Flow Diversification*

Sunil Wahal
WP Carey School of Business
Arizona State University
Tempe, AZ 85287
Sunil.Wahal@asu.edu

Albert Y. Wang
Harbert College of Business
Auburn University
Auburn, AL 36849
albertwang@auburn.edu

July 2022

Abstract

We document large variation in the cross-sectional correlation and imbalance of daily mutual fund flows from share classes catering to retail investors, retirement accounts, and financial advisors. Funds with more diversified flows on day *t* face lower immediacy requirements and outperform funds with less diversified flows over the following three days. These return differences are independent of the magnitude of net flows, and present across all funds, not just those that invest in illiquid assets. The benefits of flow diversification are especially large during unanticipated common shocks. Flow diversification can mitigate liquidity externalities.

Keywords: Mutual Fund, Diversification, Clienteles, Correlation, Liquidity, ETF
JEL Classifications: G12, G14, G23

---

* We are grateful to Lili Ge for research assistance. We thank the Center for Investment Engineering at ASU for financial support. Wahal is a consultant to Avantis Investors. Avantis did not provide data or funding for this research. We thank Mitch Firestein, Massimo Massa, and Clemens Sialm for helpful comments and suggestions.

1. Introduction

By law, mutual funds guarantee that investors receive end-of-day net asset value (NAV) on the day they redeem their shares. To accommodate investor demand, funds trade in the underlying securities after receiving flow notifications. Since trading in the underlying securities generates non-zero costs, this timing mismatch implies that these costs are borne by non-redeeming investors. Chen, Goldstein, and Jiang (2010) go one step beyond this liquidity externality, arguing that the expectation that some investors will exit a fund and impose a cost on others generates a multiplier effect akin to a bank run.[1] They argue that this process generates financial fragility, an issue of large economic importance. The potential effects of these externalities and multipliers are not lost on fund shareholders, as evidenced by the fact that many data providers track and report fund flows. For instance, Morningstar's Fund Flow Report provides considerable detail on flows over a variety of horizons and is widely followed by investors. Refinitiv Lipper and the Investment Company Institute (ICI) publish similar flow reports. Anticipating liquidity and tax externalities, it has also become routine for investment committees of financial advisory firms and other fiduciaries to monitor flows in the funds they own (see, for example, Bailey and Richards (2017), and Illan (2018)).

In this paper, we study a mechanism that permits mutual funds to mitigate the costs associated with flows. Most funds source their assets from three clienteles: direct retail investors, retirement accounts, and financial advisors/institutional accounts.[2] These three groups access funds via targeted share classes which hold nearly identical underlying portfolios but differ in terms of fees, loads, and distribution systems. Our central thesis is that to the extent that flows across these groups are imperfectly correlated, flow diversification can mitigate the costs associated with trading in underlying securities triggered by outflows. If that is the case, flow diversification should be systematically related to post-flow variation in short-horizon fund performance. And if investors recognize the potential of flow diversification ex-ante, it could also

[1] In addition to trading costs, redemptions can also result in realization of capital gains, creating a tax externality (Dickson, Shoven, and Sialm (2000) and Sialm and Zhang (2020)). This generates incremental monitoring costs since a portfolio manager needs to ensure that securities sold to accommodate redemptions are not bought back within 30 days for wash sale considerations.

[2] Institutional and advisor share classes are quite similar and the terms are often used interchangeably, so we group them together and refer to them as "advisors". (Financial advisors are, of course, "institutions" and as such, file 13-F statements to the SEC.) Institutional and advisor classes of mutual funds are, however, different from separate accounts that cater to institutional mandates and which are governed by their own investment management agreements (IMAs). See Busse, Goyal, and Wahal (2010) for details.

affect the multiplier effect that generates fragility in markets.

How might flow diversification work? Offsetting flows from different clienteles reduces both net flows that need to be traded (the first moment) and the volatility of net flows (the second moment). From an economic perspective, imperfectly correlated flows across clienteles might be related to different sensitivities to economic conditions or fundamentals that drive a fund's NAV, to behavioral differences among mutual fund investors (Christie and Huang (1995), Chang et al. (2000), and Bessembinder et al. (1996)), or to the geographic distance between the location of fund investors and portfolio investments (Ferreira, Massa, and Matos (2017).[3] Regardless of the latent reasons, ceteris paribus, reduced flow volatility may also permit portfolio managers to implement more precise flow management policies, ultimately reducing immediacy demands (see Rakowski (2010) for the link between daily flow volatility and future performance). Such a channel could generate a dispersion in short-horizon fund returns associated with flow diversification.

To study this process, we examine flows to share classes in U.S. domiciled active equity mutual funds between April 2007 and June 2020. In aggregate, roughly half of fund assets are derived from financial advisors, and the remainder are evenly split between direct retail investors and retirement accounts; *prima facie*, the potential for diversification benefits across these clienteles is large. We measure flow diversification using two fund-level measures: (a) flow imbalance (*FlowImb*), computed as the sum of signed flows across classes scaled by the sum of the absolute value of flows, and (b) flow correlation (*FlowCorr*), computed as the weighted average covariance of flows across classes, scaled by the sum of squared deviations of class-level flows from fund-level net flows. Both measures reside in the interval [-1, +1] and have intuitive properties. Flow imbalance, analogous to order imbalance in the market microstructure literature, is equal to zero when class level flows exactly offset each other and is signed in the sense that it leans towards -1 (+1) when funds experience outflows (inflows) in all classes. Flow correlation is unsigned so that -1 (+1) implies perfectly negatively (positively) correlated flows.

Depending on the platform used by investors to trade, portfolio managers receive flow notifications one or two days after an investor submits a trade on day *t*. Trades in underlying

[3] Ferreira, Massa, and Matos (2017) argue that geographic distance generates investor-stock "decoupling", which generates a natural hedge for the fund so that funds with higher decoupling have higher performance. The underlying mechanism in their paper is quite different from what we have in mind; their interest resides from the geographic location of investors (particularly internationally) whereas ours is agnostic to location but focused on differences in distribution systems.

securities must therefore be executed between *t+1* and *t+3*. Exploiting these timing conventions, we employ daily data to pinpoint variation in immediacy demands. As a precursor to assessing the importance of flow diversification, we establish two basic facts. First, we show that funds that experience large outflows on day *t* have significantly lower returns on days *t+1* through *t+3* than funds with small outflows. These return differences are not confined to funds that hold illiquid assets but widespread across funds with varying asset liquidity and investment style. The return differences are economically large, as much as one basis point per day (20 basis points per month).[4] Second, we link flow diversification to flow volatility in two ways. Using a regression-based approach, we establish that future flow volatility (measured using squared flows over the *t+1* to *t+3* horizon) is negatively related to flow diversification on day *t*, controlling for the volatility of flows prior to day *t*, and even after orthogonalizing flow diversification with respect to flow volatility. We also show that the introduction of a new share class is associated with a sharp and large decline in flow volatility. These pre-tests suggest that the mechanisms by which flow diversification could matter is not only plausible but evident in the data.

Our primary tests document a positive relationship between flow diversification on day *t*, and fund returns between *t+1* and *t+3*. Funds subject to outflows in a low-diversification quintile on day *t* subsequently underperform funds in the high-diversification quintile by about one basis point. The return difference is present for funds with outflows but not inflows, and the majority of it occurs on *t+1*; these facts suggest that it is the difference in immediacy requirements that drives these return differences. There are two ways to put this estimate into perspective. First, it is about the same magnitude as the (unconditional) flow-driven underperformance described above. Second, we can compare it to the shareholder runs results in Chen, Goldstein, and Jiang (2010); they report that large outflows in month t predict lower returns in month *t+1* of about 19 basis points per month for the most illiquid funds. By both metrics, the effects of flow diversification are large. The relation between flow diversification and fund performance is also present in regression-based tests, which explicitly control for the level of flows on day *t*, other relevant fund characteristics (including cash holdings), and cross-sectional variations across fund

[4] These results are generally consistent with studies that quarterly or monthly holdings or those that use monthly data to infer the costs incurred by mutual funds in supplying liquidity to fund shareholders (see Edelen (1999), Wermers (2000), Greene and Hodges (2002), Alexander, Cici, and Gibson (2007), Coval and Stafford (2007), Chen, Goldstein, and Jiang (2010), Edelen, Evans, and Kadlec (2013), and others). In contrast, our tests exploit is the ability to measure the plumbing of asset flows using daily data, which allows us to identify these effects with considerable precision.

styles (by using style fixed effects). Importantly, the variation in post-outflow returns is present in the entire cross-section of funds, not just those that hold illiquid assets. It is also present when our regressions isolate time series variation within a fund (by using fund-specific fixed effects).

At the heart of the liquidity arguments, as well as the potential for shareholder runs, is the idea that flows are unpredictable. If flows are perfectly anticipatable, portfolio managers could potentially implement flow management policies (such as cash buffers) that drive immediacy costs to zero. But the literature suggests that such a judgment is simplistic. Johnson (2004) shows that there is a wealth transfer even when the liquidity demands of some shareholders are predictable. Chernenko and Sunderam (2020) indicate that funds with incentives to internalize the effects of fire sales do in fact adjust flow management policies to dampen feedback effects, but are not entirely successful. Morris, Shim, and Shin (2017) identify conditions under which fund managers hoard cash, amplifying rather than reducing immediacy demands and costs. In addition, Zeng (2017) shows that rebuilding cash buffers can in fact exacerbate financial fragility. To hone in on the effects of flow predictability, we examine a set of predictable inflows and a set of unpredictable outflows. We first show large end-of-month spikes in net inflows, consistent with the payment cycle documented by Etula et al. (2019). The spikes are present in flows from all three clienteles but are especially large in retirement accounts, where automated contributions on the last day of the month are twice as large as average daily flows. On these days we observe a sharp increase in return differences between high and low flow diversification quintiles. This suggests that flow predictability is not a panacea to liquidity externalities, either because portfolio managers are unwilling to get ahead of anticipatable flows, or because the cost of doing so is large. We also examine the benefits to flow diversification when funds face unanticipated shocks to their outflows. These include four key days during the 2008 financial crisis and three days at the onset of the Covid-19 crisis during which market-wide circuit breaks were triggered. On each of these days, the return difference between high and low-diversification quintiles rises 10 to 20 times relative its unconditional average.[5]

We also consider the benefits of flow diversification at the fund family level. There are two lines of inquiry: (a) strategic family decisions, and (b) integrated trading. With respect to the

[5] Ideally, we would be able to observe cash levels at a daily frequency to determine if flow diversification is linked to cash buffers. Absent such high frequency data, we estimate monthly regressions of cash buffers on flow diversification. Despite the lack of power, the regressions suggest that cash buffers are negatively related to measures of flow diversification.

former, if fund families focus on particular distribution channels as a way to maximize family value, then flow diversification could be related to family decisions unobservable to us. There are reasons to believe that this may be the case. For instance, Massa (2003) argues that fund families rely on investor heterogeneity to increase fund offerings (but that this negatively affects performance). Bhattacharya, Lee, and Pool (2013) reason that by offering funds that only invest in other funds within the same family, fund families create an insurance pool against temporary liquidity shocks. Chernenko and Sunderam (2020) find that funds with large incentives to internalize costs across other funds in the same family adjust their cash holdings. To determine if such strategic considerations drive our results, we re-estimate post-flow return regressions on flow diversification controlling for family size (which is likely to be correlated with strategic considerations), and with explicit family fixed effects. Despite these inclusions, the influence of flow diversification on post-flow returns remains largely similar; of course, this does not imply that strategic issues are unimportant, just that flow diversification effects remain relevant in the presence of strategic family decision-making.

The second line of inquiry pertains to integrated trading structures within a fund family. Even though flows are fund-specific, buying and selling in the underlying securities is typically aggregated using an order management system (OMS) and delegated to a trading desk that manages trading across all funds in a family. Under Rule 17a-7 of the Investment Company Act of 1940, families are permitted to conduct internal crosses between funds and other accounts that have the same investment advisor. For example, if Fund A wants to purchase 100 shares of XYZ but Fund B wants to sell 40 shares, the family may be permitted to cross 40 shares internally and only trade 60 shares in the marketplace. The consequence is a reduction in the demand of immediacy.[6] Recognizing the possibility of such crosses, we compute family-level measures of flow imbalance and flow correlation by aggregating fund-level information, and then assess whether these measures generate dispersion in fund-level returns. Our regressions indicate that funds belonging to families with less heterogeneous flows have lower post-outflow returns than those with more heterogeneous flows.

The results described above suggest that flow diversification mitigates liquidity

[6] The central requirement is that the transaction occurs at an independent "current market price," which, depending on the security and exchange listing, is either the last transaction price or the most recent mid-point quote. The intuition behind this requirement is that such a price is objective, fair, independent, and most importantly, does not favor one crossing party over another. For a more complete description, see Pozen (2002).

externalities. The extra step to shareholder runs requires that some investors anticipate the exit of others. Chen, Goldstein, and Jiang's (2010) approach to studying such payoff complementarities is to determine if flow-to-performance sensitivity is higher in funds with illiquid assets, leveraging the idea that redemptions impose higher costs on shareholders remaining in illiquid funds.[7] We first reproduce their monthly regressions with daily data. The results are strikingly robust, both in direction and magnitude. We then ask whether flow-to-performance sensitivities vary with flow diversification, even in the presence of higher flow-to-performance sensitivities for illiquid funds. We find that this is indeed the case – independent of asset liquidity, funds with lower levels of flow diversification have higher flow-to-performance sensitivities. Finally, we assess whether flow diversification mitigates higher flow-to-performance sensitivities in illiquid funds – essentially asking whether flow diversification can at least partially offset strategic complementarities. The answer is yes: flow-to-performance sensitivity in illiquid funds is higher in funds with low flow diversification, and vice versa.[8]

It is useful to view our results from a broader perspective. The flavor of our diversification-based mitigation mechanism is also present in other markets. In the banking literature, for example, Allen and Gale (2000) argue that risk-sharing takes place when banks hold interregional claims on other banks, enabling insurance against local liquidity shocks. Of course, there is a tradeoff between diversification benefits and contagion costs (see, for example, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Wagner (2010), and Ibragimov, Jaffee, and Walden (2011)). In mortgage-backed securities, prepayment risk from one group of mortgagees is effectively transferred to all investors in the pool, but variation in holding periods allows pooling and affects pricing.[9] In money market funds, Kacperczyk and Schnabl (2013) show that funds with a more diversified client base take on less risk, arguing that this is because reputational costs would generate spillover effects (outflows) to other mutual funds managed by the same organization. In the same setting, Schmidt, Timmermann, and Wermers (2016), find no evidence of a diversification effect as large institutional investors redeem shares in response to redemptions by

[7] Falato et al. (2021) document a large fire-sale spillover effect among bond funds with same underlying assets, which negatively impacts the fund performance and flows.

[8] Flow diversification is distinct from the clientele effect described by Chen, Goldstein, and Jiang (2010) in which large investors are less concerned with the externalities imposed by exiting shareholders because they hold a large fraction of shares. Our results are independent of, and robust to, such a clientele effect. We defer a more thorough discussion of this and related issues to Section 5.6.

[9] Original insight into this parallel offered by the late Rick Green, as cited in Johnson (2004).

smaller investors. Finally, it is useful to recognize that market participants devise innovative solutions to address such externalities. Jin, Kacperczyk, Kahraman, and Suntheim (2021) report that swing pricing rules in which redeeming shareholders bear the cost of a fund's price impact reduce liquidity externalities and spillover effects in UK domiciled bond funds. In our sample, however, none of the funds use swing pricing rules. Of course, ETFs are not subject to the liquidity or tax externality because investors trade in the secondary market and because ETFs employ an in-kind redemption procedure in which Authorized Participants and market makers play a central role. Given that, it is perhaps unsurprising that there has been a steady shift away from mutual funds towards ETFs in the last decade (see, for example, pg. 85 of the ICI Handbook (2021) for the magnitude of the transition). Pointedly, many fund families offer portfolios as both mutual funds and ETFs.

