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Fund flow diversification: Implications for asset stability, fee-setting and performance

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ABSTRACT

We provide new evidence on the economic benefits to mutual fund families from having a portfolio of funds with diversified investor fund flows. We show that diversified fund families enjoy greater stability of assets under management, and experience significantly lower net cash outflows during an economic downturn. Given concave advisory fee schedules, the dominant industry fee structure, a reduction in asset volatility is potentially advantageous for family-level fee revenues. Consistent with this notion, we show that fund families with more diversified fund flows are able to strategically charge more competitive advisory fees across their funds. Our findings suggest that the diversification of fund families' asset flows is an important source of net performance gains for fund shareholders. These gains arise mostly in the more competitive industry segments.

Breadth and diversification of a firm's products and services contribute to growth and sustainability of fee revenue. A company with limited diversification in terms of a specific fund, type of fund (equity or fixed income) or investment style or manager risks losing AUM when such focused investments are less favored by the market. A diversified product offering, therefore, allows for product switching rather than outright redemptions and maintenance of AUM. (Source: Report prepared by the credit rating agency, DBRS, titled "Rating Companies in the Asset Management Industry," December 2015).

1. Introduction

It is well documented that investor flows into and out of open-end mutual funds can be costly for individual fund performance (see, e.g., Edelen (1999); Coval and Stafford (2007); Chen, Hanson, Hong, and Stein (2008); and Shive and Yun (2013)). What is increasingly clear, especially in the wake of the global financial crisis of 2008, is that such investor flows also contribute to the volatility of fee income accruing to mutual fund families. In this context, fund families with a diversified portfolio of funds have a significant advantage. Although fund families are generally prohibited from using inflows into some funds to strategically provide liquidity to other funds in the family, having multiple funds with less than perfectly correlated investor flows can nevertheless be of significant value. Specifically, given the prevalence in the industry of concave marginal fee schedules with respect to assets under management, fund families that experience lower asset volatility due to diversification of fund flows across family funds, enjoy greater annual fee revenue, on average.[1] In fact, by reducing asset volatility through diversification, fund families can better navigate the fee structure to their advantage, ensuring a steady revenue stream that is less susceptible

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[1] As we subsequently note, according to the NSAR-B reports filed by mutual funds, the typical concave fee contract features a marginal fee rate of 0.85% for the first $1 billion of assets, 0.78% for the next $1 billion, 0.75% for the next $3 billion, and additional marginal fee rates which are decreasing in asset value breakpoints. Deli (2002) and Massa and Patgiri (2009) show that the frequency of concave fee contracts varies between 30% and 35%. A more relevant statistic however concerns the percentage of total assets managed under concave fee contracts. Using NSAR-B data, we find that two-thirds of all mutual fund assets are managed under concave fee schedules, making concave advisory contracts the dominant industry fee structure.

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to the ebbs and flows of market dynamics and investor sentiment.[2]

Given the potential economic benefits of having a portfolio of funds with diversified investor flows and the competitive environment of the mutual fund industry, this study seeks to address two important questions. First, we hypothesize that fund families with more diversified investor fund flows are able to strategically charge more competitive advisory fees across their funds, thereby enhancing their fee revenue. Second, we explore whether the diversification of fund flows within a family leads to improved net-of-fee fund performance for investors. These hypotheses are grounded in the notion that diversified fund flows can reduce asset volatility, enabling fund families to charge lower (style-adjusted) fees and provide better net-of-fee returns to investors. To our knowledge, this is the first study to examine the important link between fund flow diversification and fee-setting policies of fund sponsors, and their impact on investor performance.

We begin by documenting the significant economic benefit to fund families in terms of enhanced fee revenues due to a reduction in asset volatility from having a diversified fund flow base. We use several proxies to measure the degree of fund flow diversification experienced by fund families. Based on the empirical distribution of concave advisory fee contracts, we provide estimates of the fee revenue enhancement enjoyed by an average fund family from greater fund flow diversification and the resulting asset stability. We further document the value of fund flow diversification in mitigating the adverse impact of investor redemptions on fund families. Specifically, we track the style-adjusted net cash flows experienced by fund families during the two years before, and the two years after the Lehman Brothers bankruptcy filing in September 2008. We find that during periods of economic distress, fund families with above-median level of flow correlations (or below median level of fund flow diversification) experience cumulative style-adjusted net cash outflows that are 8% greater than that of fund families with below-median flow correlation (or above-median level of fund flow diversification) during the 12 months after the September 2008 shock.

Our main findings concern the relationship between the measures of fund flow diversification and style-adjusted advisory fees and operating expenses charged by fund families. Using various proxies for the degree of flow diversification experienced by fund families, we show that there is a consistently negative relation between fund flow diversification and family-level style-adjusted advisory fees and operating expenses during the period 1993 to 2017. We also consider the decision of fund families to adjust their advisory fee policies, and show that more diversified fund families are 20% more likely to waive or reimburse their annual advisory fees than less diversified fund families. These findings are not simply due to economies of scale enjoyed by fund families with large market shares. In particular, we show that an increase in the level of fund flow diversification translates into lower style-adjusted fees within each quintile portfolio of fund family size. The favorable impact of fund flow diversification on fees is also not explained by fund- or style-proliferation strategies of fund families, inter-fund lending programs, heterogeneity of investors' liquidity demand, the quality of a fund family's product offerings, or the volatility of net cash flows.

Our results are consistent with strategic pricing behavior on the part of fund families that enjoy greater fee revenues associated with lower asset volatility due to the diversification of flows across their funds. Importantly, we show that the negative relationship between style-adjusted advisory fees and flow diversification arises exclusively among fund families that manage assets with concave, rather than linear, fee schedules. The lack of a relationship between fees and flow diversification among fund families with linear fee contracts suggests that economies of scale are unlikely to drive our findings. We confirm this conclusion using a subset of fund families offering prime money market funds for which we can clearly isolate the incurred cost of running a fund, and the impact of fees on gross performance. Interestingly, we find that fund families tend to charge below-average style-adjusted fees when they face stiffer within-style price competition, derive most of their revenue from the mutual fund business segment, and are better protected against *downside* liquidity risk due to the diversification of redemption flows.

To mitigate potential endogeneity concerns due to the voluntary nature of a fund family's decision to offer a diversified mix of funds across several investment styles resulting in diversified fund flows, we re-estimate our empirical models using two-stage least squares instrumental variable (IV) regressions. This analysis confirms our earlier findings. In particular, fund families with diversified fund flows tend to charge significantly lower style-adjusted advisory fees. We also construct different samples of *counterfactual* fund families to address possible concerns about the confounding effects of unobserved fund family characteristics, and use two empirical strategies in this context. First, we implement a matched sample approach where we match families with diversified fund flows with control fund families based on observable fund family characteristics. We find that our results are robust to the use of this alternative identification strategy. Second, we conduct a placebo test based on a sample of simulated fund families that derive no benefit from fund flow diversification, by construction. As expected, in this case we find no relation between fund flow diversification measures and family-level style-adjusted fees. In an additional test, we examine the relation between fees and fund flow diversification in a subset of cases that are subject to potentially exogenous variation in the degree of flow diversification. Specifically, we explore the fee implications of mutual fund families' acquisitions of fund sponsorships held by other fund families. We find that a transfer of fund sponsorship from a fund family with more diversified fund flows to one with less diversified fund flows is associated with a post-acquisition increase in the fees charged by the acquired funds.

Next, we evaluate whether the reduction in advisory fees associated with greater fund flow diversification translates into better net-of-fee performance for shareholders. To address this issue, we examine the performance of fund families as the TNA-weighted average performance of the funds in the family. We find that the TNA-weighted net-of-fee alphas of fund families, based on a number of benchmark models, are positively related to our proxy measures for the degree of fund flow diversification, after controlling for several fund family characteristics. Specifically, more diversified fund families outperform less diversified fund families by 0.56% per year. This suggests that fund flow diversification is an important source of net performance gains for shareholders. By contrast, we find no relation between the gross performance of fund families and fund flow diversification measures.

Our study makes a number of contributions to the mutual fund literature. Our primary contribution is to provide novel evidence on the impact of fund flow diversification on fund fees and the net performance experienced by fund shareholders. Our analysis also complements and extends the literature related to the motives of fund families to offer a wide range of fund products and investment objectives to investors. On the supply side, fund proliferation has been interpreted as a strategic attempt by fund families to increase the likelihood of generating star funds (Nanda, Wang, and Zheng (2004)), expand market coverage (Massa (2003)), or attenuate price competition in the industry (Khorana and Servaes (2012)). Other motivations include the desire to hedge fund

[2] Table 1 provides a brief motivating example of the revenue gains a hypothetical fund family with a concave fee schedule would enjoy from maintaining a stable asset base. The analysis presented in Table 1 shows that under the assumed fee schedules, a hypothetical fund family with a concave fee schedule (Family A) would gain $250,000 in additional annual fee revenue by maintaining a stable asset base over a two-year period (Scenario 1) compared to a scenario in which assets under management fluctuate around the same average of $500 million (Scenario 2). By contrast, a fund family with a linear fee schedule (Family B) would experience the identical total revenue under either scenario; in other words, it would not gain from a reduction in asset volatility. This example suggests that in general, mutual fund families will be better off, and increasingly so, as correlations among investor flows to their mutual funds decline.

family total risk by shifting the aggregate portfolio composition toward the market portfolio (Massa (2000)), influence fund performance (Siggelkow (2003)), or transfer this performance across different funds through strategic IPO allocations and cross-trading activities (Gaspar, Massa, and Matos (2006)).

On the demand side, a number of studies have investigated the potential benefits of fund proliferation that accrue to mutual fund investors. Examples of the benefits include lower search costs (e.g., Huang, Wei, and Yan (2007)), simplified recordkeeping (Elton, Gruber, and Green (2007)), and the elimination of switching costs (i.e., load fees) across multiple funds offered by the same fund family (Massa (2003)).

Our study contributes to this literature by highlighting an important benefit of a fund family's decision to offer a diverse product mix to investors—namely, fund flow diversification. In contrast to much of the previous literature, our focus is on fund diversity and the resulting potential for *fund flow diversification* rather than *fund proliferation* per se.[3] In terms of the latter, Massa (2003) explains fund proliferation as an attempt by fund families to attract investors even if it is not competitive in terms of fund performance. Consistent with this intuition, Massa documents a negative relation between product differentiation (based on non-performance-related fund characteristics) and fund performance. By contrast, our study focuses on the favorable impact of the diversification of fund flows experienced by funds within a family. Our evidence suggests that the diversification of fund flows yields significant economic benefits in terms of more stable fee revenues for fund families, and reduced advisory fees and improved net performance for fund shareholders.

Our study also contributes to an improved understanding of the relationship between fund family product diversification and performance. In this context, Siggelkow (2003) finds that mutual funds belonging to focused fund families perform better than similar funds offered by diversified families. Interestingly, however, he documents an overall negative effect of product focus on fund family profitability since fund providers with more diversified product offerings enjoy increased cash flows. In the context of hedge funds, De Figuerdo Jr and Rawley (2011) show that diversified fund families perform better due to the superior skills of their fund managers - it is precisely the higher skilled fund managers who are able to more easily access external capital, thereby allowing the firm to offer a more diversified product offering. Our findings complement the earlier literature by highlighting investor fund flow diversification as a key factor responsible for the beneficial impact of fund family diversification on investor performance.

2. Data and methodology

2.1. Data

We obtain mutual fund data from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund database (MFDB). Since mutual fund family names are available in the CRSP database only since 1993, our sample covers the period from January 1993 to December 2017.[4] Our final sample includes 2137 distinct fund families with 6766 funds covering all investment objectives. Specifically, our sample contains 4892 equity funds, 781 income funds, and 1093 funds that belong to other style categories. The sample includes domestic and international funds and covers retail and institutional share classes of both actively managed funds and index funds. Fund investment objectives are identified using CRSP ICDI codes, which combine information from three sources—Weisenberger (1962–1993), Strategic Insight (1993–1998), and Lipper (1998–2017)—over our entire sample period.

We follow several steps to identify CRSP mutual fund families. First, we carefully checked fund family names to account for minor variations (e.g., Deutsche Asset Mgmt versus Deutsche Asset Management, Inc.), and to account for different divisions of the same company (e.g., BNY Mellon Asset Management versus Dreyfus Corp). Following Chen, Hong, Jiang, and Kubik (2013), we then searched each fund family's name on the Investment Adviser Public Disclosure (IAPD) website administered by the Securities and Exchange Commission (SEC), and collected all of the previously registered names of that fund family. The IAPD website provides accurate historical information on all previously registered names. We also recorded all names of control entities of a fund family using the information contained in Item 10 and in Schedule D of form ADV (which states the name of the entity where books and records are kept). This allows us to account for the possibility that entities with different names may represent the same ownership structure of the fund family. To increase the reliability of our matching procedure, we also use the management company codes available in the CRSP database after 2000 to identify a fund family. Thus, if two distinct fund family names in the CRSP database belong to the same family according to IAPD historical information and, at the same time, the CRSP management company code has remained unchanged, we conclude that these two distinct fund family names refer to the same fund family. To improve the accuracy of the fund family identification procedure, we also conducted a detailed search of all fund family names using SEC action letters (which provide information on fund family reorganizations following mergers of fund families), FACTIVA, and general information available on fund families' websites.

Mutual fund performance figures, total net assets (TNA), and net cash flows are available on a monthly basis. Fund fees are available at an annual frequency, although they are accrued on a daily basis. Mutual fund fees include total operating expenses, expressed as a percentage of assets under management during the year, and fund advisory (or management) fees, which are computed as the difference between total operating expenses and distribution (or 12b-1) fees. Since fund families compete in different investment objectives for investors' flows, we calculate objective-adjusted fund family characteristics as the TNA-weighted average of the individual funds' objective-adjusted characteristics.

2.2. Empirical methodology

The main variable of interest in this study is the degree of fund flow diversification experienced by fund families. We employ a number of proxies to capture this variable. Our first proxy is the dummy variable *FAMDIV*, which is equal to 1 if a fund family offers funds in more than one investment objective and 0 otherwise. A family that offers multiple investment styles is more likely to experience some level of fund flow diversification across these styles, ceteris paribus. This variable is likely to quantify any correlation in net cash flows and any correlation in the performance of the funds offered by the fund family.

Our next two measures of family-level fund flow diversification capture primarily the correlation in net cash flows. Our second fund flow diversification proxy (*COINSURE*) is constructed as the absolute value of the difference between (a) the estimated volatility of a fund family's net cash flows (*FAMVOLCF*), and (b) the implied volatility of net cash flows, assuming a pairwise correlation of 1 between the net flows of funds within a family. Specifically, we calculate our second fund flow diversification proxy as

[3] Guo, Ma, Liu, and Mo (2023) discuss the impact of fund investor cliques on fund flow sensitivity, providing insights relevant to our examination of diversified fund flows within fund families. Fu, Hua, Chen, and Zhou (2022) demonstrate how internal information sharing enhances mutual fund performance, underscoring the strategic importance of knowledge dissemination for managing fund performance and fee-setting strategies.

