shifts primarily when funds alter their clientele structure by adding or removing share classes.[8] In contrast, the client effect arises from unpredictable variation in investors' liquidity needs that lies outside managerial control.

To separate these forces, we extract the average (permanent) component of *FlowCorr* using a backward-looking 60-day moving average (MA) process, interpreting it as the conditional expectation of *FlowCorr* from clienteles. Deviations

[7] We use dollar rather than proportional flows because trading externalities depend on the dollar value of trades faced by portfolio managers. In addition, value-weighted proportional flows mechanically produce a degenerate covariance-to-variance ratio because share-class assets sum to fund assets. Section V.E considers an equal-weighted alternative based on proportional flows.

[8] The slow-moving component also shifts when a share class is added to or removed from so-called model portfolios used by RIAs, Wirehouses, independent broker–dealers, and wealth managers. Such changes result in substantial flows that can change the correlation structure across clienteles.

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from the average represent the idiosyncratic, unpredictable correlation in liquidity needs across investors. We denote these components *ExpFlowCorr* and *UnexpFlowCorr*, respectively. Importantly, this decomposition is not intended as a statistical forecasting model. Instead, it provides a parsimonious way to separate predictable liquidity patterns that managers can internalize from deviations from the average that cannot be managed ex ante. Unexpected flow correlation may still be correlated with unobserved market, investor demand, or fund-level shocks. Accordingly, we interpret *UnexpFlowCorr* as a measure of synchronized liquidity needs that moderates the effect of unexpected outflows on future fund returns, rather than a fully exogenous shock.

B. Data and Sample

We use the Morningstar Mutual Fund Database, which provides daily data on flows and returns for 7,489 funds at the share class level. Morningstar receives daily data on NAVs, assets, and returns through direct feeds from fund managers, fund administrators, custodians, trusts, advisors, and fund companies. To construct our sample, we start with all U.S.-domiciled open-end equity mutual funds in the database. We exclude index funds because they attract a particular type of clientele and because Vanguard, the largest index fund provider, does not provide daily flow data to Morningstar. The sample period spans January 2007 through December 2024.

We supplement daily flow data with additional information on fund characteristics (i.e., expenses, turnover, load, and age) from the CRSP survivorship-bias-free Mutual Fund database. To merge Morningstar with CRSP, we first match on CUSIP. When CUSIP is unavailable, we use TICKER, and if neither identifier is available (representing 13% of the sample), we manually match observations using fund and share-class names. After matching, our sample consists of 6,548 funds and 22,076 share classes. At the end of 2024, our sample represents approximately 60% of total assets in active U.S. equity mutual funds. We extract equity style classifications from Morningstar along with their benchmark returns. We aggregate reported variables across share classes at the fund level by value weighting them using lagged total net assets (TNA) of each share class. The average fund in our sample has 4.17 share classes, with more than 91% of funds reporting daily observations for at least two share classes.

To determine clienteles, we map share classes into three categories used by Morningstar and other practitioners: i) retail, ii) retirement, and iii) advisor/institutional, hereafter referred to simply as institutional. We merge institutional and advisor share classes into one group because, in practice, fund families use these labels interchangeably. To do this, we start with the existing Morningstar mappings, but for share classes not categorized by Morningstar, we rely on CRSP classifications.[9] At the end of 2024, the percentages of aggregate assets corresponding to retail, retirement, and institutional groups are 21%, 18%, and 61%, respectively.

[9]CRSP classifies share classes into retail or institutional groups but does not flag retirement classes. We classify non-retail and non-institutional classes as retirement if the fund name has a suffix in the following list: J, K, K6, R, R1, R-1, R2, R-2, R2E, R-2E, R3, R-3, R4, R-4, R5, R-5, R5E, R-5E, R6, R-6, Retire, and Retirement.

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C. Descriptive Statistics

Definitions for key variables of interest appear in the Appendix. With exceptions noted later, most tests are based on the sample of fund-days with net outflows, measured after aggregating flows across all share classes. This is because i) trading costs associated with inflows are borne by both entering and incumbent shareholders, ii) the literature described earlier largely focuses on externalities generated by outflows, and iii) it is relatively inexpensive to equitize inflows in the futures market and then minimize trading costs by slowly purchasing target securities. Descriptive statistics for the outflow-only sample are provided in Table A1.

The average *FlowCorr* in the sample is only 0.20, but its standard deviation is more than twice as large. Given the MA filter used in the decomposition, it is not surprising that the standard deviation of *ExpFlowCorr* is close to its mean (0.16 compared to 0.19), but that the standard deviation of *UnexpFlowCorr* is much higher than its mean (0.39 compared to 0.01). Although *UnexpFlowCorr* is transitory by construction, it is precisely these short-lived deviations that generate immediacy demands, making them economically relevant. The cross-sectional average autocorrelation of *FlowCorr* is 0.10 based on the full sample of all fund days. Also of interest is the distribution of cash buffers, particularly in the context of expected flow correlation. The average cash buffer (*Cash*), defined as the sum of cash and cash equivalents scaled by total assets, is 3.97%.[10] But the standard deviation is more than twice the mean (9.42%), and the median is 1.83%, implying active management of cash levels.

IV. Flow Diversification

A. Determinants of Flow Correlation

We start by examining the determinants of flow correlation. Since our purpose is to broadly understand flow correlation, we use the full panel of fund-day observations, including days with net inflows and outflows. Graph A of Figure 1 shows monthly average *FlowCorr* over the sample period. The long-run average is 0.20 with elevated values during the financial crisis (2008–2009) and other common liquidity shocks. Interestingly, each of the local peaks in the graph corresponds to December. Graph B plots monthly averages and confirms the notable increase in flow correlation in December, consistent with end-of-year portfolio rebalancing and tax-motivated trading by investors. Graph C shows daily flow correlations from 10 days before to 10 days after the end of the month, where day 0 is the last trading day of the month. There is a striking increase in flow correlations 2 days before the last trading day of the month, consistent with a systematic liquidity demand related to the monthly payment cycle termed "dash for cash" by Etula et al. (2020).

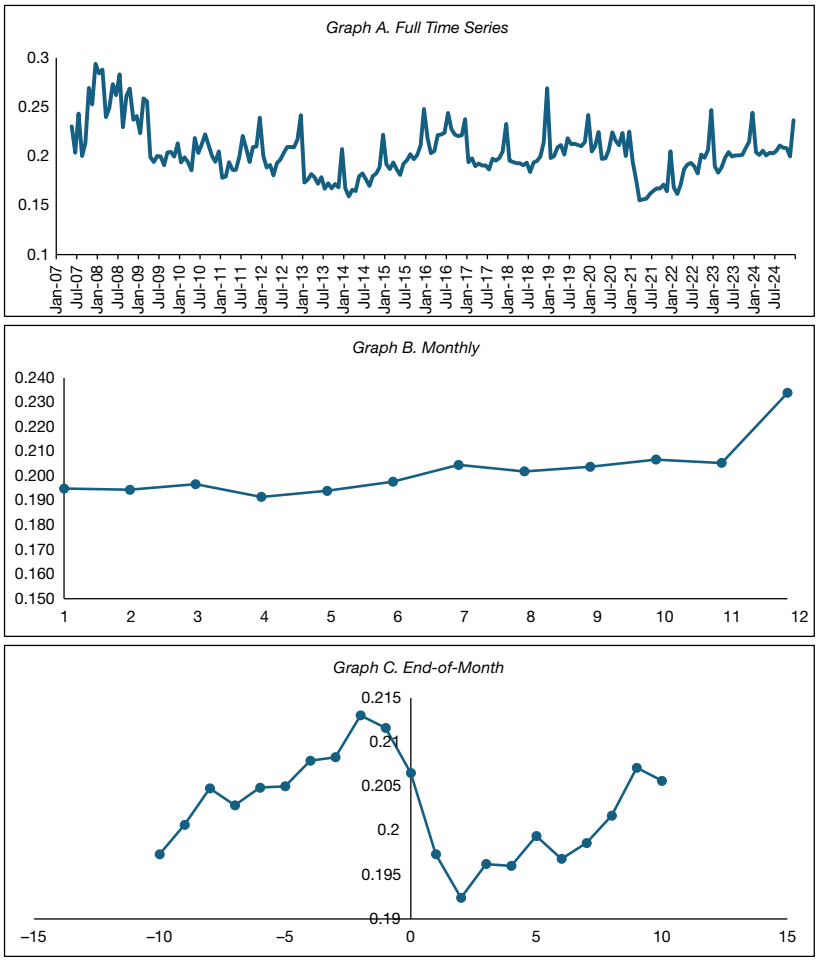
[10]Morningstar cash holdings include cash and cash equivalents and can exceed 100% of total assets for some funds, reflecting securities lending, short positions, or derivatives. To ensure that our results are not driven by these extreme observations, we winsorize *Cash* at the 0.5th and 99.5th percentiles. We use the 99.5th percentile because it provides a conservative upper tail adjustment while preserving economically meaningful variation in cash buffers.

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FIGURE 1

Time-Series Patterns in Flow Correlation

Graph A of Figure 1 plots the monthly average daily flow correlation from January 2007 to December 2024. Graph B reports the average daily flow correlation in each calendar month. Graph C contains the average daily flow correlation from 10 trading days before to 10 trading days after the end of the month (day 0 denotes the last trading day of the month).



Collectively, Graphs B and C imply that flow correlation responds systematically to recurring calendar-based liquidity demands.

