FLOW

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Abstract

Using identical periods and specifications, we compare flows to three investment vehicle types: active mutual funds (AMFs), index mutual funds (IMFs), and exchange-traded funds (ETFs). The commonplace positive correlations between aggregate AMF flows and market returns, are now only prominent for ETF flows. The monthly flow-performance relation of ETFs is over four times larger than AMFs. Vehicle-type performance, previously ignored, is the main driver of the flow-performance relation. Extant theories are hapless in explaining our flow-performance findings. Consistent with existing theories, flow-induced fire sales and trading are similar for all vehicles.

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Flow is at the epicenter of the $22 trillion U.S. asset management industry. Despite an expansive literature examining active mutual fund flows, the emergence of index mutual funds and exchange-traded funds (ETFs) renders our understanding of flows incomplete. In this paper, we explore if the seminal findings of the active mutual fund flow literature are applicable to passive investment vehicles. We revisit the literature by conducting a comparison of flows to equity active mutual funds, index mutual funds and ETFs. This facilitates a comparison of identical empirical specifications over identical periods. In doing so, we re-evaluate the appropriateness of extant theories.

First, we follow Warther (1995) in examining aggregate flows. We find that aggregate ETF flows are negatively correlated to both active and index mutual fund flows—consistent with investors moving capital between vehicles. Monthly aggregate mutual fund flows exhibit time-series persistence, while aggregate ETF flows appear random. Revisiting Warther's (1995) classic estimation, the unexpected component of aggregate active fund flows and ETF flows have positive correlations with market returns. Using data from the most recent five years, Warther's result is now non-evident for active funds, yet persists for ETFs. Following the logic of Warther that investor demand drives both stock returns and mutual fund flows, our results suggest that ETFs have replaced mutual funds as the conduit for these demand shocks.

Second, we study flows to individual funds. Prominent empirical findings in the literature are that active fund flows are persistent and have a positive and convex relation to past performance. Monthly index fund and ETF flows exhibit lower time-series persistence and have standard deviations that are almost twice that of active funds. Compared to active funds, index funds and ETFs are less likely to be held in employee benefit plans. Low flow persistence for ETFs is consistent with Del Guercio and Tkac's (2002) conjecture that retirement account contributions cause persistent flows for active mutual funds.

While the previous literature estimates the flow-performance relation within the cross-section of active equity funds, we broaden the cross-section to include index funds and ETFs. All investment vehicles exhibit significant positive flow-performance sensitivities at the annual and monthly level. At the annual level, flow-performance for both active funds and ETFs is nine times that of index funds. At the monthly level, flow-performance for ETFs is four times that of active funds and over twice that of index funds. These flow-performance estimates, from our broad cross-section, are much larger than those produced within a vehicle-specific cross-section. Thus, the typical estimate from the literature (following Ippolito, 1992) is only the tip of the iceberg. At the monthly level, for index funds and ETFs, well over half of the flow-performance relation is related to the average performance of the vehicle. Thus, the overall performance of ETFs has a bigger impact on flow than a particular ETF's performance relative to other ETFs. At the annual level, 75% of active fund and ETF flow-performance is attributable to vehicle performance.

The ETF flow-performance relation is sharply more convex than active funds, while the relation for index funds is nearly linear.[1] Finally, we find no compelling

[1] Del Guercio and Reuter (2012) show that return chasing is a distinct characteristic of the incentives of direct sold funds. To ensure that the contrast in passive funds is not driven by the sales method or marketing, we split funds each month on the expense ratio relative to the other funds of the same Lipper category. Broker sold index funds are characterized by high expense ratios as discussed in the ICI 2017 publication "Trends in the Expenses and Fees of Funds, 2016" and the 2014 Reuters article titled "Analysis" High-priced index funds? The worst deal for investors." These tests assume that those in the upper part of the split are more likely to compensate brokers. For all splits ETFs continue to exhibit extreme convexity, while index funds remain linear.

evidence of a smart-money effect, in that flows predict future performance over the next month. The results for active mutual funds and index funds are sensitive to portfolio construction. For ETFs, we are unable to reject the no-smart money null.

Our flow-performance results are inconsistent with the litany of explanations in the literature, including Berk and Green (2004) and Spiegel and Zhang (2013). The behavior of ETF investors is most like the rational expectations investors modeled in Berk and Green (2004), despite ETF managers having zero skill. Easley, Michayluk, O'Hara, and Putninš (2018) extend Berk and Green (2004) and argue that some index ETFs are, in fact, active.[2] The authors argue that alternative weighting chasing is comparable to the skill chasing of active funds. In untabulated results we find that the magnitude of return chasing remains statistically significant for products we categorize as purely passive. Also, neither theory provides an explanation for the dominance of vehicle-type performance in the flow-performance sensitivities.

Our results also relate to the monitoring intensity of passive managers. One strand of literature claims that passive managers are passive owners because they have little power to exit and little value from monitoring.[3] Another strand suggests that the size of passive fund positions incentivizes them to be vocal monitors.[4] Our results support the latter, since managers are compensated by increased assets under management which is

[2] Cheng, Massa, and Zhang (2019) study non-US ETFs and also argue that they are active, Cheng et al.'s contention, unlike Easley et al., is based on legal features that allow non-US based ETFs to deviate considerably from their index.

[3] Bebchuk and Hirst (2018), Bihde (1993), Edmans, Levit, and Reilly (2018) theorize that the inability to exit or to alter weightings in a non-proportional manner reduces index funds incentive to monitor. Empirically, Heath, Macciocchi, Michaely, and Riggenberg (2019) find that passive investors are passive monitors.

[4] Fisch, Hamdani, Solomon (2019) theorize that despite index funds ability to exit, the ability of end investors to exit creates competition for assets among funds leading to a strong incentive to be active monitors. Empirically, Boone and White (2015), Appel, Gormley, and Keim (2016), Crane, Michenaud, and Weston (2016) find that index funds are active firm owners.

significantly related to past returns. Following the logic of Lewellen and Lewellen (2018), passive managers are incentivized to actively participate in value-enhancing corporate decisions.

Finally, we document the relation between flow and the underlying holdings. In sharp contrast to the flow-performance results, these findings are generally consistent with the existing literature. In the spirit of Edelen (1999) and Lou (2012) we examine the relation between flow and trading at the fund and stock holdings levels. For active mutual funds and ETFs there is a strong, near proportional, relation between flows and trading. The lower sensitivity of index mutual fund trading to flows is consistent with cash management strategies. Following Coval and Stafford (2007) we find that ETFs and active mutual funds induce fire sales in their holdings. Thus, stocks that are held in vehicles that experience dramatic net outflows have contemporaneous negative returns, followed by long-run positive returns. Despite the similarity of the price pressure coefficients for active mutual funds and ETFs, accounting for the extreme volatility of passive fund flows suggests that their impact on the underlying is much larger. These results dovetail with Ben-David, Franzoni, and Moussawi (2018), who use daily data to claim that ETF flow causes volatility in the underlying stocks. Li (2019) attributes 30% of the size and value effect to active mutual fund flows, while our results portend that ETF flows play an outsized role contributing to equity returns.

1. Background on investment vehicle structures

The evolution of the asset management industry impacts the mechanism through which capital flows are exchanged between investors and funds and are reallocated into the market. Dating back to the Netherlands in 1774 with a fund called, "Eendragt Maakt

Magt," which translates to "Unity Creates Strength," the original pooled investment vehicles were structured as essentially flowless closed-end funds.[5] Flows occur only during the initial public offering and liquidation, with investors trading fund shares with each other on an exchange at periods in between. A new era in the industry began in 1924 with the introduction of the first open-end fund, the Massachusetts Investment Trust (Henriques, 1997). However, it was not until the 1980s that open-end funds emerged as the preeminent investment vehicle.[6] By 2017, open-end funds managed seventy times the assets of closed-end funds.[7] For over fifty years, all mutual funds were "actively managed" such that managers strive to deliver high returns to investors.