[4] In 2018, the SEC phased out Form N-SAR and replace it with the more streamlined Form N-CEN, which lacks detailed information on the structure of advisory fees. Our research represents the most thorough analysis of advisory fees available to date, offering an unprecedented insight into the fee-setting policies of mutual funds.

$$COINSURE_t = \left| \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,t-1} w_{j,t-1} \rho_{i,j,t,k} \sigma_{i,t,k} \sigma_{j,t,k}} - \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,t-1} w_{j,t-1} \sigma_{i,t,k} \sigma_{j,t,k}} \right| \tag{1}$$

where $\rho_{i,j,t}$ is the pairwise correlation of net cash flows estimated over the period t-$k+1$ to t between share class i and share class j at time t; $w_{i,t-1}$ is the weight of share class i in the fund family's portfolio; and $\sigma_{i,t,k}$ is the standard deviation of share class i's net cash flows during the period t-$k+1$ to t. We compute the percentage net cash flows as $(TNA_t - TNA_{t-1}(1+r_t))/TNA_{t-1}$.[5] Following Huang et al. (2007), we also filter out the top and bottom 2.5% tails of the distribution of net cash flows to guard against possible errors due to fund mergers and splits. Cash flow volatilities, $\sigma_{i,t,k}$, are estimated using data for the prior 36 months ($k = 36$), with a minimum requirement of 12 months of valid observations within the 36-month window.[6]

One limitation of the fund flow diversification proxy specified in Eq. (1) is that it does not account for cross-sectional variation in the total volatility of net cash flows across the fund families in the sample. Accordingly, we scale the fund flow diversification variable *COINSURE* by the volatility of net cash flows to obtain a more precise estimate of a fund family's flow diversification level.

Our third proxy of family-level fund flow diversification is based on the correlation between idiosyncratic net cash flows of different investment styles offered by the fund family. This measure is estimated in two steps. In the first step, for each investment style g at time t, we compute the idiosyncratic net cash flows over the previous $k = 36$ months (with a minimum of 12 months of valid observations). The idiosyncratic net cash flows are estimated as the residuals from a regression of the average style net cash flows for style g on the average industry-wide net cash flows. Second, in each month t, we estimate the pairwise style correlation, $\gamma_{g,q,t}$, between idiosyncratic cash flows of investment styles g and q. Finally, we compute the inverse measure of family-level fund flow diversification as the TNA-weighted average investment style correlation among idiosyncratic cash flows:

$$CORRSTL_t = \sum_{g=1}^{G} \sum_{q=1}^{Q} w_{g,t-1} w_{q,t-1} \gamma_{g,q,[t-k+1,t]} \tag{2}$$

Since our primary interest concerns the cross-sectional relationship between family-level fund flow diversification and advisory fees, our empirical tests employ Fama-MacBeth cross-sectional regressions with heteroskedasticity and autocorrelation consistent (HAC) standard errors. We test the robustness of the family-level findings to the introduction of year, family, and style fixed effects with standard errors clustered at the family groupings.

3. Descriptive statistics

3.1. Sample summary

Panel A of Table 2 contains the summary statistics of our sample of mutual fund families over the period January 1993 to December 2017. The average fund family has total net assets (TNA) of $12.2 billion, which corresponds to an industry market share of 0.16%. On average, fund families have been in operation for about 16 years since the first fund's inception, manage 8 fund portfolios, and invest across 5 investment objectives.[7] The average correlation in net cash flows across different investment styles within the fund family (*CORRSTL*) is about 0.68, with this number varying between 0.12 for highly diversified fund families, and 1.0 for undiversified (e.g., single-fund) families. In addition, by diversifying their product offerings, fund families are able to significantly reduce the total volatility of net cash flows across different fund portfolios (*COINSURE*) by about 22% on average. To assess the economic significance of the value of fund flow diversification, consider that the average yearly volatility of net cash flows experienced by a fund family, assuming a pairwise correlation of one among the constituent funds' flows, equals 14%. On average, fund families are able to reduce net cash flow volatility from 14% to 11%, which is an economically meaningful reduction.

Using TNA-weighted variables, the family-level turnover, *FAMTURNR*, of 0.80 is associated with average total operating expenses, *FAMOPEX*, of 1.17%, and advisory fees, *FAMADVFEE*, of 1.06%. Importantly, as much as 18% (29%) of the typical family's product offerings consists of index (institutional) fund products. Also, fund families are heavily concentrated (64%) in equity style products, with fixed income products representing only 23% of the total product offerings (the remaining 13% is represented by hybrid funds in the ICDI categories of mixed/others mutual funds).[8]

In Panel B of Table 2 we report summary statistics for fund family advisory contracts separately for the top 100 fund families based on assets under management, and all other fund families. Our objective is to quantify the economic relevance of concave fee schedules in terms of fund family assets and total industry market share. To this end, we collect information on the structure of the advisory contract reported by all mutual funds in the semi-annual NSAR-B forms filed by all mutual funds with the SEC between 1995 and 2017. Following Deli (2002), we compute the concavity of the advisory contract as the difference between the first and last marginal compensation rates divided by the applicable marginal compensation rate. This variable is positive when the fund family fee schedule is concave, and equals zero when fund family advisory contracts are linear.[9] Overall, the evidence in Panel B of

[5] We reached similar conclusions when we estimated Equation (1) using alternative definitions of net cash flows. First, we computed net cash flows as $\frac{TNA_t - TNA_{t-1}(1+r_t)}{TNA_{t-1}(1+r_t)}$ in order to account for possible distortions due to very large negative returns that could result from fund liquidations (Berk and Green (2004)). Second, we computed net cash flows as $\frac{TNA_t - TNA_{t-1}(1+r_t) - MERGER_t}{TNA_{t-1}}$, where $MERGER_t$ represents the increase in the fund's total net assets following the merger in month t (Sapp and Tiwari (2004)). The results of such tests can be obtained from the authors upon request.

[6] Our findings are qualitatively unchanged with alternative values of k equal to 12, 24, 48, and 60 months.

[7] We use the Mutual Fund Links (MFLINKS) tables to identify mutual fund portfolios.

[8] In our sample, the mutual fund industry's assets have grown from $2.6 trillion in 1995 to about $18.5 trillion in 2017. Over this period, the average fund family TNA has grown from $5.9 billion to over $20.6 billion, and the typical fund family offers an average of 5 distinct investment styles. The 5 largest fund families (by TNA) control an aggregate market share of 46% as of 2017, or a 12% increase since 1995. Further, the total number of fund families in our sample increased from 507 in 1995 to about 780 by 2017, with the percentage of single-style families varying between 20% and 25%. These summary statistics of fund families are very similar to those reported by Khorana and Servaes (2012) over the earlier period from 1976 to 2009, and to the summary statistics reported by the 2017 Investment Companies Institute (ICI) Factbook.

[9] We match data from the semi-annual NSAR-B forms with that from CRSP Mutual Fund Database using fund family names between 1995 and 2009, and the SEC matching table of NASD tickers between 2010 and 2017.

Table 1
The Effect of the Asset Volatility on Fund Family Fee Revenue: An Example.

	Scenario 1: Stable Family TNA (in '000s)		Scenario 2: Volatile Family TNA (in 000's)	
	Year 1	Year 2	Year 1	Year 2
Total Net Assets (TNA):				
Fund 1	$300,000	$200,000	$100,000	$400,000
Fund 2	$200,000	$300,000	$100,000	$400,000
Fund Family	$500,000	$500,000	$200,000	$800,000
Fund Family A: Concave Fee				
Asset management fee	1.00%	1.00%	1.00%	0.75%
Fee Revenue Fund 1	$3,000	$2,000	$1,000	$3,750
Fee Revenue Fund 2	$2,000	$3,000	$1,000	$3,750
Fee Revenue Fund Family A	$5,000	$5,000	$2,000	$7,500
Average annual fee revenue of Fund Family A	$5,000		$4,750	
Incremental annual fee under Scenario 1 (Stable Family TNA)	**$250**			
Fund Family B: Linear Fee				
Asset management fee	1.00%	1.00%	1.00%	1.00%
Fee Revenue Fund 1	$3,000	$2,000	$1,000	$4,000
Fee Revenue Fund 2	$2,000	$3,000	$1,000	$4,000
Fee Revenue Fund Family B	$5,000	$5,000	$2,000	$8,000
Average annual fee revenue of Fund Family B	$5,000		$5,000	
Incremental annual fee under Scenario 1 (Stable Family TNA)	**$0**			

This table presents a simple motivating example contrasting the fee revenue (in thousands) earned by two hypothetical fund families, each offering two funds over a two-year period, under alternative scenarios. Under the first scenario (Stable Family TNA), both fund families maintain total net assets (TNA) of $500,000,000 in each of the two years. Under the second scenario (Volatile Family TNA), both fund families have total net assets of $200,000,000 in the first year and $800,000,000 in the second year. Thus, the average annual total net assets amount to $500,000,000 under both scenarios. The first fund family, Family A, offers two funds with a concave advisory fee schedule comprising a fee rate of 1% for assets below the $300 million (inclusive), and 0.75% thereafter. The second fund family, Family B, employs a linear fee schedule and charges an annual fee equal to 1% of the assets under management. The table below shows the incremental fee revenue accruing to each fund family under Scenario 1 (Stable Family TNA) compared to Scenario 2 (Volatile Family TNA). The illustration suggests that Fund Family A, which faces a concave fee schedule, would gain $250,000 in average annual fee revenue under the stable TNA scenario (Scenario 1) over the two-year period considered. By contrast, Fund Family B, which faces a linear fee schedule, would have the identical fee revenue under the stable TNA scenario (Scenario 1) and the volatile TNA scenario (Scenario 2). In other words, there is no fee revenue gain from stabilizing the asset base for the fund family with the linear fee schedule.

Table 2 indicates that the top 100 fund families control 95% of industry assets. Importantly, among the top 100 fund families, on average about 65% of a family's assets are invested in funds with a concave fee schedule. Among the other fund families that control the remaining 5% of industry assets, on average about 52% of the fund family's assets are invested in funds with a concave fee schedule. Thus, almost two-thirds (= 65%*95% + 52%*5%) of the fund industry's assets are managed under concave advisory contracts.

3.2. *Product diversity and fund flow diversification benefits*

By increasing the total number of funds or the total number of categories, fund families can expand their industry coverage and offer mutual fund investors the option of moving in and out of different funds within the fund family at very low (switching) cost. To the extent that net cash flows of multiple fund products or multiple investment styles are less than perfectly correlated at the family level, fund families can achieve considerable net cash flow diversification and significantly reduce their exposure to overall cash flow volatility. Fig. 1 illustrates this point clearly by showing the relationship between the number of styles offered by fund families and the associated level of fund flow diversification.

Panel A of Fig. 1 shows that fund flow diversification increases—but at a marginally decreasing rate—as a function of the number of fund categories offered by a fund family. For instance, fund families that offer only one investment category of funds experience a 3.33% reduction in net cash flow volatility, on average, with this fund flow diversification benefit varying between 0 (5th percentile) and 34% (95th percentile), depending on the degree of fund flow diversification across funds within that category. By contrast, a fund family that offers an average number (5) of investment styles experiences a reduction of about 52% in cash flow volatility, with this coinsurance effect ranging between 7% (5th percentile) and 79% (95th percentile). Panel B of Fig. 1 depicts the relationship between the volatility of net cash flows experienced by a fund family and the number of investment styles represented by the funds offered by it. As may be seen, fund families offering the average number (5) of investment styles in terms of their funds have an annualized cash flow volatility of 10% which is about two-thirds of the corresponding fig. (15%) for single-fund families.

4. Family-level benefits of fund flow diversification: asset volatility and financial stability

We begin by establishing the economic benefits of fund flow diversification for fund families in terms of the reduction in asset volatility they experience. As previously highlighted, the concave nature of fee schedules suggests that mitigating asset volatility is advantageous for fund families, as it contributes to an increase in their total fee revenue. We first quantify the sensitivity of asset volatility to fund flow diversification, establishing a foundational understanding of how diversification influences financial stability. Subsequently, we will assess the economic benefits of fund flow diversification, specifically in relation to the stability it imparts to assets, and its consequential impact on the fee revenue accrued by a typical fund family. The empirical evidence underscores the significant advantages that fund flow diversification offers to mutual fund families, notably in reducing flow-related liquidity risk and enhancing annual fee revenue. These findings underscore the strategic importance of fund flow diversification in the financial management and operational stability of mutual fund families.

4.1. *The impact of fund flow diversification on fund family fee revenue*

In this subsection we first quantify the sensitivity of asset volatility to fund flow diversification. Specifically, we aim to quantify the extent to which flow diversification can mitigate the fluctuations in total assets managed by a fund family. In Panel A of Table 3, we report the coefficients of the relationship between total asset volatility and fund flow diversification of a fund family. The dependent variable in all models is the 36-month volatility of family-level total net assets (*ASSETVOL*). The independent variable, *DIVERSIFICATION*, is represented by one of the following family-level fund flow diversification proxies: (a) a dummy variable that equals 1 for diversified multi-fund families (*FAMDIV*) in models (i) and (iv); (b) the value of the fund family's flow diversification estimated using share-class net cash flows (*COINSURE*) in models (ii) and (v); and (c) the fund family's pairwise correlation in idiosyncratic

Table 2
Descriptive Statistics.

Panel A: Summary statistics of the mutual fund sample

	Mean	Percentiles				
		P5	P25	P50	P75	P95
FAMTNA ($M)	12,187.9	7.3	37.2	290.4	2615.7	45,799.9
FAMFLOWS	1.59%	−3.89%	−0.87%	0.22%	1.95%	9.35%
FAMAGE	16.27	0.83	4.00	10.25	20.50	62.25
NPFOLIO	8.45	1.0	1.0	3.0	8.0	38.0
NINVOBJ	4.84	1.0	1.0	2.0	6.0	18.0
FAMTURNR	0.800	0.070	0.259	0.504	0.937	2.510
FAMOPEX	1.17%	0.40%	0.83%	1.13%	1.48%	2.04%
FAMADVFEE	1.06%	0.35%	0.74%	1.01%	1.32%	1.94%
FAMRET	−0.03%	−3.10%	−0.62%	0.00%	0.57%	2.94%
CORRSTL	0.683	0.122	0.369	0.797	1.000	1.000
COINSURE	22.05%	0.00%	0.00%	17.43%	39.64%	62.95%

Panel B: Summary statistics of the fund family advisory contract structure.