2. Institutional Details

Investors who submit a trade prior to market close on day t receive the NAV struck at market close on the same day. A portfolio manager's knowledge of client purchases or sales varies depending on the platform used by the investor. In most standard trading platforms, flows are reported to portfolio managers by 10:00 PM PST. In the majority of retirement platforms, however, portfolio managers may learn about flows as late as 10:45 AM PST on day $t+1$.[10] In the case of inflows, these delays generate cash drag to the underlying portfolio starting with the market close on day t. Portfolio managers can potentially shrink cash drag by equitizing inflows using the futures market. This has both costs and benefits. The costs include: (a) the incremental costs of trading the futures contract, (b) the tracking error between holdings and the target portfolio because the futures contract does not precisely match the target portfolio,[11] (c) an increase in short term capital gains for investors because 60 percent of gains are taxed at the long-term capital gains rate, and 40 percent of the gains are taxed at the ordinary income tax rate, regardless of the holding period. On the other hand, the equitization process allows the portfolio manager to break up trades in desired securities over multiple (future) days, potentially reducing trading costs.

[10] Much of the transaction processing between fund companies and distributors takes place via Fund/Serv, an arm of the DTCC. For details regarding the timing of the processing, see https://www.dtcc.com/wealth-management-services/mutual-fund-services/fund-serv.

[11] In small cap funds, for example, it is common for funds to use the S&P 500 E-mini futures contract rather than the Russell 2000 futures contract because of its greater liquidity.

In the case of outflows, investors receive cash on *t+1*, which means that by the time a portfolio manager receives flow notification, cash may have already been delivered to the investor. Investor redemptions must ultimately result in the sale of current holdings, but the presence of cash balances (a) prevents the fund from becoming levered, and (b) allows stock sales to be deferred for a day or two. Morris, Shim, and Shin (2017) show that cash hoarding to meet redemption risk emerges in a global game and find evidence of such behavior in bond funds. Chernenko and Sunderam (2020) find that funds with large incentives to internalize their price impact adjust their cash buffers accordingly. Regardless of the timing and mitigation strategies, investors remaining in the fund pay all implicit and explicit costs, including market impact, commissions, stamp duties, and ticket charges. The cash flow timing mechanism described above implies that trading generated by cash inflows and redemptions need not take place on day *t+1*, and can be stretched out several days. Therefore, in measuring post-flow performance we consider returns from *t+1* to *t+3*.

3. Sample Construction and Classifications

3.1 Data and Sample

Our primary data source is the EPFR Global Fund Database, which provides daily data on flows and returns at the share class level. EPFR receives daily raw data on NAVs, assets, and dividends using direct feeds from fund managers, fund administrators, custodians, trusts, advisors, and fund companies. EPFR data are increasingly common in studies that require high frequency data on flows such as Raddatz and Schmukler (2012), Jotikasthira, Lundblad and Ramadorai (2012), and Fratzscher (2012).

To construct our sample, we start with all US-domiciled open-end equity mutual funds in the database. We exclude passive/index funds, leaving us with 3,511 unique funds (12,632 fund-share-class observations).[12] The time series is from April 2007 to June 2020. At the end of 2019, our sample represents about 60 percent of total assets in active US mutual funds.

We supplement daily flow data with additional monthly or quarterly data on fund characteristics from the CRSP survivorship-bias-free Mutual Fund database and Morningstar. For cash levels, we use Morningstar rather than the N-SAR filings used by Chernenko and Sunderam (2020) because cross-sectional coverage for our sample is better. (We spot check a handful of

[12] The Vanguard Group does not provide daily flow data to EPFR or Morningstar.

records to ensure that Morningstar's cash data are the same as that reported in N-SAR filings.) We extract equity style classifications (using the ubiquitous 3x3 size and value/growth grid) from Morningstar. Fund expenses, turnover, volatility, and age are drawn from CRSP. A subset of our tests also require information on the use of derivatives and swing pricing rules. For derivatives information, we follow the procedures in Kaniel and Wang (2020), scraping the necessary filings from the SEC's Edgar database for funds in our sample. Specifically, we extract derivative equity contract information from quarterly Form N-PORT. The N-PORT filing includes the derivative instrument, the name of the underlying asset, portfolio weight, notional amount, expiration date, and the unrealized appreciation or depreciation for each derivative position. The derivative instruments include forwards/futures, options, swaps, and warrants. For futures and forwards, we identify whether the position is long or short. For swing pricing, we rely on the N-CEN form.[13] The information we extract from C-CEN is based on the question C.21, "Did the fund (if not a Money Market Fund, Exchange-Traded Fund, or Exchange-Traded Managed Fund) engage in swing pricing?" Both N-PORT and N-CEN are only available after 2019.

3.2 Clientele Classification

Mutual funds offer a large number of share classes differing in their loads, expense ratios, and distribution systems (see Nanda, Wang, and Zheng (2009) for early history and nomenclature). These variants package the same underlying product (portfolio) for different clienteles. To provide economically meaningful distinctions, we classify all share classes into three categories: (a) retail, (b) retirement, and (c) advisor. We include "institutional" share classes in the advisor category since these terms are used interchangeably to facilitate investment from registered investment advisors (RIAs).

Morningstar classifies each class into one of these three categories. For fund-classes in EPFR that we are unable to merge with Morningstar, we use CRSP. CRSP classifies fund-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,

[13] Jin et al. (2021) obtain swing pricing data on UK-based corporate bond funds from the Financial Conduct Authority (FCA) database. In the United States, the SEC adopted amendments to Rule 22c-1 under the Investment Company Act to permit a registered open-end management investment company to use swing pricing. The SEC also adopted amendments to Form N-1A and Regulation S-X which add a new item to Form N-CEN that require a fund to publicly disclose information regarding its use of swing pricing.

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. This process leaves 437 share classes that cannot be merged to either Morningstar or CRSP. For these cases, we read the fund prospectuses to classify each class based on minimum initial investment requirements (using $25,000 as a breakpoint between advisor and retail classes).

Panel A of Table 1 shows the number and percentage of funds in each investment style. Panel B contains the aggregate dollar value (and percentage) of assets in each style at the end of 2019. In general, large-cap funds represent a large proportion of the sample, both by number and dollar value. Panel C shows the percentage of fund assets in each share class, computed from aggregate values at the end of 2019. Across styles, between 50-60 percent of the assets originate from advisors. Another 20-30 percent are derived directly from retail share classes, while the remainder are sourced from retirement accounts. These magnitudes imply that flows from each group are quantitatively important, and that at least in principle, could offset each other to some degree.

4. Flow Diversification

4.1 Measurement

To measure flow diversification, we define flows for class *k* in fund *i* at time *t* (k=1, 2,…K) as

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

TNA represents total net assets and *r* is the net return after fees. Aggregating flows across all classes, net flows for fund *i* at time *t* are

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

Our first measure, flow imbalance (*FlowImb*), sums signed flows across different classes, scaling by the sum of the absolute value of flows.

$$FlowImb_{i,t} = \frac{\sum_{k=1}^{K} Flows_{i,k,t}}{\sum_{k=1}^{K} |Flows_{i,k,t}|} \tag{3}$$

Intuitively, this measure is similar to order imbalance in the market microstructure literature, residing in the interval [-1, +1]. Since the numerator is signed, the measure is negative (positive) when a fund has net negative (positive) net flows. If flows across different share classes exactly offset each other, flow imbalance is equal to zero. Heterogeneity in flows is therefore represented by the distance of the measure from zero. Higher flow imbalance in absolute value (distance from zero) implies less flow diversification.

The second measure, flow correlation (*FlowCorr*), uses the covariance of flows across classes. We compute the weighted sum of the cross-products, and scale it by the total squared deviation of flows in each class from the fund's net flows.

$$FlowCorr_{i,t} = \frac{\sum_{k\neq l} cov(flows_{i,k,t}, flows_{i,l,t})}{var(flows_{i,k,t})}$$

$$= \frac{\sum_{k=1}^{K-1}\sum_{j=k+1}^{K}[w_{k,t-1}\left(Flows_{i,k,t} - Flows_{i,t}\right) \times w_{j,t-1}\left(Flows_{i,j,t} - Flows_{i,t}\right)]}{\sum_{k=1}^{K} w_{k,t-1}^2 (Flows_{i,k,t} - Flows_{i,t})^2} \qquad (4)$$

where $w_{k,t-1} = \frac{TNA_{i,k,t-1}}{TNA_{i,t-1}}$ is the weight of class <u>k</u> in fund *i* at time *t-1*. Flow correlations are also bounded by -1 and +1. Since *FlowCorr* is unsigned, positive (negative) values indicate positively (negatively) correlated flows across classes. Less correlated flows imply a higher level of flow diversification.

An example in useful in providing intuition and illustrating the measures. Consider a fund with two classes, *k* and *l*, with assets at *t-1* equal to \$10 and \$100 respectively. Class *k* requires outflows of \$5 while *l* receives inflows of \$20. Net flows to the fund are \$15. Flow imbalance computed using equation (3) above is 0.6, indicating that outflows are offset by inflows, and resulting in a positive flow imbalance. In interpreting *FlowImb*, therefore, it is often useful to separately examine net inflows or outflows (i.e., *FlowImb* | sign ($Flows_{i,t}$)). Flow correlation computed using equation (4) is -0.345, reflecting the negative covariance of flows between *k* and *l*, but not the fact that net flows are positive.

Table 2 shows the distribution of the flow diversification measures. Panel A contains means, standard deviations, and percentiles of flow imbalances and correlations separately for fund-days with inflows and outflows. As expected, the mean flow imbalance is -0.82 for outflows and 0.78 for inflows. For inflows and outflows, the mean flow correlation is positive, 0.20 and 0.14, respectively. Both measures display considerable variation, as evidenced by the large inter-quartile ranges.

Panel B shows various fund-level characteristics for *FlowImb* or *FlowCorr* quintiles. Relative to intermediate quintiles, the extreme flow imbalance quintiles (labeled negative imbalance and positive imbalance, respectively) generally consist of funds that are smaller in size, younger, and who generally hold a larger fraction of their assets in cash. Flow correlation quintiles show similar dispersion.

4.2 Flow Diversification and Flow Volatility

As a purely mechanical effect, offsetting flows from different classes reduce the net flows that a fund needs to trade. Imperfectly correlated demand from different clienteles can also reduce flow volatility. To pin down magnitudes, we estimate regressions of flow volatility on the flow diversification measures while controlling for lagged flow volatility. We measure flow volatility using the square root of the sum squared daily fund flows over a three-day window using a *t+1* to *t+3* timing convention. A short window allows us to isolate flow volatility immediately after flows on day *t*. The cost is limited degrees of freedom and, therefore, imprecision in the measurement of flow volatility. Somewhat larger windows (e.g., five days) do not affect our conclusions.

Panel A of Table 3 contains the regressions for outflows and inflows samples separately. Since flow volatility is likely autocorrelated, we also control for non-overlapping lagged flow volatility, measured using squared flows between *t-2* and *t*. Because we are interested in both the time series (within each fund) and cross-sectional relationship between flow volatility and flow diversification, we estimate separate models with fund fixed effects and style fixed effects. In all specifications, we include year fixed effects to control for unobservable aggregate shocks to fund flows. Newey-West standard errors are clustered at the fund level.

Flow diversification is negatively related to flow volatility, controlling for lagged flow volatility. In the outflows subsample with fund fixed effects (the first two columns in Panel A), the coefficient on *FlowImb* is -0.02, implying that lower flow imbalance (more diversified flows) is related to lower flow volatility. Similarly, the coefficient on *FlowCorr* is 0.02, indicating that more correlated flows (less diversified flows) are related to higher flow volatility. Both coefficients have small standard errors and are similar if we use style fixed effects. In terms of magnitude, an increase (decrease) in *FlowImb* (*FlowCorr*) from 25 percentile to 75 percentile is associated with a 5% (7%) increase in flow volatility. Regressions with style fixed effects in the next two columns present similar results.

Since flow volatility is likely autocorrelated, flow diversification and lagged flow volatility may contain similar information about future flow volatility. To orthogonalize flow diversification, we first regress *FlowImb* or *FlowCorr* measured on day *t* on lagged flow volatility measured day *t-2* to *t* (with fund fixed effects); the residuals represent orthogonalized flow diversification, Orth*FlowImb* or Orth*FlowCorr*. We then regress flow volatility from day *t+1* to *t+3* on Orth*FlowImb* or Orth*FlowCorr*, controlling for lagged flow volatility. The results are presented in the last two columns of the outflows and inflows subsamples. The orthogonalized versions of *FlowImb* and *FlowCorr* continue to be related to future flow volatility.

An event-based approach provides a somewhat sharper link between flow volatility and flow diversification. When a fund adds a share class, it potentially diversifies its client base and hence its flows. If that is the case, we expect a decline in flow volatility. We identify the date on which a fund adds or removes a share class, and then calculate three-day flow volatility before and after the event. The results are in Panel B. Across all events, the average pre-event and post-event three-day flow volatilities are 0.45% and 0.23%, respectively. The difference, -0.22%, has a standard error of 0.01%. The removal of share classes is a rarer event, which is associated with a modest increase in flow volatility from 0.17% to 0.25%. Perhaps unsurprisingly, the reduction in volatility diminishes with the number of pre-event share classes. For example, when the number of share classes increases from two to three, the decline in flow volatility is -0.35%. With more than seven share classes, the change of flow volatility associated with a share class addition is quite small and is statistically indistinguishable from zero.

The above results verify a link between flow diversification and flow volatility. We turn now to whether this influences immediacy demands in the face of redemptions and, therefore, fund returns.

5. Flow Diversification and Future Returns

5.1 The Relation between Flows and Future Returns

A number of studies suggest that large outflows force mutual funds to engage in costly trading, generating an externality for non-redeeming shareholders and 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), Falato et al. (2021) and others). Most of these studies either use quarterly holdings of the underlying securities or monthly fund flows/returns to establish these effects. In contrast, we exploit timing conventions and the granularity of daily data to isolate the impact of flows in a more precise manner. Each day, we sort funds into quintiles based on their net flows, separately for outflows and inflows. We then compute returns over the following three days, as well as cumulative three-day returns (*t+1* to *t+3*). We use these horizons for two reasons. First, as discussed in Section 2, there is variation in flow notifications received by portfolio managers. In response to flows on day *t*, some managers can trade on *t+1* while others may not be able to do so till *t+2* or even *t+3*. Second, portfolio managers can sometimes use liquidity management tools to adjust their immediacy requirements, at least for a few days. For inflows, portfolio managers may be able to equitize cash in the futures market before trading in individual securities. For outflows, managers can use cash buffers to meet redemption requests. These tools impose costs, both explicit (trading costs in the futures market) and implicit (tracking error, cash drag).

The first block of Panel A in Table 4 shows average returns for each quintile. The bottom row in the block reports the return difference between the large and small flow quintile, with standard errors in parentheses. For funds experiencing outflows, the difference in the day *t+1* return between the large and small flow quintile is 0.73 basis points with a standard error of 0.20. Over the three-day period, the return difference is 1.34 basis points with a standard error of 0.33%. For inflows, the equivalent return differences are 0.18 and 0.38 basis points, respectively, neither of which are statistically distinguishable from zero.