In 1975, Jack Bogle of Vanguard introduced the first index mutual fund, a "passive" investment product that strives only to deliver the return of an index. In contrast to their closed-end forbearers, all open-end mutual funds, regardless of mandate, operate as pass-thru vehicles. As such, the number of fund shares fluctuates daily due to the creation and redemption process in which the manager exchanges cash for fund shares with all investors. Following standard nomenclature, we hereafter refer to open-end funds as simply "mutual funds."

The final industry transition relevant to this study occurred in 1993 when State Street introduced the SPDR S&P 500 ETF (SPY).[8] Like closed-end funds, ETFs are traded by individuals on stock exchanges. Unlike closed-end funds, ETF flow is a daily

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[5] The Investment Funds Institute of Canada, "The History of Mutual Funds," See https://www.ific.ca/en/artciles/who-we-are-history-of-mutual-funds/

[6] The Investment Company Institute Perspective, "The 1990s: A Decade of Expansion and Change in the U.S. Mutual Fund Industry." See https://www.ici.org/pdf/per06-03.pdf

[7] See the 2018 Investment Company Fact Book.

[8] SPY is structured as a unit investment trust (UIT) that has an explicit liquidation date. As of 2019 there are only eight ETFs remaining with this legal structured. A modified version of the open-end structure is now the preeminent fund structure for ETFs.

occurrence. Like index mutual funds, the majority of ETFs are passive products. Unlike index mutual funds, the secondary ETF market enhances investors' passive trading capabilities by allowing them to not only buy and sell, but also to trade on leverage and sell short. Unlike mutual funds, ETF flow occurs through in-kind creation and redemption with authorized participants (APs). The creation (redemption) mechanism, known as the primary ETF market, involves the AP delivering a pre-specified basket of the underlying (ETF shares) to the ETF manager in exchange for a sizeable block of ETF shares (underlying basket).[9] This innovation yields distinct interpretations of fund flows. Whereas mutual fund flows are the result cash exchanges with all investors, ETF flows are a consequence of APs activity in the primary market. Despite this nuance, it is the activity of secondary market ETF investors that translates into primary market flows. For example, buy orders that push an ETF price above the net asset value (NAV) drives AP creation activity, resulting in an inflow for the fund. Since the fund rarely has to trade in the underlying, ETFs are able to offer lower expense ratios, greater tax efficiencies, and greater transparency (Poterba and Shoven (2002)).

In recent years investors have taken note of active mutual funds' high fees and inability to beat their passive peers as documented by Crane and Crotty (2018) and Gruber (1996). Following sizeable inflows, index mutual funds and ETFs now are challenging the historical dominance of active mutual funds. Using data from the Investment Company Institute (ICI) 2018 Fact Book on domestic equity funds, Figure 1 plots the total assets managed by active mutual funds, index mutual funds, and ETFs

[9] APs are self-clearing broker-dealers that enter into a contract with the Sponsor regarding the terms of share creation and redemption. APs are not compensated from the ETF and have no legal obligation to create or redeem. APs pay a flat fee to transact in the primary market and receive compensation from commissions from their clients or from any arbitrage profits. See Antoniewicz and Heinrichs (2014) for further details.

annually from 1996 to 2017. At the beginning of the period the combined assets of passive funds accounted for just 6.05% of the industry, a figure that grew to 44.34% by 2017. The total market value of ETFs now comprises over 18% of the total market value of industry assets and 47.17% of passive assets. Indicative of the broader passive investing trend is the total new flows plotted in Panel B. Early in the sample period cash flows to active mutual funds dominated those of passive products, but beginning in 2006 active funds in aggregate experienced more than a decade of negative new cash flows. In contrast, cash flows to passive funds have been positive throughout.

[Insert Figure 1]

The role of active mutual fund flows in financial markets is widely studied (Christoffersen et al., 2014). The growing influence of passive investments is just beginning to be acknowledged by academics with Cremers et al. (2016) focusing on the role of indexing competition on active funds, Chang, Hong, and Liskovich (2015) finding price impact of indexing using a regression discontinuity design, and Baltussen, Bekkum, and Da (2018) attributing changes in index serial dependence on the proliferation of passive products. As summarized by Ben-David, Franzoni, and Moussawi (2017), ETF research has focused on the impact on the underlying. For instance, ETF ownership has been found to increase stock volatility by Ben-David, Franzoni, and Moussawi (2018), equity co-movement by Da and Shive (2018), stock return predictability by Brown, Davies, and Ringgenberg (2018), hedge fund participation in stocks by Huang, O'Hara, and Zhong (2018), and decrease corporate bond yield spreads by Dannhauser (2017). In this paper, we focus on the flow fundamentals of these relatively new investment vehicles. Related to this paper is Clifford, Fulkerson, and Jordan (2014), who document ETF flow-performance sensitivity between 2001 and 2010.

2. Data

Fund level data including assets under management, fees, objective codes, fund name, turnover ratio, and management name comes from the Center for Research in Security Prices (CRSP) Mutual Fund Database. Following Ben-David, Franzoni, and Moussawi (2018) we restrict our sample to broad based US equity and sector funds.[10] We eliminate any funds that on average have more than 80% of their assets invested in other mutual funds or ETFs. We delete any observations with total net assets less than $5 million or missing monthly returns, expense ratio, or total net assets. To avoid the incubation bias identified in Evans (2004), all observations before the CRSP starting data or after the CRSP end date are deleted. Flow for fund f in month t is computed following the literature as percentage growth of new assets,

$$Flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1}(1+R_{f,t})}{TNA_{f,t-1}} = \frac{Dollar\ Flow_{f,t}}{TNA_{f,t-1}}. \tag{1}$$

Quarterly flows are computed as the sum of monthly flows during the period. Fund alpha is computed using lagged betas from a 36-month rolling regression, with a minimum requirement of 30 months of data.

[10] The sample includes only funds with Lipper Objective Codes of *CA, EI, G, GI, MC, MR, SG, SP, BM, CG, CS, FS, H, ID, N, RE TK, TL, S,* or *UT.*

Using fund names from CRSP we follow Appel, Gormley, and Keim (2016), Busse and Tong (2012) and Iliev and Lowry (2014) to identify funds with an index strategy.[11,12] Since many ETFs have similar name strings as index funds, we rely on the CRSP ETF identifier variable, the ETF Global database, and name searches for common terms associated with this distinct vehicle.[13] A fund is identified as an index mutual fund if at any point in fund history it is flagged by the name search or a CRSP index fund flag equal to D or B and is not flagged as an ETF. We delete exchange-traded notes, leveraged, inverse, and active ETFs from our sample using fund name searches, a CRSP ETF identifier equal to N, a CRSP index identifier equal to E, and data from ETF Global.[14,15] To address Vanguard's structure, we create two portfolios for the ETF and mutual fund share classes. Finally, to account for multiple share classes, total net assets are summed across share classes of a portfolio and the other characteristics are asset value-weighted. We winsorize flow, expense ratio, turnover ratio, return, and all alpha measures at the one percent and 99 percent levels by fund type. Table 1 presents the summary statistics by year in Panel A for the funds identified in our sample between 2000 and 2017.