	Top 100 Families	Other Families
Total Industry Market Share	95.0%	5.0%
Proportion of fund family assets in funds with concave fee schedules:		
Mean	65.2%	51.6%
P25	26.8%	12.4%
P50	78.3%	44.1%
P75	99.6%	98.1%
Percentage of family funds with concave fee schedules	44.3%	22.9%
Estimated concavity of fee schedules of family funds	0.167	0.132
Fund family marginal fee rate	0.6%	0.9%

This table presents the summary statistics for our sample of U.S. mutual fund families during the period January 1993 to December 2017. Panel A presents the descriptive statistics of the following fund family characteristics: Total assets under fund family's management (*FAMTNA*) in $M; monthly percentage objective-adjusted net cash flows (*FAMFLOWS*); years since inception of the oldest fund of the fund family (*FAMAGE*); number of fund portfolios (*NPFOLIO*) and number of investment objectives (*NINVOBJ*); value-weighted portfolio turnover (*FAMTURNR*); value-weighted annual operating expense (*FAMOPEX*); value-weighted annual advisory fee (*FAMADVFEE*); style-adjusted after-fee returns (*FAMRET*); the correlation of idiosyncratic net cash flows at the style level estimated over a 36-month window (*CORRSTL*) and a proxy measure of family-level fund flow diversification based on share-class cash flows (*COINSURE*). Panel B presents the summary statistics of fund family advisory contracts for the top 100 fund families by assets under management, and all other fund families. The data on the fund family advisory contracts is sourced from the NSAR-B form available in the SEC archives over the period from 1995 to 2017. Panel B illustrates the total industry market share controlled by each fund family group, the average and percentile statistics of the proportion of fund family assets in fund products with concave fee schedules; the percentage of family funds (out of the total number of funds offered by the family) with concave fee schedules; the fund family TNA-weighted marginal fee rate; and the estimated concavity of fee schedule of family funds, computed as the difference between the first and the last marginal fee rates divided by the applicable marginal fee rate.

style-level net cash flows (*CORRSTL*) in models (iii) and (vi). Other lagged fund family characteristics (unreported for brevity) include: the logarithm of the number of fund portfolios (*LNPFOLIO*) and investment styles (*LNINVOBJ*); the logarithm of family total net assets (*LFAMTNA*); the logarithm of fund family age since inception (*LFAMAGE*); percentage net cash flows (*FAMFLOWS*); style-adjusted after-fee realized returns (*FAMRET*); style-adjusted portfolio turnover (*FAMTURNR*); and the volatility of net percentage cash flows (*FAMCFVOL*). We control for differences in fund product offering characteristics by including the following (unreported) variables: percentage of assets under management invested in equity-oriented investment styles (*EQUITYPCT*); percentage of assets under management invested in income-oriented investment styles (*INCOMEPCT*); a dummy variable that equals 1 if $>$75% of fund family assets are issued to institutional share (*INSTNPCT*); and a dummy variable that equals 1 if $>$75% of fund family assets are represented by index fund products (*INDEXPCT*). In models (i)-(iii) of Panel A of Table 3, we run Fama-MacBeth cross sectional regressions with *HAC* standard errors. In all other models of Panel A of Table 3, we estimate pooled OLS regressions with time and family fixed effects, and standard errors clustered at the family level (*Family*).

The estimated coefficient of the fund flow diversification proxy *FAMDIV* in model (i) of Panel A of Table 3 confirms that diversified fund families (*FAMDIV* $=1$) enjoy a 7% lower cross sectional average asset-based volatility. Similarly, the coefficient of the cash flow diversification proxy, *COINSURE*, in model (ii) of Panel A of Table 3 suggests that a one-standard-deviation (0.222) increase in *COINSURE* is associated with a 3% reduction in the asset-based volatility of a fund family, on average. These findings are qualitatively robust to the inclusion of fixed effects in models (iv) to (vi) of Panel A of Table 3. They are also consistent with the findings of Cipriani and La Spada (2021) who find that following exogenous liquidity shocks, diversified fund families offering different fund products—i.e., prime funds and government funds within the same money market fund style—are able to retain almost 90% of their assets. They suggest that having a negative correlation between the investor flows to funds offered by a family could lower the total asset volatility and aggregate business risk of the fund sponsor.

Next, we quantify the change in the total fee revenue of a typical fund family across different levels of fund flow diversification. In order to do this, we first estimate the empirical distribution of the fee/asset breakpoints, marginal fee schedules, and asset volatility characteristics observed across fund families. Using a representative fund family with initial total net assets of $2 billion and the empirically observed monthly asset growth of 2% over a period of 120 months (i.e., 10 years), we estimate the incremental fee revenue that would accrue to the fund

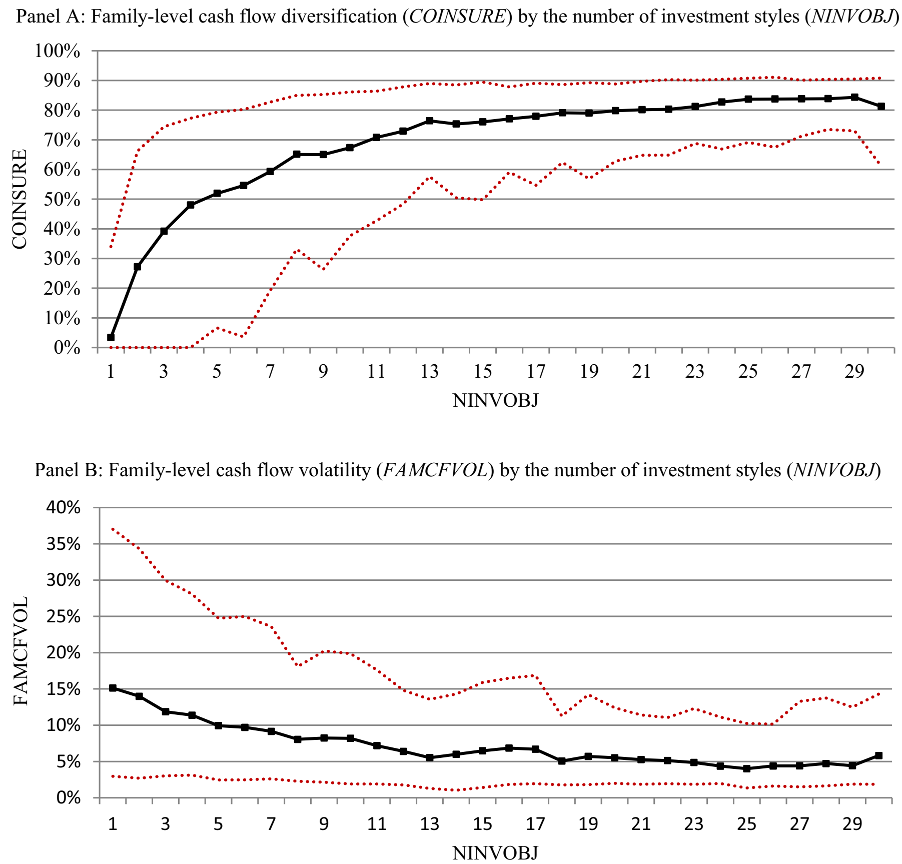

Fig. 1. Product Diversity, Fund Family Cash Flow Volatility and Fund Flow Diversification.
This figure illustrates the time-series-cross-section relationship between measures of fund flow diversification experienced by fund families as a function of the number of distinct investment styles offered (*NINVOBJ*). In Panel A the fund flow diversification measure (*COINSURE*) is the average percentage reduction in cash-flow volatility experienced by a fund family, relative to the hypothetical case with perfectly correlated flows across the family's funds. In Panel B the measure of fund flow diversification (*FAMCFVOL*) is the volatility of net cash flows experienced by the fund family. The dotted curves in both panels illustrate the 5-th and 95-th percentiles of the distribution of the two measures, *COINSURE* and *FAMCFVOL*. We present these statistics for fund families offering no more than thirty investment styles to ensure sufficient within-group number of observations. The sample period extends from 1993 to 2017.

family if it were able to reduce its asset volatility.[10] We consider a range of asset volatilities calibrated to the empirically observed values in the cross section of the fund families.

Fig. 2 illustrates the simulated annual fee revenue for a fund family with a concave fee schedule for different asset volatility (*Sigma*) scenarios.[11] As expected, the analysis shows that the fee revenue is inversely related to the asset volatility experienced by a fund family. For instance, a one-standard-deviation (3%) reduction in the family's asset volatility from, say, 6.5% to 3.5% would translate into an $11 million increase in the end-of-period annual fee revenue accruing to the fund family. This implies that a fund family could earn a 6.1 basis-points-higher applicable fee rate—representing an increase from an applicable fee rate of 0.62% with asset volatility of 6.5% to an applicable fee rate 0.68% with asset volatility of 3.5%—as a result of greater fund flow diversification. This finding confirms that fund families with lower asset volatility gain a significant economic advantage in advisory fee-setting policies. We reach qualitatively similar conclusions about the relationship between fee revenue and asset volatility using different specifications of the concave fee schedule.[12]

4.2. *The impact of fund flow diversification on flow-related liquidity risk*

We next provide evidence on the benefits of fund flow diversification in terms of its impact on the flow-related liquidity risk faced by open-end mutual funds. Specifically, we estimate the cross-sectional variation in net cash flows experienced by fund families with different levels of fund flow diversification, both before and after the flow-related liquidity shock associated with the bankruptcy of Lehman Brothers in September 2008. Fig. 3 documents the difference in the cumulative style-adjusted net cash flows between fund families with above- and below-median

[10] We obtain the concave fee/asset breakpoints from Items 48.A to 48.K of the semi-annual NSAR-B forms available from SEC archives from 1995 to 2017. Our simulation is calibrated to the median percentile distribution of fee breakpoints. Specifically, it reflects a marginal fee rate of 0.850% for the first $1 billion of assets, 0.775% for the next $1 billion, 0.750% for the next $3 billion, 0.725% for the next $5 billion, 0.700% for the next $2.5 billion, 0.680% for the next $2.5 billion, 0.651% for the next $4 billion, 0.485% for the next $2.5 billion, 0.470% for the next $13.5 billion, and 0. 450% thereafter.

[11] We omitted the subplot of simulated fee revenue for a fund family with a linear (i.e., constant) fee rate. As expected, reducing asset volatility offers no revenue benefits to the fund family in this case.

[12] We used the 25th (75th) percentile of the empirical distribution of concave fee schedules to simulate the fee revenue of a fund family with TNA equal to the 25th (75th) percentile of the observed fund family TNA distribution.

Table 3
Fund Flow Diversification and Total Asset Volatility of the Fund Family.

Panel A: The relationship between total asset volatility and diversification – Full sample

	Dep. Variable	Proxy	DIVERSIFICATION	Family Controls	Std.Err.	Obs.
(i)	ASSETVOL	FAMDIV	−0.070*** (0.002)	Yes	HAC	93,007
(ii)	ASSETVOL	COINSURE	−0.156*** (0.007)	Yes	HAC	92,615
(iii)	ASSETVOL	CORRSTL	0.066*** (0.003)	Yes	HAC	92,963
(iv)	ASSETVOL	FAMDIV	−0.020*** (0.006)	Yes	Family	93,007
(v)	ASSETVOL	COINSURE	−0.017*** (0.003)	Yes	Family	92,615
(vi)	ASSETVOL	CORRSTL	0.029*** (0.007)	Yes	Family	92,963

Panel B: Change in total asset volatility of a fund family around the September 2008 event.

	Dep. Variable	Proxy	DIVERSIFICATION	Family Controls	Std.Err.	Obs.
(i)	$\Delta\overline{ASSETVOL}$	FAMDIV	−0.206 (0.139)	Yes	H/Family	540
(ii)	$\Delta\overline{ASSETVOL}$	COINSURE	−0.088*** (0.030)	Yes	H/Family	540
(iii)	$\Delta\overline{ASSETVOL}$	CORRSTL	0.044** (0.019)	Yes	H/Family	540

This table presents the estimated coefficients from regressions that model family-level asset volatility as a function of selected fund family characteristics over the period 1993 to 2017. In Panel A, the dependent variable is the 36-month volatility of fund family's total net assets (*ASSETVOL*). In models (i)-(iii) of Panel A, we estimate Fama-MacBeth cross sectional regressions with *HAC* standard errors (in parentheses). In models (iv)-(vi) of Panel A, we estimate pooled OLS regressions with time and family fixed effects and standard errors clustered at the family level (*Family*). In Panel B, we report the results from regressions of the degree of family-level asset stability in the 12 months before and after September 2008, on measures of fund flow diversification. The dependent variable is the change in the annual style-adjusted asset-based volatilities computed in the 12 months after September 2008 (inclusive) and the 12 months before September 2008, $\Delta\overline{ASSETVOL}$. Standard errors are adjusted for heteroskedasticity and clustered at the fund family level (*H/Family*), and are reported below the coefficients in parentheses. In Panels A and B, we include the following lagged fund flow diversification proxies (*DIVERSIFICATION*): (a) a dummy variable for multi-style fund families, *FAMDIV*; (b) the percentage cash flow coinsurance (*COINSURE*); and (c) the correlation of idiosyncratic style net cash flows (*CORRSTL*). Other untabulated lagged family-level control variables in Panels A and B include: the logarithm of the number of fund portfolios (*LNPFOLIO*) and investment styles (*LNINVOBJ*); the logarithm of family total net assets (*LFAMTNA*); the logarithm of fund family age since inception (*LFAMAGE*); net cash flows (*FAMFLOWS*); style-adjusted net realized returns (*FAMRET*); total volatility of net cash flows (*FAMCFVOL*); and style-adjusted portfolio turnover (*FAMTURNR*). Additional (untabulated) variables include the percentage of family TNA in index, institutional, equity, and income funds. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

fund flow diversification.[13] For this purpose, we use the following two representative proxy measures of fund flow diversification: (a) the coinsurance of share-class cash flows expressed in percentage terms (*COINSURE*), and (b) the correlation of idiosyncratic net cash flows estimated at the style level (*CORRSTL*). The graph tracks the difference in the cumulative style-adjusted net cash flows in the two years before and the two years after the September 2008 crisis.

The evidence presented in Fig. 3 suggests that fund families with below-median value of *COINSURE* experienced about 10% greater cumulative style-adjusted net cash outflows, compared to fund families with above-median *COINSURE* value, in the two years after the event (*Low-High COINSURE*). Similarly, fund families with above-median style-related flow correlation, *CORRSTL*, experienced cumulative style-adjusted net cash outflows that were, on average, 7% greater than that of fund families with below-median *CORRSTL (High-Low CORRSTL)*. By contrast, there seems to be no difference in the net cash flows of fund families with above- and below-median value of fund flow diversification in the 2 years preceding September 2008.