A formal regression analysis appears in Table 1. The dependent variable is *FlowCorr* on day *t*, and the independent variables capture the degree to which flow correlation is related to fund-specific attributes, responds to time-varying market conditions, and reflects changes in investor heterogeneity. Column 1 includes fund fixed effects that control for unobservable, time-invariant fund characteristics. Column 2 additionally includes style-quarter fixed effects to absorb any liquidity shocks that may be clustered within each style and quarter. Robust standard errors, clustered at the fund-quarter level, appear in parentheses. We do not include cash

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TABLE 1

Determinants of Flow Diversification

The dependent variable in Table 1 is *FlowCorr* on day *t*, defined as the value-weighted average covariance of flows across share classes, scaled by the average of squared deviations of share-class-level flows from fund-level net flows. Independent variables are defined in the Appendix and are contemporaneous unless specified otherwise. The sample consists of all fund-days over the 2007–2024 period. Robust standard errors, clustered at the fund-quarter level, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
Log (Fund size)	−0.004***	−0.003***	−0.004***	−0.003***	−0.004***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expense ratio	0.027***	0.045***	0.027***	0.045***	0.027***	0.045***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Turnover	−0.006*	−0.005*	−0.006*	−0.005*	−0.006*	−0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Std. Dev. ($Flow_{t-2,\,t}$)	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log (Age)	−0.011***	−0.027***	−0.011***	−0.027***	−0.011***	−0.027***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Load	−0.002	0.577***	−0.002	0.577***	−0.002	0.577***
	(0.144)	(0.166)	(0.144)	(0.166)	(0.144)	(0.166)
Flow-perf. sensitivity	0.000	0.003	0.000	0.003	0.000	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Rm_t	−0.025**	−0.023**	−0.025**	−0.023**	−0.025**	−0.023**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$Rm_{t-3,\,t-1}$	−0.086***	−0.084***	−0.086***	−0.084***	−0.086***	−0.084***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
Sentiment	−0.016***	−0.023***	−0.016***	−0.023***	−0.016***	−0.023***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
December indicator	0.036***	0.034***	0.036***	0.034***	0.036***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Month-end indicator	0.008***	0.007***	0.008***	0.007***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share class increase indicator			−0.021***	−0.019***		
			(0.005)	(0.005)		
Retail class increase indicator					−0.035***	−0.032***
					(0.009)	(0.009)
Institutional class increase indicator					−0.024***	−0.022***
					(0.006)	(0.006)
Retirement class increase indicator					−0.019	−0.019
					(0.016)	(0.016)
Constant	0.255***	0.240***	0.255***	0.240***	0.255***	0.240***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Style-quarter FE		Yes		Yes		Yes
N	8,172,510	8,172,510	8,169,259	8,169,259	8,172,510	8,172,510
Adj-R^2	0.060	0.062	0.060	0.062	0.060	0.062

holdings as a control in these regressions because cash holdings are a managerial response to predictable liquidity risk (see discussion in Section V.A).

Using column 2, larger and older funds have significantly lower flow correlation, consistent with more established funds attracting broader and more heterogeneous investor bases: a 1-standard-deviation increase in fund size and age reduces flow correlation by 4.53% and 14.89%, respectively. By contrast, higher expense ratios and loads are associated with higher flow correlation, consistent with fee structures segmenting investors into more homogeneous clienteles; the corresponding effects are 9.83% and 2.80%, respectively. Higher turnover funds, which trade more frequently and likely attract shorter horizon or performance-sensitive investors, also exhibit more synchronous flows.

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Market-level factors also matter. Contemporaneous and lagged market returns are negatively related to *FlowCorr*, consistent with declining markets generating redemptions across investors. The negative coefficient on sentiment is consistent with mutual fund flows reflecting investor sentiment (Frazzini and Lamont (2008)) and sentiment shifts producing more correlated liquidity demands. The December and month-end indicators are both positive and highly significant, matching the spikes in Figure 1: flow correlation is almost 20% higher in December and 4% higher in the final trading days of the month. These results indicate that broad market conditions and recurring calendar effects contribute meaningfully to synchronized investor liquidity demands.

Columns 3 and 4 add an indicator equal to 1 when a new share class is introduced. The coefficient is −0.02, with a standard error of 0.005, implying a 10% reduction relative to the sample average *FlowCorr* of 0.20. Columns 5 and 6 separate retail, institutional, and retirement class additions. Retail and institutional additions substantially reduce flow correlation, suggesting that new distribution channels introduce investors with liquidity needs less synchronized with existing clienteles. Retirement class additions, which typically attract slow-moving contribution-driven flows, do not significantly affect flow correlation, perhaps because only 258 such additions occur in our sample.

B. Background Externalities and Prerequisites

A number of studies use monthly data to show that large outflows force mutual funds to engage in costly trading, generating an externality for non-redeeming shareholders. However, as discussed in Section II, redemption-driven trading occurs over the next few days (intra-month). We therefore replicate these findings in a daily setting to provide a benchmark for interpreting the economic significance of flow diversification. We form separate quintiles for outflows and inflows on day t and examine returns on $t+1$, $t+2$, and $t+3$ and the cumulative return from $t+1$ to $t+3$. Panel A of Table A2 shows that the difference in $t+1$ to $t+3$ cumulative returns between small versus large outflow quintiles is 1.22 basis points, with a standard error that is one-third of that. In other words, funds experiencing larger outflows have lower subsequent returns. Panels B and C show that these return differences exist in both liquid and illiquid funds. As expected, return differences only exist for fund-days with outflows.

Since our measure of flow correlation is constructed from class-, not investor-level flows, it is important to verify that higher flow correlation is associated with greater flow volatility. To do so, we estimate regressions of subsequent flow volatility on *FlowCorr*. We measure flow volatility using the square root of the sum of squared daily flows over a 3-day window (using a $t+1$ to $t+3$ timing convention) and control for market volatility (VIX), fund size, and past flows. Robust standard errors are clustered at the fund-quarter level. Panel A of Table 2 reports these flow-volatility regressions for fund-days with net outflows. Column 1 presents a univariate regression with fund fixed effects (to absorb time-invariant fund heterogeneity), and column 4 additionally includes day fixed effects (to absorb common volatility spikes). In both specifications, future flow volatility is reliably positively related to *FlowCorr*. Since flow volatility is persistent, the regressions in

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columns 2 and 5 add lagged flow volatility as a predictor. As expected, the coefficient on lagged volatility is positive, but the coefficient on *FlowCorr* remains significantly positive. Lastly, columns 3 and 6 add measures of market volatility (VIX), fund size, and lagged flows. Each successive model is more stringent, and throughout the specifications, the coefficient on *FlowCorr* remains positive.

Flow volatility is a reduced-form proxy for unexpected flows, but we can also assess whether flow correlation is related to unexpected flows directly. One could measure unexpected flows using a time series model, but the median autocorrelation in daily flows is only 0.03, implying that at the daily level, flows are largely unpredictable. To avoid overfitting a weakly persistent process, we use outflows in $t + 1$ as the dependent variable. Panel B of Table 2 reports the results for fund-days with net outflows. In the univariate specifications (with either fund or fund and day fixed effects), the coefficients on *FlowCorr* are -0.229 and -0.163, showing that higher flow correlation, or lower flow diversification, is associated with larger next-day outflows. Adding lagged flow volatility in columns 2 and 5 attenuates the coefficients modestly, confirming the results in Rakowski (2010). In the full specifications that include controls for past flows (which further account for the modest serial correlation in daily flows described previously), fund size, expense ratios, turnover, cash levels, and loads, the coefficients on *FlowCorr* remain statistically significant at -0.249 and -0.177. These estimates imply that a 1-standard-deviation increase in *FlowCorr* is associated with larger next-day redemptions: the implied effects are 3.78% and 4.10% of the mean next-day outflow in the outflow-only sample, respectively.

Overall, the results in Table 2 establish that higher *FlowCorr* is related to both elevated future flow volatility and larger unexpected outflows, the mechanisms through which liquidity externalities arise. These findings validate the central premise of our identification strategy: flow correlation, even when measured through share-class flows rather than investor-level flows, captures economically significant differences in the synchronization of liquidity demands that are not captured by flow volatility alone.

V. The Effects of Flow Diversification

A. Flow Diversification and Cash Buffers

If fund managers recognize that greater flow diversification lowers outflows, then, ceteris paribus, they should optimally hold less precautionary cash. The economic tradeoff underlying this prediction is between holding costly precautionary cash ex ante and incurring trading costs ex post when redemptions arrive. Holding cash creates cash drag, but this cost is relatively predictable and can be managed through the size of the buffer. In contrast, redemption-induced trading may require funds to sell securities quickly, generating explicit trading costs, bid–ask spread, and price impact that reduce fund NAVs. Thus, predictable flow correlation can be incorporated into cash-buffer decisions, whereas higher unexpected flow correlation is more likely to generate short-run trading pressure and lower post-outflow returns.

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TABLE 2

Flow Diversification, Future Flow Volatility, and Subsequent Flows

Table 2 examines whether *FlowCorr* predicts future flow volatility and subsequent outflows. In Panel A, the dependent variable is daily flow volatility (Std. Dev. ($Flow_{t+1,\,t+3}$)), measured as the square root of the sum of squared daily fund flows from $t+1$ to $t+3$. In Panel B, the dependent variable is Fund flow on day $t+1$. Independent variables are defined in the Appendix and are measured at day t unless specified otherwise. *FlowCorr* is the value-weighted average covariance of flows across share classes, scaled by the average of squared deviations of share-class-level flows from fund-level net flows. The sample consists of fund-days with net outflows over the 2007–2024 period. Robust standard errors, clustered at the fund-quarter level, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
Panel A. StdDev($Flow_{t+1,\,t+3}$) Regressions						
FlowCorr	0.680***	0.470***	0.114***	0.433***	0.273***	0.054*
	(0.030)	(0.030)	(0.029)	(0.029)	(0.028)	(0.030)
Std. Dev. ($Flow_{t-2,\,t}$)		0.299***	0.298***		0.290***	0.291***
		(0.024)	(0.024)		(0.024)	(0.024)
$VIX_{t-2,\,t}$			0.001			0.523
			(0.002)			(0.320)
Log (Fund size)			0.634***			0.740***
			(0.043)			(0.038)
Log (Fund flow)			0.475***			0.315***
			(0.045)			(0.037)
Constant	2.607***	1.942***	−9.365***	2.656***	2.001***	−22.188***
	(0.030)	(0.062)	(0.921)	(0.031)	(0.062)	(6.514)
N	5,149,587	5,144,264	5,071,573	5,149,457	5,144,135	5,071,510
Adj-R^2	0.038	0.087	0.087	0.051	0.096	0.096
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE				Yes	Yes	Yes
Panel B. $Flow_{t+1}$ Regressions						
FlowCorr	−0.229***	−0.209***	−0.249***	−0.163***	−0.148***	−0.177***
	(0.020)	(0.022)	(0.025)	(0.019)	(0.021)	(0.023)
Std. Dev. ($Flow_{t-2,\,t}$)		−0.030**	−0.030*		−0.026*	−0.026*
		(0.014)	(0.016)		(0.014)	(0.016)
Fund flow			0.008			0.009
			(0.013)			(0.013)
Log (Fund size)			−1.155***			−1.141***
			(0.036)			(0.037)
Expense ratio			0.392***			0.225***
			(0.083)			(0.078)
Turnover			0.019			0.064
			(0.082)			(0.088)
Cash			−0.005***			−0.006***
			(0.002)			(0.002)
Load			−0.025			0.150***
			(0.041)			(0.042)
Constant	−1.781***	−1.714***	20.359***	−1.793***	−1.735***	20.129***
	(0.018)	(0.036)	(0.707)	(0.018)	(0.036)	(0.703)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE				Yes	Yes	Yes
N	5,121,114	5,116,074	4,741,277	5,120,999	5,115,960	4,741,127
Adj-R^2	0.021	0.022	0.023	0.027	0.028	0.029