[Insert Table 1]

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[11] Index funds are flagged if the CRSP fund name contains the following strings: *SP, DOW, Dow, DJ* or if the lowercase version of the CRSP fund name contains: *index, idx, indx, ind_* (_indicates space), *composite, russell, s&p, s and p, s & p, msci, Bloomberg, kbw, nasdaq, nyse, stoxx, ftse, wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, or 5000.*

[12] The methodology is hand validated. Mairs & Power GE RSP is incorrectly identified as an index fund. Vanguard small cap fund converted from an active fund to an index fund in January 1990.

[13] ETFs are identified if the CRSP fund name contains: ETF or the lowercase version of the CRSP fund name contains: *ishares, spdr, holdrs, streettracks, exchange traded, or exchange-traded.*

[14] ETNs are identified if the CRSP fund name contains: ETN or the lowercase version of the CRSP fund name contains: *exchange traded note, or exchange-traded note.*

[15] Inverse and leveraged funds are identified if the lower case version of their name contains the following strings: *plus, enhanced, inverse, 2x, 3x, ultra, 1.5x, 2.5x.*

Table 1 documents that the same trends with our sample as the previous section documents with ICI data. In 2017 there were 2,189 distinct active mutual funds, a reduction of nearly 20% from the 2008 peak. In contrast, the number of index mutual funds in our sample has been stable with 256 distinct funds in 2017, while the number of ETFs has nearly doubled to 507 funds. The Table shows that the average fund of all types has experienced expense ratio compression. Further, the mean active mutual fund had outflows in five out of the last ten years, while both index mutual funds and ETFs had inflows. Because the number of ETFs is low in the beginning periods of this sample, our flow analysis uses data that starts in 2005. Panel B of the table presents the distribution of fund characteristics for the investment vehicles over the 2005 to 2017. Panel B also presents the average cross-sectional (XS STD) and time-series (TS STD) standard deviations of returns and flow. Regardless of the standard deviation measure or computational frequency, ETF flows are more volatile than index fund flows and, in turn, index fund flows are more volatile than actively managed fund returns. This suggests that while passive in name and mandate, underlying investors are more active.

Holdings level data is obtained from CRSP for securities with share codes 10 or 11. While Thomson Reuters is widely used for this data, we follow Shive and Yun (2013) and rely only on CRSP holdings data for reports between June 2008 and December 2017 to address Thomson Reuters data integrity issues [detailed by Ben-David, Franzoni, and Moussawi (2018) and Zhu (2017)]. While ETFs report holdings monthly, we align the holdings data by only considering quarterly frequencies. Observations with number of shares in excess of shares outstanding are deleted following Frazzini (2006). Data on stock characteristics comes from the CRSP monthly stock file with any observation with missing returns, price, or volume deleted.

3. Results

This section details our results. We first study the aggregate flows to the different investment vehicles. The paper continues by examining the determinants of flows to individual funds and concludes with the impact of flows on the underlying.

3.1. *Aggregate flows*

Warther (1995) bifurcates active mutual fund flow into an expected and unexpected component and finds that expected flows into active funds are uncorrelated with market returns, while unexpected flows display a strong positive correlation with market returns. In this section, we study the aggregate flows of actively managed funds, index funds, and ETFs. To compute aggregate flows we sum total dollar flows to all funds of a vehicle group normalized by the lagged market capitalization of the CRSP value-weighted index.[16]

Table 2 presents summary statistics of the aggregate flows to the different investment vehicles. Panel A shows that aggregate passive fund flows, particularly ETF flows, are much more volatile than active fund flows. Reflecting the general trend out of active mutual funds the 75 percentile of active mutual fund aggregate flows is negative. Panel B presents the correlation of aggregate flows. For both active and index mutual funds there is positive and significant monthly autocorrelation suggestive of the

[16] Warther (1995) uses a numerator measure computed with ICI data. ETF data from ICI is different due to issues of reinvested dividends. To maintain comparability, we elect to use a variation of the measure.

persistence of aggregate fund flows. Aggregate ETF flows have autocorrelation that is statistically and economically equivalent to zero. The contemporaneous correlations of active and index mutual fund flows are positively correlated, but aggregate ETF flows are negatively related to the aggregate flows of mutual funds. Although correlations do not imply causality, the strong negative flow correlations, and particularly, the more pronounced correlation between ETFs and index fund flows, are consistent with investors treating mutual funds and ETFs as substitutes. Further, the contemporaneous correlation of the CRSP value-weighted index return and aggregate flows to both active mutual funds and ETFs are positively correlated.

[Insert Table 2]

In Panel C we estimate the time-series models of aggregate flows for all investment flows. For active and index mutual funds the first lag is statistically significant. The second lag is insignificant, but the third lag is strongly significant for active mutual funds only. As suggested by the summary statistics, for ETFs there is no significant relationship between any of the lagged flows. Tests for autocorrelation of the residuals are reported at the bottom of the Table using the LaGrange multiplier tests of Breusch (1978) and Godfrey (1978). For the passive funds there is no significant autocorrelation of the residuals, but for active mutual funds there is until three lags are included in the model confirming the results of Warther (1995).

Given the autocorrelation results for active mutual funds of Panel C in Table 2 and to conform to Warther (1995) we use the AR(3) model to estimate the expected and unexpected components of net flows. We then regress CRSP index returns on the expected and unexpected components of aggregate flows to the different investment vehicles for the full sample period in Panel A and for the past five years in Panel B of Table 3. As in Warther, the coefficient on unexpected active mutual fund flows is large and highly significant in tests of the full sample period, while the coefficient on the predictable portion of flows is positive but insignificant. For index mutual funds there is no relationship between either of the components of flows. For ETFs the unexpected coefficient is positive in the full sample period, but half the size of the active fund coefficient. The expected coefficient is negative, although from the previous results ETF aggregate flows are almost completely random. In the more recent period, the relations between the components of flow and broad market returns change. Over the last five years, unexpected ETF flows remain significantly positively related to index returns. For active mutual funds there is no longer a significant relationship between either component of flow and the adjusted R^2 is negative. For index mutual funds the coefficients remain insignificant. Columns (5)—(7) look for evidence of a lag in the other direction by regressing unexpected flows on concurrent and lagged market returns. Over the full sample period, unexpected aggregate active mutual fund flows lag index returns given the positive and statistically significant coefficients on contemporaneous and one-month lagged CRSP index returns. However, there is no statistically significant relation in the more recent period. Instead, over the last five years unexpected aggregate ETF flows now have a positive and significant relation to contemporaneous and one-month lagged index returns.

[Insert Table 3]

Reconciliation with aggregate flow theories. As Ben-Rephel, Kandal, and Wohl (2011) detail, three hypotheses may explain the contemporaneous relation between aggregate flows and returns. The information hypothesis predicts that news about the market moves flows and the index in the same direction. Our results show that in aggregate the relationship may be evolving as the asset management industry changes. Over the last five year, the exchange-trading of ETFs have generated unpredictable aggregate flows that are positively correlated with market valuation at the monthly level. The impact of active mutual funds has diminished. The evolving relation suggests that ETFs may be replacing active mutual funds as conduits of demand shocks.

The second hypothesis is the return chasing or feedback trading hypothesis that suggests investors react to lag returns. The results from the right side of Table 3 show that aggregate active mutual funds exhibited return chasing over the full period. However, similar to the contemporaneous correlation the effect for active mutual funds is not present in the most recent five years. In contrast, lagged CRSP returns in the most recent five years exhibit a modestly significant positive relation with unexpected aggregate ETF flows. This change implies that as ETF investors have become more prominent market participants, they may follow a positive feedback trading strategy.

The third hypothesis of aggregate flows exerting price pressure is rejected by Warther for active mutual funds at the monthly level, but confirmed at the daily level by Ben-Rephael, Kandel, and Wohl (2011) and Edelen and Warner (2001). In untabulated results, we find evidence that only lagged aggregate ETF flows are significantly negatively related to the CRSP index when concurrent flows are removed. Following Warther's logic this suggest there is an overreaction in the market to aggregate ETF flows that subsequently reverts, indicative of the price pressure.