Next, we examine the relation between the diversification of fund flows (*DIVERSIFICATION*) experienced by fund families and their flow-related liquidity risk in a multivariate cross-sectional regression framework. Our liquidity risk proxy is the change in the average annual style-adjusted asset volatility, $\Delta\overline{ASSETVOL}$, computed during the 12 months after September 2008 (inclusive) relative to the 12 months before September 2008.[14] Our estimation model is as follows:

$$\Delta y_{i,t} = \alpha + \beta\, DIVERSIFICATION_{i,t-1} + \gamma y_{i,t-1} + \Theta' X_{i,t-1} + \varepsilon_i, \tag{3}$$

where i indicates the fund family, t is the year after September 2008, $\Delta y_{i,t}$ is the change in flow-related liquidity risk as measured by $\Delta\overline{ASSETVOL}$, from the one year before to the one year after September 2008, and $X_{i,t-1}$ is the vector of lagged fund family characteristics. We use three proxy measures of the degree of family-level fund flow diversification described previously. These include (a) the diversification of fund flows expressed in percentage terms (*COINSURE*), and (b) the correlation of idiosyncratic net cash flows estimated at the style level (*CORRSTL*). The third flow diversification proxy is the dummy variable *FAMDIV*, which equals 1 if a fund family offers funds in more than one investment objective, and 0 otherwise. The vector of lagged fund family characteristics, $X_{i,t-1}$, includes all of the variables described earlier in Panel A of Table 3. All of the independent variables are measured as the

[13] Fund families are sorted by fund flow diversification proxies on September 2007 (i.e., one year before the shock) to reduce the risk that the liquidity shock might contaminate the sorting of the diversification proxies.

[14] In an unreported test, we also considered as an alternative liquidity risk proxy the change in the average annual style-adjusted net fund flow, $\Delta\overline{FAMFLOWS}$, during the 12 months after September 2008 (inclusive) compared to the 12 months before September 2008. Consistent with the evidence presented in Fig. 3, we find that diversified fund families experienced style-adjusted net cash flows that were on average 7.9% higher than undiversified fund families during the 12 months after September 2008.

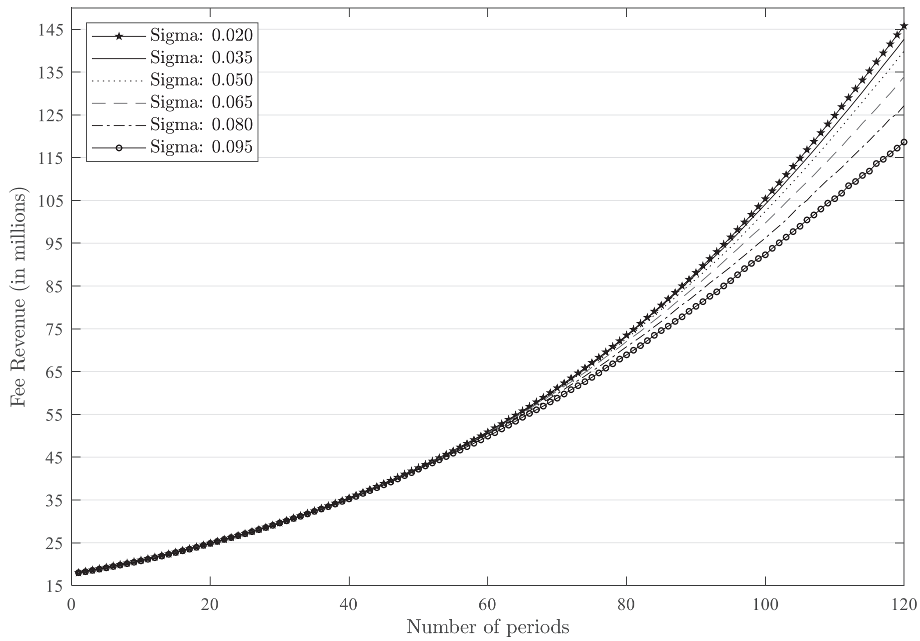

Fig. 2. Simulated Fee Revenue of a Fund Family across Different Asset Volatility Scenarios.
This figure plots the findings of simulated tests of the effect of different asset volatility scenarios on the advisory fee revenue accruing to a fund family given the observed concave advisory fee schedules. The asset volatility scenarios (*Sigma*) range between 0.02 and 0.095 (with 0.015 increments), and are calibrated on the empirically observed distribution of fund family's cash flow volatility. We run 100,000 simulations assuming an initial fund family size of $2 billion, an operating time period of 120 months (or 10 years), and the empirically observed marginal fee breakpoint schedule of 0.850% for the first $1 billion of assets, 0.775% for the next $1 billion, 0.750% for the next $3 billion, 0.725% for the next $5 billion, 0.700% for the next $2.5 billion, 0.680% for the next $2.5 billion, 0.651% for the next $4 billion, 0.485% for the next $2.5 billion, 0.470% for the next $13.5 billion, and 0. 450% for any assets value above $35 billion. This breakpoint fee schedule corresponds to the 50th percentile of the fee schedule distribution available from the semi-annual NSAR-B forms obtained through the SEC archives over the sample period from 1995 and 2017. The figure presents the resulting simulated advisory fee revenue of the fund family for each asset volatility scenario over the 120 simulated months.

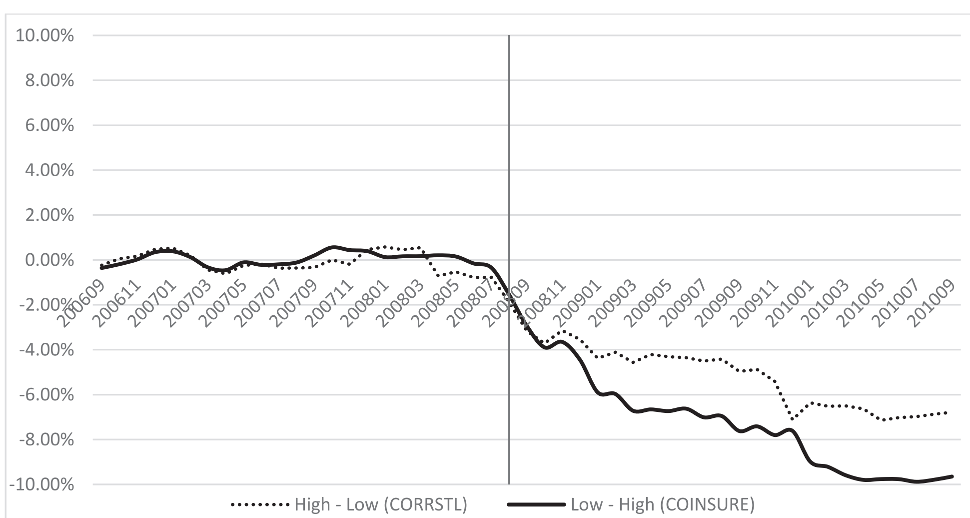

Fig. 3. Cumulative Style-adjusted Net Cash Flows of Mutual Fund Families.
Before/After the Flow-related Liquidity Shock of September 2008.
This figure plots the difference in cumulative style-adjusted net cash flows experienced by fund families with high (above-median) and low (below-median) flow diversification levels in the two years before and the two years after the flow-related liquidity shock induced by the bankruptcy of Lehman Brothers on September 2008. We first separate fund families into above- and below-median fund-flow diversification as of September 2007 (i.e., one year before the flow-related shock) to reduce the risk that the shock might contaminate fund family rankings. Our lagged fund flow diversification proxies of fund families include: (a) the correlation of idiosyncratic net cash flows estimated at the style level (*CORRSTL*); and (b) the absolute percentage cash flow coinsurance of share-class cash flows (*COINSURE*). We then track the difference in cumulative net cash flows of fund families with above- and below-median fund flow diversification in the two years before and the two years after the exogenous shock of September 2008.

average values of the variables in the year prior to September 2008.

Panel B of Table 3 reports the results from estimating the model specified in Eq. (3). The findings show that a greater degree of fund flow diversification is associated with lower average asset-based volatility ($\Delta\overline{ASSETVOL}$) during the 12 months after September 2008 (relative to the pre-crisis period). These findings are both statistically and economically significant. For example, the estimated coefficient of the variable *COINSURE* (−0.088) in Model (ii) suggests that a one standard deviation (0.222) increase in fund flow diversification is associated with a 2% reduction in the asset-based volatility of a fund family during the 12 months after September 2008. We obtain qualitatively similar results when we consider the alternate proxy for the degree of fund flow diversification, *CORRSTL*, as the key explanatory variable of interest.

In summary, the results in this section suggest that the benefits of fund flow diversification for fund families are quite substantial, both in terms of increasing their annual fee revenue and mitigating flow-related liquidity risk.[15] In the following sections, we examine whether fund shareholders benefit from the potential economic gains from fund flow diversification that accrue to fund families.

5. Family-level Fund Flow diversification and investor fees

5.1. Does fund flow diversification result into lower style-adjusted fees? a portfolio approach

We now test our first hypothesis on the relationship between advisory fees and fund flow diversification using a portfolio approach. Table 4 reports the average fund family style-adjusted fees across quintile portfolios based on fund family characteristics and a proxy for flow diversification. We first sort fund families into quintile portfolios of the following lagged characteristics: the number of investment styles offered by the fund family (*NINVOBJ*) in Panel A of Table 4 and the total size (TNA) of the fund complex (*FAMTNA*) in Panel B. Within each of these quintile portfolios of family characteristics, we then rank fund families into quintile portfolios based on the lagged value of our representative measure of fund flow diversification, *COINSURE*. Each panel of the table reports the average value-weighted style-adjusted fees for each of the resulting 25 cross-tabulated portfolios.

Over the entire sample, as seen in the first column of both panels in Table 4, we observe a monotonic decrease in *FAMADVFEE* from the lowest to the highest fund flow diversification quintile. Consistent with our prediction on the effect of fund flow diversification on fee-setting policies, the mean difference between *High* and *Low* fund flow diversification is a statistically significant 0.3%. Further, in unreported results, we find a similar inverse relationship between fund flow diversification and style-adjusted family-level operating expenses.

The relationship between *FAMADVFEE* and *COINSURE* remains negative and significant after controlling for the number of investment styles offered by a fund family, *NINVOBJ*. Specifically, the mean difference in *FAMADVFEE* between the portfolios of high and low *COINSURE* is always negative within each quintile portfolio of *NINVOBJ*. Thus, fee-setting policies do not simply reflect the style-proliferation strategies adopted by fund families.

In Panel B of Table 4 we control for the fund family TNA (*FAMTNA*). Unsurprisingly, fund families with greater market share are associated with below-average style-adjusted expenses, hence confirming the existence of significant economies of scale being passed on to fund investors (see also Warner and Wu (2011)). Nonetheless, it is clear that fund flow diversification is associated with lower style-adjusted fees within each quintile portfolio of fund family size. This suggests that the economic benefits of fund flow diversification are not simply driven by economies of scale. Importantly, even within the smallest quintile of fund family size, families characterized by *High COINSURE* charge significantly below-average advisory fees.[16]

In an unreported result we confirm that the favorable impact of fund flow diversification on style-adjusted fees is robust to the use of the alternative diversification proxy based on style-adjusted cash flow correlation, *CORRSTL*.

5.2. Family-level diversification and investor style-adjusted fees: A multivariate analysis

In this subsection we report the results from a battery of tests designed to assess the relationship between family-level fees and fund flow diversification proxies in a multivariate framework. Since style characteristics could affect the value-weighted fees charged by a family across different products, our dependent variable is the TNA-weighted *style-adjusted* advisory fees (*FAMADVFEE*). The use of style-adjusted fees is equivalent to using fund style fixed effect estimators at the fund family level. In addition, as individual fund-level fees are calculated net of the average investment objective fees, family-level fees are, by construction, not affected by changes in the product-mix policies adopted by the family.[17] To address concerns related to the correlation between fund family fees and other observable fund family characteristics, we employ the Fama-MacBeth regression framework to analyze the cross-sectional relationship between fund flow diversification and advisory fees. Specifically, we use the following regression specification:

$$FAMADVFEE_{i,t} = \theta + \gamma\, DIVERSIFICATION_{i,t-1} + \boldsymbol{\delta}\, \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t,} \qquad (4)$$

where the independent variable $DIVERSIFICATION_{i,t-1}$ is represented by one of the following family-level fund flow diversification proxies: (a) a dummy variable that equals 1 for diversified multi-fund families (*FAMDIV*) in column (i); (b) the value of the fund family's flow diversification estimated using share-class net cash flows (*COINSURE*) in columns (ii) and (iii); and (c) the fund family's pairwise correlation in idiosyncratic style-level net cash flows (*CORRSTL*) in columns (iv) and (v).

The vector of lagged fund family characteristics,$X_{i,t-1}$, includes all of the variables described earlier in Panel A of Table 3. Importantly, in all model specifications we also interact *DIVERSIFICATION* with *LFAMTNA* and *LFAMAGE* to isolate the effect of firm size and years of operation on the fee-diversification relationship.

We also include two additional variables that are likely to influence the advisory fee-setting policies of mutual fund families. The first variable is the value-weighted style-adjusted redemption fee, *EXITGATE*, which isolates the effect of redemption risk on advisory fees. Chordia (1996) argues that exit fees are highly successful at locking-in fund investors by increasing the cost of share redemptions. We conjecture that if exit gates are effective at curbing redemption risk, they would significantly decrease the fee revenue uncertainty faced by load fund families. The lower redemption risk would then enable load fund families to compete more aggressively by reducing advisory fees to attract investors with low liquidity needs (Nanda, Narayanan, and Warther (2000)).

The second variable is the number of star funds offered by a fund family, *FAMNSTAR*. A star fund is one whose performance places it in the top 5% of monthly style-adjusted returns during the past 12 months. It is reasonable to assume that "star"-producing fund complexes can

[15] Nanda and Wei (2018) also provide evidence that mutual funds attempt to manage their flow-related liquidity risk. Specifically, they document that mutual funds try to mitigate their exposure to flow-related liquidity shocks by reducing their portfolio overlap with peer funds when they experience heightened flow correlations.

[16] In an unreported test we also control for the age of the fund family (*FAMAGE*) and its level of fund flow volatility (*FAMCFVOL*). Our findings indicate that younger fund families and those facing higher cash-flow-related liquidity risk are likely to charge above-average style-adjusted fees.

[17] Our conclusions do not change when we use the median—rather than the mean—investment objective fees to adjust family-level fees.

Table 4
The Effect of Product Offerings, Family Size and Flow Diversification on Fees.