We test these predictions in two complementary ways. The first relates end-of-quarter cash buffers to average flow correlation over the quarter (*ExpFlowCorr*). Column 1 of Panel A in Table 3 reports a univariate regression with fund-year fixed effects, and column 3 augments this specification with fund and style-year fixed effects. The coefficients on *ExpFlowCorr* are 0.744 and 0.898, both of which are statistically significant. A 1-standard-deviation increase in *ExpFlowCorr* predicts a 2.78% and 3.35% increase in end-of-quarter cash buffers, respectively. In columns 2 and 4, we add controls for fund size, fund flows over the quarter, fund returns,

TABLE 3

Flow Diversification and Cash Holdings

Panel A of Table 3 contains regressions in which the dependent variable is end-of-quarter cash and cash equivalents scaled by total assets, winsorized at the 0.5th and 99.5th percentiles. The unit of observation is a fund-quarter, and the sample consists of all fund quarters. *ExpFlowCorr* is the average flow correlation over the quarter. Regressions (2) and (4) include the following control variables: Log (Fund size), Log (Fund flow), Fund returns, Std. Dev. (Flow), Expense ratio, Turnover, and Load. In Panel A, robust standard errors clustered at the fund level appear in parentheses. Panel B contains regressions in which the dependent variable is cash on day $t + 20$ minus cash on day $t - 20$. The unit of observation is a fund-day, and the sample consists of all fund-days over the 2007–2024 period. All regressions include the same control variables as in Panel A, measured on day t, with the exception of Std. Dev. ($Flow_{t-2,\,t}$), which uses a 3-day window. The Share Class Increase Indicator is equal to 1 if the number of share classes increases on day t. The Large share class increase indicator is equal to 1 if the number of post-increase share classes is less than or equal to four (i.e., if the number of share classes increases from one, two, or three). The Small share class increase indicator is equal to 1 if the number of post-increase share classes is greater than four. Outflow Indicator is equal to 1 if the fund receives net outflows on day t. In columns 6, 8, and 10, standard errors are clustered at the fund and day level. In columns 5, 7, and 9, standard errors are based on Driscoll and Kraay (1998). Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	Panel A. Regressions of End-of-Quarter Cash				*Panel B. Regressions of Daily Changes in Cash*					
	1	2	3	4	5	6	7	8	9	10
ExpFlowCorr	0.744***	0.384**	0.898***	0.476*	−0.083	−0.099				
	(0.201)	(0.195)	(0.272)	(0.260)	(0.072)	(0.078)				
Share class increase indicator							−0.123**	−0.119**		
							(0.050)	(0.053)		
Large share class increase indicator									−0.216**	−0.217**
									(0.087)	(0.090)
Small share class increase indicator									−0.038	−0.029
									(0.055)	(0.058)
Outflow indicator					0.024**	0.021*				
					(0.011)	(0.011)				
ExpFlowCorr × Outflow					0.170***	0.158**				
					(0.063)	(0.065)				
Controls		Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-year FE	Yes	Yes								
Style-year FE			Yes	Yes						
Fund FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE						Yes		Yes		Yes
N	140,345	130,736	141,240	131,425	8,021,220	8,021,140	8,017,388	8,017,194	8,021,069	8,021,261
Adj-R^2	0.834	0.846	0.691	0.690	0.021	0.021	0.019	0.021	0.019	0.021

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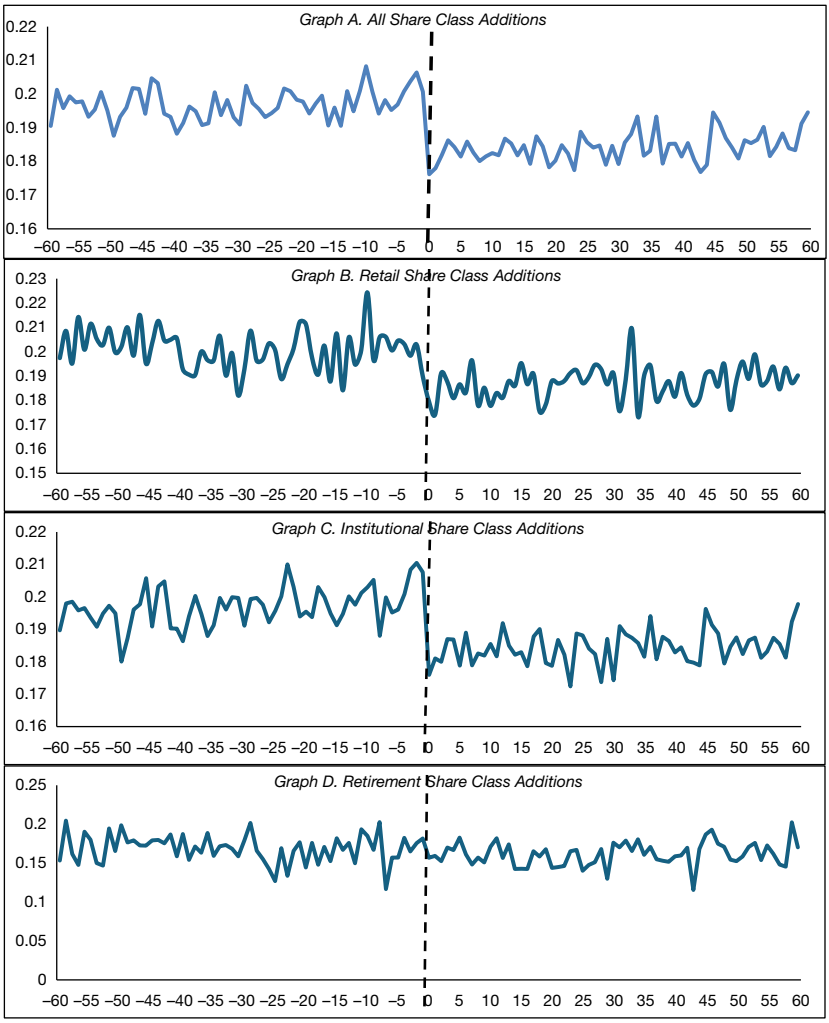
daily flow volatility, expense ratios, loads, and turnover. The inclusion of these controls attenuates the coefficients on *ExpFlowCorr*, but they remain statistically significant.

The second approach exploits changes in clientele composition by examining share-class additions, which should expand the investor base, reduce average flow correlation, and reduce cash buffers. Over our sample period, there are 6,552 share-class additions from a different clientele. Graph A of Figure 2 plots the cross-sectional

FIGURE 2

Change of Flow Correlation Around Share-Class Additions

Figure 2 presents an event-study analysis of flow correlation around share-class additions. Each graph shows average flow correlations from 60 trading days before to 60 trading days after the addition of a share class from a different clientele on day 0. Graph A presents results for all share class additions. Graphs B through D present results separately for retail, institutional/advisor, and retirement share class additions.



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average *FlowCorr* from 60 days before to 60 days after the addition of a share class. The graph shows a 6.39% decrease in flow correlation sharply centered around day 0. Graphs B through D repeat the analysis separately for retail, institutional, and retirement share classes. For retail and institutional additions, we continue to observe large declines in flow correlation around day 0. There is no significant decline around the addition of retirement share classes, likely reflecting the limited number of such events in our sample (only 258 events, compared to 1,834 retail class additions and 4,460 institutional share class additions).

Panel B of Table 3 examines whether these declines in flow correlation translate into reductions in cash buffers. Cash holdings are reported at month- or quarter-end, but share-class additions are not subject to such discreteness. To manage these differing frequencies, we assume that daily cash equals the most recently reported value, updating it when new cash data becomes available. The dependent variable in our regressions is the change in cash buffers from day $t-20$ to day $t+20$.[11] Because this sample includes both inflows and outflows, we first ask whether changes in cash buffers are symmetric for inflows and outflows. Columns 5 and 6 show regressions of change in cash on *ExpFlowCorr*, an indicator variable equal to 1 for outflows, and the interaction between the two variables. Column 5 uses fund fixed effects with standard errors based on Driscoll and Kraay (1998), while column 6 uses fund and day fixed effects with standard errors clustered by fund and day.[12] The interaction term is positive, implying that the relation between predictable flow correlation and changes in cash buffers is stronger for outflows than inflows.

Next, we examine the effect of changes in the number of share classes on changes in cash. Columns 7 and 8 regress this change in cash on an indicator variable equal to 1 if the number of share classes increases on day t with the same set of control variables as in Panel A. In both specifications (that use fund or fund and day fixed effects), share-class additions are associated with a reduction of roughly 3% in cash holdings.

The impact of adding a share class is likely nonlinear and depends on the pre-increase number of share classes. For example, an increase from two to three share classes is quite different from seven to eight. In columns 9 and 10, we replace the share-class increase indicator variable with separate indicators for large and small share-class indicators, in which "large" is defined as cases where the post-increase number of share classes is four or less. The coefficients on large additions remain negative and significant, implying a 5.3% decline in cash holdings. In contrast, the coefficients on small additions are indistinguishable from 0, suggesting that only economically meaningful expansions in clienteles drive reductions in precautionary cash buffers.

[11]Using this convention maximizes the precision in measurement because some cash holdings in the Morningstar database are reported on a monthly basis and others on a quarterly basis.

[12]Because cash holdings are reported at month- or quarter-end and assigned to daily observations until updated, adjacent fund-days may share the same underlying cash observation. In addition, the $t-20$ to $t+20$ cash-change window creates dependence across nearby observations, and cash holdings may be correlated across funds on the same day. We therefore use standard-error adjustments that allow for serial and cross-sectional dependence. Section V.B.2 discusses related inference issues in the return regressions.

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B. The Effects of Flow Diversification on Fund Performance

1. Univariate Sorts and Multivariate Evidence

We start our analysis of flow diversification and fund performance with sorts because they provide model-free and easy-to-interpret summary estimates. In Table 4, we sort all funds with outflows on day t into quintiles based on *FlowCorr*, *UnexpFlowCorr*, and *ExpFlowCorr*, and then compute benchmark-adjusted returns over subsequent horizons. Risk effects are unlikely to be important at short horizons, so factor model alphas are unnecessary. However, since liquidity differences associated with investment styles can be meaningful, we use benchmark-adjusted returns based on each fund's equity style classification. Because flow diversification is measured on day t and trading externalities arise through short-horizon trading costs, we focus on benchmark-adjusted returns over days $t+1$, $t+2$, and $t+3$ and the cumulative return from $t+1$ to $t+3$. Standard errors are computed from the time series of quintile returns with Newey–West adjustments to account for overlapping return windows.