3.2. *Persistence and flow-to-performance relationship of individual funds*

In this subsection, we seek to understand the flow dynamics for individual funds. A large body of literature documents that flows are predictable using past returns and past flows (Ippolito (1992), Chevalier and Ellison (1997), Coval and Stafford (2007), and Lou (2012)). Our study of individual fund flows begins with an analysis of the relation between flow and lagged returns and flows. As shown in Coval and Stafford (2007), up to twelve months of past flows and fund returns are significantly positively related to monthly flows. In Table 4 we confirm those finding using Fama-MacBeth, pooled, and fund fixed effects regressions at both the monthly and quarterly level in Panel A and Panel B, respectively. For all specifications, active mutual fund flows demonstrate sharp positive levels of persistence at the first lag, and moderate and consistently positive persistence for twelve monthly or eight quarterly lags. The sum of the monthly flow coefficients range from 0.54 to 0.65 implying that one dollar of flow in the current month yields 54 to 65 cents of extra flow during the next twelve months. Although this effect dampens when we examine two years of quarterly flows, the null that the sum of the slopes is zero is easily rejected. For passive vehicles, the evidence of flow persistence is mixed. Fama-MacBeth and pooled estimations produce flow coefficient sums that are statistically significant, but always lower than that of active funds. Regardless of whether we focus on monthly or quarterly passive flow, the fund fixed effects specifications are unable to reject the null that the sum of lagged flow coefficients is zero.

[Insert Table 4]

Reconciliation with persistence explanations. The autocorrelations of active mutual fund flows are consistent with the explanation that fund investors herd toward a manager or utilize these funds in their retirement accounts with little monitoring as discussed in Del Guercio and Tkac (2002). The absence of passive fund flow persistence reflects the infrequent use in retirement accounts. As discussed in Brown, Liang, and Weisbenner (2007) and Mitchell et al. (2006), despite being offered in nearly all 401(k) plans, index funds are less likely to be added to a plan menu and are used by just half of participants. ICI 2018 Fact Book data shows that index funds are underrepresented in 401(k) assets.[17] Unlike mutual funds, ETFs have not generally been adopted in 401(k) retirement plans.[18]

Irrespective of the specification or measurement frequency, last period's returns are significantly positively related to flows for all three vehicles. Similarly, the one-year sums of monthly return coefficients are all positive and statistically significant. ETF flows have a higher response to relative performance than actively managed funds in most specifications. Comparisons of index funds with ETFs or actively managed funds are specification specific. Over two years, the sums of quarterly lagged return coefficients tell a different story. The actively managed sum is approximately the same of as it one-year monthly sum. For index funds and ETFs, their two-year quarterly sums are lower than their one-year monthly sums. In fact, nearly all of the passive quarterly sums are statistically insignificant from zero. A reversal of the return-flow relation for passive products after the first year is the source of the decay.

Table 4, Panels A and B, follows the literature and considers the traditional flow-performance sensitivity relative to other funds of the same type (within type performance). Thus, the performance of a particular index fund is relative to other index

[17] See https://www.ici.org/pdf/2018_factbook.pdf
[18] See https://www.marketwatch.com/story/retirement-accounts-a-holy-grail-that-remain-out-of-reach-for-etfs-2017-02-06

funds. Panel C broadens the estimation of the flow-performance relation by partitioning relative performance into within type performance and vehicle-type performance, the performance of a fund's vehicle type relative to other vehicles. The first set of coefficients is analogous to the slopes in Panels A and B, while the second set of coefficients describes flow in the vehicle type in response to the vehicle type's relative performance. One-month lagged estimations are reported in columns 1, 3, and 5. Both index funds and ETFs display more elevated immediate flow-performance sensitivity for both components of relative performance than active mutual funds. For both index funds and ETFs, the coefficient for vehicle-type performance is larger than that of the traditional within type performance.

In columns 2, 4, and 6, of Table 4, Panel C, we consider performance over the last twelve months. The sums of the coefficients reveal that the total relation for actively managed funds and ETFs is similar, while the sum of the coefficients for index funds is more diminutive, and marginally significant. Comparison of the vehicle-type performance sums and the total performance sums is dramatic. The within type performance that is featured in the vast mutual fund literature only accounts for about a fourth of the total flow-performance sensitivity, suggesting that the cross-sectional nature of the classic estimations masks the more drastic impact of vehicle-type flows. As such, Panels A and B drastically understate the extent to which the flow-performance relation for passive products outshines that of active funds.

Reconciliation with flow-performance theory. Berk and Green (2004) deliver the in vogue model of the active mutual fund industry. They argue that mutual fund managers have differing abilities to select stocks and decreasing returns to scale in deploying their abilities. Mutual fund return performance provides a signal of managers' abilities.

Investors notice fund performance and direct flow to funds with managers with high expected ability until all managers' post-fee performance is expected to equate to a passive benchmark. The evidence from Table 4 poses a two-pronged challenge to Berk and Green (2004). First, at the core of Berk and Green are rational investors who don't ascribe ability to passive products, and as such, flows respond to neither passive returns (Table 4, Panels A and B) nor the performance of other funds with the same vehicle type (Table 4, Panel C). Perhaps investment vehicle flow is attributable to both a performance-learning component (a la Berk and Green) that affects active vehicles and yet unknown component that affects all vehicles. This more holistic reasoning is at odds with Panel A, which shows, at the annual and monthly frequency, flows are more responsive to passive performance than active performance. Second, the investors posited by Berk and Green immediately direct flow in response to an active vehicles' performance. As such, flow persistence plays no role in Berk and Green. Table 4 shows that passive products have scant flow persistence and immediate flow response to performance while active fund have considerable persistence and slow response to performance. Thus, comparing our passive and active flow findings, the characteristics of passive flow appear much closer to what Berk and Green's model designates as active flow than actual active flows.

Easley et al. (2018) expand Berk and Green's (2004) rational expectations model to include both purely passive funds and what they term "passive aggressive" funds. The latter funds are ETFs in form, but due to alternative weightings or factor-based investment mandates are deemed to be more active in nature. Their model predicts that purely passive investment will appear much different than active. In contrast, passive aggressive funds will be more similar to active funds. In their model the skill chasing of

Berk and Green relates to portfolio construction techniques that selects exposure to certain factors and industries. In untabulated results, we repeat the analysis of Tables 4 using only the subset of passive funds that are benchmarked to common indices. The return chasing behavior of passive funds and the convexity of ETF flows remains, although return chasing is now similar across all investment vehicles. The robustness of these results suggests that other dynamics beyond the passive aggressive nature of ETFs are important drivers of flows. Further, we are unfamiliar of any theory in the extant literature that makes sense of performance-based flows to types of vehicles.

Having found that fund investors, particularly ETF investors, chase returns we continue by characterizing the shape of the flow-to-performance relationship. In equity mutual funds, the flow-to-performance relationship is convex, implying that investors disproportionately chase funds with high returns and fail to sell funds with low returns. In Figure 2, we separate active mutual funds, index mutual funds, and ETFs into groups of 20 in Panel A and groups of ten in Panel B based on the fund's excess return over the CRSP value-weighted index in month t. For each group we compute the average flow in the next month, $t + 1$. Both figures depict the familiar convex shape of active mutual fund flows with larger flows accruing to funds in the top portion of lagged return distribution. The relationship for index mutual funds is more linear with disproportionate flows for only the top 5% of funds. Flows for even the worst performing funds, while close to zero, are still positive. Most apparent is the extreme convexity of ETF flows with outsize growth in flows for funds in the top 20% of prior month returns.