Panel A: Fund family fees by number of investment styles (*NINVOBJ*) and fund flow diversification (*COINSURE*)

	All Sample	NINVOBJ					High - Low
		Low	q2	q3	q4	High	
All Sample	–	0.09%	0.13%	−0.02%	−0.10%	−0.20%	−0.28%***
Low COINSURE	0.11%	0.22%	0.14%	0.10%	0.03%	−0.03%	−0.25%***
q2	0.08%	0.06%	0.21%	0.25%	0.06%	−0.04%	−0.16%***
q3	−0.08%	0.01%	−0.02%	−0.11%	−0.09%	−0.14%	−0.17%***
q4	−0.13%	−0.10%	−0.11%	−0.14%	−0.16%	−0.16%	−0.14%***
High COINSURE	−0.19%	−0.05%	−0.22%	−0.22%	−0.18%	−0.27%	−0.20%*
High - Low	−0.30%***	−0.27%***	−0.36%***	−0.33%***	−0.20%***	−0.24%***	

Panel B: Fund family fees by family size (*FAMTNA*) and fund flow diversification (*COINSURE*)

	All Sample	FAMTNA					High - Low
		Low	q2	q3	q4	High	
All Sample	–	0.28%	0.12%	−0.06%	−0.17%	−0.23%	−0.51%***
Low COINSURE	0.11%	0.36%	0.20%	0.11%	−0.01%	−0.10%	−0.54%***
q2	0.08%	0.39%	0.29%	0.13%	−0.05%	−0.19%	−0.63%***
q3	−0.08%	0.17%	0.00%	−0.07%	−0.19%	−0.25%	−0.51%***
q4	−0.13%	0.04%	−0.13%	−0.17%	−0.18%	−0.22%	−0.33%***
High COINSURE	−0.19%	−0.02%	−0.17%	−0.24%	−0.22%	−0.30%	−0.36%***
High - Low	−0.30%***	−0.38%***	−0.37%***	−0.35%***	−0.21%***	−0.19%***	

This table presents average value-weighted style-adjusted fees for quintile portfolios based on lagged values of family-level fund flow diversification and other selected fund family characteristics, for the period from 1993 to 2017. We first sort fund families into quintile portfolios based on the following lagged fund family characteristics: the number of investment styles offered by the fund family (*NINVOBJ*) in Panel A; and the total size (TNA) of the fund complex (*FAMTNA*) in Panel B. For each of these quintile portfolios of selected fund family characteristics, we then sort families into quintile portfolios based a proxy measure of family-level fund flow diversification based on share class cash flows, *COINSURE*. For each of the 25 cross-tabulated portfolios, we then compute the average style-adjusted advisory fees (*FAMADVFEE*). For each panel, we also report the difference between the two extreme quintile portfolios (*High-Low*) of each fund family characteristic within quintile portfolios and across the entire sample. The *t*-statistics are adjusted for serial correlation using the Newey-West lags of order 3. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

charge above-average advisory fees. Nanda et al. (2004) argue that fund families can try to improve the odds of generating star funds by resorting to a fund proliferation strategy. Since this strategy of expanding the product mix in an attempt to produce more star funds could also lower intra-family cash flow correlation, the number of star funds within a fund family could indirectly affect the fee-flow diversification relationship.

The results from estimating Eq. (4) are presented in Panel A of Table 5. Estimated loadings of the dependent variable, *FAMADVFEE*, on the different fund flow diversification proxies are consistent with the favorable impact of fund flow diversification on fees. Specifically, fund families with more stable assets charge significantly lower style-adjusted advisory fees. For example, the estimated coefficient (−0.202) of the dummy variable *FAMDIV* in Panel A of Table 5 implies that diversified families charge a style-adjusted fee that is about 20 basis points lower than that of undiversified fund families. In order to assess the economic significance of this result consider that an average diversified fund family manages approximately $20 billion in assets, spread across 13 fund portfolios and 8 investment styles. Thus, a 20 basis point reduction in fees implies that fund investors could save in excess of $40 million in style-adjusted advisory fees across the range of product offerings of the average fund family.

In model (iii) we estimate the relation between *FAMADVFEE* and the alternate proxy for fund flow diversification, *COINSURE*. The cross-sectional relation between fees and flow diversification remains negative and significant. The coefficient of the variable *COINSURE* (−0.455) suggests that a one standard deviation (0.222) increase in fund flow diversification is associated with a 10-basis-points reduction in the style-adjusted advisory fee. This finding suggests that family-level fund flow diversification accounts for about half (10 basis points) of the 20 basis points reduction style-adjusted advisory fees identified in column (i). The other half is attributable to family-level return-based correlation. In models (ii) and (iii), we exclude the control variable *FAMCFVOL*, as this variable is highly correlated with the diversification proxy, *COINSURE*, by construction.[18]

Importantly, the positive coefficients of *FAMCFVOL* in models (i), (iv), and (v) confirm that fund families facing above-average cash flow volatility are more likely to charge higher value-weighted style-adjusted advisory fees in an attempt to preserve their fee income. For example, the coefficient of *FAMCFVOL* (0.261) in model (i) suggests that a 1% (0.031) reduction in monthly cash flow volatility is associated with a reduction in style-adjusted advisory fees equal to 3 basis points ($= 0.031 * \sqrt{12} * 0.261$), or equivalently a reduction in annual advisory fees by $7 million, on average.[19]

The results in Table 5 are robust to controlling for a host of fund family characteristics known from prior literature to affect advisory fees. Explicitly, larger fund families (*LFAMTNA*) enjoy greater economies of scale, which are then passed along to fund investors as lower (style-adjusted) fees (see also Warner and Wu (2011)). After controlling for family size, fund families that offer multiple styles (*LNINVOBJ*) or multiple portfolios (*LNPFOLIO*) are associated with above-average style-adjusted advisory fees. Further, the positive relationship between family-level fees and value-weighted style-adjusted fund portfolio

[18] In an unreported test, we find our conclusions hold after controlling for the few (45) instances of family-level inter-fund lending programs (ILPs) approved by the SEC between 1993 and 2017 as exemptions to Section 17(a) of the 1940 Act, which prohibits loan transactions among affiliated funds (see Agarwal and Zhao (2019) for a more detailed discussion of ILPs). This suggests that the family-level relationship between fund flow diversification and style-adjusted advisory fees does not simply reflect the lower liquidation costs of within-family ILPs.

[19] In additional tests, we also find that fund family advisory fee-setting policies are more competitive when the family is better hedged against downside (rather than upside) fund flow correlation. These findings are available upon request.

Table 5
Multivariate Analysis: Fund Family Advisory Fees and Fund Flow Diversification.

Panel A: Fee-diversification relationship – Full sample.

	FAMDIV	COINSURE		CORRSTL	
	(i)	(ii)	(iii)	(iv)	(v)
DIVERSIFICATION	−0.202***	−0.238***	−0.455***	0.149***	0.269***
	(0.067)	(0.042)	(0.135)	(0.038)	(0.088)
x LFAMTNA	0.044***		0.052***		−0.026*
	(0.012)		(0.020)		(0.013)
x LFAMAGE	−0.022		0.018		0.009
	(0.025)		(0.050)		(0.034)
LFAMTNA	−0.127***	−0.103***	−0.109***	−0.105***	−0.085***
	(0.010)	(0.006)	(0.007)	(0.006)	(0.011)
LFAMAGE	0.026	0.008	0.002	0.013	0.006
	(0.022)	(0.013)	(0.016)	(0.014)	(0.025)
LNPFOLIO	0.016	0.015	0.018	0.018	0.014
	(0.017)	(0.017)	(0.019)	(0.017)	(0.017)
LNINVOBJ	0.039	0.110***	0.043	0.104***	0.094***
	(0.031)	(0.028)	(0.027)	(0.030)	(0.030)
FAMFLOWS	−0.130	−0.075	−0.068	−0.127	−0.128
	(0.079)	(0.083)	(0.085)	(0.079)	(0.079)
FAMRET	−0.078	−0.091	−0.099	−0.091	−0.089
	(0.126)	(0.129)	(0.128)	(0.127)	(0.127)
FAMTURNR	0.070***	0.072***	0.072***	0.071***	0.070***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
EXITGATE	0.076	0.144	0.263	0.095	0.212
	(4.765)	(4.735)	(4.809)	(4.742)	(4.785)
FAMNSTAR	0.005	0.006	0.003	0.006	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
FAMCFVOL	0.751**			0.569*	0.608*
	(0.306)			(0.303)	(0.312)
R-sq	44.0%	43.3%	43.4%	43.5%	43.7%
N	96,155	96,155	96,155	96,041	96,041

Panel B: Advisory fees and fund flow diversification controlling for the concavity of fee schedules

	FAMDIV		COINSURE		CORRSTL	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
CONCAVITY	−0.021***	0.007*	−0.021***	−0.015***	−0.021***	−0.116***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.011)
DIVERSIFICATION	−0.073***	0.005	−0.050***	−0.007	0.033***	0.003
	(0.004)	(0.004)	(0.008)	(0.007)	(0.005)	(0.005)
x CONCAVITY		−0.091***		−0.173***		0.108***
		(0.005)		(0.020)		(0.012)
Family Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	45.2%	44.7%	44.8%	44.3%	44.3%	44.9%
N	56,648	56,648	56,648	56,648	56,648	56,648

Panel C: Fund family decision to waive advisory fees (*FEEWAIVED*) and diversification proxies

	FEEWAIVED		
	(i)	(ii)	(iii)
DIVERSIFICATION	0.719***	1.054***	−0.804***
	(0.138)	(0.366)	(0.233)
Proxy	FAMDIV	COINSURE	CORRSTL
Family Controls	Yes	Yes	Yes
R-sq	10.0%	7.6%	8.2%
N	49,357	49,048	49,311

Panel D: Strategic fee-setting and diversification proxies for the subsample of money market funds

	FAMDIV		COINSURE		CORRSTL	
	CHGF-INCF	INCF	CHGF-INCF	INCF	CHGF-INCF	INCF
	(i)	(ii)	(iii)	(iv)	(v)	(vi)

(*continued on next page*)

Table 5 (*continued*)

Panel D: Strategic fee-setting and diversification proxies for the subsample of money market funds

	FAMDIV		COINSURE		CORRSTL	
	CHGF-INCF	INCF	CHGF-INCF	INCF	CHGF-INCF	INCF
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
DIVERSIFICATION	−0.057***	0.003	−0.162***	0.009	0.383***	−0.048
	(0.009)	(0.008)	(0.014)	(0.011)	(0.081)	(0.087)
Family Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	20.6%	31.5%	20.6%	32.1%	21.3%	34.2%
N	31,186	31,186	31,186	31,186	29,140	29,140

Panels A, B, and D of this table present the estimated coefficients from cross sectional regressions that model fund family fees as a function of selected fund family characteristics over the period 1993 to 2017. In Panel A, the dependent variable is the TNA-weighted style-adjusted advisory fee (*FAMADVFEE*). Lagged fund flow diversification proxies (*DIVERSIFICATION*) include: (a) a dummy variable for multi-style fund families, *FAMDIV*; (b) the percentage cash flow coinsurance (*COINSURE*); and (c) the correlation of idiosyncratic style net cash flows (*CORRSTL*). Lagged family-level control variables include: the logarithm of the number of fund portfolios (*LNPFOLIO*) and investment styles (*LNINVOBJ*); the logarithm of family total net assets (*LFAMTNA*); the logarithm of fund family age since inception (*LFAMAGE*); net cash flows (*FAMFLOWS*); style-adjusted net realized returns (*FAMRET*); total volatility of net cash flows (*FAMCFVOL*); style-adjusted redemption fees (*EXITGATE*); number of star funds offered by the family (*FAMNSTAR*); and style-adjusted portfolio turnover (*FAMTURNR*). We also interact *DIVERSIFICATION* with *LFAMTNA* and *LFAMAGE*. Additional (untabulated) variables include the percentage of family TNA in index, institutional, equity, and income funds. In Panel B, we repeat the analysis of Panel A using data from the semi-annual NSAR-B from 1995 to 2017 to compute the concavity of fund family advisory fee schedules, *CONCAVITY*. This variable is computed as the TNA-weighted style-adjusted difference between the first and the last marginal fee rates divided by the applicable marginal fee rate. In Panel C, we report the results of a probit model (with family-clustered standard errors in parentheses) in which the dichotomous dependent variable, *FEEWAIVED*, equals 1 if the fund family decided to waive fund fees. In Panel D, we repeat the analysis of Panel A using as dependent variable the family-level value-weighted difference between charged (*CHGF*) and incurred (*INCF*) fees for the subset of money market funds. One, two, and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

turnover (*FAMTURNR*) is consistent with Chalmers, Edelen, and Kadlec (1999) who argue that portfolio turnover represents the largest component of fund trading costs, which are usually transferred to investors via higher advisory fees.

The negative and significant loadings of *FAMADVFEE* on *EXITGATE* across all model specifications suggest that fund families that experience lower redemption risk as a result of above-average style-adjusted exit fees are more likely to charge lower style-adjusted advisory fees. Also, the positive coefficients of *FAMNSTAR* confirm the existence of a premium for a high-quality product offering. The estimates suggest that for each additional star fund, a fund family charges 2-basis-points higher value-weighted and style-adjusted advisory fees, on average. In unreported results we obtained results qualitatively similar to those presented in Panel A of Table 5 when we use *FAMOPEX* as the alternative dependent variable.[20]

Overall, the evidence in Panel A of Table 5 confirms the existence of significant benefits associated with family-level fund flow diversification. Consistent with our expectation, fund families with lower asset volatility resulting from reduced fund flow correlations are able to more competitively price their fund products, which in turn, results in lower style-adjusted advisory fees to fund shareholders.[21]

5.3. *Concavity of advisory fee contracts and strategic fee-setting policies*

In this subsection, we conduct three additional tests of the relationship between fund family advisory fees and fund flow diversification. First, we quantify the effect of the concavity of fund family fee schedules on the fee-diversification relationship using data from the semi-annual NSAR-B forms filed by all mutual funds between 1995 and 2017. As noted in Panel B of Table 2, on average, almost two-thirds of fund family assets are managed under concave advisory fee schedules. Since total fee revenue is inversely related to asset volatility for fund families with concave fee schedules, we expect such fund families to lower their advisory fees if they are able to reduce their asset volatility through greater fund flow diversification. We test this conjecture by first estimating the concavity of the fund families' advisory fee schedules. The average concavity of a fund family's fee schedule, *CONCAVITY*, is measured as the TNA-weighted style-adjusted difference between the first and the last marginal fee rates for the funds in the family divided by the respective applicable marginal fee rate.[22] We then repeat the analysis of Panel A of Table 5 by including an interaction term between the concavity variable, *CONCAVITY*, and each of the fund flow diversification proxies—namely, *FAMDIV*, *COINSURE*, and *CORRSTL*.

Panel B of Table 5 presents the findings of this test. Despite the reduction in the number of available observations to 56,648, due to the need to match observations across the CRSP Survivor-Bias-Free Mutual Fund database and NSAR-B data, estimated coefficients on the interaction term between the variable *CONCAVITY* and the diversification proxies are both economically and statistically significant. The sign of the coefficient is consistent with the predicted effect of asset volatility on the fund family's incremental fee revenue and fee-diversification relationship under concave fee schedules. Importantly, the loadings of fund family style-adjusted advisory fees on the diversification variables are statistically insignificant among those families with linear fee schedules (refer to the coefficients of the *DIVERSIFICATION* variable in models (ii), (iv), and (vi) of Panel B of Table 5). This finding is consistent with the

[20] We also re-estimated our models for the subsample of the top 100 fund families (by industry market share) and for diversified-only fund families. The estimated coefficients (untabulated for brevity) are qualitatively similar to those obtained in Panel A of Table 5 covering the full sample of fund families.

[21] Estimates based on pooled OLS regressions with family- and time-fixed effects with standard errors clustered by family groupings yield qualitatively similar results to those in Table 5. We also estimate pooled OLS regressions where the dependent variable is the yearly change in value-weighted style-adjusted advisory fees, Δfee_t. Further, we employ a dummy variable, $I_{\Delta fee>0}$, which equals 1 if there is a positive change in advisory fees, and estimate logit regressions with year fixed effects. Estimates based on the OLS and logit regression models suggest that fund families with above- (below-) average fund flow diversification are more likely to decrease (increase) fees in the following year. These results are available upon request.