The return differences described above are monotonic across quintiles, suggesting that the costs associated with flows are not just in the extremes. The quintiles are well diversified, containing 162 funds on average, so we do not expect particular fund styles to dominate the results. Nonetheless, we also compute style-adjusted returns that subtract the asset-weighted returns of all funds in the same Morningstar style box. The advantage of style-adjusted returns, relative to index benchmarks, is that they include trading costs. The results are reported in the next block within Panel A. The average large-minus-small flow quintile three-day spread for outflows is 1.25 basis points with a standard error of 0.26 basis points. As with raw returns, there are no differences in returns across quintiles for inflows.[14]

Since trading costs are larger for illiquid assets, we also report separate returns for funds that invest in illiquid versus liquid assets. In doing so, we use the Chen, Goldstein, and Jiang (2010) definition which regards small-cap, mid-cap and single-country non-US funds as illiquid, and all others as liquid. Panel B shows that for outflows in illiquid funds, the large-minus-small three-day return difference is 1.91 basis points with a standard error of 0.42. But even in funds that trade more liquid securities (Panel C), the equivalent return difference is 0.83 basis points with a standard error of 0.33 basis points.

Finally, we use an event-based approach to isolate these effects. The basic idea is simple. Funds that distribute large capital gains (perhaps because of redemptions over the prior year) must raise cash prior to the pay date. To do this, they have to sell securities, incurring trading costs that affect returns. To assess if this is detectable in the data, we extract capital gains distributions and pay dates from the CRSP Mutual Fund database. We sum short- and long-term capital gains and calculate a payout ratio as the sum of capital gains scaled by NAV on the record date. We then use the median of this payout ratio (which is 5.15% across about 14,000 pay dates in our sample) to classify funds into high and low capital gains distribution groups (high CG and low CG). The remainder of funds are tabulated in a separate no-CG group.

Panel D reports flows and style-adjusted returns over the two week period prior to the pay date (labeled *t-1* to *t-5* and *t-1* to *t-10* respectively). Funds in the high CG group experience outflows, losing 1.09% of their assets over the prior two weeks. More importantly, these high CG funds underperform low CG funds by 5.32 basis points in the prior week and 7.11 basis points in the prior two weeks (with standard errors are 1.21 and 1.58 basis points, respectively). As with the results in Panels A, B, and C, this suggests that flow-induced trading generates non-zero costs.

One way to assign economic content to the return differences in Table 4 is to compare them to prior studies. A return difference of one basis point per day corresponds to roughly 20 basis points per month (or 2.4 percent per year). By way of comparison, Chen, Goldstein, and Jiang (2010) calibrate statistics from Christoffersen, Evans, and Musto (2007) as well as Edelen (1999) to indicate that a fund facing heavy redemptions (above the 95th percentile) generates monthly costs of between 37 and 76 basis points. Using their data but focusing on the least liquid funds,

[14] For readers interested in return differences across funds within a Morningstar assigned style, we report the full matrix in Appendix Table A1. We observe return differences in both large and small cap funds, as well as in value and growth funds; the effects of flow-induced trading are apparently pervasive across all fund styles.

Chen, Goldstein, and Jiang (2010) imply that large outflows in month *t-1* predict lower returns in month *t* in the order of 19 basis points. Alexander, Cici, and Gibson (2015) report that outflow-driven stock sales subsequently outperform discretionary sales by 1.55% per year. The above three estimates are generally derived from extremely large outflows. Our daily data show similar magnitudes from the extremes but also detect return differences in funds with more moderate outflows. A second way to think of economic significance is to compare these return differences to explicit costs paid by investors. The Investment Company Institute reports that expense ratios between 2007 and 2020 averaged about 70 basis points per year, or about 0.28 basis points per day (Table 6.1, pg. 133 of the ICI Factbook 2021). At the minimum, the flow-induced costs in Table 4 are comparable in magnitude.

5.2 The Relation between Flow Diversification and Future Returns

Our primary interest is in the relation between flow diversification and fund performance. We start with a simple portfolio approach, forming flow diversification quintiles on each day and examining future returns. Panel A of Table 5 contains average returns for *FlowImb* and *FlowCorr* quintiles in basis points with standard errors in parentheses. Since the results in Table 4 are invariant with respect to benchmark-adjusted or style-adjusted returns, in this and future tables, we only report raw returns. For cumulative returns, standard errors are computed after adjusting for autocorrelation induced by overlapping data (using the Newey-West method).

For outflows sample, over *t+1* to *t+3*, funds with high flow imbalance (quintile 1, labeled High Imb) earn 5.79 basis points compared to 7.20 basis points for funds with low flow imbalance (quintile 5, labeled Low Imb), a spread of 1.41 basis points with a standard error of only 0.25 basis points. Much of this spread accrues on t+1 (0.83 basis points). Similarly, the three-day spread in returns between the high correlation and low correlation quintiles is -0.46 basis points with a standard error of 0.19 basis points. In both cases, the spread in returns for funds with inflows is statistically indistinguishable from zero.

Since flow diversification may be correlated with fund flows (i.e. if funds with diversified clienteles receive offsetting flows, their net flows may be systematically lower), we also use independent double sorts on fund flows and the flow diversification measures. To ensure that each group is well diversified, we use terciles for each sorting metric on day *t*, generating a 3x3 matrix. Panel B shows three-day returns (*t+1* to *t+3*) for these 3x3 sorts to keep the presentation manageable. Holding the magnitude of outflows roughly constant, there are still large spreads in returns generated by *FlowImb* and *FlowCorr*. For example, when outflows are large, the spread between low imbalance and high imbalance terciles is 1.88 basis points with a standard error of 0.33 basis points. The spreads also exist in the other terciles (0.84 basis points for small outflows), indicating that the return differences are not driven by extreme flows. Similarly, the spread in returns generated by the flow correlation measure is -0.93 basis points with a standard error of 0.32 basis points for large outflows. Notably, all of the variation in returns comes from outflows; in Panel B, there are no meaningful differences in returns, even when there are large inflows.

Table 6 reports regressions of three-day cumulative returns on prior flow imbalance and flow correlation. The regression approach offers some advantages relative to portfolio sorts. It explicitly allows us to control for flows on day *t*, as well as other covariates that may affect realized fund returns through liquidity management tools discussed Section 2. With style or fund fixed effects, it also allows us to extract information from cross-sectional or time series variation. We estimate separate regressions for outflows and inflows, controlling for year fixed effects, and using fund-level clustered standard errors. Consistent with Table 4, outflows on day *t* are negatively related to future three-day returns. In contrast, for inflows, the coefficient on log(flow) is indistinguishable from zero. The other standard control variables (TNA, turnover, and expense ratio) take on expected signs so we do not discuss them further.

In Panel A with style fixed effects, flow imbalance is positively related to future returns. However, this relation is largely driven by outflows, where the coefficient on *FlowImb* is 1.46 and has a standard error of 0.58. To put this into perspective, moving from the 25^{th} percentile to the 75^{th} percentile of the distribution of flow imbalance, the coefficient implies a three-day return difference of -0.80 basis points. This is of the same order of magnitude as the 1.41 basis points from the portfolio sorts in Table 5. In contrast, the coefficient on flow imbalance for inflows is indistinguishable from zero. Flow correlations tell a similar story. For outflows, the coefficient of -0.61 (with a standard error of 0.36) implies a return difference of -0.31 basis points from the inter-quartile range of flow correlations. And as with *FlowImb*, the coefficient on *FlowCorr* for inflows is indistinguishable from zero.

Panel B uses fund fixed effects, focusing on time series variation for each fund. For outflows, the magnitudes of the return differentials implied by the coefficients are similar (-0.70 basis points for *FlowImb* and -0.44 basis points for *FlowCorr*). Unlike Panel A, however, there are hints that flow diversification measures also have some traction with inflows. The coefficient on flow imbalance for inflows is -1.13 with a standard error of 0.59, and for flow correlation, the coefficient is -0.81 (standard error = 0.40). Evaluating the impact of a movement in *FlowImb* and *FlowCorr* from the 25th to the 75th percentile, these imply three-day return differences of -0.45 and -0.48 basis points, respectively.

Since non-linearities in flows can play a significant role, we also estimate regressions similar to those in Table 6 but replace flows on day *t* with indicator variables corresponding to the lowest and highest quintile of flows. The omitted category consists of funds in the middle 60 percent of the distribution. To prevent cluttering tables, we only report coefficients on the flow diversification and flow quintiles (and their interaction effects) in Appendix Table A2 and provide a brief discussion here. In regressions that use *FlowImb*, the total effect of extremely large outflows is the sum of the coefficients on *FlowImb* and the interaction effect with quintile 1. In Panel A (using style fixed effects), that return difference is quite large, 4.18 basis points (2.75+1.43). For quintile 5 (small outflows), the effect is still positive (2.85 basis points) but substantially smaller. For small inflows, the effect is unimportant at -0.06 basis points (-0.70+0.64). But for large inflows (corresponding to quintile 5), the return differential is again quite large, -4.84 basis points. If we use fund fixed effects (Panel B), the magnitudes are comparable. Estimates from the flow correlation regressions paint a similar picture.

5.3 Flow and Liquidity Management

The evidence thus far indicates that outflows generate liquidity externalities and that flow diversification can mitigate those externalities. Fund managers can control the costs associated with flows in at least four ways. In this section, we discuss these methods while seeking to determine if they influence our conclusions.

The most obvious way to control liquidity externalities is to hold cash reserves. Higher cash levels reduce immediacy demands, allowing portfolio managers to meet redemptions but delay the sale of underlying securities. To do so comes at a cost, generating cash drag on the portfolio and lowering future returns. In a perfect world, we would be able to observe cash levels daily to determine their influence. The best we can do (as in Table 6) is to use cash levels observed over the prior month. With that caveat in mind, the coefficients on cash in both Panels A and B of Table 6 are indistinguishable from zero, and more importantly, do not affect inferences with respect to flow diversification. A second way to control immediacy needs is to impose loads on fund shareholders. We estimate the regressions in Table 6 after including loads and report the results in Appendix Table A3. As with cash levels, the presence of loads does not alter our conclusions with respect to flow diversification; both *FlowImb* and *FlowCorr* are similar in sign and magnitude to coefficients in Table 6. A third mechanism available to portfolio managers is to impose swing pricing rules in which redeeming shareholders bear the cost of a fund's trading. Jin, Kacperczyk, Kahraman, and Suntheim (2021) use investor-level transaction data in UK corporate bond funds to show that swing pricing rules prevent outflows that occur during times of market stress. An important aspect of swing pricing rules is that fund management companies are allowed, but not required to, use these alternative pricing structures. To determine if swing pricing is prevalent in our sample, we extract information from N-CEN for all US-domiciled mutual funds on whether the fund is engaged in swing pricing. Unlike their UK peers, none of the US equity funds in our sample employ swing pricing between 2019 and 2020. Finally, a fourth technology that portfolio managers can avail of is to provide redemptions in-kind. Aggarwal, Ren, Shen, and Zhao (2022) report that 66% of their sample of funds report the right to so, but that actual redemptions only occur in 3.6% of fund-quarters (13.1% of funds).

Although our concern is largely with outflows, we also investigate liquidity management with respect to inflows. Portfolio managers can equitize the inflows in the futures market and then gradually trade the underlying securities. This can control the demand for immediacy in underlying securities. We collect information on derivatives usage by the funds in our sample from N-PORT filings following the processes in Kaniel and Wang (2020). Although such quarterly data are only available for the last two years of the sample, persistence in the usage of futures contracts is high: the probability that a fund using futures contract in quarter t also uses it in quarter $t+1$ is over 95%. Using these data, we re-estimate the flow regressions in Table 6, including an indicator variable if the fund has a long position in equity futures contracts, and an interaction term between the indicator variable and flow diversification measures. We do not report the details of those regressions except to note that for inflows, the coefficient on the interaction term with *FlowImb* (*FlowCorr*) is 2.71 (1.67) with a standard error of 1.31 (0.89). Although the evidence is far from definitive, it suggests that portfolio managers are active in managing liquidity issues associated with inflows, and that in doing so, mitigate the impact of flow diversification on fund performance.

5.4 Anticipatable and Unanticipated Shocks

Etula et al. (2019) document a spike in payments at the end of the month, a reflection of the monthly payment and settlement cycle. They show that even though this payment cycle is fully anticipatable, it still generates meaningful price pressure in financial markets. Mutual fund investors are also subject to these payment cycles. Figure 1 shows the proportion of daily flows scaled by total monthly flows for the funds in our sample from 10 days before to 10 days after the last trading day of the month.[15] The proportion of flows prior to the end of the month ranges from 4% to 5% across the three clientele groups. Each group experiences substantial increases in flows on days *t+1* or *t+2*. Retail investor flows rise to over 6% on day *t+1*, while the advisor and retirement group flows rise to 8% and 10.5%, respectively. These spikes occur throughout the time series and are not driven by end-of-year (or quarter) flows.

Do these spikes in flows generate differences in returns related to our flow diversification measures? To explore this issue, we calculate the daily difference in returns across flow diversification quintiles in the 20-day period surrounding the end of the month. Based on the results in Table 5, we focus on funds experiencing outflows. Figure 2 shows average quintile return spreads based on *FlowImb*, with the dashed horizontal line representing the average spread over the entire period, not including days *t+1* to *t+3*. There is a clear increase in quintile spreads on *t+2* and *t+3*; the average spread is 0.77 basis points, but the spread on *t+2* and *t+3* rises to 1.97 and 1.82 basis points, respectively. Figure 3 shows the equivalent quintile spreads based on flow correlations. The average quintile spread here is -0.17 basis points, and on *t+1* and *t+2* drops to -0.63 and -1.38 basis points, respectively. These results are somewhat surprising. To the extent that the timing of these flows is predictable, portfolio managers should be able to use the aforementioned liquidity management tools to minimize liquidity costs. The fact that we continue to see dispersion in fund returns based on flow diversification suggests that portfolio managers are either unwilling or unable to effectuate these mechanisms, or that the costs of doing so are prohibitively large.

It is also interesting to look at flows that cannot be anticipated by portfolio managers. To

[15] For monthly payrolls, payments, deductions and automatic transfers to retirement and investment accounts take place either on the last day of the month (for monthly payrolls) or on the last Friday of the month. We center the figure around the last trading day, not the calendar day.

do so, we examine return spreads across flow diversification quintiles on four key dates during the 2008 Financial Crisis, and three dates in Covid-19 Pandemic on which market-wide circuit breakers were triggered.[16] Table 7 shows each of these events, the return on the S&P 500 on each of those days, as well as the spreads in flow imbalance or flow correlation quintiles in the days thereafter. Once again, we only present the results for the outflows sample.

Panel A shows that the benefits to flow diversification, as measured by flow imbalance, were extraordinarily large during these events. Focusing on the *t+1* to *t+3* cumulative returns, the quintile return spread for dates during the Financial Crisis ranges from 24 basis points to 41 basis points. For the Covid-19 circuit breakers, the spreads vary from 44 to 52 basis points. These return spreads are orders of magnitude larger than the unconditional average spread of 1.41 basis points in Table 5. Panel B shows equivalent statistics for quintiles based on flow correlation. Again, the (absolute) spreads range from 9 basis points to 48 basis points, substantially large than the 0.46 basis points reported in Table 5.

5.5 Family Effects

We consider the importance of family effects for flow diversification arising from two distinct channels.