Panel A shows that funds in the lowest *FlowCorr* quintile earn higher subsequent returns than funds in the highest quintile, but the standard errors are large. For example, the 3-day spread in benchmark-adjusted returns between low and high

TABLE 4

Flow Diversification and Short-Horizon Fund Returns

Table 4 reports portfolio sorts that examine the relation between flow diversification and subsequent fund returns. We sort all fund-days with net outflows on day t into quintiles based on *FlowCorr* (Panel A), *UnexpFlowCorr* (Panel B), and *ExpFlowCorr* (Panel C). *FlowCorr* is defined as the value-weighted average covariance of flows across share classes, scaled by the average of squared deviations of share-class-level flows from fund-level net flows. *ExpFlowCorr* is the predictable component of *FlowCorr* based on a backward-looking 60-day moving average, and *UnexpFlowCorr* is the deviation of *FlowCorr* from this predictable component. Table 4 reports benchmark-adjusted returns on $t+1$, $t+2$, $t+3$, the cumulative return from $t+1$ to $t+3$, and the cumulative return from $t+1$ to $t+20$, all in basis points. The last row in each panel shows the difference in returns between low and high quintiles with Newey–West standard errors in parentheses. The last column in each panel reports the time series average of the number of funds in each quintile. The sample consists of all fund-days with net outflows over the 2007–2024 period. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	XR_{t+1}	XR_{t+2}	XR_{t+3}	$XR_{t+1,\,t+3}$	$XR_{t+1,\,t+20}$	No. of Funds
Panel A. Benchmark-Adjusted Returns on Sorts of FlowCorr						
1 (Low)	−1.959	−1.390	−1.400	−4.670	−29.215	230
2	−1.641	−1.254	−1.623	−4.622	−28.742	229
3	−1.566	−1.522	−1.445	−4.514	−28.345	229
4	−1.937	−1.415	−1.564	−4.883	−28.425	229
5 (High)	−2.173	−1.678	−1.491	−5.224	−30.872	229
Low–High	0.214	0.288	0.091	0.554	1.662	
	(0.184)	(0.176)	(0.184)	(0.354)	(1.426)	
Panel B. Benchmark-Adjusted Returns on Sorts of UnexpFlowCorr						
1 (Low)	−1.796	−1.405	−1.281	−4.460	−28.345	230
2	−1.729	−1.301	−1.378	−4.385	−28.049	229
3	−1.781	−1.310	−1.447	−4.616	−27.210	229
4	−1.859	−1.413	−1.790	−4.828	−28.242	229
5 (High)	−2.247	−1.796	−1.543	−5.534	−32.654	229
Low–High	0.451**	0.391**	0.262	1.071***	4.128***	
	(0.182)	(0.168)	(0.163)	(0.297)	(1.098)	
Panel C. Benchmark-Adjusted Returns on Sorts of ExpFlowCorr						
1 (Low)	−2.077	−1.599	−1.643	−5.458	−31.400	230
2	−1.975	−1.493	−1.628	−4.895	−29.382	229
3	−1.738	−1.135	−1.306	−4.138	−27.581	229
4	−1.652	−1.338	−1.341	−4.284	−27.458	229
5 (High)	−1.996	−1.604	−1.532	−4.981	−29.389	229
Low–high	−0.080	0.005	−0.110	−0.467	−1.461	
	(0.220)	(0.191)	(0.196)	(0.426)	(2.634)	

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FlowCorr quintiles is 0.55 basis points with a standard error of 0.35. The muted relation is unsurprising because the permanent component of *FlowCorr* is anticipated by fund managers and baked into cash buffers, reducing the need for immediate trading. Panel B shows quintiles based on *UnexpFlowCorr* and reveals a starkly different picture. Here we observe a strong, monotonic relation between unexpected flow correlation and subsequent returns; the 3-day benchmark-adjusted return spread between the lowest and highest *UnexpFlowCorr* quintiles is 1.07 basis points with a standard error of 0.30. By contrast, Panel C shows no meaningful difference in benchmark-adjusted returns across quintiles formed on *ExpFlowCorr*, consistent with the interpretation that fund managers understand predictable flow patterns from their share-class-based clientele and adjust cash buffers accordingly.

It is uncommon to measure trading-cost effects over longer horizons because cumulating returns over many days introduces substantial noise. Nonetheless, we examine returns over a 20-trading-day horizon for two reasons. First, a longer horizon allows us to verify that the return differences associated with flow diversification are not reversed, ensuring that the benefits accrue to longer term shareholders. Second, the 20-day horizon provides a useful bridge to the monthly return frequencies commonly used in the mutual fund literature. The last column in each panel in Table 4 shows results using 20-day benchmark-adjusted returns with 19 lags used in the Newey–West standard errors. In Panel A, the difference in returns between the low and high *FlowCorr* quintiles rises to 1.66 basis points but with a standard error of 1.43; the equivalent spread in returns for *UnexpFlowCorr* quintiles quadruples relative to the 3-day window, reaching 4.13 basis points with a standard error of 1.10. This indicates that the return differences associated with unexpected flow correlation are not transitory.

Table 5 complements the previous evidence with regressions of 3-day cumulative benchmark-adjusted returns (in basis points) on prior flow correlation measures. The regressions allow us to explicitly control for outflows on day t, as well as other covariates that may affect short-horizon fund returns. In addition to the usual controls, two variables are of particular importance. First, including cash buffers ensures that flow diversification is relevant beyond precautionary cash holdings. Second, lagged flow volatility isolates the influence of flow diversification from the broader flow volatility channel. Even with these control variables, a remaining concern is that unobservable fund-manager skill could be correlated with flow diversification, creating an omitted-variable bias. In column 1, we use fund fixed effects to absorb the variation in returns due to skill. Given our return measures are constructed over overlapping short-horizon windows, fund fixed effects also allow us to exploit within-fund variation over time without restricting identification to within-quarter changes. Column 2 adds day fixed effects to capture common liquidity or market-wide shocks on certain days.

Unlike the sorts, the multivariate regressions reveal a statistically significant negative relationship between *FlowCorr* and subsequent returns. In columns 1 and 2, the coefficients on *FlowCorr* are -0.44 and -0.52 with standard errors of 0.13 and 0.12; a 1-standard-deviation decrease in *FlowCorr* is associated with a 3.88% and a 4.53% increase in the average 3-day benchmark-adjusted return, respectively. Columns 3 and 4 replace *FlowCorr* with its decomposed counterparts. Consistent with the portfolio sorting results in Table 4, the coefficients on *UnexpFlowCorr* are

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TABLE 5

Flow Diversification and Short-Horizon Fund Returns: Multivariate Regressions

Table 5 contains panel regressions in which the dependent variable is the 3-day cumulative benchmark-adjusted return from $t+1$ to $t+3$ in basis points. Columns 1 and 2 use *FlowCorr* measured on day *t*. Columns 3 and 4 decompose *FlowCorr* into *ExpFlowCorr* and *UnexpFlowCorr* using a backward-looking 60-day moving-average filter, measured from $t-61$ to $t-1$, corresponding to one quarter. Other independent variables are defined in the Appendix and are measured at day *t* unless specified otherwise. The sample consists of fund-days with net outflows over the 2007–2024 period. Robust standard errors, clustered at the fund-quarter level, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4
FlowCorr	−0.443***	−0.517***		
	(0.128)	(0.121)		
ExpFlowCorr			0.004	−0.024
			(0.600)	(0.577)
UnexpFlowCorr			−0.480***	−0.557***
			(0.129)	(0.122)
Log (Fund size)	−1.893***	−2.005***	−1.889***	−2.000***
	(0.122)	(0.119)	(0.122)	(0.119)
Log (Fund flow)	0.056	−0.031	0.055	−0.032
	(0.041)	(0.038)	(0.041)	(0.038)
Expense ratio	2.075***	1.074	2.059***	1.050
	(0.681)	(0.744)	(0.680)	(0.743)
Turnover	−0.008	−0.010	−0.008	−0.010
	(0.039)	(0.040)	(0.039)	(0.040)
Std. Dev. ($\text{Flow}_{t-2,\,t}$)	0.002	−0.001	0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Cash	−0.022	−0.027	−0.022	−0.027
	(0.024)	(0.023)	(0.024)	(0.023)
Load	1.292***	−0.175	1.292***	−0.176
	(0.263)	(0.276)	(0.263)	(0.276)
Constant	29.456***	33.713***	29.296***	33.558***
	(2.559)	(2.488)	(2.558)	(2.489)
Fund FE	Yes	Yes	Yes	Yes
Day FE		Yes		Yes
N	4,648,066	4,647,985	4,648,066	4,647,985
Adj-R^2	0.003	0.104	0.003	0.104

negative and statistically significant, while the coefficient on *ExpFlowCorr* is indistinguishable from 0. A 1-standard-deviation decrease in *UnexpFlowCorr* implies a 3% improvement in the 3-day benchmark-adjusted return (0.22 basis points). Table 6 extends the analysis to 20-day benchmark-adjusted returns (in percentage), allowing us to assess whether the trading-cost effects associated with flow diversification persist rather than reverse. The coefficients on *FlowCorr* remain negative and statistically significant. Moreover, decomposing *FlowCorr* again reveals that the predictive power resides in *UnexpFlowCorr*: the coefficient on *ExpFlowCorr* remains statistically indistinguishable from 0, while the coefficient on *UnexpFlowCorr* continues to be negative and statistically significant. Quantitatively, a 1-standard-deviation decrease in *UnexpFlowCorr* implies a 1.5% increase in the 20-day benchmark-adjusted return (0.47 basis points).

Taken together, the return evidence in this section and the cash-holding results in Section V.A support the interpretation that predictable differences in flow correlation are partly absorbed through managerial liquidity management, while unexpected increases in flow correlation are associated with lower post-outflow returns.

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TABLE 6

Flow Diversification and 20-Day Benchmark-Adjusted Fund Returns

Table 6 reports panel regressions in which the dependent variable is the 20-day cumulative benchmark-adjusted return from $t+1$ to $t+20$ in percentage. Columns 1 and 2 use *FlowCorr* measured on day t. Columns 3 and 4 decompose *FlowCorr* into *ExpFlowCorr* and *UnexpFlowCorr* using a backward-looking 60-day moving-average filter, measured from $t-61$ to $t-1$, corresponding to one quarter. Other independent variables are defined in the Appendix and are measured at day t unless specified otherwise. The sample consists of fund-days with net outflows over the 2007–2024 period. Robust standard errors, clustered at the fund-quarter level, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4
FlowCorr	−0.010**	−0.010**		
	(0.004)	(0.004)		
ExpFlowCorr			0.010	0.017
			(0.036)	(0.035)
UnexpFlowCorr			−0.012***	−0.012***
			(0.004)	(0.003)
Log (Fund size)	−0.151***	−0.151***	−0.151***	−0.151***
	(0.008)	(0.008)	(0.008)	(0.008)
Log (Fund flow)	0.010***	0.003***	0.010***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Expense ratio	0.082*	0.042	0.082*	0.041
	(0.046)	(0.051)	(0.046)	(0.050)
Turnover	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Std. Dev. ($Flow_{t-2,\,t}$)	0.000***	−0.000***	0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash	−0.002	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Load	0.086***	−0.019	0.086***	−0.019
	(0.019)	(0.020)	(0.019)	(0.020)
Constant	2.534***	2.656***	2.527***	2.647***
	(0.162)	(0.159)	(0.161)	(0.158)
Fund FE	Yes	Yes	Yes	Yes
Day FE		Yes		Yes
N	4,329,763	4,329,747	4,329,763	4,329,747
Adj-R^2	0.022	0.115	0.022	0.115

2. Statistical Inference and Economic Magnitudes

In Tables 5 and 6, inference is based on robust standard errors clustered at the fund-quarter level. Because overlapping return windows and panel dependence may affect inference, Table A3 reports alternative specifications using Driscoll–Kraay standard errors, clustering by fund, and two-way clustering by fund and day. Across all specifications, the statistical significance of *UnexpFlowCorr* is unchanged.