[Insert Figure 2]

We follow Sirri and Tufano (1998) and others by estimating a piecewise linear regression that defines three segments of performance to allow for different sensitivities. Each month funds are ranked relative to funds of the same type according to their return in excess of the CRSP equal-weighted index, CRSP value-weighted index, the average performance of other funds of the same type in the same Lipper category, and raw returns. This produces three performance variables for fund j of type f in month t:

- $Low_{j,f,t-1} = \min(0.2, Rank_{j,f,t-1})$,
- $Mid_{j,f,t-1} = \min(0.6, Rank_{j,f,t-1} - Low_{j,f,t-1})$,
- $High_{j,f,t-1} = Rank_{j,f,t-1} - (Low_{j,f,t-1} + Mid_{j,f,t-1})$. (2)

This procedure allows for the slopes to be estimated separately for funds in the lowest quintile, the three middle quintiles, and the top quintile. We then regress monthly flows on the three piecewise past performance variables, lagged values of the log of fund age, log of assets, expense ratio, twelve-month fund return volatility, and contemporaneous aggregate category flows. The regressions also include month and style fixed effects and standard errors that are clustered at the fund and date level. Regression results are presented in Table 5.

[Insert Table 5]

Comparing the coefficient for the low region to that of the high region we can characterize the flow-to-performance relationship for all fund types in our study. The statistical significance of the difference between the coefficients is determined by a Wald test. Table 5 indicates that regardless of the benchmark used to measure excess return there is statistically significant convexity in the flow-performance relationship for active mutual funds and ETFs, but there is no evidence of convexity for index mutual funds. Focusing on the coefficients on the top performing funds, moving from the 80th percentile to the 90th percentile increases flow to an active mutual fund by 4.8 to 5.1 percentage points, but to an ETF by 13.9 to 16.9 percentage points. For index mutual funds flows increase by 2.0 to 3.0 percentage points, but this finding is insignificant when ranked on performance relative to funds in the same Lipper objective code and raw returns. In the low region moving from the 20 percentile of performance to the 10 percentile lowers flows by just 2.0 to 2.6 percentage points for active mutual funds and 3.0 to 5.7 percentage points for ETFs, an effect that is disproportionate when compared to the top performers. For low performance index mutual funds, a similar move lowers flows by 2.3 to 3.0 percentage points, nearly symmetric to the effect for high performing funds.[19]

Focusing on the control variables we find that older funds of all types have significantly lower flows. In contrast larger ETFs have lower flows, but for active funds the result is reverse although the effect is economically small. ETF investors appear to be much more cost sensitive than active mutual funds. Index mutual fund expense ratio is insignificantly related to flows supporting the findings of Choi, Laibson, and Madrian (2009), Elton, Gruber, and Busse (2004) and Hortaçsu and Syverson (2004).

Reconciliation with convexity explanations. We are unable to reconcile these results with current explanations for mutual fund convexity. Goetzmann and Peles' (1997) behavioral-bias explanation does not fit the ETF—active mutual fund comparison. Sophisticated traders are more present in ETFs than mutual funds because of the ability

[19] In untabulated results, we show that the results for passive funds remain for only the subset of funds following common benchmarks and are robust to the market share specification of Spiegal and Zhang (2013). Further for ETFs there is no difference in the flow to performance sensitivity in different market states as found for active funds by Franzoni and Schmalz (2017).

to sell short and trade on margin. As such, we expect behavioral biases to be less apparent in ETFs, yet the convexity of ETF flows is many multiples greater than that of actively mutual funds. Both ETF and index fund marketing focus less on recent performance and more on expenses and exposure to customized risk. Further, most ETFs do not charge 12b-1 fees that can pay for marketing expenses. Sirri and Tufano's marketing explanation should imply similar convexity, yet their convexity level differences are drastic.[20] In considering hedge funds, Getmansky (2012) and Getmansky et al. (2015) show how flow-performance nonlinearities can arise from inflow and outflow restrictions, and from strategy capacity costs. These characteristics are absent from ETFs, so these models also seem unlikely to be fruitful in understanding ETF performance-flow convexity.

Smart Money. The results so far have established that all fund investors chase returns, but that ETF investors are hyperactive in driving cash flows to previous winners while failing to proportionately punish losing funds. In contrast, Carhart (1997) and Hendricks, Patel, and Zeckhauser (1993) advocate the strategy of selling losers and not chasing winners. To examine if ETF investors are smart in their allocation decisions we follow Gruber (1996), Keswani and Stolin (2008) and Zheng (1999) by examining the performance of new money portfolios using a fund-level approach. The process begins by computing four monthly performance measures for each fund: excess return over the CRSP value-weighted index and the alphas from the one-, three-, and four-factor models. Using fund flows as signals the following portfolios are formed:

[20] Outsized fees are another way in which ETFs can compensate brokers as suggested by ICI and Reuters. It is also possible that funds signal their skill in tracking their benchmark through their expense ratios. To account for these potential forms of marketing and signalizing in unreported results we remove funds based on their position in the style-date expense ratios. The convexity of flow results in this section are robust for these subsamples.

1. All funds of type f equal-weighted (EW)
2. All funds of type f value-weighted (VW)
3. Equally-weighted in all funds of type f with positive new cash flow
4. Equally-weighted in all funds of type f with negative new cash flow
5. In all funds of type f with positive new cash flow and weighted by the funds' dollar flow
6. In all funds of type f with negative new cash flow and weighted by the funds' dollar flow

Under the fund-level approach the performance of the portfolios is found by averaging the estimates for individual funds using the particular weighting scheme. Table 6 reports the results of the tests. Panel A presents the time-series average performance of each portfolio in the first row with the t-statistic for its difference from zero below.

[Insert Table 6]

There is no evidence that allocation to aggregate equal- or value-weighted portfolios is smart. The absolute performance is negative and significant for nearly all measures for all vehicles. For equally-weighted portfolios there is some evidence of mutual fund investors buying funds that subsequently outperform the average fund, but not absolute positive performance. In this weighting scheme the funds with negative new cash flows also have lower performance in the following month. Equally-weighted index funds with negative new cash flow have statistically negative one-, three-, and four-factor performance, but the positive cash flow portfolios do not have performance statistically distinguishable from zero. Equally-weighted positive and negative cash flows portfolios of ETFs both have statistically significant negative performance the next month.

Panel B presents the results of the difference in portfolio returns. Comparing the value-weighted portfolio to the equal-weighted portfolio indicates that invested money slightly outperforms the average. Next, we follow the literature by building a long-short strategy that buys funds with positive new cash flow and shorts those with negative new cash flows, to provide evidence on investors' ability to select funds by exiting poor performers and purchasing good performers. For active and index mutual funds the returns to the long-short portfolios are mostly positive and for some performance measures of the equally-weighted strategy, are significant, confirming the results of Zheng (1999). However, there is no evidence that cash-flow weighted long-short portfolios outperform in the next month. There is also no evidence that the long-short strategy is profitable in ETFs with most coefficients statistically insignificant and nearly half of the ETF long-short strategies having negative returns. The results of these tests provide inconclusive evidence that either active or index mutual fund investors make smart allocation decisions. There is no evidence that ETF investors are smart. Perhaps, this reflects the hedging property of ETFs—some investors may short ETFs as a hedge against a long portfolio position, trading on relative outperformance.[21]

Although the primary purpose of Table 6 is to compare the degree of smart money between investment vehicles, Table 6 also provides a comparison of performance across vehicles. Focusing on the value-weighted results, estimates for alpha are remarkably similar. Comparing alpha for each factor model, we are unable to reject the null of no

[21] Brown, Davies, and Riggenberg (2018) theorize that ETF flows are the ideal setting to study the impact of non-fundamental demand shocks. In their empirical tests they find evidence that a strategy that shorts funds in the top decile of flows (inflows) and buys the bottom decile of flows (outflows) generates positive excess returns. These results are driven by leveraged ETFs, since their estimation using an unleveraged, mature ETF sample produces results that are similar to ours.

difference alpha between all three vehicles vehicle at all common levels of significance. Although we found our evidence of flow-performance sensitivity difficult to reconcile with models such as Berk and Green (2004), this evidence provides support of their model. Their model predicts that flows eradicate differences in vehicle-type performance.