[22] We would like to stress that our concavity proxy is value-weighted at the fund family level. Thus, for a fund family to earn a concave compensation it must offer at least one fund with a concave advisory fee contract.

notion that diversification of fund flows and the resulting reduction in asset volatility would not impact total fee revenue for fund families with linear fee schedules The above finding also suggests that the observed negative relation between fees and flow diversification for fund families with concave fee schedules is not driven simply by economies of scale. If the economies of scale were indeed the driving force for the relationship, we would expect to see a similar significantly negative relation between fees and flow diversification proxies in the case of fund families with linear fee schedules. In summary, the evidence in Panel B of Table 5 helps rule out economies of scale as a potential explanation for the fee-flow diversification relationship we document in this study.

Our second test of the fee-diversification relationship examines the likelihood of fund families' decision to waive annual advisory fees conditional on their fund flow diversification. Using the responses to Item 053 of the semi-annual NSAR-B form between 1995 and 2017, we construct the dummy variable *FEEWAIVED*, which equals 1 if the fund family decided to voluntarily waive or reimburse advisory fees to shareholders during the period covered by NSAR-B files. We then estimate a probit model of the relationship between the dependent variable, *FEEWAIVED*, and fund family diversification proxies. The findings of this probit model are presented in Panel C of Table 5. In line with the previous findings documented in Table 5, the marginal effect of *FAMDIV* suggests that diversified fund families are about 20% more likely to waive their advisory fees than undiversified fund families.

Our third test employs data from iMoneyNet, the leading provider of monthly information on money market funds (MMFs) offered by 320 distinct fund families from 1995 to 2017. As of December 2014, iMoneyNet covered $2.72 trillion of MMF assets, corresponding to 99.7% of the entire MMF universe and 14% of the mutual fund industry assets covered by the CRSP mutual fund database. In addition to other fund characteristics, iMoneyNet provides valuable information on the MMFs' incurred advisory fees (*INCF*) which represent the actual cost of running the fund, and the fees charged to investors (*CHGF*). Since the impact of any economies of scale is reflected in the incurred fees, the difference between charged (*CHGF*) and incurred (*INCF*) fees, allows us to better identify the strategic nature of fee-setting policies of the fund families. Specifically, we repeat the analysis of Panel A of Table 5 using as dependent variable the family-level value-weighted difference between *CHGF* and *INCF*. The results of this test are presented in Panel D of Table 5. Overall, the findings based on the MMF sample are consistent with our expectations. For instance, the estimated coefficient of the indicator variable *FAMDIV* in model (i) suggests that MMFs offered by diversified fund families waive their fees by almost 6 basis points, on average. Unsurprisingly, the same result does not hold in models (ii), (iv) and (vi) where the dependent variable is the family-level value-weighted *incurred* fee, *INCF*. The evidence presented in Panel D of Table 5 also suggests that the relationship between fees and flow diversification proxies is not driven by cross-sectional differences in fund performance as MMFs are known to realize very similar gross yields (see, e.g., Christoffersen & Musto, 2002).[23]

5.4. Incentives to lower fees: Price competition and the fee-diversification relationship

It is reasonable to expect that the incentive to lower fees in response to fund flow diversification would be stronger for fund families that operate in more competitive industry segments. In this subsection we examine this issue by assessing the impact of competition on the incentives for more diversified fund families to lower their advisory fees.

We use two proxies to empirically quantify the intensity of within-style price competition (*FEECOMPETITION*). Khorana and Servaes (1999) and Wahal and Wang (2011) argue that mutual fund starts influence the way incumbent funds and their fund families compete within the industry, and that fund starts are related to the ability of fund families to attract additional fee income. Accordingly, our first proxy is the within-style percentage of new fund products launched by other fund families with an *initial* advisory fee below the average fee of incumbent funds in that style, *NFSTARTS*. Following Khorana and Servaes (1999), we define a newly launched fund as a fund with less than one year of operations since inception. We expect this proxy to directly quantify the degree of price pressure exerted by newly launched funds on the advisory fee-setting policies of incumbent fund families.

Our second proxy measure of price competition among peer funds is the within-style average redemption fee charged by competing fund families, *EXITGATE*. Nanda et al. (2000) argue that in the presence of investor heterogeneity in liquidity needs, funds would compete by charging lower advisory fees to attract investors with low liquidity needs, while at the same time using exit gates to lock in those investors with greater liquidity needs. Our expectation is that fund families that operate in investment styles characterized by higher average exit fees charged by competitors would face significantly lower redemption risk, and will be able to price their products more aggressively when experiencing lower asset volatility, ceteris paribus.

Table 6 reports the estimated coefficients from multivariate regressions of value-weighted style-adjusted fund family fees (*FAMADVFEE*) on selected fund family characteristics.[24] The main independent variables of interest are the different fund flow diversification proxies described previously. Our price competition proxies are *NFSTARTS* in columns (i) to (iii) and *EXITGATE* in columns (iv) to (vi). To quantify the direct effect of price competition on the fee-diversification relationship, we interact each flow diversification proxy measure with each of the two price competition proxies. Other lagged control variables (untabulated for brevity) include the fund family characteristics previously introduced in Table 3.

The negative loadings of *FAMADVFEE* on *FEECOMPETITION* in columns (i) through (iii) confirm that fund families that compete in investment styles characterized by an above-average percentage of new-fund starts, charge significantly lower style-adjusted advisory fees. Importantly, the estimates based on models (ii) and (iii) suggest that the negative fee-flow diversification relationship is primarily driven by diversified fund families that face within-style competitive pressures. This is evidenced by the significant coefficients of the interaction term, *FEECOMPETITION x DIVERSIFICATION*. These results are qualitatively similar to those obtained from estimating models (iv), (v), and (vi), which employ the alternative proxy for price competition based on within-style average redemption fee, (*EXITGATE*).[25] In summary, the results of this subsection confirm that diversified fund families have a stronger incentive to lower their advisory fees when they face greater competition.

6. Fund flow diversification and family-level performance

A natural question in light of our earlier results is whether the benefits of lower advisory fees (and operating expenses) charged by diversified fund families flow through to investors in the form of improved

[23] Interestingly, we reach similar conclusions regarding the fee-flow diversification relationship when we compute the fund flow diversification proxies using only the sample of prime and government money market funds. This suggests that fund families do not necessarily need to offer funds across multiple investment styles to enjoy the benefits of flow diversification.

[24] Our results are also qualitatively similar when the dependent variable is family-level operating expenses, *FAMOPEX*. These results are available upon request.

[25] In unreported tests, we analyze a more homogeneous sample of S&P500 index funds that are known to face fierce fee competition from peer funds. Our findings indicate that S&P500 index funds offered by more diversified fund families charge advisory fees that are on average lower by 12 basis points, compared to fees charged by less diversified fund families.

Table 6
Within-style Price Competition and the Relationship between Advisory Fee and Fund Flow Diversification.

	FAMDIV	COINSURE	CORRSTL	FAMDIV	COINSURE	CORRSTL
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
DIVERSIFICATION	−0.083***	0.099***	0.071***	−0.040	0.541***	−0.038
	(0.010)	(0.019)	(0.011)	(0.045)	(0.054)	(0.048)
FEECOMPETITION	−2.531*	−3.647***	−7.973***	−4.445	−2.988	−18.394***
	(1.408)	(1.059)	(1.124)	(3.614)	(2.001)	(1.713)
x DIVERSIFICATION	−2.221	−23.918***	9.437***	−5.166*	−47.397***	16.813***
	(1.396)	(2.866)	(1.707)	(3.099)	(3.699)	(3.577)
Fee Competition Proxy	NFSTARTS	NFSTARTS	NFSTARTS	EXITGATE	EXITGATE	EXITGATE
Family Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	47.7%	47.2%	47.6%	47.1%	46.9%	46.9%
N	96,436	96,329	95,844	96,436	96,329	95,844

This table presents the estimated coefficients from multivariate regressions of fund family fees on selected fund family characteristics over the period 1993 to 2017. The dependent variable is the value-weighted style-adjusted advisory fee (*FAMADVFEE*) in percentage. The main independent variables of interest include the lagged fund-flow diversification proxies: (i) a dichotomous variable for multi-fund family offering >1 investment objective (*FAMDIV*); (ii) the total percentage coinsurance of share-class net cash flows (*COINSURE*); and (iii) the correlation of idiosyncratic net cash flows at the style level (*CORRSTL*). We use two different proxies to quantify the degree of fee competition in each investment style (*FEECOMPETITION*). In columns (i) to (iii), our first proxy of fee competition is the family-level (TNA-weighted) exposure to the percentage of newly-launched fund products offered by other fund families with an initial advisory fee below the average advisory fee of incumbent funds in that investment style, *NFSTARTS*. We define newly-launched fund products as funds with less than one year of operations since inception. In columns (iv) to (vi), our second proxy of fee competition is the family-level TNA-weighted average redemption fee charged by funds of other fund families in each style where the fund family competes, *EXITGATE*. In the presence of heterogeneous liquidity demand, this variable is supposed to capture the high degree of competition for investors with low-liquidity demand. We also interact each flow diversification variable with the competition proxies considered. Lagged control variables (untabulated for brevity) are those described in Table 5. In all models, we run Fama-MacBeth cross sectional regressions with HAC standard errors (in parentheses). One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

net-of-fee family-level fund performance. In this section we test our second hypothesis on the relationship between fund family performance and several fund flow diversification proxies to quantify the benefits that accrue to shareholders from investing in more diversified families. Since fund families offer products with different investment strategies, we estimate their after-fee performance using various benchmarks. We benchmark equity fund returns using the Carhart (1997) four-factor model (*4-FACTOR*). Since our sample includes fund families offering balanced and international funds, we also employ a six-factor model (*6-FACTOR*) that includes the excess returns on the Morgan Stanley Capital International (MSCI) index covering Europe, Australia, and the Far East, and the Barclays US Aggregate Bond Index (ex-Lehman US Aggregate Bond Index). In order to benchmark the performance of fixed income funds, we follow Blake, Elton, and Gruber (1993) and augment the Carhart four-factor model using the excess returns of the following six bond indices: Barclays U.S. Treasury Long, Barclays U.S. Treasury Intermediate, Barclay U.S. Treasury Bill 3–6 m, Barclays U.S. Corp Investment Grade, Barclays U.S. High-Yield Composite, and Barclays GNMA 30-Year (*10-FACTOR*). We estimate risk-adjusted returns as the monthly abnormal returns based on the various factor models, where the factor loadings are estimated over the previous 36 months (with a minimum of 30 months of available observations).

We examine the relation between fund flow diversification and fund family performance in a multivariate setting. Family-level performance is calculated as the value-weighted average performance of the funds within the family. Fund performance is assessed as either the net, or the gross risk-adjusted return using one of the factor models (relevant to the fund's style) mentioned above. Fund family-level controls include all of the control variables discussed in Table 3. In addition, we include the degree of product differentiation within each investment objective (*PDTDIFF*), as Massa (2003) emphasizes the importance of controlling for product differentiation when evaluating a fund family's incentives to compete on fund performance. This variable is computed as the standard deviation of the fees charged across all funds active in a style, standardized by their maximum value over the whole period. We estimate panel regressions with time fixed effects and standard errors (in parentheses) clustered by both family and time.

The estimated loadings on the different flow diversification proxy measures (*DIVERSIFICATION*) are reported in Table 7. The estimated loadings on the diversification proxies are all consistent with our prediction that more diversified fund families offer, on average, better *after-fee* risk-adjusted performance as a result of their more aggressive fee-setting policies. For example, the coefficient of the variable *FAMDIV* (0.047) in model (i) implies that a more diversified family outperforms a less diversified family by about 56 basis points a year, based on the 4-factor model.[26] About 64% of this outperformance—i.e., 36 basis points a year—is explained mostly by lower advisory fees among diversified families, as indicated by the difference in the estimated loadings of after-fee (0.047) and gross-of-fee (0.017) risk-adjusted performance.

Across different model specifications, more diversified fund families outperform other fund families by between 50 and 60 basis points per year net of fees, which is substantial in economic terms. We obtain qualitatively similar results when we use one of the other two proxies of fund family diversification as the main independent variables in models (iv) to (ix), or estimate the coefficients (untabulated for brevity) of Fama-MacBeth cross-sectional regressions with heteroscedasticity and autocorrelation consistent (HAC) standard errors. Importantly, our findings on the positive relationship between fund family performance and fund flow diversification are not explained by fund family size (*LFAMTNA*) or fund families' product proliferation strategies (*PDTDIFF*).

Table 7 also reports the relationship between the fund family's gross performance and fund flow diversification. As can be seen, the relationship between gross risk-adjusted returns and fund flow diversification proxies is statistically and economically insignificant. Overall, the positive relationship between net (but not gross) fund family performance and fund flow diversification documented in Table 7 is consistent with our previously documented finding that more diversified fund

[26] The 0.56% outperformance in annual risk-adjusted returns is economically significant, especially when considered alongside the findings of French (2008), who reports that active mutual fund managers, on average, underperform passive benchmarks by approximately 0.67% per year. In this context, an outperformance of 0.56% is particularly noteworthy, and underscores the potential value of fund flow diversification as a strategy for mutual fund families to enhance their value proposition to investors.

Table 7
Fund Family Gross and Net Performance and Fund Flow Diversification Proxies.