Moving from statistical inference to economic quantities, several comparisons help contextualize the size of the effects. The baseline impact of large outflows on returns is about 1.22 basis points (Table A2), and the sort-based performance spread associated with unexpected flow correlation is 1.07 basis points (Table 4). Thus, the mitigation of liquidity externalities due to flow diversification is of the same order of magnitude as the externality it offsets. A second benchmark is the underperformance attributable to flow volatility documented by Rakowski (2010). His estimates come from regressions using daily data and show that the difference in 3-factor alphas between low and high flow volatility quartiles is 0.89 basis points per day (as reported in his Table 3), again comparable to the performance spread in Table 4.

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One concern is that because daily *FlowCorr* is volatile, it may have limited influence on managerial decisions or longer term performance.[13] Several considerations indicate otherwise. First, our decomposition shows that daily *FlowCorr* contains an average component relevant for managerial decisions. Table 3 shows that higher *ExpFlowCorr* is associated with higher cash buffers, consistent with managers incorporating predictable flow correlation into liquidity management. Second, the longer horizon return effects are also meaningful. The 20-day return spread associated with unexpected flow correlation is 4.13 basis points, about 24%–34% of the next-month outflow effect reported by Chen, Goldstein, and Jiang (2010) for the least liquid funds.[14]

Our results imply that predictable differences in flow correlation are incorporated into liquidity management, but managers' ability to influence flow diversification is limited. In practice, the main levers available to managers are the creation of new share classes and the opening of additional distribution channels, both of which can broaden the clientele base and alter expected flow patterns. Unexpected synchronization in individual investors' liquidity needs, however, is harder to manage directly. This limitation motivates the exploration of alternative architectural mechanisms through which asset managers or regulators might mitigate outflow externalities. We turn to these next.

C. Alternative Mechanisms

Several mechanisms can mitigate redemption-induced trading. Swing pricing shifts trading costs from remaining investors to redeeming shareholders (Jin, Kacperczyk, Kahraman, and Suntheim (2022)), although none of the U.S. equity funds in our sample employ swing pricing based on N-CEN filings from 2019 to 2024. Redemption-in-kind allows funds to meet redemptions by transferring securities rather than selling them, but actual usage is rare: Agarwal, Ren, Shen, and Zhao (2023) document only 2,985 redemptions-in-kind across 58,443 fund-years. Asset managers have also converted mutual funds into ETFs, which use in-kind redemption processes to reduce trading and tax externalities under Rule 6c-11 (Du, Starks, and Xiaolan (2023)). Relatedly, the expiration of Vanguard's patent on ETFs as a share class in 2023 has prompted some asset managers to seek regulatory approval to include ETFs as a share class within a mutual fund.[15] These mechanisms share a common objective: shifting trading activity away from the fund.

Our results indicate that flow diversification itself operates as a natural buffer. While redemptions create immediacy demands that can depress fund returns,

[13]Of course, a variable need not be persistent to be economically important on an ex ante basis. As a case in point, the daily market risk premium is not predictable, and yet portfolio managers routinely equitize cash inflows because of the *expected* underperformance of being in cash.

[14]The performance degradation in Chen, Goldstein, and Jiang (2010) is for the most illiquid funds, whereas ours are based on the full sample of all funds, implying that this comparison is, if anything, conservative.

[15]Funds that are granted dual-class permission give mutual fund investors an exchange privilege that permits them to trade their mutual fund holdings for the equivalent ETF share class without triggering capital gains distributions. The "cost" of the subsequent shared tax exposure is that ETF shareholders could pay for taxes on gains that they would otherwise not be exposed to (see, e.g., https://www.morningstar.com/funds/etf-share-classes-are-go-dimensional-heres-what-investors-need-know).

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greater heterogeneity in investor liquidity needs reduces the likelihood that redemptions arrive simultaneously. This mitigating effect is particularly important in settings where shareholders anticipate the redemptions of others, since such expectations can generate multiplier effects or shareholder runs, contributing to fragility in financial markets. We turn to this next.

D. Multiplier Effects

Chen, Goldstein, and Jiang (2010) argue that investors in illiquid funds face a higher degree of strategic complementarity because redemptions from illiquid assets impose larger trading costs on remaining shareholders. Exploiting this insight, their test of strategic complementarity consists of regressions of flows on prior performance in which the key explanatory variable is the interaction between an illiquidity indicator and prior performance.

If a fund has diversified flows, then shareholders may be less concerned with the exit of other investors, weakening strategic complementarities. This intuition translates into two tests. First, we aim to determine whether funds with higher flow diversification have lower flow-performance sensitivity, notwithstanding the higher flow-performance sensitivity of illiquid funds. Second, we ask whether flow-performance sensitivities in illiquid funds vary with flow diversification; in other words, can flow diversification at least partially offset strategic complementarities, even when they exist? To implement these tests, we make two modifications to the Chen, Goldstein, and Jiang (2010) approach. First, because we use higher frequency daily flow data to measure liquidity effects, we measure performance over the prior 3 days rather than using alphas from a factor model.[16] Second, we estimate regressions at the fund rather than the share-class level to align our fund-level flow correlation measure built from share-class flows. Aside from these changes, the regressions closely mirror Table 2 and contain the same set of control variables. Our key additions are i) an indicator variable *FlowCorr*(I), equal to 1 for funds with higher flow correlation (above median) or lower flow diversification; ii) interaction terms between *FlowCorr*(I) and prior performance; and iii) triple interaction terms between *FlowCorr*(I), prior performance, and the illiquidity indicator. We estimate these regressions separately for the fund-days with inflows versus outflows because strategic complementarities should be most relevant for outflows.

Panels A and B of Table 7 report results for outflows and inflows, respectively. The dependent variable is winsorized proportional fund flows (at the 1st and 99th percentiles). The first two columns in each panel include fund fixed effects, while the last two columns add day fixed effects to absorb common shocks in the time series. Across all specifications, the interaction term between the illiquidity indicator and prior performance is positive and statistically significant, replicating the

[16]Daily data are more precise to measure liquidity effects but likely poorer in measuring flow-performance sensitivities. Chen, Goldstein, and Jiang (2010) use factor models and style-adjusted excess returns measured over the past 6 months. However, there is little theoretical guidance on the appropriate lookback period for flow-performance sensitivities, so all choices are somewhat arbitrary. We use a 3-day period to roughly correspond to tests in earlier tables. The results are similar using a 10-day window.

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TABLE 7

Daily Flow-Performance Regressions

Table 7 reports regressions of daily fund flows on prior fund performance, flow correlation, asset illiquidity, and their interactions. The dependent variable is proportional flow on day *t*, winsorized at the 1st and 99th percentiles. *Perf.* is the cumulative fund return over the prior 3 days. Panel A reports results for fund-days with cumulative outflows over the prior 3 days, and Panel B reports results for fund-days with cumulative inflows over the prior 3 days. *FlowCorr(I)* is an indicator equal to 1 for funds with higher flow correlation (above median) or lower flow diversification. The *Illiq. Indicator* is defined by Chen, Goldstein, and Jiang (2010). All regressions include the following control variables: Log (Fund flow), Log (Fund size), Expense ratio, Turnover, Std. Dev. (Flow), Log (Age), and Load. Control variables are defined in the Appendix and measured on day $t-1$, with the exception of Std. Dev. (Flow), which is measured over a 3-day window. Standard errors, clustered at the fund-quarter level, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	Panel A. Prior 3-Day Outflows				*Panel B. Prior 3-Day Inflows*			
	1	2	3	4	5	6	7	8
Perf.	0.358***	0.392***	0.170***	0.200***	0.394***	0.379***	0.385***	0.367***
	(0.017)	(0.018)	(0.030)	(0.030)	(0.027)	(0.027)	(0.044)	(0.044)
Illiq. indicator	0.006	0.007*	0.003	0.004	0.001	−0.000	−0.000	−0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Perf. * Illiq. indicator	0.116***	0.054**	0.166***	0.113***	0.059*	0.085**	0.092***	0.121***
	(0.022)	(0.025)	(0.022)	(0.025)	(0.034)	(0.036)	(0.035)	(0.037)
FlowCorr(I)	0.009***	0.009***	0.008***	0.009***	0.014***	0.013***	0.012***	0.011***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perf. * *FlowCorr*(I)	0.098***	0.035	0.084***	0.029	0.265***	0.299***	0.270***	0.307***
	(0.016)	(0.022)	(0.016)	(0.021)	(0.024)	(0.038)	(0.024)	(0.037)
Illiq. Indicator * *FlowCorr*(I)		−0.001		−0.001		0.002		0.001
		(0.001)		(0.001)		(0.001)		(0.001)
Illiq. Indicator * *FlowCorr*(I) * Perf.		0.116***		0.100***		−0.056		−0.064
		(0.032)		(0.031)		(0.049)		(0.049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes			Yes	Yes		
Fund FE and Day FE			Yes	Yes			Yes	Yes
N	5,062,421	5,062,421	5,062,014	5,062,014	3,213,593	3,213,593	3,213,296	3,213,296
Adj-R^2	0.025	0.025	0.036	0.036	0.072	0.072	0.080	0.080

results in Chen, Goldstein, and Jiang (2010). Using monthly data, their estimates imply that flow-performance sensitivity is 52% higher in illiquid funds; by comparison, in column 3 with fund and day fixed effects, the equivalent increase in flow-performance sensitivity is 49.4% (0.166/(0.170 + 0.166)), remarkably similar in magnitude.

Columns 1 and 3 show that the interactions between *FlowCorr*(I) and prior performance are positive and significant, indicating that flow-performance sensitivity is higher in funds with larger flow correlation. In column 3, which includes fund and day fixed effects, the magnitude of this difference is economically meaningful: dividing the coefficient on the interaction between *FlowCorr*(I) and *Perf.* by the coefficient on *Perf.* alone implies that flow-performance sensitivity is 49% (0.084/0.170) higher for funds with lower flow diversification. Panel B shows a similar positive interaction for inflows, suggesting that less diversified clienteles may be more performance-sensitive. These results show that even in the presence of strategic complementarities, flow diversification continues to play an important mitigating role.