3.3. *Flows and the underlying*

Trading. For flows to exert material impacts on the underlying securities they must be associated with trading activity. Previous literature has documented the negative externalities imposed on long-term investors by the liquidity provisions of the open-end fund structure. For ETFs the trading decisions of an investor are internalized, so the indirect effect of flows through diseconomies of scale and the direct effects of the liquidity provision may not be as prevalent. Mutual fund managers have the discretion greater discretion in responding to flows than passive funds, which may mitigate the impact of flow-related trading. ETFs rarely trade in the underlying, instead the AP exercises his discretion in deciding to accumulate a creation basket or to sell the redemption basket. To examine if there is a differential response by funds to flows we follow the methodologies of Edelen (1999) and Lou (2012).

Edelen (1999) conducts his study at the fund level. We compute the net trading activity measure of Fang, Peress, and Zheng (2014) using end of quarter holdings data. For fund j of investment vehicle type f in quarter q with set of N holdings the measure is computed as

$$Net\ Trading\ Activity_{j,q} = \frac{Trading\ Buy_{j,q} - Trading\ Sell_{j,q}}{Total\ Assets_{j,q-1}}, \tag{3}$$

where

$$Trading\ Buy_{j,q} = \sum_{i=1}^{N} prc_{i,q} * \Delta shares_{i,g,q} if\ \Delta shares_{i,g,q} > 0 \quad (4)$$

$$Trading\ Sell_{j,q} = \sum_{i=1}^{N} -prc_{i,q} * \Delta shares_{i,g,q} if\ \Delta shares_{i,g,q} < 0. \quad (5)$$

We regress this proxy on flows and, in some specifications, the portion of fund assets held in cash because Edelen, Evans, and Kadlec (2007) show that higher levels of cash holdings should desensitize a funds' trading from flows. The regressions use quarter fixed effects and the standard errors are clustered at the date and fund level. The results are shown in Table 7. A 1% increase in flow is associated with an increase in security turnover of 65% for active mutual funds, 58% for index mutual funds, and 78% for ETFs. Trading by index mutual funds is significantly negatively related to the amount of cash holdings. For active mutual funds and ETFs the coefficients are insignificant. Overall the evidence suggests that flow-induced trading occurs most often for ETFs followed by active mutual funds and index mutual funds.

[Insert Table 7]

Having documented an association between trade and flows, we continue to examine how holdings adjust following Lou (2012). In a frictionless market all managers would be expected to adjust the portfolio proportionately if flows are uninformed. In actual financial markets, fund managers may deviate from one-for-one scaling by using their cash reserve to absorb flows and for active managers they may selectively transact in only a subset of securities, based on their expectations and liquidity considerations.

We investigate the scaling response of the investment vehicles to fund flows by regressing the percentage change in split-adjusted shares of stock i held by fund j of type f between quarters q and $q-1$, $trade_{i,j,f,q}$, on contemporaneous fund flow, previous fund ownership of the stock, the $Amihud$ illiquidity proxy, and their interaction with flow. The results are presented in Table 8. If managers follow a proportional response strategy the coefficient on flow will equate to one. For the outflow sample, active mutual funds and ETFs both follow a dollar-for-dollar response with coefficients close to one. In contrast, the coefficient on index fund flow is approximately 0.7 indicating that for each dollar of outflows the manager only sells $0.70 of his existing holdings corroborating the previous finding on the importance of cash holdings for index funds. The results of the inflow sample again indicate that ETFs are able to allocate nearly each dollar of inflow to existing benchmark assets. In contrast, mutual funds deviate from perfect scaling with active and index mutual funds investing only $0.85 and $0.53 of every dollar inflow into existing positions. Given the evidence of index fund cash management, similar ETFs may be able to more closely replicate their benchmark.

[Insert Table 8]

Fire Sales. We next examine if there is evidence of flow-induced price pressure for the equity holdings following Coval and Stafford (2007). Flow-induced sales (buys) are identified as reductions (increases) in shares owned by funds experience flows in the lower (upper) decile of funds. We use the Pressure 3 measure of Coval and Stafford (2007) computed as,

$$Pressure3_{i,f,t} = \frac{\sum_j \max\left(0, \Delta Holdings_{i,j,f,t} \middle| flow_{j,f,t} > Percentile(90th)\right)}{Shares\ oustanding_{i,t-1}} - \frac{\sum_j \max\left(0, -\Delta Holdings_{i,j,f,t} | flow_{j,f,t} < Percentile(10th)\right)}{Shares\ oustanding_{i,t-1}} \quad (5)$$

Stocks with measures below the 10th percentile that are negative are considered fire sale stocks and those with measures above the 90th percentile are considered forced buys. Following the literature, we look for extreme returns that subsequently reverse indicative of flow-induced price pressure, rather than informed trading.

Table 9 presents the abnormal returns relative to those of the average stock held by the funds of the same type around flow-induced transactions for the different investment vehicles. Panel A presents the results with monthly returns and Panel B with quarterly returns. Following the literature, we calculate average abnormal returns each month and then use the time-series of mean abnormal returns for statistical inference, giving equal weight to each monthly observation rather than each individual observation. We require at least 25 stocks to be affected in a period to be included as a monthly observation. In this setting we consider flows between January 2009 and December 2017 to account for the issues in the holdings data discussed in the data section.

[Insert Table 9]

In Panel A, we find the same pattern of abnormal returns that subsequently revert for active mutual funds and ETFs. Stocks exposed to active mutual fund and ETF extreme outflows have significantly negative abnormal returns in the period of forced selling and the months immediately before. For ETFs the stocks had significantly positive abnormal returns between months four to six months prior to the event. For both it takes about six months for the pressure of flow-induced sales to dissipate. Index mutual funds show no signs of causing flow-induced price pressure in the exposed stocks, perhaps reflecting their reliance on a cash buffer. For flow-induced purchases there is evidence of active mutual funds and ETFs pushing the prices of exposed stocks higher, but no significant reversion. Panel B repeats the analysis with quarterly data.

The results of this subsection show similar impact of flows to the underlying portfolios for both active mutual funds and ETFs. However, the volatility of ETF flows is nearly double that of mutual funds. Together the similar coefficients and greater volatility suggest that the actual impact of ETFs is significantly greater. In contrast, index funds appear to manage their portfolios in consideration of the liquidity provisions provided to underlying investors.

4. Conclusion

The rise of passive investing has changed the investment universe. We provide the first comparison of active mutual fund, index mutual fund and ETF investment flows using identical periods and specifications. Our estimation emulates the premier empirical studies of active mutual fund to provide a more complete understanding of flows to all investment vehicles

At the aggregate level, ETF flows appear to play the role that active flows played in the past. Warther's finding of a contemporaneous, positive relation between market returns and aggregate active mutual fund flows has subsided over the past five years.

Instead, correlation with ETFs flows remains suggesting that these emerging investment vehicles have become investors preferred conduit of demand shocks.