5.5.1 Strategic Considerations

If a family's objective function is to maximize its value, then it may be optimal for some families to focus on particular distribution systems while other families diversify across several distribution channels. For example, some fund families focus exclusively on an advisor channel while others diversify across several. The existing literature suggests that there are strategic considerations behind these choices. Massa (2003) argues that fund families can rely on investor heterogeneity to increase fund offerings. Bhattacharya, Lee, and Pool (2013) indicate that families create an insurance pool against temporary liquidity shocks by offering funds that only invest in other funds within the same family. Chernenko and Sunderam (2020) suggest that cash holdings are adjusted by funds with large incentives to internalize price impact across other funds in the family (their "Advisor Internalize" measure). Although these are strategic effects, legal considerations are important in effectuating them. Fund boards serve as a fiduciary to fund

[16] Strahan and Tanyeri (2015) and Schmidt et al. (2016) find that immediately after Lehman's collapse in 2008, investors exited from risky money market funds, forcing fire-sales of underlying assets. Falato, Goldstein, and Hortaçsu (2021) document large outflows in corporate-bond funds during the COVID-19 crisis.

shareholders, not the fund family or investment advisor. As a result, cross-fund actions require navigating important legal requirements and boundaries. Since legal considerations do not obviously preclude strategic behavior, we assess its importance for flow diversification in a simple way. We re-estimate the regressions in Table 6 but including (the logarithm of) family size as a control variable, and including family specific fixed effects. The latter in particular serves as a catch-all of unobservable but latent family choices.

The results appear in Table 8. Panel A includes family fixed effects. Despite their inclusion, the coefficients on *FlowImb* and *FlowCorr* are quite similar to those in Table 6. Panel B includes even more stringent controls – both family and style fixed effects. Here too the coefficients are largely similar.

5.5.2 Integration of Trading Functions

A second channel by which family effects could matter is not strategic but driven by the nature of the trading function. In most fund management complexes, trading is a consolidated function, providing services to all funds; the prototypical setup involves fund managers submitting trading interests to an Order Management System (OMS), which then aggregates order flow across funds and allows traders to trade the net demand. This opens up the possibility of flow diversification benefits across funds operating through Rule 17a-7 of the Investment Company Act of 1940, which permits crosses between mutual funds and other accounts that have the same investment advisor so long as certain requirements are met.[17] The central requirement of the rule is that the transaction occurs at an independent and objective market price that does not favor one fund over the other. The industry standard is to use the last transaction price or the most recent mid-point quote.

Unfortunately, internal crosses cannot be directly observed from market data because there are no pre- or post-trading reporting obligations.[18] However, internal crosses are widely used in

[17] If the family manages institutional assets from a plan sponsor subject to ERISA, technically those assets may not be used in internal crosses. However, the Department of Labor does grant exemptions, referred to as Prohibited Transaction Exemptions (PTEs). Details are in "Cross-Trades of Securities by Investment Managers", Federal Register, Volume 63, No. 54, 13696-13701, March 20, 1998, and Department of Labor (2006). See also https://www.sec.gov/news/public-statement/investment-management-statement-investment-company-cross-trading-031121.

[18] To our knowledge, the only study that observes internal crosses is Chan et al. (2018). Even in their paper, however, 17A-7 transactions are not directly observable but inferred from proprietary data via commission structures and family identifiers.

the asset management industry and can potentially leave a footprint in fund returns. Given that, we compute family-level measures of *FlowImb* and *FlowCorr* by aggregating fund and clientele-level information across all active funds in a family. In doing so, we focus on funds that invest solely in US securities because non-US securities do not have readily available market quotations during US trading hours. We compute (a) family-level flow imbalance ($FlowImb^F$) as the sum of signed flows across funds scaled by the sum of the absolute value of fund flows, (b) family-level flow correlation ($FlowCorr^F$) as the weighted average covariance of flows across funds, scaled by the sum of squared deviations of fund flows from family-level net flows. We then estimate fund-level regressions equivalent to those in Table 6 but with family-level flow diversification measures. The regression estimates appear in Table 9.

Family-level flow diversification measures show benefits similar to those in Table 6. In Panel A, which utilizes style and year fixed effects, and for the outflows sample, the coefficient on $FlowImb^F$ is 1.23 with a standard error of 0.53; the coefficient on $FlowCorr^F$ is -1.06 with a standard error of 0.49. The coefficients in Panel B (with fund fixed effects) are similar. In both cases, the economic effects of flow diversification are comparable to those in Table 6 – the implied change in three-day returns in moving from the 25th percentile of the distribution of flow diversification to the 75th percentile ranges from 0.64 to 0.88 basis points when funds experience outflows.[19]

5.6 Multiplier Effects

Chen, Goldstein, and Jiang (2010) devise a procedure to identify multiplier effects caused by mutual fund redemptions. They argue that investors who hold illiquid funds face a higher degree of strategic complementarity than investors in liquid funds because redemption costs in illiquid assets are larger. Exploiting this observation, their central test consists of regressions of flows on prior performance in which the key independent variable is the interaction between an illiquidity dummy and prior performance. They conduct their analysis at the share class (not fund) level, using monthly flow and return data. Since the interaction term between the illiquidity

[19] There can also be an interaction between the strategic effect discussed in Section 5.5.1 and the trading channel in 5.5.2. For example, many (but not all) fund families offer ETFs that are equivalent to their counterpart mutual funds. Since ETFs and funds are different veheicles, however, transactions between the fund and its matching ETF are prohibited so that cross-subsidization is not possible. (Vanguard is an exception in the sense that ETFs are treated a separate share class, courtesy a patent. See Mider, Massa, and Cannon (2019) for a discussion of the share class approach and heartbeat trades.)

dummy and prior performance is positive in their sample, they conclude that outflows are more sensitive to poor performance in illiquid funds.

Our interest arises from the idea that if a fund has diversified flows, then investors may be less concerned with the exit of other investors. This idea translates into two tests. First, we wish to determine whether funds with higher flow diversification have lower flow-to-performance sensitivity, notwithstanding the higher flow-to-performance sensitivity of illiquid funds. Second, we ask whether flow-to-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? We modify the Chen, Goldstein, and Jiang (2010) approach to suit these purposes. Because we use daily data, we measure performance using returns over the prior three days rather than monthly alphas from a factor model. Other than that, the regressions are very similar to their Table 2 and contain the same set of control variables. The key additions are: (i) flow diversification indicator variables *FlowImb*(I) and *FlowCorr*(I) defined so that the variables take on a value of one for low levels of flow diversification using the median or the 20th percentile as a cutoff,[20] (ii) interaction terms between the flow diversification indicator variables and prior performance, and (iii) triple interaction terms between the flow diversification indicator variables, performance, and the illiquidity dummy. We estimate separate regressions for the full panel, as well as the subsample in which prior returns are negative, but only report the latter in a table. The results appear in Table 10, with the main variables of interest appearing above the dashed line. Since the control variables (below the dashed line) take on expected signs and are consistent across specifications, we do not discuss them further.

At the outset, taking the Chen, Goldstein, and Jiang (2010) result to daily data leaves their conclusions unaltered. The interaction term between the illiquidity dummy and past performance is consistently positive. Using monthly data, their regressions imply that flow-performance sensitivity is 52% higher in illiquid funds (the combined coefficients of prior performance and the interaction term between illiquidity and prior performance are 52% higher than the coefficient on prior performance). In our daily sample, using the first model in Panel A, the equivalent increase in flow-to-performance sensitivity is 85% (0.35 / (0.35+0.41)).

The first two models in each panel include the flow diversification indicator variables and

[20] For *FlowImb*, we use the absolute value of *FlowImb* in order to compare funds with positive and negative flow imbalance.

their interactions with performance, while also including the interaction of the illiquidity dummy with prior performance. In each of the regressions, the interactions between *FlowImb*(I) and *FlowCorr*(I) with performance is positive, indicating that flow diversification influences flow-to-performance sensitivities. Based on the results in Panel B (which uses a 20th percentile cutoff), the flow-to-performance sensitivity in less diversified funds is higher than that in more diversified funds (50% higher using *FlowImb(I)* and 23% higher using *FlowCorr(I)*)). The implication is that even with strategic complementarities, flow diversification remains important. The last two models in each panel include the triple interaction terms between the flow diversification indicator variables, performance, and the illiquidity dummy. The coefficient on this variable is positive in all four specifications, implying that flow-to-performance sensitivities are larger in illiquid funds with low levels of flow diversification. The magnitude of the effect varies across specifications. For example, using 20th percentile as a cutoff for flow diversification, the flow-performance sensitivity in illiquid funds is 1.89 times higher when the flow is less diversified and flow diversification is measured by *FlowCorr* (55% versus 19%). Nonetheless, it appears that flow diversification generates variation in flow-to-performance sensitivities that can at least partially offset the larger flow-to-performance sensitivities in illiquid funds.[21]

Chen, Goldstein, and Jiang (2010) argue that an investor with a large stake is less concerned with externalities imposed by the exit of other shareholders and "injects strategic stability", reducing the incentives that generate shareholder runs. To test this hypothesis, they estimate separate flow-to-performance regressions for share classes oriented towards retail versus institutional investors, restricting the sample to funds in which institutional share classes hold more than 75% of the fund's assets. They find that the flow-to-performance sensitivity of illiquid funds is only higher in retail share classes, concluding that investor composition matters. To investigate whether this large investor mechanism affects inferences with respect to flow diversification, we follow their lead and restrict the sample to funds with more than 75% of assets derived from institutional share classes. We then re-estimate the regressions in Table 10 using the 20th percentile of flow diversification as a cutoff for the flow diversification indicator variables. The results, again restricted to the sample where prior returns are negative, are presented in Table 11.

The first two columns show specifications which include interaction terms between the

[21] Returns measured over the prior three days are noisy. We also employ returns over longer horizons (5 and 20 days). The results, reported in Appendix Table A4, are similar.

illiquidity indicator variable and prior performance, as well as interaction terms between the flow diversification indicator variables and prior performance. Interestingly, and in contrast to Chen, Goldstein, and Jiang (2010), the interaction term between the illiquidity indicator and prior performance remains positive, even in a sample restricted to funds with mostly institutional assets. More importantly, from our perspective, the interaction terms between the flow indicator variables and prior performance are also positive, implying that flow-to-performance sensitivity, even in the presence of large investors, is still influenced by flow diversification. Comparing to the regressions in Table 10, the coefficients imply that the flow-performance sensitivity in less diversified funds is higher than that in more diversified funds (68% higher with *FlowImb(I)* and 90% higher with *FlowCorr(I)*)). The last two columns show the triple interaction effects. Here too the coefficients are positive with small standard errors, implying that flow diversification moderates the higher flow-to-performance sensitivity in illiquid funds. For example, when flow diversification is measured by *FlowCorr*, the flow-performance sensitivity in illiquid funds is 1.77 times higher when the flow is less diversified (75% versus 27%). Our results suggest that at the daily frequency, strategic complementarities exist independent of investor composition, which is consistent with Schmidt, Timmermann, and Wermers (2016), who find strong daily interactions between institutional investors of different levels of sophistication in the September 2008 run episode.

6. Additional Evidence from Investment Styles

Our tests utilize the full cross-section of funds. To the extent that liquidity is more expensive in small stocks, it is possible that flow diversification benefits are only important for funds that invest in small stocks. We separate the sample into small versus large cap funds, and then recalculate the quintile spreads in Table 5. We do not report the results in a table, but they are easily described. Focusing on outflows, the 3-day quintile spread based on flow imbalance is 1.64 basis points in small-cap funds and 1.06 basis points in large-cap funds, with standard errors of 0.35 and 0.26 basis points respectively. Using flow correlations, the quintile spread is -0.63 basis points in small-cap funds and -0.22 basis points in large-cap funds, also with small standard errors. Thus the benefits of flow diversification appear to accrue even in funds that invest in liquid securities.

More generally, it is possible that investment style is correlated with flow diversification –

for example, if small cap growth funds receive more correlated flows because of common signals or behavioral biases. To determine if this influences our conclusions, we adjust returns in two ways. We first subtract the equivalent index return from fund returns (labeled benchmark-adjusted returns). Since style benchmarks are at the intersection of size and value/growth, this has the added advantage of controlling for liquidity differences between small/large and value/growth stocks. Panels A and B of Appendix Table A5 contain benchmark-adjusted returns to flow diversification quintiles. As would be expected, the average returns within each quintile are smaller (and often negative). More importantly, the spreads between quintiles 1 and 5 are quite similar to Table 5. Since index returns do not incorporate transaction costs, we also compute style-adjusted returns by subtracting the asset-weighted returns for all funds within a style (labeled style-adjusted returns). The return spreads drop somewhat but the decline is quite small. For example, for outflows, *FlowImb* generates a return spread of 1.37 basis points after index adjustments. The return spread further drops to 1.12 basis points after subtracting live returns from funds in the same style. Finally, Appendix Table A6 contains regressions equivalent to Table 6 but using benchmark-adjusted (Panel A) and style-adjusted (Panel B) 3-day returns as the dependent variable. Controlling for other covariates, flow diversification measures generate a spread in both benchmark-adjusted and style-adjusted returns, mostly driven by outflows.

7. Conclusion

The twin externalities associated with pooling of claims in mutual funds are well-known: shareholders exiting from a fund generate costs because they require immediacy in underlying securities, and because they accelerate the distribution of capital gains. These costs are borne by shareholders remaining in the fund. In this paper, we study a mechanism that mitigates the externality associated with this structure.

Mutual funds source their assets from a variety of clienteles. To the extent that flows from different clienteles are imperfectly correlated, this generates flow diversification: outflows from one clientele can be offset by inflows from another, reducing the volatility of daily flows. Flow diversification attenuates immediacy requirements, thereby mitigating the liquidity externality in mutual funds. The externality itself is large. In our data, the spread in daily returns between funds with large outflows and those with small outflows is as much as one basis point per day. Moreover, these return spreads are even present in funds that invest in liquid assets, not just investment styles devoted to illiquid securities. The potential benefits of flow diversification are equally large. Holding constant flows, flow diversification generates a spread in daily returns almost equal to the liquidity externality itself, in the order of one basis point per day.

References

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbar-Salehi, 2015. Systemic risk and stability in financial networks. American Economic Review 105(2): 564-608.

Aggarwal, Vikas, Ren, Honglin, Ke Shen and Haibei, Zhao, 2022. Redemption in kind and mutual fund liquidity management. Working Paper, Georgia State University.

Alexander, Gordon, Gjergji Cici, and Scott Gibson, 2007. Does motivation matter when assessing trad performance? An analysis of mutual funds. Review of Financial Studies 20(1): 125-150.

Allen, Franklin, and Douglas Gale, Financial Contagion, 2000. Journal of Political Economy 108(1): 1-33.

Bailey, Jeffrey, and Thomas Richards, 2017. A primer for investment trustees: Understanding investment committee responsibilities. CFA Institute Research Foundation.

Bessembinder, Hendrik, Kalok Chan, and Paul Seguin, 1996. An empirical examination of information, differences of opinion, and trading activities. Journal of Financial Economics 40: 105-134.

Bhattacharya, Utpal, Jung Lee, and Veronika Pool, 2013. Conflicting family values in mutual fund families. Journal of Finance 68(1): 173-200.

Busse, Jeffrey, Amit Goyal, and Sunil Wahal, 2010. Performance and Persistence in Institutional Investment Management. Journal of Finance 65(2): 765-790.

Chan, Yue-Cheong, Jennifer Conrad, Gang Hu, and Sunil Wahal, 2018. Trading by crossing. Working paper, Hong Kong Polytechnic University.

Chang, Eric, Joseph Cheng, and Ajay Khorana, 2000. An examination of herd behavior in equity markets: An international perspective. Journal of Banking and Finance 24: 1651-1679.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. Journal of Financial Economics 97: 239-262.

Chernenko, Sergey and Adi Sunderam, 2020. Do fire sales create externalities? Journal of Financial Economics 135(3): 602-628.

Christie, William and Roger Huang, 1995. Following the pied piper: Do Individual returns herd around the market? Financial Analysts Journal 4: 31-37.

Christoffersen, Susan, Richard Evans, and David Musto, 2013. What do consumers' fund flows maximize? Evidence from their brokers' incentives. Journal of Finance 68(1): 201-235.

Coval, Joshua and Erik Stafford, 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86(2): 479–512.