We next turn to the specifications most relevant for our mechanism, which include the triple interaction terms between *FlowCorr*(I), prior performance, and the illiquidity indicator. The goal is to ask whether flow-performance sensitivities in illiquid funds vary with flow diversification. Across all columns in Panel A, the

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coefficients on the triple interaction are significantly positive, indicating that illiquid funds with low flow diversification exhibit the strongest strategic complementarities. In column 4, which includes fund and day fixed effects, the flow-performance sensitivity of illiquid funds with high flow diversification is 0.200 + 0.113 = 0.313. For low flow-diversification funds, the coefficient on the triple interaction is 0.100, implying that the increase in flow-performance sensitivity is almost 31% higher (0.100/0.313). In contrast, in Panel B, the triple interaction effect is indistinguishable from 0. Taken together, these results indicate that while low flow diversification is associated with greater performance sensitivity more generally, the amplification of strategic complementarities in illiquid funds is concentrated in outflows, where redemption externalities are most relevant.

E. Alternative Measures of Flow Diversification

As robustness checks, we consider two alternative approaches that vary either by the weighting scheme or the underlying construction of flow diversification. The first alternative replaces value weights with equal weights while using proportional (instead of dollar) flows. Panel A of Table A4 shows that performance regressions using this measure generate very similar inferences. The second alternative measure focuses on flow imbalance, summing signed dollar flows across the K share classes and scaling by the sum of their absolute values. The measure is analogous to order imbalance in the market microstructure literature and resides in the interval $(-1,+1)$. Since the numerator is signed, the measure is negative when a fund has outflows, and as a result, higher flow imbalance in absolute value (distance from 0) indicates less offsetting flow across share classes and hence lower flow diversification. Because our focus is on outflows, we use the absolute value of flow imbalance in our tests ($|FlowImb|$). The regression results in Panel B of Table A4 also show a negative coefficient on the unexpected component of $|FlowImb|$, but the coefficient on the expected component is indistinguishable from 0.

VI. Conclusion

The pooling of claims in mutual funds, combined with redemption-on-demand, generates liquidity externalities: transaction costs generated by existing shareholders are passed on to non-redeeming shareholders. A large literature documents that redemptions transmit trading costs, amplify illiquidity, and in some settings induce strategic complementarities that can generate fragility. In this article, we study a mechanism that mitigates these externalities. When liquidity needs across investors and investor clienteles are imperfectly correlated, funds benefit from flow diversification: outflows from one client or clientele can be offset by inflows from another, thereby reducing daily flow volatility and lowering unexpected outflows. This leads to lower immediacy requirements, mitigating the liquidity externality inherent in the mutual fund structure.

We develop a novel measure of flow diversification using share-class-level variation in daily flows. Funds with more diversified flows experience lower future flow volatility, have smaller subsequent outflows, and hold smaller cash buffers. While predictable differences are absorbed through managerial liquidity

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management, unexpected increases in flow correlation are associated with lower post-outflow returns. The magnitude of the return spread associated with unexpected flow diversification is comparable to the liquidity externality itself, underscoring its relevance for both investors and asset managers.

Our findings show that liquidity provision in delegated asset management depends not only on portfolio liquidity but also on the correlation structure of investor liquidity demands. By highlighting investor heterogeneity as a natural buffer against redemption externalities, the paper connects flow-performance sensitivity, strategic complementarities, and emerging fund-design innovations such as share-class engineering and fund-to-ETF conversions.

Appendix

Variable Definitions

FlowCorr: Value-weighted average pairwise cross-product of deviations of share-class-level flows from fund-level net flows, scaled by the average squared value-weighted deviation across share classes.

ExpFlowCorr: The expected (permanent) component of *FlowCorr*, based on a backward-looking moving average (MA) process of order q, with $q = 60$.

UnexpFlowCorr: The unexpected (transitory) component of *FlowCorr*, defined as the difference between *FlowCorr* and *ExpFlowCorr*.

Log (Fund size): The natural logarithm of the fund's daily total net assets (in $ million).

Fund flow: Daily dollar fund flow, aggregated across share classes (in $ million).

Log (Fund flow): The natural logarithm of the absolute value of the fund's daily dollar flows.

Proportional flow (%): Daily fund flow scaled by the fund's total net assets.

No. of share classes: The number of share classes associated with a fund on day t.

Expense ratio (%): Expense ratio in percentage.

Turnover: Turnover ratio.

Age: Fund age in months.

Std. Dev. (Flow): The square root of the sum of squared daily dollar flows over three consecutive days.

Load (%): The sum of a fund's front-end load and back-end load in percentage.

Cash (%): Cash and cash equivalents scaled by total assets. Cash equivalents include short-term instruments such as time deposits, commercial paper, money market funds, repurchase agreements, Treasury bills and bonds with nominal maturity below 92 days, currencies, and currency derivatives.

Flow-perf. Sensitivity: The slope of a regression of daily fund flows on 3-day past returns using a 60-day rolling window, requiring at least 20 observations.

Rm: S&P500 daily index returns.

$R_{t+1,\,t+n}$: Cumulative fund returns from $t + 1$ to $t + n$.

$XR_{t+1,\,t+n}$: Cumulative benchmark-adjusted fund returns from $t + 1$ to $t + n$, where the benchmark is the Morningstar assigned benchmark for the fund.

TABLE A1

Descriptive Statistics

Table A1 reports descriptive statistics for the main variables used in the article. Variable definitions appear in the Appendix. *FlowCorr* measures daily flow correlation across share classes and is decomposed into an expected component (*ExpFlowCorr*), defined as a backward-looking 60-trading-day moving average, and an unexpected component (*UnexpFlowCorr*), defined as the residual. Proportional flow is winsorized at the 1st and 99th percentiles, and Cash is winsorized at the 0.5th and 99.5th percentiles. The sample consists of all fund-days with net outflows over the 2007–2024 period.

	Mean	Median	Std. Dev.	Min	p1	p10	p25	p75	p90	p99	Max
FlowCorr	0.203	0.226	0.426	−1	−0.977	−0.324	−0.041	0.481	0.749	0.999	1
ExpFlowCorr	0.192	0.177	0.165	−1	−0.167	0.004	0.084	0.288	0.401	0.657	1
UnexpFlowCorr	0.011	0.035	0.394	−1.947	−1.068	−0.486	−0.198	0.234	0.473	0.945	1.598
Fund flow ($million)	−1.83	−0.17	33.56	−22,687.93	−23.66	−2.23	−0.67	−0.03	−0.01	0.00	0.00
Proportional flow (%)	−0.142	−0.053	0.304	−1.884	−1.884	−0.280	−0.114	−0.023	−0.009	−0.001	0.000
Fund size ($ million)	1,479.65	309.94	6,820.15	<0.001	1.77	19.61	78.29	1,046.07	2,797.27	17,444.08	307,889.20
Std. Dev. ($Flow_{t-2,\,t}$)	2.372	0.279	31.746	0	0.001	0.017	0.074	0.969	3.179	32.685	17,388.290
Expense ratio (%)	1.126	1.087	0.393	<0.001	0.181	0.708	0.901	1.324	1.588	2.256	6.477
Turnover	0.786	0.520	5.318	<0.001	0.030	0.160	0.290	0.894	1.410	4.380	843.870
Load (%)	0.732	0.333	0.913	0	0	0	0	1.222	2.281	3.257	5.211
Age (months)	17.834	16.011	12.744	0.003	0.611	4.175	9.096	23.688	31.197	70.293	100.532
Cash (%)	3.970	1.828	9.423	0	0	0.065	0.709	3.629	6.871	56.047	90.669
No. of share classes	4.17	4	2.19	2	2	2	2	5	7	11	21
$R_{t+1,\,t+3}$ (bp)	10.840	20.903	236.71	−6,453.16	−708.90	−239.68	−91.92	125.69	247.06	617.90	12,423.41
$XR_{t+1,\,t+3}$ (bp)	−4.864	−3.447	105.64	−6,422.99	−309.02	−104.83	−44.34	35.69	92.57	289.74	12,657.44
$R_{t+1,\,t+20}$ (%)	0.723	1.189	5.81	−90.76	−18.83	−5.55	−1.85	3.79	6.55	14.64	142.73
$XR_{t+1,\,t+20}$ (%)	−0.301	−0.207	2.54	−92.61	−7.76	−2.90	−1.31	0.79	2.14	6.52	145.61

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$VIX_{t-2,t}$: Average daily VIX index from $t-2$ to t.

Sentiment: The monthly change in the University of Michigan Index of Consumer Sentiment.

Perf: Cumulative fund return over the prior 3 days.

Indicator Variables

December: A dummy variable equal to 1 if the month is December, and 0 otherwise.

Month-end: A dummy variable equal to 1 if day t is in the last three trading days of the month, and 0 otherwise.

Share class increase: A dummy variable equal to 1 if there is an increase in the number of share classes on day t, and 0 otherwise.

Retail class increase: A dummy variable equal to 1 if a retail share class is added on day t and no such class existed prior and 0 otherwise.

Institutional class increase: A dummy variable equal to 1 if an institutional/advisor share class is added on day t and no such class existed prior and 0 otherwise.

Retirement class increase: A dummy variable equal to 1 if a retirement share class is added on day t and no such class existed prior, and 0 otherwise.

Large share class increase: A dummy variable equal to 1 if the number of post-increase share classes is less than or equal to four.

Small share class increase: A dummy variable equal to 1 if the number of post-increase share classes is more than four.

FlowCorr(I): A dummy variable equal to 1 if *FlowCorr* is above the sample median.