	Dependent variable	Proxy	DIVERSIFICATION		Additional Controls	
			Net	Gross	LFAMTNA	PDTDIFF
(i)	4-FACTOR	FAMDIV	0.047**	0.017	−0.028***	−0.421***
			(0.022)	(0.023)	(0.004)	(0.130)
(ii)	6-FACTOR	FAMDIV	0.048**	0.022	−0.024***	−0.386***
			(0.020)	(0.024)	(0.004)	(0.119)
(iii)	10-FACTOR	FAMDIV	0.041*	0.010	−0.021***	−0.646***
			(0.023)	(0.030)	(0.005)	(0.163)
(iv)	4-FACTOR	COINSURE	0.110**	0.050	−0.027***	−0.388***
			(0.050)	(0.058)	(0.005)	(0.132)
(v)	6-FACTOR	COINSURE	0.128***	0.049	−0.023***	−0.364***
			(0.048)	(0.049)	(0.004)	(0.121)
(vi)	10-FACTOR	COINSURE	0.136**	0.094	−0.019***	−0.617***
			(0.057)	(0.068)	(0.005)	(0.163)
(vii)	4-FACTOR	CORRSTL	−0.073**	−0.008	−0.025***	−0.433***
			(0.030)	(0.026)	(0.005)	(0.134)
(viii)	6-FACTOR	CORRSTL	−0.067**	0.004	−0.022***	−0.395***
			(0.028)	(0.025)	(0.004)	(0.123)
(ix)	10-FACTOR	CORRSTL	−0.079**	−0.044	−0.019***	−0.681***
			(0.033)	(0.033)	(0.005)	(0.163)

This table presents the loadings of monthly fund family risk-adjusted returns on fund family cash flow diversification measures for the period 1993 to 2017. The dependent variable is fund family before-fee (*Gross*) or after-fee (*Net*) returns adjusted using one of the following factor models: (a) the Carhart (1997) four-factor model (*4-FACTOR*); (b) the four-factor model augmented with the excess returns of the MSCI EAFE index (inclusive of Europe, Australia, and the Far East) and the Lehman US Aggregate Bond Index (*6-FACTOR*); and (c) the four-factor model augmented with the excess returns of the following six bond indices: Barclays U.S. Treasury Long, Barclays U.S. Treasury Intermediate, Barclay U.S. Treasury Bill 3–6 m, Barclays U.S. Corp Investment Grade, Barclays U.S. High-Yield Composite, and Barclays GNMA 30-Year (*10-FACTOR*). To mitigate look-ahead bias, we estimate fund family risk-adjusted returns as the one-month abnormal return from the factor model, where the loadings on the various factors are estimated over the previous 36 months (with a minimum of 30 observations). We estimate the loadings of the dependent variable on the following fund family's cash flow diversification proxies (*DIVERSIFICATION*): (a) a dichotomous variable for multi-fund family offering >1 investment objective (*FAMDIV*); (b) the total percentage coinsurance of share-class net cash flows (*COINSURE*); and (c) the correlation of idiosyncratic net cash flows at the style level (*CORRSTL*). We report the coefficients on the following two control variables: the logarithm of fund family total net assets (*LFAMTNA*); and the degree of product differentiation within the investment objective (*PDTDIFF*), computed as the standard deviation of the fees charged across all the funds active in the category standardized by their maximum value over the whole period. The family-specific index of product differentiation is then constructed by weighting the indexes of all the categories in which the fund family is operating by the total net assets of the funds the family is managing in such categories (see Massa (2003) for more details on the construction of this variable). Other fund family lagged control variables (untabulated for brevity) are identical to those described in Table 5. We estimate time series cross section regressions with time and style fixed effects and standard errors (in parentheses) clustered by family and time (*Family-Time*). One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

families charge lower style-adjusted fund advisory fees.

7. Robustness tests

A potential concern with our primary results is the interpretation of the negative relationship between measures of fund flow diversification and the value-weighted style-adjusted advisory fees charged by a fund family. To address this, we conduct a series of robustness tests designed to assess whether this relationship is indicative of a causal link or merely a correlation driven by unobserved family characteristics. Our robustness tests involve controlling for various family characteristics, such as family size and other observable traits, to isolate the effect of fund flow diversification on advisory fees. Despite our earlier results confirming that the negative relation between fees and flow diversification is not driven solely by economies of scale, we further explore this relationship to ensure that our findings are not confounded by other factors. By conducting these tests, we aim to provide a clearer interpretation of the causal mechanisms at play. Specifically, we seek to determine whether increased diversification of fund flows within a family directly leads to more competitive advisory fees or if the observed relationship is merely a reflection of underlying family characteristics that are correlated with both diversification and fee levels.

7.1. *Counterfactual fund families and fee-flow diversification sensitivity*

We begin with a test of the robustness of the relation between value-weighted style-adjusted advisory fees and the proxy measures of fund flow diversification we employ, using different samples of *counterfactual* fund families. Our aim is to rule out the possibility that the observed relation is merely due to chance, and to mitigate potential concerns about the effect of unobserved fund family characteristics on this relationship. To this end, we construct counterfactual fund families using two empirical strategies. Our first empirical approach consists of constructing a sample of simulated fund families by randomly replacing each of their constituent fund share classes with a "mirror" fund share class belonging to one of the other fund families. A "mirror" fund class in month *t* is defined as one that: (1) operates in the same investment style as the constituent fund class offered by the fund family, (2) belongs to the same quintile portfolio of sorted fund class TNA, and (3) has the highest cash flow correlation with the original fund class offered by the fund family. Next, we compute all of the value-weighted characteristics described in Table 3 for each counterfactual fund family. Since these simulated fund families are not expected to experience any real fund flow diversification benefits by construction, we should not expect to see a significant relationship between fees and flow diversification proxies for such families.

Our second approach to constructing counterfactual fund families relies on matching treatment effect estimators. This approach quantifies the average difference in potential outcomes (i.e., advisory fees) across treatment groups — i.e., fund families with diversified fund flows versus families with undiversified flows. Matching estimators typically assume that there is a set of observed characteristics such that the outcomes are independent of treatment, conditional on the characteristics. In the present context, the matching estimators compare the observed fee policy of a fund family in one treatment group (e.g., diversified fund flows) with the fee policy of the "closest" fund family in the other treatment group (e.g., undiversified fund flows), conditional on all fund family covariates. For this purpose, we employ three matching estimators based on alternative ways of constructing matched outcomes: propensity score matching (PSM), inverse probability weighting (IPW), and nearest-neighbor matching (NNM). We then compute the average treatment effect (ATE) as the difference in the potential mean outcome value for each of these estimators.

We begin by illustrating the findings of the first approach based on simulated fund families in Panel A of Table 8. The dependent variable in models (i), (iii), and (v) of Panel A is the value-weighted style-adjusted advisory fee, *FAMADVFEE*. In all other models we repeat the analysis using *FAMOPEX* as an alternative dependent variable. The main independent variables of interest are the fund family's flow diversification proxies. We also include the independent variable *FAMCFVOL* to quantify the sensitivity, if any, of advisory fees to the cash flow volatility of simulated fund families. Additional (untabulated) control variables are identical to those discussed in Table 3.

Consistent with our expectation and irrespective of the diversification proxy used in Panel A of Table 8, none of the estimated loadings is statistically significant at conventional levels. This conclusion also extends to the estimated coefficients on the variable *FAMCFVOL*. Overall, the evidence from this first "placebo" test confirms that the fee-flow diversification relationship documented in Table 5 is not spurious. Rather, the results in Table 5 reflect genuine diversification benefits from less than perfectly correlated fund flows of the constituent funds of a fund family.

The above conclusion is also supported by the findings of the second test based on average treatment effect estimators, and reported in Panel B of Table 8. After conditioning on fund family covariates, the sample mean of the difference in potential outcomes for the "treated" fund families (i.e., families with diversified fund flows) and "untreated" fund families averages 6 basis points. This estimate is equivalent to \$10 million lower style-adjusted advisory fees for diversified fund families. This finding suggests that a portion of the 20 basis points fee difference between diversified and undiversified fund families reported in Panel A of Table 5, is likely due to differences in covariates of the two treatment groups.

7.2. Endogeneity of the fund family decision to diversify: An IV analysis

If fund families voluntarily choose to diversify their product offerings, their diversification decision may not be random but rather a deliberate choice based on information available to them. In this context, assuming that a fund family's status can be treated as exogenous could be misleading. If a fund family's decision to diversify is correlated with its advisory-fee-setting policy, the estimated coefficient of the fund flow diversification proxy in Eq. (4) will be biased. In this section, we address this issue by estimating a two-stage-least-square instrumental variable (2SLS-IV) regression with family fixed effects, using a set of instruments to predict the decision of a fund family to diversify while leaving family-level fees unaffected.[27]

Following Campa and Kedia (2002), our first set of instrumental variables (IVs) includes the total number of other fund families in each investment objective that are diversified in the previous year (*PNUMDIV*) and the percentage of total assets managed by other diversified fund families in each investment objective in the previous year (*PTNADIV*). The second set of IVs includes the total number of mutual fund mergers in the previous year (*MGRNUM*) and the total dollar volume of mutual fund mergers in the previous year (*MGRVOL*).[28] Importantly, since total operating expenses (*FAMOPEX*) and advisory fees (*FAMADVFEE*) are style-adjusted, they are orthogonal, by construction, to any unobservable style characteristics that could affect fund family fee-setting policies.

Table 9 reports the findings of the second stage of the 2SLS-IV regressions with family fixed effects, at both monthly and yearly frequencies in models (ii), (iv), (vi), and (viii).[29] In all models, the estimated parameters of the IV regression are negative and significantly different from zero at the 1% level. Importantly, although the statistical significance of the coefficients remains particularly high, with *t*-statistics of about 12 in column (ii), the loading of style-adjusted advisory fees on *FAMDIV* decreases somewhat in terms of economic magnitude. Loadings on all other control variables remain similar to those documented in Table 5.

7.3. Exogenous shock: Sponsorship acquisitions and fee-diversification relationship

In this subsection, we exploit an exogenous shock to the family-level fund flow diversification to obtain a cleaner identification of the relation between flow diversification and fees. Specifically, we examine changes in fund-level fees following fund families' sponsorship acquisitions of intact target mutual funds. In contrast to mutual fund mergers, in which the target fund disappears following its absorption by incumbent fund(s) of the acquiring fund family, target funds of sponsorship acquisitions survive as independent entities. This event is ideal for exploring the implications of the differences in fund flow diversification between the acquiring and the target fund family for a fund's style-adjusted advisory fees.[30]

We start by examining within a univariate framework the impact of the difference in fund flow diversification between the acquiring fund family and the selling fund family (*ΔCOINSURE*) on the fees charged by intact target funds. For all intact target funds, we first average their style-adjusted fees over the previous −24 to −1 months (month 0 of the event is excluded from the average fee calculation), and the 1 to 24 months following the event month. For notational ease, we refer to these two intervals as −2 and 2, respectively, and identify this time window as (−2,2). We then allocate intact target funds to three portfolios of sorted *ΔCOINSURE*, so that the *LOW30* (*HIGH30*) portfolio comprises target funds experiencing the highest reduction (increase) in fund flow diversification following the acquisition event in month 0.

[27] We test for endogeneity of fund family diversification decisions (proxied by the dummy variable *FAMDIV*) using the Hausman specification test. We could reject the null hypothesis of no endogeneity at the 1% level.

[28] We believe that our IVs satisfy the validity criterion, as fund families operating in investment objectives populated by more diversified fund families (i.e., higher *PNUMDIV* or *PTNADIV*) should have greater incentives from competition to diversify their product offerings. At the same time, our IVs should also satisfy the exclusion criterion, since the decision of other fund families to diversify should not directly affect the attributes of an unaffiliated fund in the second stage, except through the product diversification decision of its fund family.

[29] In the first stage, we use all of the exogenous family variables, along with the previous IVs, as explanatory variables in the fund family's decision to diversify.

[30] Following Luo and Qiao (2012), we identify a sponsorship acquisition by a fund family if in a given month, one or several equity mutual funds sign off their old (i.e., selling) fund family and sign on a new (i.e., acquiring) fund family. We further augment this identification strategy by using Item 10 and Schedule D of form ADV, which state the names of the control entities (of both the selling and the acquiring fund families) where books and records are kept. This reduces the likelihood that fund families with different names may in fact belong to the same ownership structure.

Table 8
Robustness Test: Counterfactual Fund Families: Fee-setting Policies and Flow Diversification.

Panel A: Simulated sample of fund families without any genuine fund flow diversification, by construction

	Dep. Variable	Proxy	DIVERSIFICATION	FAMCFVOL	Family Controls	R^2	Obs.
(i)	FAMADVFEE	FAMDIV	0.005 (0.016)	−0.003 (0.020)	Yes	24.2%	84,107
(ii)	FAMOPEX	FAMDIV	−0.013 (0.017)	−0.023 (0.017)	Yes	51.2%	84,107
(iii)	FAMADVFEE	COINSURE	0.006 (0.018)	– –	Yes	22.4%	84,107
(iv)	FAMOPEX	COINSURE	−0.020 (0.021)	– –	Yes	50.2%	84,107
(v)	FAMADVFEE	CORRSTL	0.009 (0.016)	−0.007 (0.019)	Yes	23.5%	84,034
(vi)	FAMOPEX	CORRSTL	0.008 (0.019)	−0.026 (0.016)	Yes	51.0%	84,034

Panel B: Treatment effect estimators and the relationship between fees and fund family cash flow diversification

	Dep. Variable	ATE - PSM	ATE - IPW	ATE - NNM	Family Controls	Obs.
(i)	FAMADVFEE	−0.048*** (0.004)	−0.059*** (0.003)	−0.057*** (0.004)	Yes	84,034
(ii)	FAMOPEX	−0.032*** (0.005)	−0.038*** (0.004)	−0.046*** (0.005)	Yes	84,034

This table presents the estimated coefficients from regression models relating fund family fees to flow diversification proxies and cash flow volatility for a sample of *counterfactual* fund families. The dependent variable (in percentage terms) is the value-weighted style-adjusted advisory fee (*FAMADVFEE*). For robustness, we repeat the analysis using the value-weighted style-adjusted total operating expenses (*FAMOPEX*). We construct counterfactual fund families using two different empirical approaches. Our first approach consists of replacing each constituent fund class of a family with a "mirror" fund class of another fund family. A "mirror" fund class in period *t* is one that: (1) operates in the same investment style of the constituent fund class of the fund family; (2) belongs to the same quintile portfolio of sorted fund TNA; and (3) has the highest cash-flow correlation with the constituent fund class of the fund family. After repeating this substitution for all funds of a fund family, the resulting counterfactual fund family is one without any genuine fund flow diversification benefit from mirrored fund classes, by construction. Lagged fund flow diversification proxies in Panel A include: (a) a dichotomous variable for multi-fund family offering >1 investment objective (*FAMDIV*); (b) the total percentage coinsurance of share-class net cash flows (*COINSURE*); and (c) the correlation of idiosyncratic net cash flows at the style level (*CORRSTL*). In Panel A, we estimate Fama-MacBeth regressions with HAC standard errors (in parentheses). Our second approach to estimating counterfactual fund families relies on matching treatment effect estimators. This approach utilizes fund family covariates (e.g., size, age, turnover, fund product mix, etc.) to make treatment (cash flow diversification) and outcome (fee-setting policies) independent once we condition on those covariates. Specifically, the matching scheme pairs the observed fee policy of a fund family in one treatment group (e.g., diversified fund families) with the fee policy of the "closest" (i.e., counterfactual) fund family in the other treatment group (e.g., undiversified fund families). In Panel B, we report the findings of three treatment effect estimators: the Propensity Score Matching (PSM), the Inverse Probability Weighting (IPW), and the Nearest-Neighbor Matching (NNM). For each of these estimators we report the average treatment effect (ATE), computed as the average difference in potential outcome means. Other fund family lagged control variables (untabulated for brevity) included in all models of Panel A and Panel B are identical to those described in Table 5. The sample period is from 1993 to 2017. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A of Table 10 illustrates the average annualized change in style-adjusted total operating expenses (*ΔFAMOPEX*) and advisory fees (*ΔFAMADVFEE*) of intact target funds for each portfolio of sorted *ΔCOINSURE* over the event window (−2, 2), as well as the difference in variable means between high (*HIGH30*) and low (*LOW30*) portfolios of sorted *ΔCOINSURE* (*t*-statistics are reported in parentheses). For robustness, Panel A of Table 10 also illustrates the average annualized change in style-adjusted total operating expenses (*ΔFAMOPEX*) and advisory fees (*ΔFAMADVFEE*) of intact target funds for each portfolio of sorted change in style idiosyncratic cash flow correlation, *ΔCORRSTL*, over the event window (−2, 2). On average, intact target funds belonging to the group of funds that experienced the highest (*HIGH30*) increase in fund flow diversification relative to the original fund family) experienced a 0.17% reduction in style-adjusted advisory fees during the time window (−2, 2). Thus, absorption by a fund family with more diversified fund flows results in a lowering of style-adjusted fund fees.