Department of Labor, 2006, Report of the working group on plan asset rules, exemptions and cross-trading, https://www.dol.gov/ebsa/publications/AC_1106c_report.html.

Dickson, Joel, John B. Shoven, and Clemens Sialm, 2000. "Tax Externalities of Equity Mutual Funds," NBER Working Papers 7669, National Bureau of Economic Research, Inc.

Edelen, Roger, 1999. Investor flows and the assessed performance of open-end mutual funds. Journal of Financial Economics 53(3): 439–466

Edelen, Roger, Richard Evans, and Greg Kadlec, 2013. Shedding light on 'invisible' costs: Trading costs and mutual fund performance. Financial Analysts Journal 69)1, 33-44.

Etula, Erkko, Kalle Rinne, Matti Suominen, and Lauri Vaitttinen, 2019. Dash for cash: Monthly market impact of institutional liquidity needs. Review of Financial Studies 33(1): 75-111.

Falato, Antonio, Itay Goldstein, and Ali Hortaçsu, 2021. Financial fragility in the COVID-19 crisis: The case of investment funds in corporate bond markets. Journal of Monetary Economics 123: 35-52.

Falato, Antonio, Ali Hortaçsu, Dan Li, and Chaehee, Shin, 2021. Fire-Sale Spillovers in Debt Markets. Journal of Finance 76(6): 3055-3102.

Ferreira, Miguel, Massimo Massa, and Pedro Mators, 2017, Investor-stock decoupling in mutual funds. Management Science 64(5), 2144-2163.

Fratzscher, Marcel, 2012. Capital flows, push versus pull factors and the global financial crisis. Journal of International Economics 88: 341-356.

Greene, Jason and Charles Hodges, 2002. The dilution impact of daily fund flows on open-end mutual funds. Journal of Financial Economics 65(1): 131-158.

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden, 2011. Diversification disasters. Journal of Financial Economics 99: 333-348.

Illan, Ivan, 2018. How monitoring mutual fund flows gives unique stock market insight. Forbes Financial Council. https://www.forbes.com/sites/forbesfinancecouncil/2018/03/05/how-monitoring-mutual-fund-flows-gives-unique-stock-market-insight/?sh=9847fae35f65

Jin, Dunhong, Marcin Kacperczyk, Bige Kahraman, and Felix Suntheim, 2021. Swing pricing and fragility in open-end mutual funds. Review of Financial Studies, Forthcoming.

Johnson, Woodrow, 2004. Predictable investment horizons and wealth transfers among mutual fund shareholders. Journal of Finance 59(5): 1979-2012.

Jotikasthira, Chotibhak, Christian Lundblad, and Tarun Ramadorai, 2012. Asset fire sales and purchases and the international transmission of funding shocks. Journal of Finance 62(5): 2015-2050.

Kacperczyk, Marcin and Philipp Schnabl, 2013. How safe are money market funds? Quarterly Journal of Economics: 1073-1122.

Kaniel, Ron and Pingle Wang, 2020. Unmasking mutual fund derivative use. Working Paper, University of Rochester.

Massa, Massimo, 2003. How do family strategies affect fund performance? When performance-maximization is not the only game in town. Journal of Financial Economics 67: 249-304.

Mider, Zachary, Annie Massa and Christopher Cannon, 2019, https://www.bloomberg.com/graphics/2019-vanguard-mutual-fund-tax-dodge/

Morris, Stephen, Ilhyock Shim, and Hyun Song Shin, 2017. Redemption risk and cash hoarding by asset managers. Journal of Monetary Economics 89: 71-87.

Nanda, Vikram, Jay, Wang, and Zheng, Lu, 2009. The ABCs of mutual funds: On the introduction of multiple share classes. Journal of Financial Intermediation 18(3): 329-361.

Pozen, Robert C., 2002, The mutual fund business, Chapter 6: Brokerage transactions for mutual funds, 240-285, Houghton Mifflin Company, New York.

Raddatz, Claudio and Sergio Schmukler, 2012. On the international transmission of shocks: Micro-evidence from mutual fund portfolios. Journal of International Economics 88: 357-374.

Rakowski, David, 2010. Fund Flow Volatility and Performance. Journal of Financial and Quantitative Analysis 45: 223-237.

Schmidt, Lawrence, Allan Timmermann, and Russ Wermers, 2016. Runs on Money Market Mutual Funds. American Economic Review 106(9): 2625-2657.

Sialm, Clemens, and Hanjiang Zhang, 2020. Tax-efficient asset management: Evidence from equity mutual funds. Journal of Finance 75(2): 735-777.

Strahan, Philip, and Basak, Tanyeri, 2015. Once burned, twice shy: Money market fund responses to a systemic liquidity shock. Journal of Financial and quantitative Analysis 50: 119-144.

Wagner, Wolf, 2010. Diversification at financial institutions and systemic crises. Journal of Financial Intermediation 19, 373–386.

Wermers, Russ, 2000. Mutual fund performance: An empirical decomposition into stock-Picking talent, style, transactions costs, and expenses. Journal of Finance 55(4):1655–1695.

Zeng, Yao, 2017. "A dynamic theory of mutual fund runs and liquidity management," ESRB Working Paper Series 42, European Systemic Risk Board.

Table 1

Style distribution of funds and share classes

The sample consists of US-domiciled active equity mutual funds between April 2007 and June 2020. Funds are classified into style categories (based on size and value grids) by Morningstar. Panel A shows the number of funds, and the percentage of funds in parentheses, in each style. Panel B shows the aggregate dollar value of funds at the end of 2019 (in $ billions) and the percentage of the aggregate dollar value in parentheses, in each style. Panel C reports the total assets in each clientele group as a percentage of total assets of funds at the end of 2019, in each style. Clientele classifications are based on share class identification and are described in section 3.2

Panel A: Number and percentage of funds in each style			
	Small	Mid	Large
Growth	252	245	578
	(6.7)	(6.5)	(15.3)
Neutral	338	173	1281
	(8.9)	(4.6)	(33.9)
Value	214	160	541
	(5.7)	(4.2)	(14.3)
Panel B: Aggregate dollar value (and percentage) of funds in each style			
Growth	110	179	640
	(4.6)	(7.4)	(26.5)
Neutral	70	59	791
	(2.9)	(2.4)	(32.7)
Value	61	100	409
	(2.5)	(4.1)	(16.9)
Panel C: Percentage of fund assets in each clientele group			
Growth			
Advisor	56.7	50.0	53.5
Retail	27.6	33.0	32.9
Retirement	16.3	16.9	13.6
Neutral			
Advisor	61.2	57.4	57.1
Retail	28.3	32.5	31.8
Retirement	10.5	10.0	11.1
Value			
Advisor	52.4	55.9	51.4
Retail	27.5	21.2	27.4
Retirement	20.2	26.4	21.2

Table 2

Distribution of Flow Diversification Measures

Flow imbalance (*FlowImb*) on day *t* is the sum of signed flows across share classes scaled by the sum of the absolute value of flows. Flow correlation (*FlowCorr*) on day *t* is the weighted average covariance of flows across share classes, scaled by the sum of squared deviations of class-level flows from fund-level net flows. Panel A shows the distribution of the two measures separately for outflows and inflows, including the cross-sectional average of first-order autocorrelation, ρ (1). In Panel B, we form quintiles based on *FlowImb* or *FlowCorr* each day. The panel shows the time series average of *FlowImb*, *FlowCorr*, TNA (in $ millions), fund age (in years), expense ratio (in percent), turnover (in percent), total load (in percent), cash as a percentage of total assets, flow as a percentage of total assets on day t, and fund return on day *t* (in basis points).

Panel A: Distribution of flow diversification measures									
	Mean	S.D.	Min	25th Perc.	Med.	75th Perc.	90th Perc.	Max	ρ (1)
Outflows									
FlowImb	-0.82	0.27	-1.00	-1.00	-0.98	-0.74	-0.35	0	0.06
FlowCorr	0.20	0.43	-1.00	-0.03	0.23	0.49	0.76	1.00	0.07
Inflows									
FlowImb	0.78	0.30	0.00	0.60	0.95	1.00	1.00	1.00	0.05
FlowCorr	0.14	0.43	-1.00	-0.10	0.12	0.42	0.71	1.00	0.08
Panel B: Fund-level characteristics in flow imbalance and flow correlation quintiles									
FlowImb Quintile	*FlowImb*	TNA	Age	Exp. Ratio	Turnover	Load	Cash	Flow	Return
1 (Neg. Imb.)	-1.00	899	15.85	1.17	73.35	2.49	3.30	-0.17	3.97
2	-0.95	1,282	19.43	1.15	70.67	4.26	2.43	-0.17	4.11
3	-0.52	1,352	18.45	1.16	68.77	4.22	2.54	-0.05	3.65
4	0.49	1,329	15.81	1.14	69.13	4.14	2.93	0.08	3.03
5. (Pos. Imb.)	0.98	776	11.19	1.15	74.61	3.21	3.80	0.26	1.82
FlowCorr Quintile	*FlowCorr*	TNA	Age	Exp. Ratio	Turnover	Load	Cash	Flow	Return
1 (Low Corr.)	-0.45	819	14.80	1.15	70.52	0.03	3.18	-0.01	3.09
2	-0.01	1,023	15.36	1.12	71.80	0.04	2.99	0.00	3.21
3	0.19	1,360	17.81	1.13	72.62	0.04	2.92	-0.02	3.46
4	0.41	1,437	17.47	1.15	69.80	0.04	3.05	-0.02	3.49
5 (High Corr.)	0.76	958	14.46	1.20	71.59	0.03	3.73	-0.02	3.11

Table 3

Flow Volatility and Flow Diversification

Flow volatility is measured as squared daily fund flows over a three-day period. Panel A contains regressions of flow volatility between *t+1* and *t+3*, regressed on lagged flow volatility (*t-2*, *t*), *FlowImb* on day *t*, and *FlowCorr* on day *t*. Some specifications also included orthogonalized versions of Orth*FlowImb* and Orth*FlowCorr*, which use the residual from a first-stage regression of *FlowImb* or *FlowCorr* on lagged flow volatility. Newey-West standard errors, clustered at the fund level, appear in parentheses. Panel B contains the cross-sectional average of flow volatilities over a three-day period before and after an increase or decrease in the number of share classes. The first column shows the number of share classes prior to the change.

Panel A: Flow volatility regressions ($FlowVol_{t+1,t+3}$)

	Outflows						Inflows					
$FlowVol_{t-2,t}$	0.22	0.22	0.33	0.34	0.23	0.23	0.18	0.18	0.30	0.30	0.18	0.18
	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.020)	(0.02)	(0.01)	(0.01)
FlowImb	-0.02	-	-0.03	-	-	-	0.02	-	0.04	-	-	-
	(0.00)		(0.00)				(0.00)		(0.00)			
FlowCorr	-	0.02	-	0.01	-	-	-	0.01	-	0.02	-	-
		(0.00)		(0.00)				(0.00)		(0.00)		
Orth*FlowImb*	-	-	-	-	-0.02	-	-	-	-	-	0.02	-
					(0.00)						(0.00)	
Orth*FlowCorr*	-	-	-	-	-	0.02	-	-	-	-	-	0.01
						(0.00)						(0.00)
Constant	0.16	0.13	0.11	0.11	0.13	0.13	0.15	0.16	0.11	0.14	0.16	0.16
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed Effects	Fund	Fund	Style	Style	Fund	Fund	Fund	Fund	Style	Style	Fund	Fund
Adj-R^2	0.16	0.16	0.10	0.10	0.16	0.16	0.20	0.20	0.11	0.10	0.20	0.20

Panel B: Flow volatility before and after changes in the number of share classes

	Increase in Share Class					Decrease in Share Class				
	N	FlowVol (Pre)	FlowVol (Post)	ΔFlowVol	Std. Err.	N	FlowVol (Pre)	FlowVol (Post)	ΔFlowVol	Std. Err.
All Events	4,844	0.45	0.23	-0.22	0.01	1,066	0.17	0.25	0.08	0.02
# Share Classes (Pre)										
2	1,307	0.60	0.24	-0.35	0.02	129	0.20	0.44	0.24	0.05
3	832	0.60	0.25	-0.34	0.02	196	0.18	0.28	0.10	0.03
4	878	0.50	0.22	-0.27	0.02	210	0.22	0.25	0.03	0.03
5	658	0.47	0.27	-0.20	0.03	153	0.20	0.26	0.05	0.04
6	446	0.39	0.22	-0.17	0.04	109	0.15	0.21	0.05	0.04
7	259	0.29	0.20	-0.09	0.05	93	0.15	0.20	0.05	0.04
>=8	464	0.28	0.18	-0.10	0.06	176	0.09	0.13	0.04	0.04

Table 4

Post-Flow Average Returns

We sort funds into flow quintiles each day *t* and report average returns on *t+1*, *t+2*, *t+3*, and *t+1* to *t+3*. We report raw returns and style-adjusted returns. To compute style-adjusted returns, we subtract the asset-weighted return of all funds in the same investment style. In Panel B, illiquid funds are small-cap, mid-cap, and single country ex-US funds. In Panel D, we sort all pay dates associated with capital gains distributions into two groups, high and low CG based on the median of the payout ratio. We then report flows (in percent) and style-adjusted returns (in basis points) for funds in each group. Newey-West standard errors appear in parentheses.

	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								
Returns								
Large Flows	1.27	2.63	3.08	6.71	2.25	3.00	3.06	8.06
2	1.43	2.83	3.38	7.37	2.39	3.03	3.34	8.48
3	1.65	2.73	3.30	7.38	2.69	3.10	3.26	8.78
4	2.02	2.80	3.36	7.88	2.65	3.02	3.16	8.53
Small Flows	2.02	2.87	3.47	8.06	2.43	3.00	3.28	8.44
Large-Small	0.73	0.25	0.39	1.34	0.18	0.00	0.21	0.38
	(0.20)	(0.20)	(0.19)	(0.33)	(0.22)	(0.21)	(0.22)	(0.37)
Style-Adjusted Returns								
Large Flows	-0.71	-0.14	-0.29	-1.11	0.20	0.09	-0.02	0.28
2	-0.63	0.00	0.04	-0.59	0.51	-0.02	0.17	0.67
3	-0.50	-0.01	0.01	-0.51	0.85	0.15	0.03	1.05
4	-0.09	0.00	0.07	-0.02	0.72	0.12	0.03	0.86
Small Flows	-0.02	0.02	0.15	0.14	0.59	-0.02	0.16	0.75
Large-Small	0.69	0.16	0.44	1.25	0.39	-0.10	0.19	0.47
	(0.16)	(0.15)	(0.15)	(0.26)	(0.20)	(0.18)	(0.19)	(0.32)
Panel B: Illiquid Funds (Returns)								
Large Flows	0.60	2.44	2.57	5.46	2.11	2.79	2.80	7.52
2	0.90	2.82	2.90	6.45	2.53	2.79	2.82	7.95
3	1.09	2.85	2.68	6.43	2.62	3.04	3.11	8.59
4	1.40	2.56	3.03	6.78	2.57	3.12	3.05	8.56
Small Flows	1.49	2.89	3.19	7.37	2.46	2.76	2.93	7.97
Large-Small	0.89	0.45	0.62	1.91	0.35	-0.03	0.13	0.45
	(0.25)	(0.25)	(0.25)	(0.42)	(0.30)	(0.28)	(0.30)	(0.48)
Panel C: Liquid Funds (Returns)								
Large Flows	2.02	3.28	3.21	8.11	2.95	3.66	3.38	9.59
2	1.76	3.04	3.66	8.05	3.30	3.48	3.51	9.89
3	2.14	3.28	3.52	8.52	3.28	3.61	3.40	9.89
4	2.39	3.24	3.58	8.79	3.21	3.42	3.25	9.46
Small Flows	2.56	3.30	3.50	8.94	3.03	3.70	3.75	10.08
Large-Small	0.54	0.02	0.29	0.83	0.08	0.04	0.36	0.49
	(0.19)	(0.20)	(0.18)	(0.33)	(0.27)	(0.26)	(0.27)	(0.44)
Panel D: Flows and Style-Adjusted returns before Capital Gains Pay Dates								
	Flows (%)				Style-Adjusted Returns (basis points)			
	High CG	Low CG	No CG	H-L	High CG	Low CG	No CG	H-L
t-1, t-5	-0.58	-0.06	-0.09	-0.52	-2.97	2.35	-0.02	-5.32
t-1, t-10	-1.09	-0.09	-0.20	-1.00	-1.28	5.83	-0.06	-7.11

Table 5

Average Returns to Sorts on Flows and Flow Diversification

In Panel A, we form quintiles (labeled 1 through 5) based on the distribution of the flow imbalance and flow correlation on day *t* separately for outflows and inflows. The table shows the time-series average of returns on days *t+1*, *t+2*, *t+*3, and the cumulative return from *t+1* to *t+3*. Differences in extreme quintile returns ("5-1") also show Newey and West (1987) standard errors in parentheses. In Panel B, we form terciles based on flows (shown as small, mid, and large flows) and independent terciles based on *FlowImb* or *FlowCorr*. For each 3x3 group, we report average three-day returns ($Ret_{t+1,t+3}$). The bottom row shows the spread in returns for each flow tercile, with Newey-West adjusted standard errors in parentheses.