At the individual fund level, the volatility of index fund and ETF flows is nearly twice that of active mutual funds, at both the monthly and quarterly frequency. Passive vehicles demonstrate much less flow-persistence than active funds, consistent with Del Guercio's and Tkac's (2002) contention that investment products that are used in defined contribution plans illicit slower investor reactions to performance.

On an annual basis, all investment vehicles exhibit significant monthly flow-performance sensitivities, with the greatest relation exhibited by ETFs. The two year flow-performance sensitivity of passive funds diminishes, while it remains significant for active mutual funds. By considering all investment vehicles, we are able to bifurcate return performance into the performance of a fund relative to other funds in its product type (within type performance) and the performance of its vehicle type relative to others types (vehicle-type performance). At the annual level, flow-performance sensitivity is similar for active mutual funds and ETFs, but the relative performance of the vehicle-type component is four times as large as the within type component. Thus, the literatures' previous estimate of flow-performance sensitivity that focuses on the performance of active funds relative to each other neglects three-quarters of the flow-performance relation. When it comes to convexity, we show that ETF flow-performance is much more convex than that of active managed funds, while index funds demonstrate little, if any, convexity. Our flow-performance and convexity results are difficult to reconcile with explanations from the mutual fund literature. We are able to reject the smart-money hypothesis for ETF flows and the results for active and index mutual funds are inconclusive.

In contrast, the results on the relation between flows and the underlying securities are generally consistent with the active mutual fund literature. The associations between flows and underlying portfolio effects are similar across for active mutual funds and ETFs, while index mutual funds are more reliant on cash management. Specifically, the evidence on the trading response to flows and fire sales are similar for active mutual funds and ETFs. Although these associations are similar per unit of flow, elevated flow volatility for ETFs over mutual funds leads to more dramatic total impact.

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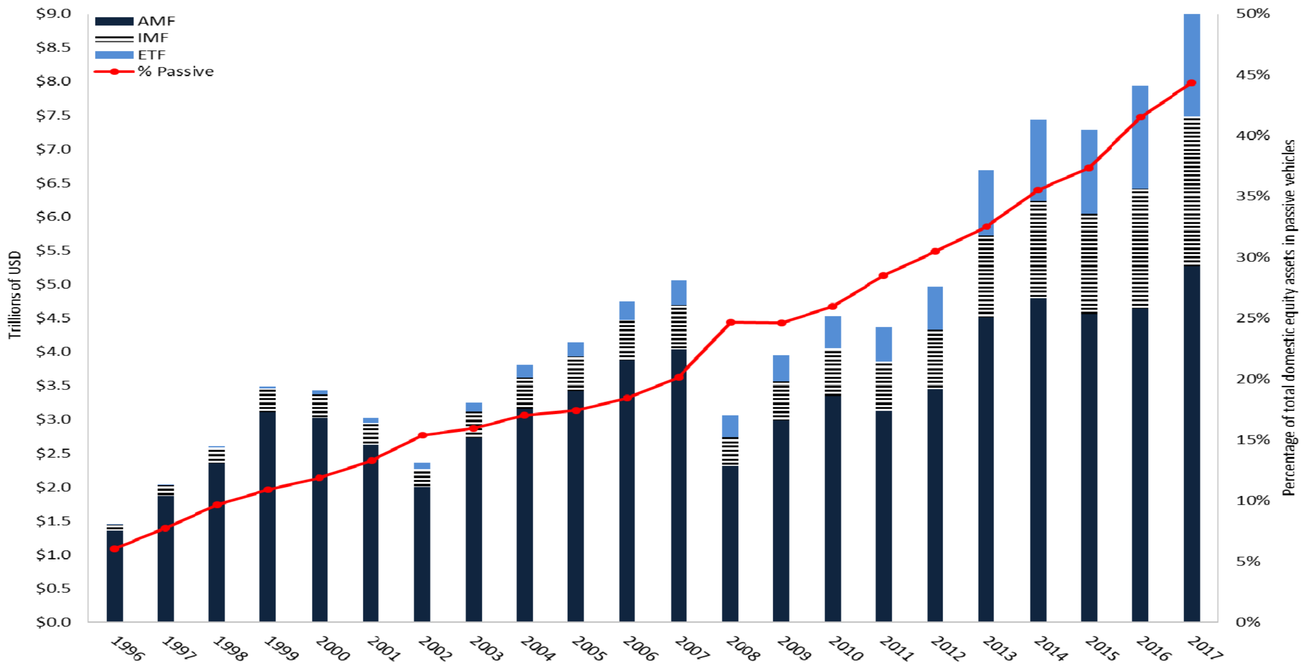
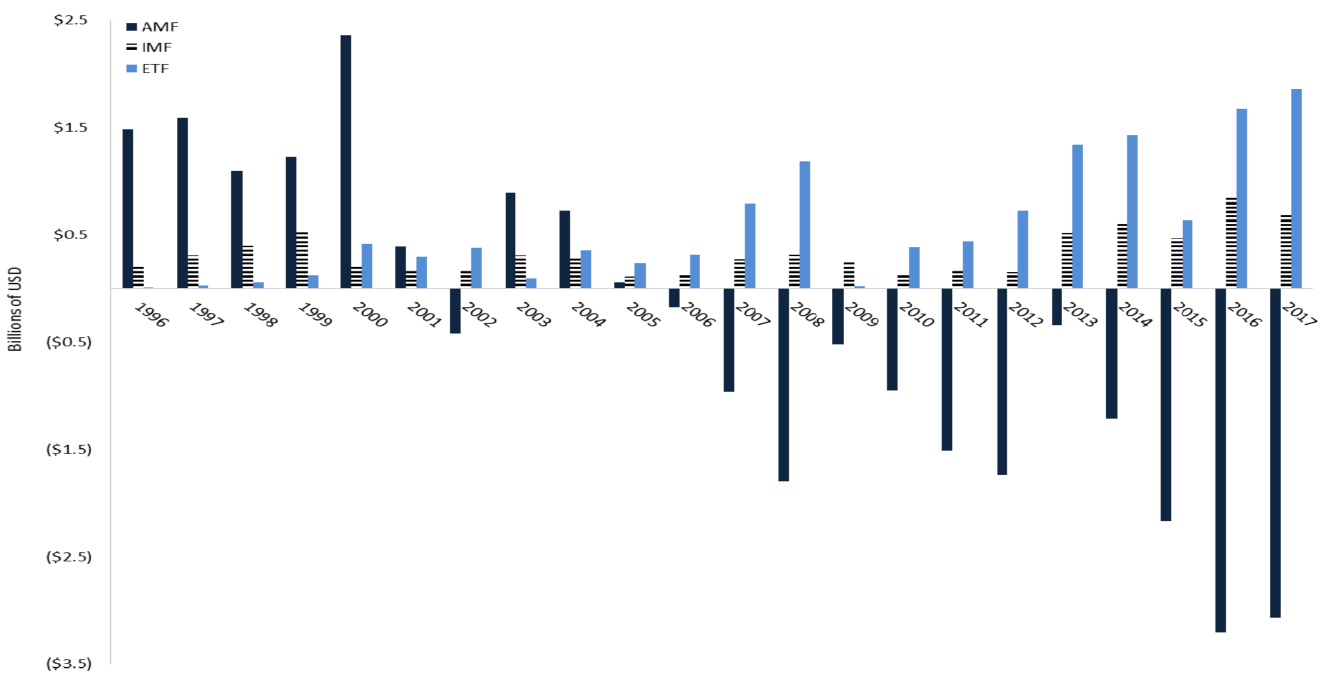
Figure 1