By contrast, intact target funds in *LOW30* portfolio that switched from a more diversified (selling) fund family to a less diversified (acquiring) fund family experienced an 8-basis-points increase in style-adjusted advisory fees. The evidence in Panel A of Table 10 remains qualitatively unchanged when we examine the change in total operating expenses (*ΔFAMOPEX*) following sponsorship acquisition of funds, or sort funds into portfolios based on the alternative variable *ΔCORRSTL*.

In Panel B of Table 10 we examine within a multivariate framework, the relationship between the change in the target fund's style-adjusted fees (or operating expenses) and the change in the degree of fund flow diversification between the acquiring and the selling fund family. The dependent variable in models (i) and (ii) is the change in advisory fees of intact target funds, *ΔFAMADVFEE*, over the time window (−2, 2). In models (iii) and (iv) we repeat the analysis using the change in total operating expenses (*ΔFAMOPEX*) as the dependent variable of interest. The main independent variable is the change in fund flow flow diversification proxied by *ΔCOINSURE* (models (i) and (iii)) or *ΔCORRSTL* (models (ii) and (iv)). In each specification we include a set of control variables described earlier in Table 3 (robust standard errors are reported in parentheses).

Identification of the regressions in Panel B of Table 10 relies on a cross-sectional comparison of intact target funds with higher difference in fund flow diversification between the acquiring and the selling family (the treatment group) to those with lower difference in fund flow diversification between the acquiring and the selling family (the control group). These multivariate regressions essentially use a difference-in-difference approach to estimate the effect of the sponsorship acquisition event on the treatment group.[31] The first difference is the change in the target fund's fees in the time window (−2, 2). The second difference is the difference in fund flow diversification between the treatment and the control groups.

[31] For the purpose of illustration, we discuss the case with two groups. In reality, we treat the change in fund flow diversification as a continuous variable in the regression models, but the intuition is the same.

Table 9
Robustness Test: IV Regressions (Second Stage).

	Dep. Variable	DIVERSIFICATION	Family Controls	2SLS-IV	Obs.
(i)	FAMADVFEE	−0.052*** (0.005)	Yes	Yes	80,146
(ii)	FAMOPEX	−0.055*** (0.005)	Yes	Yes	80,146

This table presents a series of robustness tests on the multivariate relationship between fund family fees and selected fund family characteristics for the period 1993 to 2017. In model (i) the dependent variable (in percentage terms) is the value-weighted style-adjusted advisory fee (*FAMADVFEE*). In model (ii), the dependent variable (in percentage terms) is the value-weighted style-adjusted total operating expenses (*FAMOPEX*). The main independent variable of interest is the dummy variable *FAMDIV*, which is equal to 1 if the fund family is a multi-fund family offering >1 investment objective, and 0 otherwise. Other lagged control variables include all of the fund family characteristics described previously in Table 5. We report the second-stage estimated coefficients of two-stage least square instrumental variable (2SLS–IV) regressions with fund family fixed effect. We use a set of instruments to predict a fund family's decision to diversify its product offerings. Lagged instrumental variables include: (a) the total number of (other) diversified fund families operating in each investment objective (*PNUMDIV*); (b) the percentage of total assets managed by other diversified fund families operating in each investment objective (*PTNADIV*); (c) the total number of fund mergers (*MGRNUM*); and (d) the total dollar volume of fund mergers (*MGRVOL*). Standard errors are clustered by fund family (in parentheses). One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results in Panel B of Table 10 show that the coefficients of the fund flow diversification proxy, *ΔCOINSURE*, in models (i) and (iii) are negative and statistically significant at the 1% level. This suggests that a higher degree of fund flow diversification at the acquiring family level is associated with lower fees following the sponsorship acquisition event. These findings are also economically meaningful. For instance, the coefficient of *ΔCOINSURE* (−1.31) in model (i) of Panel B of Table 10 suggests that a one-standard-deviation (0.054) increase in *ΔCOINSURE* is associated with a 7-basis-points reduction, on average, in the style-adjusted advisory fees of the intact target funds during the post-acquisition interval. This result is robust to controlling for differences between the acquiring and the selling fund families and the inclusion of a variable *LOWERFEE*, which equals 1 if the acquiring fund family charges lower value-weighted and style-adjusted advisory fees than the selling fund family. Our findings are qualitatively similar when we consider the alternative measure for fund flow correlation, *ΔCORRSTL*, in models (ii) and (iv).

Collectively, the evidence in Table 10 is consistent with our previous findings on the negative association between fund flow diversification and the fees charged by fund families.

8. Concluding remarks

In this study we provide novel evidence on the economic benefits to fund families and their investors due to the diversification of fund flows accruing to the mutual funds offered by the fund families. Using several proxies for the fund flow diversification experienced by fund families, we show that the diversification of fund flows helps reduce the asset volatility experienced by fund families—and, more importantly, increases the fee revenue accruing to fund families. The increase in fee revenue due to fund flow diversification allows fund families to strategically set their advisory fees. More specifically, fund families with a more stable asset base as a result of fund flow diversification are more likely to offer lower average style-adjusted fees across their fund offerings—or completely waive the fees—when facing stiffer competition. As a result, fund flow diversification results in significant economic benefits to mutual fund shareholders, as more diversified fund families offer improved net-of-fee performance to investors.

Table 10
Robustness Test: Sponsorship Acquisitions and Fee-Diversification Relationship.

Panel A: Fee changes of intact target funds following fund families' sponsorship acquisition events

	Window	LOW30	MID40	HIGH30	HIGH - LOW
	(i)	(ii)	(iii)	(iv)	(v)
N (Intact Targets)		176	221	176	
Intact targets sorted by *ΔCOINSURE*:					
ΔFAMADVFEE	(−2, +2)	0.08%	−0.05%	−0.17%	−0.25%
(*t*-stat)		(2.19)	(−0.95)	(−3.74)	(−4.89)
ΔFAMOPEX	(−2, +2)	0.05%	−0.01%	−0.14%	−0.19%
(*t*-stat)		(2.03)	(−0.60)	(−4.12)	(−4.34)
Intact targets sorted by *ΔCORRSTL*:					
ΔFAMADVFEE	(−2, +2)	0.04%	−0.01%	−0.14%	−0.18%
(*t*-stat)		(2.08)	(−1.01)	(−2.97)	(−3.35)
ΔFAMOPEX	(−2, +2)	0.03%	0.00%	−0.11%	−0.14%
(*t*-stat)		(1.69)	(0.72)	(−2.32)	(−2.81)

Panel B: Multivariate regressions of fee changes of intact target funds following the acquisition event

	ΔFAMADVFEE (−2, +2)		ΔFAMOPEX (−2, +2)	
	(i)	(ii)	(iii)	(iv)
ΔCOINSURE	−1.316*** (0.386)		−1.295*** (0.392)	
ΔCORRSTL		1.112** (0.503)		1.164** (0.497)
LOWERFEE	−0.028** (0.013)	−0.027** (0.013)	−0.027** (0.013)	−0.029** (0.013)
Controls	Yes	Yes	Yes	Yes
R-sq	1.8%	2.20%	2.60%	2.5%
N	565	565	565	565

This table evaluates the relationship between family-level fund flow diversification and fund's style-adjusted fees around the exogenous shock of sponsorship acquisitions of intact target funds. In a sponsorship acquisition the selling fund family transfers its equity fund business to the acquiring fund family. Contrary to fund mergers where the target fund is completely absorbed by the incumbent fund(s) of the acquiring family, the target funds of sponsorship acquisitions remain instead an intact entity. In Panel A, we consider the effect of differences in fund flow diversification between the acquiring and the selling fund families, on the changes in total operating expenses (Δ*FAMOPEX*), and the changes in fund advisory fees (Δ*FAMADVFEE*) experienced by intact target funds around the sponsorship acquisition event. In detail, we first average each of these fees over the previous −24 to −1 months (the month 0 of the event is excluded from the calculation of the average fees), and the 1 to 24 months following the event month. For notational ease, we refer to these two intervals as the time window (−2, 2). We then allocate intact target funds to portfolios of sorted Δ*COINSURE*, so that the *LOW30* (*HIGH30*) portfolio comprises target funds experiencing the highest reduction (increase) in fund flow diversification following the acquisition event. Panel A illustrates the average change in style-adjusted fund fees over the time window (−2, 2) for each portfolio of sorted Δ*COINSURE* (Δ*CORRSTL*), as well as the difference between the high (*HIGH30*) and the low (*LOW30*) fund flow diversification portfolios (*t*-statistics are reported in parentheses). Panel B presents the findings of multivariate regressions of the change in fund's style-adjusted fees on change in the fund flow diversification between the acquiring and the selling fund family. The dependent variable in models (i) and (ii) is the change in advisory fees of target funds (*ΔFAMADVFEE*), while the dependent variable in models (iii) and (iv) is the change in total operating expenses of target funds (*ΔFAMOPEX*). The main independent variable of interest is the change in the fund flow diversification between the acquiring and the selling fund families, Δ*COINSURE* (Δ*CORRSTL*). We also present the coefficient of the dummy variable *LOWERFEE,* which is equal to 1 if the acquiring fund family has lower value-weighted-style adjusted advisory fees than the selling fund family, and 0 otherwise. Other lagged control variables are those described in Table 5. Standard errors are reported in parentheses. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix A. Variable definitions

Variable name	Variable definition
FAMDIV	Dummy variable for diversified fund families. This variable is equal to 1 if a fund family offers multiple investment styles, and 0 otherwise.
COINSURE	The fund flow diversification proxy of a fund family is computed as the difference between the family-level total volatility of share-class net cash flows (*FAMCFVOL*) and the family-level volatility of net cash flows assuming a pairwise correlation of one between all share-class cash flows within the family (refer to Eq. (1)). Family-level total volatility of net cash flows, *FAMCFVOL*, is computed as $\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t-1} w_{j,t-1} \rho_{i,j,t} \sigma_{i,t,k} \sigma_{j,t,k}}$ where $\rho_{i,j,t}$ is the pairwise correlation of net cash flows between share classes *i* and *j* estimated over the period *t-k + 1* to *t*, $w_{i,t-1}$ is the weight of share class *i* in the fund family's portfolio, and $\sigma_{i,t,k}$ is the volatility of share class *i*'s net cash flows over the period *t-k + 1* to *t*. Volatilities are estimated over the previous $k = 36$ months, with a minimum requirement of 12 months of valid observations within the 36-month window. Since the resulting flow diversification proxy does not account for the possible cross-sectional variation in the total volatility of a fund family's net cash flows under the assumption of perfect correlation among the constituent funds' cash flows, we scale *COINSURE* by this volatility to arrive at a more precise estimate of the percentage fund family's flow diversification level.
CORRSTL	The correlation of cash flows of a fund family is estimated in two steps. In the first stage, for each investment style in period *t*, we compute the idiosyncratic style cash flows over the previous $k = 36$ months as the residual from a regression of average style net cash flows on average industry-wide net cash flows. Second, in each month *t*, we estimate the pairwise investment style correlations, $\gamma_{g,q,[t-k+1:t]}$, of idiosyncratic cash flows of styles *g* and *q*. We then compute the inverse measure of family-level fund-flow diversification as the TNA-weighted correlation of idiosyncratic style cash flows: $\sum_{g=1}^{G}\sum_{q=1}^{Q} w_{g,t-1} w_{q,t-1} \gamma_{g,q,[t-k+1:t]}$.
FAMTNA	Fund family total assets under management.
FAMAGE	Fund family age, computed as the number of years since inception of the oldest fund portfolio offered by the fund family.
NPFOLIO	Total number of fund portfolios offered by a fund family.
NINVOBJ	Total number of distinct investment styles offered by a fund family.
FAMOPEX	Family-level TNA-weighted and style-adjusted fund total operating expenses.
FAMADVFEE	Family-level TNA-weighted and style-adjusted fund advisory fees.
FAMRET	Family-level TNA-weighted and style-adjusted fund realized returns.
FAMFLOWS	Percentage net cash flows of a fund family, computed as the TNA-weighted and style-adjusted fund percentage net cash flows.
FAMTURNR	Family-level TNA-weighted and style-adjusted fund portfolio turnover.
MGRNUM	Total number of mutual fund mergers in the previous year. This instrumental variable captures the incentives of a fund family to diversify following a more active market for fund mergers.
MGRVOL	Total dollar volume of mutual fund mergers in the previous year. This instrumental variable captures the incentives of a fund family to diversify following a more active (by dollar volume) market for fund mergers.
PNUMDIV	Average fraction of diversified mutual fund families (*FAMDIV*) operating in investment style *g* in the previous year. This instrumental variable captures the incentives of a fund family to diversify in an investment style where there is a higher concentration of diversified fund families.
PTNADIV	Average fraction of total industry-wide TNA accounted for by diversified mutual fund families (*FAMDIV*) operating in investment style *g* in the previous year. This instrumental variable captures the incentives of a fund family to diversify in an investment style where there is a higher concentration of assets under the management of diversified fund families.
FAMNSTAR	Number of star funds offered by the fund family. The top 5% funds with the highest monthly average objective-adjusted returns are defined as the star funds for that month.
NFSTARTS	Family-level value-weighted (TNA-weighted) exposure to the percentage of newly-launched fund products *with an initial below-average advisory fee* (offered by other fund families), in each investment style where the fund family competes.
EXITGATE	Family-level value-weighted (TNA-weighted) exposure to the average redemption fee charged by the mutual funds offered by other fund families in each investment style where the fund family competes.
PDTDIFF	Degree of product differentiation within the investment objective (*PDTDIFF*), computed as the standard deviation of the fees charged across all the funds active in the category, standardized by their maximum value over the whole period. The family-specific index of product differentiation is then constructed by weighting the indexes of all the categories in which the fund family is operating by the total net assets of the funds the family is managing in such categories (see Massa (2003) for more details on the construction of this variable).
CONCAVITY	This variable is the fund family's TNA-weighted and style-adjusted concavity of fund advisory fee schedules. The concavity of family fund's advisory fees is estimated as the difference between the first and the last marginal fee rates divided by the applicable marginal fee rate. The first and last marginal fee rates are obtained from Sections A to K of Item 048 of the semi-annual NSAR-B forms available through the SEC archives from 1995 to 2017.
FEEWAIVED	A dichotomous dependent variable which equals 1 if the fund family decided to waive or reimburse fund advisory fees. This variable is obtained by coding Item 053 of the semi-annual NSAR-B forms available through the SEC archives from 1995 to 2017.
CHGF-INCF	Family-level TNA-weighted difference between charged advisory fee (CHGF) and incurred advisory fee (INCF) of prime money market funds

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