Panel A: Average Returns for Single Sorts on Flow Diversification

FlowImb					*FlowCorr*				
Outflows	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,t+3}$	Outflows	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,t+3}$
1 (High Imb)	1.63	1.89	2.48	5.79	1 (Low Corr.)	1.58	2.75	3.34	7.39
2	1.92	1.76	2.87	6.30	2	1.79	2.50	3.30	7.31
3	2.08	2.06	2.77	6.67	3	1.91	2.63	3.41	7.64
4	2.12	1.98	2.62	6.48	4	1.66	2.67	3.20	7.23
5 (Low Imb)	2.46	2.14	2.82	7.20	5 (High Corr.)	1.40	2.63	3.17	6.93
5-1	0.83	0.25	0.34	1.41	5-1	-0.18	-0.11	-0.17	-0.46
	(0.16)	(0.17)	(0.16)	(0.25)		(0.17)	(0.18)	(0.18)	(0.19)
Inflows					Inflows				
1	2.52	3.18	3.22	8.67	1	2.90	2.82	3.27	8.74
2	2.40	3.08	3.45	8.68	2	2.68	3.17	2.97	8.54
3	2.58	3.31	3.18	8.78	3	2.72	2.97	3.43	8.83
4	2.70	2.94	3.22	8.58	4	2.84	3.03	3.04	8.64
5	2.48	2.93	3.16	8.31	5	2.81	3.04	3.31	8.89
5-1	-0.04	-0.25	-0.07	-0.35	5-1	-0.09	0.22	0.04	0.15
	(0.23)	(0.23)	(0.23)	(0.37)		(0.23)	(0.23)	(0.23)	(0.38)

Panel B: Average 3-day Returns ($Ret_{t+1,t+3}$) for Independent Double Sorts on Flows Diversification and Flows

Outflows				Outflows			
	Large	Mid	Small		Large	Mid	Small
1 (High Imb)	6.05	6.77	6.95	1 (Low Corr.)	7.68	7.41	7.70
2	6.26	7.03	7.38	2	7.76	7.12	7.95
3 (Low Imb)	7.93	7.49	7.79	3 (High Corr.)	6.75	6.64	7.49
3-1	1.88	0.72	0.84	3-1	-0.93	-0.77	-0.20
	(0.33)	(0.32)	(0.32)		(0.32)	(0.35)	(0.32)
Inflows				Inflows			
	Large	Mid	Small		Large	Mid	Small
1 (High Imb)	7.38	6.22	5.98	1 (Low Corr.)	8.35	8.56	8.59
2	5.65	7.45	5.18	2	8.25	8.77	8.41
3 (Low Imb)	6.43	6.43	5.21	3 (High Corr.)	8.00	8.90	8.42
3-1	-0.95	0.21	-0.77	3-1	-0.34	0.34	-0.17
	(1.14)	(1.06)	(1.19)		(0.43)	(0.39)	(0.47)

Table 6

Regressions of 3-Day Returns on Flow Diversification

The table shows panel regressions of three-day returns ($Ret_{t+1, t+3}$) on flow imbalance, flow correlation, and other control variables measured on day *t*. Flow imbalance (*FlowImb*) is the sum of signed flows across share classes scaled by the sum of the absolute value of flows. Flow correlation (*FlowCorr*) is the weighted average covariance of flows across share classes, scaled by the sum of squared deviations of class-level flows from fund-level net flows. Control variables include natural logarithm of fund assets, natural logarithm of fund flow, VIX, fund turnover, expense ratio, and cash holding as a percentage of assets. Newey-West standard errors, clustered at the fund level, are in parentheses.

	Outflows	Inflows	Outflows	Inflows
Panel A: Style and Year Fixed Effects				
FlowImb	1.46	-0.87	-	-
	(0.58)	(0.64)		
FlowCorr	-	-	-0.61	-0.52
			(0.36)	(0.38)
Log (TNA)	0.31	-0.46	0.43	-0.42
	(0.14)	(0.14)	(0.12)	(0.12)
Log (Flow)	-0.27	0.14	-0.36	0.11
	(0.11)	(0.10)	(0.11)	(0.09)
VIX	3.89	3.61	3.89	3.61
	(0.05)	(0.08)	(0.06)	(0.08)
Turnover	-0.04	-0.77	-0.03	-0.76
	(0.23)	(0.23)	(0.24)	(0.23)
Exp. Ratio	-0.01	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Cash / TNA	-0.03	-0.03	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
N	1,865,993	1,301,325	1,865,993	1,301,217
Adj-R^2	0.02	0.02	0.02	0.02
Panel B: Fund and Year Fixed Effects				
FlowImb	1.74	-1.13	-	-
	(0.64)	(0.59)		
FlowCorr	-	-	-0.95	-0.81
			(0.38)	(0.40)
Log (TNA)	-4.10	-4.89	-4.08	-4.84
	(0.33)	(0.36)	(0.32)	(0.35)
Log (Flow)	-0.33	0.08	-0.34	0.03
	(0.11)	(0.12)	(0.10)	(0.10)
VIX	3.86	3.59	3.86	3.59
	(0.06)	(0.08)	(0.06)	(0.08)
Turnover	-1.38	-1.28	-1.38	-1.29
	(0.55)	(0.58)	(0.55)	(0.58)
Exp. Ratio	-0.01	-0.09	-0.01	-0.09
	(0.01)	(0.02)	(0.01)	(0.02)
Cash / TNA	-0.03	-0.02	-0.03	-0.02
	(0.03)	(0.01)	(0.03)	(0.01)
N	1,865,992	1,301,320	1,865,992	1,301,212
Adj-R^2	0.02	0.02	0.02	0.02

Table 7

Return Spreads Flow Diversification Quintiles on Around the 2008 Financial Crisis and the 2020 Pandemic

On each event day listed below, we form quintiles based on the distribution of the flow imbalance and flow correlation for the outflows sample. Quintile 1 (5) contains low (high) measures of flow imbalance and correlation. The table shows event-date quintile spreads in basis points for days *t+1*, *t+2*, *t+3* and the cumulative return from *t+1* to *t+3*. Also displayed is the return on the S&P 500 (in percent) on the event date.

Event Date	Event Description	$Ret_{S\&P}$	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}	$Ret_{t+1,3}$
	Panel A: Quintile return spreads based on *FlowImb*					
Sept 15, 2008	Lehman files for bankruptcy	-4.71	13.69	12.38	14.97	41.09
Sept 16, 2008	AIG accepts bailout	1.75	16.54	14.65	6.06	37.29
Sept 17, 2008	Morgan Stanley merger talks	-4.71	12.04	6.59	9.20	27.87
Sept 29, 2008	Congress rejects TARP	-8.80	18.29	8.63	-2.76	24.16
March 9, 2020	Covid, 1st circuit breaker	-7.59	23.86	31.86	-10.38	45.36
March 12, 2020	Covid, 2nd circuit breaker	-9.51	46.52	8.87	-3.05	52.36
March 16, 2020	Covid, 3rd circuit breaker	-11.98	10.85	20.89	13.18	44.99
	Panel B: Quintile return spreads based on *FlowCorr*					
Sept 15, 2008	Lehman files for bankruptcy	-4.71	-13.17	-22.78	-0.06	-35.99
Sept 16, 2008	AIG accepts bailout	1.75	-26.86	-18.00	5.17	-39.67
Sept 17, 2008	Morgan Stanley merger talks	-4.71	-6.66	-19.96	2.08	-24.52
Sept 29, 2008	Congress rejects TARP	-8.80	-18.75	-1.81	11.43	-9.14
March 9, 2020	Covid, 1st circuit breaker	-7.59	-24.63	-2.46	-21.41	-48.45
March 12, 2020	Covid, 2nd circuit breaker	-9.51	-26.41	-6.35	-11.89	-44.60
March 16, 2020	Covid, 3rd circuit breaker	-11.98	-14.37	-14.83	15.61	-13.61

Table 8

Regressions of 3-Day Returns on Flow Diversification Measures Controlling for Family Effects
The table shows panel regressions of three-day returns ($Ret_{t+1, t+3}$) on flow imbalance, flow correlation, and other control variables measured on day *t*. Flow imbalance (*FlowImb*) is the sum of signed flows across share classes scaled by the sum of the absolute value of flows. Flow correlation (*FlowCorr*) is the weighted average covariance of flows across share classes, scaled by the sum of squared deviations of class-level flows from fund-level net flows. Control variables are identical to those in Table 6 but also include the logarithm of family TNA. Newey-West standard errors, clustered at the fund level, are in parentheses.

	Outflows	Inflows	Outflows	Inflows
Panel A: Family and Year Fixed Effects				
FlowImb	1.17	-1.49	-	-
	(0.60)	(0.68)		
FlowCorr	-	-	-0.84	-0.86
			(0.36)	(0.39)
Log (Fund TNA)	0.24	-0.57	0.31	-0.47
	(0.14)	(0.15)	(0.13)	(0.13)
Log (Flow)	-0.32	0.15	-0.37	0.07
	(0.11)	(0.11)	(0.10)	(0.09)
VIX	3.87	3.58	3.87	3.59
	(0.06)	(0.08)	(0.06)	(0.08)
Turnover	-0.49	-0.76	-0.49	-0.76
	(0.22)	(0.24)	(0.23)	(0.25)
Exp. Ratio	-0.02	-0.04	-0.012	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)
Cash / TNA	-0.03	-0.03	-0.03	-0.03
	(0.03)	(0.02)	(0.02)	(0.02)
Log(Family TNA)	-2.99	-2.89	-2.98	-2.88
	(0.38)	(0.38)	(0.38)	(0.39)
Panel B: Family, Style, and Year Fixed Effects				
FlowImb	1.12	-1.36	-	-
	(0.60)	(0.68)		
FlowCorr	-	-	-0.78	-0.85
			(0.37)	(0.39)
Log (Fund TNA)	0.16	-0.65	0.23	-0.56
	(0.15)	(0.15)	(0.13)	(0.13)
Log (Flow)	-0.32	0.14	-0.37	0.08
	(0.11)	(0.11)	(0.10)	(0.09)
VIX	3.87	3.59	3.87	3.59
	(0.06)	(0.08)	(0.06)	(0.08)
Turnover	-0.65	-0.76	-0.65	-0.76
	(0.24)	(0.24)	(0.24)	(0.246)
Exp. Ratio	-0.03	-0.04	-0.02	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)
Cash / TNA	-0.03	-0.03	-0.03	-0.03
	(0.03)	(0.01)	(0.03)	(0.02)
Log (Family TNA)	-2.99	-2.88	-2.99	-2.88
	(0.38)	(0.39)	(0.38)	(0.39)

Table 9

Regressions of 3-Day Returns on Family-Level Flow Diversification Measures

The table shows fund-level panel regressions of $Ret_{t+1,\ t+3}$ on family-level flow imbalance, flow correlation, and other control variables on day *t*. Flow imbalance is computed as the sum of signed flows across funds scaled by the sum of the absolute value of flows. Flow correlation is the weighted average covariance of flows across funds, scaled by the sum of squared deviations of fund-level flows from family-level net flows. Control variables include natural logarithm of fund assets, natural logarithm of fund flow, VIX, fund turnover, expense ratio, natural logarithm of family assets, and cash holding as a percentage of assets. Newey-West standard errors, clustered at the fund level, are in parentheses.

	FlowDiv = $FlowImb^F$		FlowDiv = $FlowCorr^F$	
	Outflows	Inflows	Outflows	Inflows
Panel A: Style and Year Fixed Effects				
FlowDiv	1.23	0.37	-1.06	0.46
	(0.53)	(0.65)	(0.49)	(0.59)
Log(TNA)	-0.19	-0.50	-0.18	-0.50
	(0.14)	(0.15)	(0.14)	(0.15)
Log(Flow)	-0.22	0.07	-0.23	0.06
	(0.11)	(0.12)	(0.11)	(0.12)
VIX	3.87	2.86	3.86	2.86
	(0.05)	(0.08)	(0.05)	(0.08)
Turnover	-0.16	-1.03	-0.12	-1.03
	(0.23)	(0.23)	(0.23)	(0.23)
Exp. Ratio	-0.01	-0.03	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Log(Family AUM)	0.20	-0.21	0.29	-0.23
	(0.08)	(0.09)	(0.08)	(0.09)
Cash /TNA	-0.02	-0.03	-0.02	-0.03
	(0.01)	(0.01)	(0.02)	(0.01)
Constant	-58.21	-32.03	-59.90	-32.07
	(1.69)	(2.26)	(1.65)	(2.14)
Panel B: Fund and Year Fixed Effects				
FlowDiv	0.89	0.51	-1.04	0.84
	(0.30)	(0.74)	(0.57)	(0.69)
Log(TNA)	-4.46	-4.09	-4.45	-4.09
	(0.36)	(0.43)	(0.36)	(0.43)
Log(Flow)	-0.36	-0.08	-0.36	-0.09
	(0.10)	(0.13)	(0.10)	(0.13)
VIX	3.82	2.82	3.82	2.82
	(0.05)	(0.08)	(0.05)	(0.08)
Turnover	-1.25	-1.25	-1.25	-1.25
	(0.49)	(0.78)	(0.49)	(0.78)
Exp. Ratio	-0.07	-0.04	-0.07	-0.04
	(0.01)	(0.02)	(0.01)	(0.02)
Log(Family AUM)	-0.86	-3.68	-0.89	-3.68
	(0.38)	(0.47)	(0.38)	(0.47)
Cash /TNA	-0.02	-0.03	-0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-16.58	20.73	-16.50	20.40
	(4.46)	(5.79)	(4.51)	(5.78)

Table 10

Daily Flow-Performance Sensitivity Regressions

The table shows regressions of daily fund flows on past fund performance. The illiquidity indicator variable (*Illiq*) is equal to one if the fund is either a small or mid-cap fund, or a single country non-US equity fund. Flow diversification indicator variables (*FlowImb*(I) and *FlowCorr*(I)) are equal to one for less diversified funds (if the underlying measures are above the median or if they are above the 20th percentile). *Perf* is the cumulative return over the prior three days. The remaining control variables are lagged by one day. All regressions include year fixed effects. Standard errors, clustered at the fund level, appear in parentheses.