TABLE A2

Post-Flow Average Benchmark-Adjusted Returns

Table A2 reports benchmark-adjusted fund returns following days with net inflows and net outflows. On each day t, funds are first sorted into inflow and outflow groups, and then into quintiles based on the magnitude of their proportional flows. For outflows, Q1 refers to the quintile with the largest redemptions, while Q5 refers to the quintile with the smallest redemptions. For inflows, Q1 refers to the quintile with the smallest inflows, while Q5 refers to the quintile with the largest inflows. The last row in each panel shows the return spread (5–1). Table A2 reports average benchmark-adjusted returns for $t+1$, $t+2$, $t+3$, and the cumulative benchmark-adjusted return from $t+1$ to $t+3$, all in basis points. Panel B reports results for illiquid funds, defined as small-cap, mid-cap, and single country ex-U.S. funds. Panel C contains results for all remaining (i.e., liquid) funds. The sample consists of all fund-days over the 2007–2024 period. Newey–West standard errors appear in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	Outflows				Inflows			
	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,t+3}$	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,t+3}$
Panel A. All Funds								
1 (Large redemptions/ Small inflows)	−2.151	−1.764	−1.705	−5.556	−1.309	−1.554	−1.539	−4.308
2	−2.168	−1.464	−1.403	−4.925	−0.699	−1.437	−1.476	−3.499
3	−2.043	−1.304	−1.479	−4.705	−0.658	−1.436	−1.478	−3.432
4	−1.626	−1.506	−1.419	−4.473	−0.944	−1.359	−1.491	−3.664
5 (Small redemptions/ Large inflows)	−1.576	−1.404	−1.554	−4.339	−0.965	−1.626	−1.743	−4.155
5–1	0.575**	0.359*	0.151	1.217***	0.344	−0.072	−0.204	0.153
	(0.231)	(0.201)	(0.224)	(0.401)	(0.220)	(0.232)	(0.204)	(0.441)

(continued on next page)

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TABLE A2 (continued)

Post-Flow Average Benchmark-Adjusted Returns

	Outflows				Inflows			
	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,t+3}$	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,t+3}$
Panel B. Illiquid Funds								
1 (Large redemptions/ Small inflows)	−2.856	−2.477	−2.298	−7.482	−1.994	−2.201	−2.109	−6.109
2	−2.830	−2.048	−2.194	−6.840	−1.581	−2.243	−2.092	−5.700
3	−2.848	−2.047	−2.403	−7.041	−1.265	−1.889	−2.101	−5.016
4	−2.594	−2.049	−2.005	−6.411	−1.347	−1.970	−2.244	−5.367
5 (Small redemptions/ Large inflows)	−2.005	−2.125	−2.166	−6.021	−1.309	−1.813	−2.193	−5.053
5–1	0.851***	0.352	0.132	1.461***	0.686**	0.388	−0.084	1.056*
	(0.272)	(0.274)	(0.268)	(0.533)	(0.292)	(0.286)	(0.283)	(0.556)
Panel C: Liquid Funds								
1 (Large redemptions/ Small inflows)	−1.249	−1.032	−0.918	−3.160	−0.494	−0.576	−0.671	−1.758
2	−1.449	−0.641	−0.657	−2.736	0.061	−0.659	−0.735	−1.356
3	−1.108	−0.584	−0.705	−2.421	0.025	−0.517	−0.746	−1.238
4	−0.748	−0.718	−0.641	−2.086	−0.355	−0.647	−0.638	−1.611
5 (Small redemptions/ Large inflows)	−0.948	−0.729	−0.662	−2.262	−0.225	−0.737	−0.836	−1.840
5–1	0.301	0.303*	0.257	0.898**	0.269	−0.161	−0.165	−0.081
	(0.184)	(0.172)	(0.178)	(0.361)	(0.210)	(0.214)	(0.207)	(0.409)

TABLE A3

Regressions of Benchmark-Adjusted Returns on Flow Correlation with Alternative Standard Errors

Table A3 shows return regressions analogous to those in Tables 5 and 6 using alternative methods for computing standard errors. The dependent variable is the benchmark-adjusted fund return measured over either a 3-day ($t+1$ to $t+3$) or 20-day ($t+1$ to $t+20$) horizon following day t. Columns 1 and 2 report regressions with fund fixed effects and Driscoll–Kraay standard errors. Columns 3 and 4 report regressions with fund and day fixed effects and standard errors clustered by fund. Columns 5 and 6 report regressions with fund and day fixed effects and standard errors clustered by fund and day. All regressions include the same control variables as in Tables 5 and 6. The sample consists of fund-days with net outflows over the 2007–2024 period. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	$XR_{t+1,t+3}$	$XR_{t+1,t+20}$	$XR_{t+1,t+3}$	$XR_{t+1,t+20}$	$XR_{t+1,t+3}$	$XR_{t+1,t+20}$
	1	2	3	4	5	6
ExpFlowCorr	0.004	0.010	−0.024	0.017	−0.024	0.017
	(1.146)	(0.057)	(0.731)	(0.039)	(0.597)	(0.038)
UnexpFlowCorr	−0.480***	−0.012**	−0.557***	−0.012***	−0.557***	−0.012***
	(0.173)	(0.005)	(0.133)	(0.003)	(0.125)	(0.003)
Log (Fund size)	−1.889***	−0.151***	−2.000***	−0.151***	−2.000***	−0.151***
	(0.366)	(0.018)	(0.195)	(0.011)	(0.136)	(0.010)
Log (Fund flow)	0.055	0.010*	−0.032	0.003**	−0.032	0.003**
	(0.150)	(0.006)	(0.055)	(0.002)	(0.040)	(0.001)
Expense ratio	2.059	0.082	1.050	0.041	1.050	0.041
	(2.035)	(0.117)	(0.871)	(0.055)	(0.830)	(0.054)
Turnover	−0.008	0.002	−0.010	0.002***	−0.010	0.002***
	(0.074)	(0.003)	(0.007)	(0.001)	(0.008)	(0.001)
Std. Dev. ($Flow_{t-2,t}$)	0.002	0.000**	−0.001	−0.000*	−0.001	−0.000**
	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Cash	−0.022	−0.002	−0.027	−0.002	−0.027	−0.002
	(0.037)	(0.002)	(0.033)	(0.002)	(0.028)	(0.002)
Load	1.292	0.086*	−0.176	−0.019	−0.176	−0.019
	(0.806)	(0.044)	(0.424)	(0.026)	(0.359)	(0.026)

(continued on next page)

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TABLE A3 (continued)

Regressions of Benchmark-Adjusted Returns on Flow Correlation with Alternative Standard Errors

	$XR_{t+1,\,t+3}$	$XR_{t+1,\,t+20}$	$XR_{t+1,\,t+3}$	$XR_{t+1,\,t+20}$	$XR_{t+1,\,t+3}$	$XR_{t+1,\,t+20}$
	1	2	3	4	5	6
Constant	29.296***	2.527***	33.558***	2.647***	33.558***	2.647***
	(8.263)	(0.422)	(3.972)	(0.207)	(2.677)	(0.188)
Fund FE and cluster DK	Yes	Yes				
Fund and day FE and cluster fund and day			Yes	Yes		
Fund and day FE and cluster funds					Yes	Yes
N	4,648,069	4,329,765	4,647,985	4,329,747	4,647,985	4,329,747
Adj-R^2	0.000	0.002	0.104	0.115	0.104	0.115

TABLE A4

Alternative Measures of Flow Diversification

Table A4 reports robustness tests using alternative measures of flow diversification. The dependent variable is the cumulative 3-day (t + 1, t + 3) benchmark-adjusted returns. Panel A uses a flow correlation measure constructed with equal weights across share classes and based on proportional (rather than dollar) flows. Panel B uses the absolute value of flow imbalance (|*FlowImb*|). *FlowImb* is defined as the sum of signed flows across the K share classes, scaled by the sum of their absolute values. In both panels, the decomposition of *FlowCorr* and |*FlowImb*| uses a backward-looking moving average filter of order q = 60 (t – 61, t – 1), corresponding to one quarter. The sample consists of fund-days with net outflows over the 2007–2024 period. Robust standard errors, clustered at the fund-quarter level, are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	Panel A. FlowCorr Constructed from Equal Weights				*Panel B. |FlowImb|*			
	1	2	3	4	5	6	7	8
FlowCorr or |*FlowImb*|	−0.204*	−0.351***			−1.291***	−0.860***		
	(0.121)	(0.115)			(0.236)	(0.225)		
ExpFlowCorr or *Exp*|*FlowImb*|			0.310	0.350			1.058	1.631**
			(0.661)	(0.637)			(0.793)	(0.759)
UnexpFlowCorr or *Unexp*|*FlowImb*|			−0.237*	−0.395***			−1.524***	−1.110***
			(0.123)	(0.116)			(0.242)	(0.231)
Log (Fund size)	−1.872***	−1.985***	−1.867***	−1.980***	−2.007***	−2.066***	−1.979***	−2.043***
	(0.122)	(0.119)	(0.122)	(0.119)	(0.125)	(0.122)	(0.126)	(0.122)
Log (Fund flow)	0.036	−0.049	0.033	−0.052	0.161***	0.025	0.161***	0.026
	(0.040)	(0.038)	(0.041)	(0.038)	(0.049)	(0.046)	(0.049)	(0.046)
Expense ratio	2.069***	1.051	2.062***	1.047	2.040***	1.038	2.023***	1.058
	(0.681)	(0.745)	(0.680)	(0.744)	(0.682)	(0.745)	(0.682)	(0.745)
Turnover	−0.008	−0.010	−0.008	−0.011	−0.008	−0.010	−0.008	−0.011
	(0.039)	(0.040)	(0.039)	(0.040)	(0.039)	(0.040)	(0.039)	(0.040)
Std. Dev. ($Flow_{t-2,\,t}$)	0.002	−0.001	0.002	−0.001	0.002	−0.001	0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cash	−0.022	−0.027	−0.022	−0.027	−0.023	−0.027	−0.022	−0.027
	(0.024)	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)
Load	1.294***	−0.177	1.296***	−0.174	1.278***	−0.179	1.289***	−0.169
	(0.263)	(0.276)	(0.262)	(0.276)	(0.263)	(0.276)	(0.263)	(0.276)
Constant	28.937***	33.245***	28.800***	33.081***	32.891***	35.663***	30.473***	33.178***
	(2.554)	(2.483)	(2.551)	(2.481)	(2.689)	(2.601)	(2.795)	(2.699)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE		Yes		Yes		Yes		Yes
N	4,648,066	4,647,985	4,648,066	4,647,985	4,648,122	4,648,041	4,648,122	4,648,041
Adj-R^2	0.003	0.104	0.003	0.104	0.003	0.104	0.003	0.104

Illiq.: A dummy variable equal to 1 if the fund is either a small- or mid-cap fund or a single-country non-U.S. equity fund, and 0 otherwise.

Outflow: A dummy variable equal to 1 if the fund has an outflow on t, and 0 otherwise.

References

Agarwal, V.; H. Ren; K. Shen; and H. Zhao. "Redemption in Kind and Mutual Fund Liquidity Management." *Review of Financial Studies*, 36 (2023), 2274–2318. https://doi.org/10.1093/rfs/hhac080.

Agnew, J.; P. Balduzzi; and A. Sundén. "Portfolio Choice and Trading in a Large 401(k) Plan." *American Economic Review*, 93 (2003), 193–215. https://doi.org/10.1257/000282803321455223.

Alexander, G.; G. Cici; and S. Gibson. "Does Motivation Matter When Assessing Trade Performance? An Analysis of Mutual Funds." *Review of Financial Studies*, 20 (2007), 125–150. https://doi.org/10.1093/rfs/hhl008.

Allen, F., and D. Gale. "Financial Contagion." *Journal of Political Economy*, 108 (2000), 1–33. https://doi.org/10.1086/262109.

Bailey, J., and T. Richards. "A Primer for Investment Trustees: Understanding Investment Committee Responsibilities." In *A Primer for Investment Trustees: Understanding Investment Committee Responsibilities*. Charlottesville, VA: CFA Institute Research Foundation (2017). https://doi.org/10.2139/ssrn.3088821.

Balchunas, E., and J. Weber. "The Mutual Fund Is Very Much Alive and Well." *Trillions*, Bloomberg Podcast (2023).