	Panel A				Panel B			
	FlowDiv using 50th Percentile				FlowDiv using 20th Percentile			
Illiq* Perf	0.35	0.34	0.22	0.34	0.35	0.34	0.01	0.19
	(0.08)	(0.08)	(0.06)	(0.10)	(0.08)	(0.08)	(0.04)	(0.09)
FlowImb(I)	0.02	-	-0.02	-	0.02	-	-0.02	-
	(0.00)		(0.00)		(0.00)		(0.00)	
FlowImb(I)*Perf	0.19	-	1.02	-	0.21	-	0.71	-
	(0.05)		(0.13)		(0.06)		(0.09)	
FlowCorr(I)	-	0.02	-	-0.01	-	0.01	-	-0.01
		(0.00)		(0.00)		(0.00)		(0.00)
FlowCorr(I)*Perf	-	0.10	-	0.76	-	0.11	-	0.66
		(0.05)		(0.10)		(0.05)		(0.09)
Illiq.**FlowImb*(I)	-	-	0.01	-	-	-	0.01	-
			(0.00)				(0.00)	
Illiq.**FlowCorr*(I)	-	-	-	0.01	-	-	-	0.01
				(0.00)				(0.00)
*Illiq.*FlowImb*(I)*Perf	-	-	0.53	-	-	-	0.59	-
			(0.16)				(0.11)	
Illiq.**FlowCorr*(I)*Perf	-	-	-	0.25	-	-	-	0.36
				(0.14)				(0.12)
Constant	0.15	0.14	0.17	0.15	0.15	0.15	0.17	0.16
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Perf	0.41	0.46	-0.05	0.09	0.42	0.47	0.08	-0.04
	(0.07)	(0.06)	(0.05)	(0.08)	(0.06)	(0.06)	(0.04)	(0.08)
Illiq.	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Flow	-0.01	-0.00	0.01	-0.00	-0.01	-0.01	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(TNA)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Exp. Ratio	-3.49	-3.33	-3.34	-3.13	-3.51	-3.35	-3.31	-3.25
	(0.67)	(0.65)	(0.66)	(0.63)	(0.67)	(0.65)	(0.65)	(0.65)
Turnover	-0.41	-0.41	-0.26	-0.28	-0.41	-0.41	-0.26	-0.27
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Volatility	-0.54	-0.54	-0.49	-0.50	-0.53	-0.53	-0.50	-0.50
	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)	(0.16)	(0.15)	(0.16)
Log(Age)	-0.02	-0.02	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total Loads	0.09	0.13	0.02	0.15	0.10	0.13	0.07	0.12
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)

Table 11

Daily Flow-Performance Regressions for Funds with at least 75% of Assets from Institutions
The sample is restricted to funds in which at least 75% of the assets are from an institutional share class. The table shows regressions of daily fund flows on the independent variables. The Illiquidity indicator variable (Illiq.) is equal to one if the fund is either a small or mid-cap fund, or a single country non-US equity fund. Flow diversification indicator variables (*FlowImb*(I) and *FlowCorr*(I)) are equal to one for less diversified funds (if the underlying measures are above the 20th percentile). *Perf* is the cumulative return over the prior three days. The remaining control variables are lagged by one day. All regressions include year fixed effects. Standard errors, clustered at the fund level, appear in parentheses.

Illiq* Perf	0.62	0.64	0.02	0.27
	(0.14)	(0.14)	(0.05)	(0.12)
FlowImb(I)	0.01	-	-0.02	-
	(0.00)		(0.00)	
FlowImb(I)*Perf	0.35	-	0.30	-
	(0.09)		(0.14)	
FlowCorr(I)	-	0.01	-	-0.01
		(0.00)		(0.00)
FlowCorr(I)*Perf	-	0.39	-	0.39
		(0.09)		(0.16)
Illiq.**FlowImb*(I)	-	-	0.02	-
			(0.00)	
Illiq.**FlowCorr*(I)	-	-	-	0.01
				(0.00)
*Illiq.*FlowImb*(I)*Perf	-	-	0.70	-
			(0.17)	
Illiq.**FlowCorr*(I)*Perf	-	-	-	0.48
				(0.20)
Constant	0.18	0.17	0.19	0.18
	(0.02)	(0.02)	(0.02)	(0.02)
Perf	0.51	0.43	-0.14	-0.18
	(0.10)	(0.11)	(0.06)	(0.10)
Illiq.	0.03	0.03	0.01	0.02
	(0.01)	(0.00)	(0.00)	(0.00)
Flow	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Log(TNA)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Exp. Ratio	-3.02	-3.06	-3.01	-3.06
	(0.83)	(0.82)	(0.83)	(0.83)
Turnover	-0.72	-0.70	-0.72	-0.70
	(0.30)	(0.03)	(0.30)	(0.30)
Volatility	-0.71	-0.72	-0.72	-0.72
	(0.24)	(0.24)	(0.24)	(0.24)
Log(Age)	-0.03	-0.03	-0.03	-0.03
	(.00)	(0.00)	(0.00)	(0.00)
Total Loads	0.01	0.04	0.01	0.04
	(0.05)	(0.05)	(0.05)	(0.05)

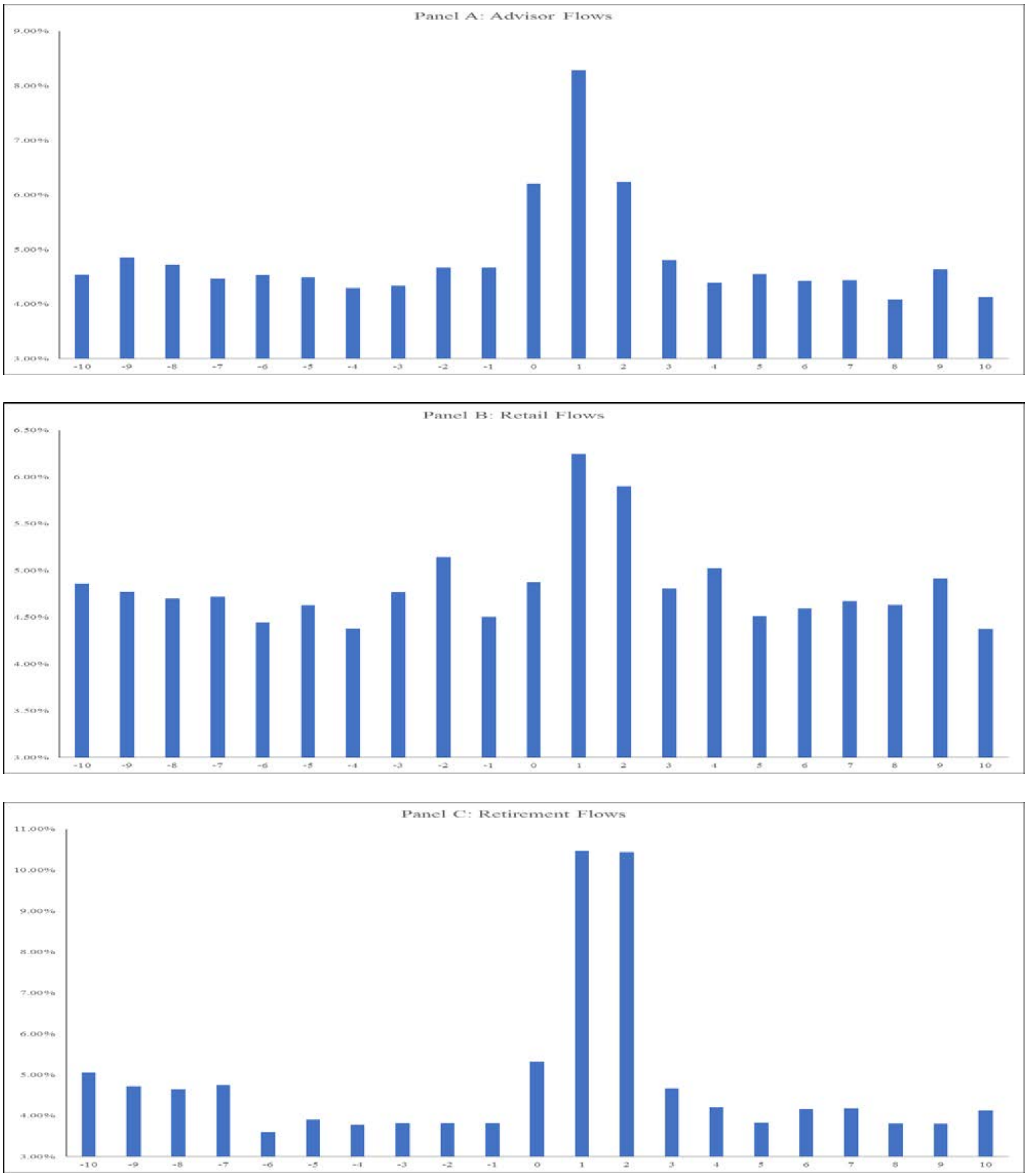

Figure 1: The figure shows the proportion of daily flows as a percentage of total monthly flows to each clientele group on specific days around the turn of the month. Day 0 is the last trading day of the month.

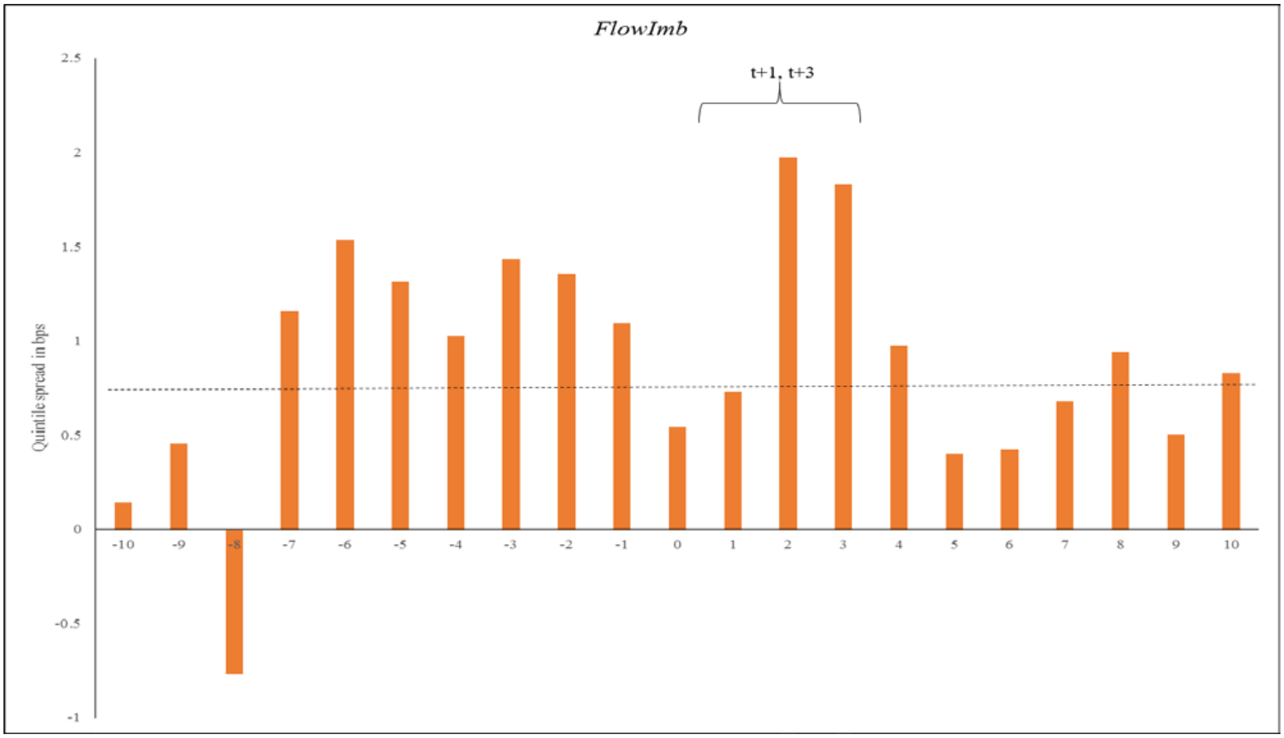

Figure 2: Average quintile spreads in basis points for each day based on the prior day's flow imbalance using the outflows sample. Day 0 is the last trading day of the month. The dashed line shows the average spread, not including t+1 through t+3.

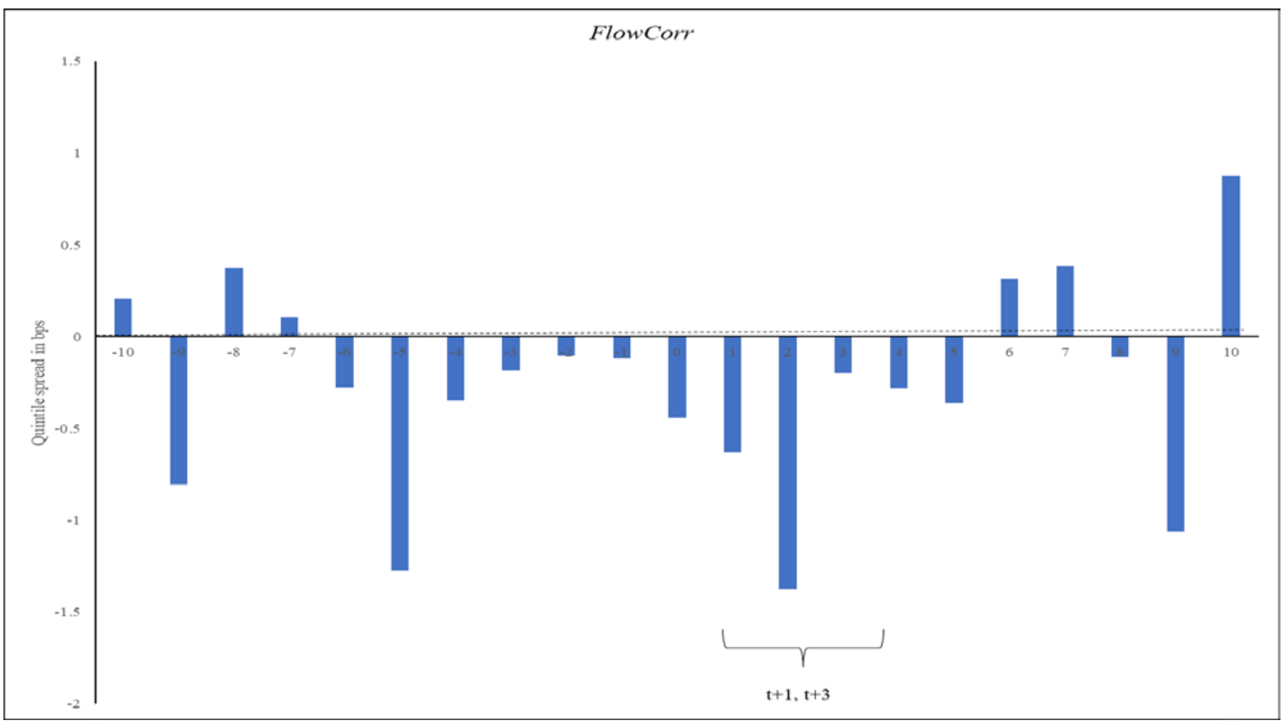

Figure 3: Average quintile spreads in basis points for each day based on the prior day's flow correlation using the outflows sample. Day 0 is the last trading day of the month. The dashed line shows the average spread, not including t+1 through t+3.

Table A1

Differences in returns between large and small by investment style
For all funds in a particular investment style, we form terciles based on outflows on day t. We then compute cumulative returns over the *t+1* to *t+3* intervals. The table reports the difference in returns for the small outflows minus large outflows terciles. Panels A and B differ in raw and benchmark-adjusted returns, respectively. Newey-West standard errors appear in parentheses.