Barber, B. M.; X. Huang; and T. Odean. "Which Factors Matter to Investors? Evidence from Mutual Fund Flows." *Review of Financial Studies*, 29 (2016), 2600–2642. https://doi.org/10.1093/rfs/hhw054.

Beggs, W. "The Company You Keep: Investment Adviser Clientele and Mutual Fund Performance." *Journal of Financial Intermediation*, 50 (2022), 100947. https://doi.org/10.1016/j.jfi.2021.100947.

Ben-Rephael, A., and R. Israelsen. "Are Some Clients More Equal Than Others? An Analysis of Asset Management Companies' Execution Costs." *Review of Finance*, 22 (2018), 1705–1736. https://doi.org/10.1093/rof/rfx043.

Bergstresser, D.; J. Chalmers; and P. Tufano. "Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry." *Review of Financial Studies*, 22 (2009), 4129–4156. https://doi.org/10.1093/rfs/hhp022.

Bessembinder, H.; K. Chan; and P. Seguin. "An Empirical Examination of Information, Differences of Opinion, and Trading Activity." *Journal of Financial Economics*, 40 (1996), 105–134. https://doi.org/10.1016/0304-405X(95)00839-7.

Bhattacharya, U.; J. H. Lee; and V. K. Pool. "Conflicting Family Values in Mutual Fund Families." *Journal of Finance*, 68 (2013), 173–200. https://doi.org/10.1111/j.1540-6261.2012.01797.x.

Bogousslavsky, V., and P. Collin-Dufresne. "Liquidity, Volume, and Order Imbalance Volatility." *Journal of Finance*, 78 (2023), 2189–2232. https://doi.org/10.1111/jofi.13248.

Britton, D. "The Slow Demise of Mutual Funds." WealthManagement.com (2019).

Campello, M., and J. Gao. "Customer Concentration and Loan Contract Terms." *Journal of Financial Economics*, 123 (2017), 108–136. https://doi.org/10.1016/j.jfineco.2016.03.010.

Chalmers, J., and J. Reuter. "What Is the Impact of Financial Advisors on Retirement Portfolio Choices and Outcomes?" NBER Working Paper No. 18158 (2010).

Chang, E. C.; J. W. Cheng; and A. Khorana. "An Examination of Herd Behavior in Equity Markets: An International Perspective." *Journal of Banking and Finance*, 24 (2000), 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5.

Chen, Q.; I. Goldstein; and W. Jiang. "Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows." *Journal of Financial Economics*, 97 (2010), 239–262. https://doi.org/10.1016/j.jfineco.2010.03.016.

Cheng, E.; F. J. Fabozzi; R. Harlow; W. Lee; and S. Zhang. "Applications of Equity Derivatives to Portfolio Management." *Journal of Asset Management*, 25 (2024), 589–599. https://doi.org/10.1057/s41260-024-00367-y.

Christie, W. G., and R. D. Huang. "Following the Pied Piper: Do Individual Returns Herd Around the Market?" *Financial Analysts Journal*, 51 (1995), 31–37. https://doi.org/10.2469/faj.v51.n4.1918.

Christoffersen, S. E. K., and D. K. Musto. "Demand Curves and the Pricing of Money Management." *Review of Financial Studies*, 15 (2002), 1499–1524. https://doi.org/10.1093/rfs/15.5.1499.

https://doi.org/10.1017/S0022109026103172

Coval, J., and E. Stafford. "Asset Fire Sales (and Purchases) in Equity Markets." *Journal of Financial Economics*, 86 (2007), 479–512. https://doi.org/10.1016/j.jfineco.2006.09.007.

Del Guercio, D.; E. Genc; and H. Tran. "Playing Favorites: Conflicts of Interest in Mutual Fund Management." *Journal of Financial Economics*, 128 (2018), 535–557. https://doi.org/10.1016/j.jfineco.2017.04.012.

Del Guercio, D., and J. Reuter. "Mutual Fund Performance and the Incentive to Generate Alpha." *Journal of Finance*, 69 (2014), 1673–1704. https://doi.org/10.1111/jofi.12048.

Del Guercio, D., and P. A. Tkac. "The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds vs. Pension Funds." *Journal of Financial and Quantitative Analysis*, 37 (2002), 523–557. https://doi.org/10.2307/3595011.

Dickson, J. M.; J. B. Shoven; and C. Sialm. "Tax Externalities of Equity Mutual Funds." NBER Working Paper No. 7669 (2000).

Driscoll, J. C., and A. C. Kraay. "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *Review of Economics and Statistics*, 80 (1998), 549–560. https://doi.org/10.1162/003465398557825.

Du, L.; L. T. Starks; and M. Z. Xiaolan. "Active ETFs Cloned from Mutual Funds: Competing for Investor Flows." Working Paper, University of Texas at Austin (2023).

Edelen, R. M. "Investor Flows and the Assessed Performance of Open-End Mutual Funds." *Journal of Financial Economics*, 53 (1999), 439–466. https://doi.org/10.1016/S0304-405X(99)00028-8.

Edelen, R. M.; R. B. Evans; and G. B. Kadlec. "Shedding Light on 'Invisible' Costs: Trading Costs and Mutual Fund Performance." *Financial Analysts Journal*, 69 (2013), 33–44. https://doi.org/10.2469/faj.v69.n1.6.

Etula, E.; K. Rinne; M. Suominen; and L. Vaittinen. "Dash for Cash: Monthly Market Impact of Institutional Liquidity Needs." *Review of Financial Studies*, 33 (2020), 75–111. https://doi.org/10.1093/rfs/hhz054.

Evans, R. B., and R. Fahlenbrach. "Institutional Investors and Mutual Fund Governance: Evidence from Retail–Institutional Fund Twins." *Review of Financial Studies*, 25 (2012), 3530–3571. https://doi.org/10.1093/rfs/hhs105.

Falato, A.; I. Goldstein; and A. Hortaçsu. "Financial Fragility in the COVID-19 Crisis: The Case of Investment Funds in Corporate Bond Markets." *Journal of Monetary Economics*, 123 (2021), 35–52. https://doi.org/10.1016/j.jmoneco.2021.07.001.

Falato, A.; A. Hortaçsu; D. Li; and C. Shin. "Fire-Sale Spillovers in Debt Markets." *Journal of Finance*, 76 (2021), 3055–3102. https://doi.org/10.1111/jofi.13078.

Ferreira, M. A.; M. Massa; and P. Matos. "Investor-Stock Decoupling in Mutual Funds." *Management Science*, 64 (2017), 2144–2163.

Frazzini, A., and O. A. Lamont. "Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns." *Journal of Financial Economics*, 88 (2008), 299–322. https://doi.org/10.1016/j.jfineco.2007.07.001.

Goldstein, I.; H. Jiang; and D. T. Ng. "Investor Flows and Fragility in Corporate Bond Funds." *Journal of Financial Economics*, 126 (2017), 592–613. https://doi.org/10.1016/j.jfineco.2016.11.007.

Greene, J. T., and C. W. Hodges. "The Dilution Impact of Daily Fund Flows on Open-End Mutual Funds." *Journal of Financial Economics*, 65 (2002), 131–158. https://doi.org/10.1016/S0304-405X(02)00137-X.

Illan, I. (2018, Mar. 5) "How Monitoring Mutual Fund Flows Gives Unique Stock Market Insight." *Forbes*.

Investment Company Institute. *2024 Investment Company Fact Book*. Washington, DC: Investment Company Institute (2024).

James, C., and J. Karceski. "Investor Monitoring and Differences in Mutual Fund Performance." *Journal of Banking and Finance*, 30 (2006), 2787–2808. https://doi.org/10.1016/j.jbankfin.2005.11.003.

Jiang, H.; Y. Li; Z. Sun; and A. Wang. "Does Mutual Fund Illiquidity Introduce Fragility into Asset Prices? Evidence from the Corporate Bond Market." *Journal of Financial Economics*, 143 (2022), 277–302. https://doi.org/10.1016/j.jfineco.2021.05.022.

Jin, D.; M. Kacperczyk; B. Kahraman; and F. Suntheim. "Swing Pricing and Fragility in Open-End Mutual Funds." *Review of Financial Studies*, 35 (2022), 1–50. https://doi.org/10.1093/rfs/hhab022.

Johnson, W. T. "Predictable Investment Horizons and Wealth Transfers Among Mutual Fund Shareholders." *Journal of Finance*, 59 (2004), 1979–2012. https://doi.org/10.1111/j.1540-6261.2004.00689.x.

Kacperczyk, M., and P. Schnabl. "How Safe Are Money Market Funds?" *Quarterly Journal of Economics*, 128 (2013), 1073–1122. https://doi.org/10.1093/qje/qjt010.

Massa, M. "How Do Family Strategies Affect Fund Performance? When Performance-Maximization Is Not the Only Game in Town." *Journal of Financial Economics*, 67 (2003), 249–304. https://doi.org/10.1016/S0304-405X(02)00253-2.

https://doi.org/10.1017/S0022109026103172

Pástor, L.; R. F. Stambaugh; and L. A. Taylor. "Fund Tradeoffs." *Journal of Financial Economics*, 138 (2020), 614–634. https://doi.org/10.1016/j.jfineco.2020.06.005.
Rakowski, D. "Fund Flow Volatility and Performance." *Journal of Financial and Quantitative Analysis*, 45 (2010), 223–237. https://doi.org/10.1017/S0022109009990500.
Rekenthaler, J. "*Farewell*, Mutual Funds." Rekenthaler Report, Morningstar (2021). https://www.morningstar.com/columns/rekenthaler-report/farewell-mutual-funds.
Schmidt, L.; A. Timmermann; and R. Wermers. "Runs on Money Market Mutual Funds." *American Economic Review*, 106 (2016), 2625–2657. https://doi.org/10.1257/aer.20140678.
Sialm, C., and L. Starks. "Mutual Fund Tax Clienteles." *Journal of Finance*, 67 (2012), 1397–1422. https://doi.org/10.1111/j.1540-6261.2012.01751.x.
Sialm, C., and H. Zhang. "Tax-Efficient Asset Management: Evidence from Equity Mutual Funds." *Journal of Finance*, 75 (2020), 735–777. https://doi.org/10.1111/jofi.12843.
Simutin, M. "Cash Holdings and Mutual Fund Performance." *Review of Finance*, 18 (2014), 1425–1464. https://doi.org/10.1093/rof/rft035.
Wermers, R. "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses." *Journal of Finance*, 55 (2000), 1655–1695. https://doi.org/10.1111/0022-1082.00263.
Yan, X. "Liquidity, Investment Style, and the Relation Between Fund Size and Fund Performance." *Journal of Financial and Quantitative Analysis*, 43 (2008), 741–767. https://doi.org/10.1017/S0022109000004270.

https://doi.org/10.1017/S0022109026103172