	Growth	Blend	Value
Panel A: Raw return differences			
Large	0.34	1.18	0.90
	(0.37)	(0.34)	(0.37)
Mid	1.81	1.95	1.19
	(0.48)	(0.68)	(0.53)
Small	1.09	2.55	1.58
	(0.48)	(0.54)	(0.56)
Panel B: Benchmark-adjusted return differences			
Large	0.35	1.22	0.93
	(0.37)	(0.34)	(0.37)
Mid	1.84	2.02	1.19
	(0.48)	(0.68)	(0.53)
Small	1.06	2.62	1.54
	(0.48)	(0.54)	(0.57)

Table A2

Non-linearity in Flow Diversification Benefits

The table shows panel regressions of $Ret_{t+1,\ t+3}$ on flow diversifications measures, flow quintiles, interaction effects between flow quintiles and flow diversification measures, and other control variables on day t. For each sample (outflows and inflows, respectively), we form quintiles based on the daily distribution of flows. For outflows (inflows), quintile 1 contains the most negative (lowest positive) flows. For outflows (inflows), quintile 5 contains the least negative (most positive) flows. The regressions use indicator variables for quintiles 1 and 5, with the intermediate quintiles (the middle 60%) as the omitted category. The regressions also contain interaction effects between the extreme quintiles and the flow diversification measures. The control variables are the same as those in Table 5 and are not shown. Newey-West standard errors, clustered at the fund level, are in parentheses.

	Flow Div. Measures			
	FlowImb		*FlowCorr*	
	Outflows	Inflows	Outflows	Inflows
Panel A: Style and Year Fixed Effects				
Flow Div.	2.75	-0.70	-0.87	-0.65
	(0.70)	(0.75)	(0.46)	(0.49)
Quintile 1 Flow Indicator	1.97	-1.34	0.28	-0.77
	(1.63)	(1.07)	(0.50)	(0.50)
Quintile 5 Flow Indicator	-1.12	3.74	-0.53	0.17
	(0.93)	(1.71)	(0.46)	(0.55)
Quintile 1 Flow Indicator * Flow Div.	1.43	0.64	-0.21	0.14
	(0.59)	(1.27)	(0.11)	(0.88)
Quintile 5 Flow Indicator * Flow Div.	0.10	-4.14	-0.33	-0.54
	(1.08)	(1.87)	(0.74)	(1.11)
Panel B: Fund and Year Fixed Effects				
Flow Div.	2.34	-0.96	-1.42	-0.74
	(0.76)	(0.83)	(0.48)	(0.51)
Quintile 1 Flow Indicator	2.01	-1.09	0.51	-0.51
	(1.76)	(1.09)	(0.55)	(0.55)
Quintile 5 Flow Indicator	-0.99	4.03	-0.56	-0.06
	(0.96)	(1.81)	(0.50)	(0.60)
Quintile 1 Flow Indicator * Flow Div.	1.34	0.70	-0.16	0.27
	(0.55)	(1.36)	(0.06)	(0.90)
Quintile 5 Flow Indicator * Flow Div.	0.01	-4.54	0.09	-0.42
	(1.18)	(1.94)	(0.77)	(1.17)

Table A3

Regressions of 3-Day Returns Controlling for Loads

The table shows panel regressions of $Ret_{t+1,\, t+3}$ on flow imbalance, flow correlation, total loads and other control variables on day t. Flow imbalance is computed as the sum of signed flows across clientele groups scaled by the sum of the absolute value of flows. Flow correlation is the weighted average covariance of flows across clienteles, scaled by the sum of squared deviations of clientele-level flows from fund-level net flows. Total loads are the sum of front-end loads and back-end loads. Other control variables are identical to those in Table 6. Newey-West adjusted standard errors, clustered at the fund level, are in parentheses.

	FlowDiv = *FlowImb*		FlowDiv = *FlowCorr*	
	Outflows	Inflows	Outflows	Inflows
Panel A: Style and Year Fixed Effects				
FlowDiv	1.16	-0.89	-0.73	-0.52
	(0.59)	(0.65)	(0.36)	(0.38)
Log (TNA)	0.29	-0.46	0.37	-0.43
	(0.14)	(0.15)	(0.13)	(0.13)
Log (Flow)	-0.29	0.14	-0.35	0.12
	(0.12)	(0.11)	(0.10)	(0.09)
VIX	3.89	3.61	3.89	3.61
	(0.06)	(0.08)	(0.06)	(0.08)
Turnover	-0.06	-0.77	-0.05	-0.77
	(0.24)	(0.24)	(0.24)	(0.24)
Exp. Ratio	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Cash / TNA	-0.03	-0.03	-0.03	-0.03
	(0.03)	(0.02)	(0.03)	(0.02)
Total Loads	0.19	-0.01	0.21	0.01
	(0.04)	(0.05)	(0.04)	(0.05)
Adj-R^2	0.02	0.02	0.02	0.02
Panel B: Fund and Year Fixed Effects				
FlowDiv	1.73	-1.11	-0.96	-0.80
	(0.65)	(0.73)	(0.38)	(0.40)
Log (TNA)	-4.12	-4.90	-4.10	-4.85
	(0.33)	(0.36)	(0.32)	(0.35)
Log (Flow)	-0.33	0.08	-0.34	0.04
	(0.12)	(0.12)	(0.10)	(0.10)
VIX	3.86	3.59	3.86	3.59
	(0.06)	(0.08)	(0.06)	(0.08)
Turnover	-1.39	-1.29	-1.39	-1.30
	(0.55)	(0.58)	(0.55)	(0.58)
Exp. Ratio	-0.02	-0.09	-0.02	-0.09
	(0.02)	(0.02)	(0.02)	(0.02)
Cash / TNA	-0.03	-0.04	-0.03	-0.03
	(0.03)	(0.02)	(0.03)	(0.02)
Total Loads	0.41	0.30	0.41	0.31
	(0.18)	(0.22)	(0.18)	(0.22)
Adj-R^2	0.02	0.02	0.02	0.02

Table A4

Daily Flow-Performance Sensitivity Regressions using 5-day and 20-day Prior Returns

The table shows regressions of daily fund flows on past fund performance. The Illiquidity indicator variable (Illiq) is equal to one if the fund is either a small or mid-cap fund, or a single country non-US equity fund. Flow diversification indicator variables (*FlowImb*(I) and *FlowCorr*(I)) are equal to one for less diversified funds (if the underlying measures are above the median or if they are above the 20th percentile). Perf is the cumulative return over the prior five days in Panel A and the prior 20 days in Panel B. The control variables are the same as in Table 10 and not reported. All regressions include year fixed effects. Standard errors, clustered at the fund level, appear in parentheses.

Panel A: 5-day window

	FlowDiv using 50th Percentile				FlowDiv using 20th Percentile			
Illiq* Perf	0.24	0.24	0.12	0.27	0.24	0.24	0.13	0.29
	(0.08)	(0.09)	(0.07)	(0.08)	(0.09)	(0.09)	(0.08)	(0.10)
FlowImb(I)	0.02	-	0.01	-	0.01	-	0.01	-
	(0.00)		(0.00)		(0.00)		(0.00)	
FlowImb(I)*Perf	0.09	-	0.12	-	0.11	-	0.13	-
	(0.05)		(0.09)		(0.07)		(0.09)	
FlowCorr(I)	-	0.02	-	0.02	-	0.02	-	0.02
		(0.00)		(0.00)		(0.00)		(0.00)
FlowCorr(I)*Perf	-	0.17	-	0.19	-	0.18	-	0.27
		(0.05)		(0.09)		(0.05)		(0.09)
Illiq.**FlowImb*(I)	-	-	0.00	-	-	-	0.00	
			(0.00)				(0.00)	
Illiq.**FlowCorr*(I)	-	-	-	-0.00	-	-	-	-0.00
				(0.00)				(0.00)
*Illiq.***FlowImb*(I)*Perf	-	-	0.27	-	-	-	0.23	
			(0.11)				(0.11)	
Illiq.**FlowCorr*(I)*Perf	-	-	-	0.15	-	-	-	0.17
				(0.08)				(0.09)

Panel B: 20-day window

	FlowDiv using 50th Percentile				FlowDiv using 20th Percentile			
Illiq* Perf	0.14	0.14	0.08	0.21	0.14	0.14	0.05	0.21
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.06)
FlowImb(I)	0.00	-	0.00	-	0.00	-	-0.00	-
	(0.00)		(0.00)		(0.00)		(0.00)	
FlowImb(I)*Perf	0.05	-	-0.05	-	0.10	-	0.02	-
	(0.03)		(0.05)		(0.03)		(0.04)	
FlowCorr(I)	-	0.01	-	0.01	-	0.01	-	0.01
		(0.00)		(0.00)		(0.00)		(0.00)
FlowCorr(I)*Perf	-	0.14	-	0.22	-	0.12	-	0.16
		(0.03)		(0.05)		(0.04)		(0.03)
Illiq.**FlowImb*(I)	-	-	0.00	-	-	-	0.01	
			(0.00)				(0.00)	
Illiq.**FlowCorr*(I)	-	-	-	-0.01	-	-	-	-0.00
				(0.00)				(0.00)
*Illiq.***FlowImb*(I)*Perf	-	-	0.16	-	-	-	0.12	
			(0.06)				(0.05)	
Illiq.**FlowCorr*(I)*Perf	-	-	-	0.13	-	-	-	0.08
				(0.06)				(0.04)

Table A5

Benchmark-Adjusted and Style-Adjusted returns to flow diversification quintiles
Each day, we form quintiles based on the distribution of the flow imbalance and flow correlation. Quintile 1 (5) contains low (high) measures of flow imbalance and correlation. Panels A and B show benchmark-adjusted returns computed by subtracting matching index returns from fund returns. For large-value and large growth funds, we use the Russell 1000 Value and Growth Indices. For small-value and small-growth, we use the Russell 2000 value and growth indices. For large blend, midcap blend and small-cap blend, we use the Russell 3000, Russell 2500 and Russell 2000 respectively. For midcap value and midcap growth, we use Russell midcap value and Russell midcap growth, respectively. In Panels C and D, style-adjusted returns are computed by subtracting the asset-weighted returns of all funds in the same investment style from the fund's return. The row "5-1" contains spread returns, with Newey and West (1987) standard errors in parentheses.

	FlowImb					*FlowCorr*			
Panel A: Outflows (Benchmark-Adjusted Returns)									
1	-1.60	-0.95	-0.85	-3.42	1	-1.33	-0.97	-0.84	-3.16
2	-1.26	-0.67	-0.83	-2.77	2	-1.13	-0.92	-0.90	-2.96
3	-1.28	-0.69	-0.79	-2.77	3	-1.07	-1.02	-0.75	-2.87
4	-1.18	-0.72	-0.81	-2.72	4	-1.39	-0.84	-1.03	-3.27
5	-0.83	-0.64	-0.56	-2.05	5	-1.50	-1.01	-1.04	-3.56
5-1	0.77	0.32	0.29	1.37	5-1	-0.17	-0.04	-0.20	-0.40
	(0.14)	(0.15)	(0.14)	(0.24)		(0.18)	(0.17)	(0.17)	(0.20)
Panel B: Inflows (Benchmark-Adjusted Returns)									
1	1.66	-1.45	0.97	1.15	1	-0.25	-1.06	-0.74	-2.09
2	1.58	-2.37	2.00	1.16	2	-0.44	-0.79	-0.84	-2.09
3	1.42	-2.86	-0.20	-1.66	3	-0.29	-0.84	-0.60	-1.77
4	1.12	-0.98	0.72	0.76	4	-0.10	-0.90	-0.84	-1.85
5	-0.65	-2.80	-0.84	-4.33	5	-0.31	-0.91	-0.85	-2.09
5-1	-2.30	1.85	-1.82	-5.48	5-1	-0.06	0.15	-0.12	-0.01
	(1.98)	(1.39)	(1.49)	(2.68)		(0.21)	(0.21)	(0.21)	(0.38)
Panel C: Outflows (Style-Adjusted Returns)									
1	-0.71	-0.11	-0.14	-0.95	1	-0.43	-0.05	0.06	-0.42
2	-0.43	-0.03	-0.15	-0.60	2	-0.24	-0.08	-0.04	-0.34
3	-0.43	0.07	0.04	-0.31	3	-0.23	-0.11	0.11	-0.24
4	-0.35	-0.04	-0.05	-0.45	4	-0.48	-0.03	-0.11	-0.62
5	-0.03	0.08	0.12	0.17	5	-0.60	0.02	-0.08	-0.65
5-1	0.68	0.19	0.26	1.12	5-1	-0.17	0.07	-0.13	-0.23
	(0.13)	(0.13)	(0.13)	(0.20)		(0.15)	(0.14)	(0.14)	(0.13)
Panel D: Inflows (Style-Adjusted Returns)									
1	0.07	1.29	0.95	2.34	1	0.63	-0.14	0.14	0.66
2	0.44	0.00	2.23	2.77	2	0.42	0.17	0.01	0.60
3	0.99	-1.15	-0.64	-0.89	3	0.55	0.01	0.28	0.83
4	0.68	0.36	0.53	1.53	4	0.71	0.07	-0.01	0.79
5	-0.42	0.42	-0.27	-0.38	5	0.57	0.04	0.16	0.79
5-1	-0.49	1.85	-1.22	-2.72	5-1	-0.07	0.19	0.02	0.13
	(1.66)	(1.27)	(1.22)	(2.63)		(0.19)	(0.20)	(0.20)	(0.14)

Table A6

Regressions of 3-Day Benchmark- and Style-Adjusted Returns on Flow Diversification Measures
The table shows panel regressions of style-adjusted returns on flow imbalance, flow correlation, and other control variables on day t. Panel A uses benchmark-adjusted returns, defined as fund returns subtracted by the equivalent index returns. Panel B uses style-adjusted returns, defined as fund returns subtracted by the asset-weighted returns for all funds within a style. Flow imbalance is computed as the sum of signed flows across share classes scaled by the sum of the absolute value of flows. Flow correlation is the weighted average covariance of flows across share classes, scaled by the sum of squared deviations of class-level flows from fund-level net flows. Control varaiables are identical to those in Table 6. All regressions use year fixed effects. Newey-West adjusted standard errors, clustered at the fund level, are in parentheses.

	FlowDiv = *FlowImb*		FlowDiv = *FlowCorr*	
	Outflows	Inflows	Outflows	Inflows
Panel A: Benchmark-Adjusted Returns				
FlowDiv	1.07	0.11	-0.27	-0.19
	(0.26)	(0.32)	(0.16)	(0.18)
Log (TNA)	-3.07	-3.05	-2.97	-3.08
	(0.20)	(0.20)	(0.20)	(0.20)
Log (Flow)	0.27	0.01	0.19	0.03
	(0.04)	(0.05)	(0.04)	(0.04)
VIX	-0.24	-0.24	-0.24	-0.25
	(0.02)	(0.02)	(0.02)	(0.02)
Turnover	-1.11	-0.98	-1.11	-0.98
	(0.46)	(0.42)	(0.46)	(0.42)
Exp. Ratio	-0.01	-0.02	-0.01	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Cash / TNA	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Panel B: Style-Adjusted Returns				
FlowDiv	0.48	0.31	-0.25	-0.14
	(0.27)	(0.23)	(0.14)	(0.16)
Log (TNA)	-2.83	-2.68	-2.81	-2.73
	(0.19)	(0.19)	(0.18)	(0.19)
Log (Flow)	0.06	-0.10	0.05	-0.05
	(0.04)	(0.04)	(0.03)	(0.04)
VIX	0.05	0.02	0.05	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Turnover	-0.99	-0.78	-0.99	-0.78
	(0.45)	(0.39)	(0.45)	(0.39)
Exp. Ratio	-0.02	-0.03	-0.02	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)
Cash / TNA	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)