Assets and flows to domestic equity funds



Panel A: Total assets to domestic equity funds

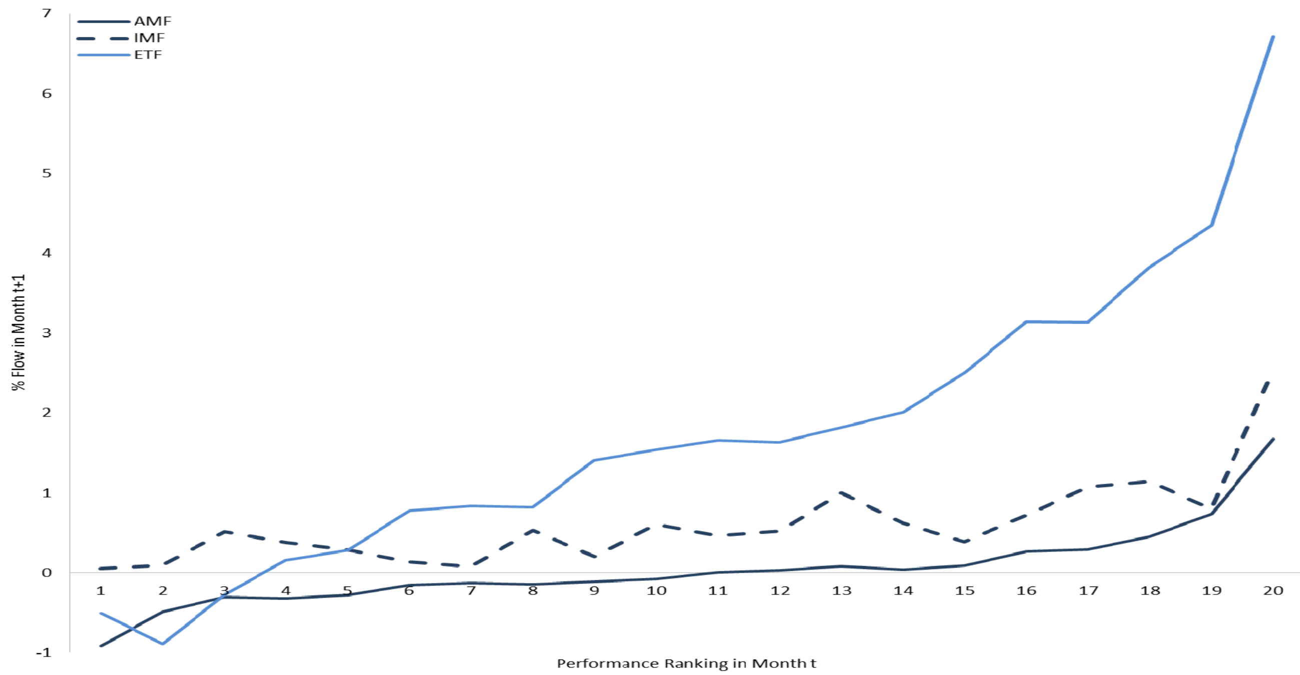


Panel B: New cash flows annually

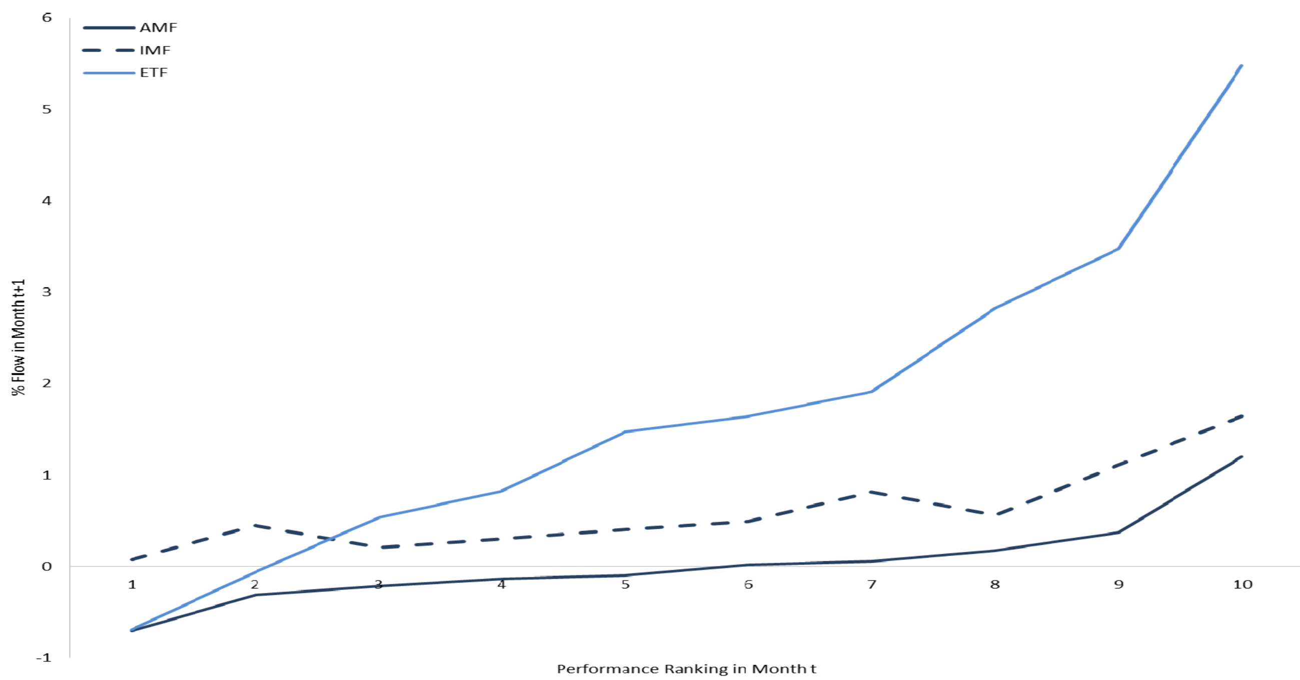
This figures plots the total assets in Panel A and new cash flows in Panel B to active mutual funds (AMF), index mutual funds (IMF), and exchange-traded funds (ETFs) using data from the Investment Company Institution (ICI) Factbook. The annual data sample is from 1996 to 2017.

Figure 2

The flow-performance relationship



Panel A: Flow-performance relation for funds split into twenty groups



Panel B: Flow -performance relation for funds split into deciles

This figure splits active mutual funds, index mutual funds, and exchange-traded funds (ETFs) into groups based on the monthly excess return of the fund over the CRSP value weighted index. For each group we then compute the average flow in the next month.

Table 1

Summary statistics

This table presents in Panel A the annual summary statistics on active mutual funds (AMFs), index mutual funds (IMFs), and exchange-traded funds (ETFs) with at least five million in assets. The statistics for each year include the number of distinct funds, the total assets in billions of dollars, the average monthly flow in percent, the average fund size in billions of dollars, and the average expense ratio in percent. In Panel B the distribution of fund characteristics is presented for the sample period January 2005 to December 2017. Included are the median cross-sectional and times-series standard deviations of flows and returns. The cross-sectional statistics are measured as the mean of the fund type measure at each date. Time-series statistics are the average of measure of each individual fund over the sample period.

Panel A: Fund characteristics by year

	AMF					IMF					ETF				
Year	# Funds	Assets	Flow	Size	Exp	# Funds	Assets	Flow	Size	Exp	# Funds	Assets	Flow	Size	Exp
2000	1,842	2,352	1.26	1.46	1.31	165	327	1.26	2.33	0.70	14	35	0.98	2.04	0.49
2001	2,106	2,084	1.05	1.12	1.34	203	305	1.28	1.70	0.71	40	56	7.76	1.63	0.31
2002	2,281	1,625	0.66	0.88	1.37	220	251	1.27	1.36	0.72	67	76	5.61	1.21	0.31
2003	2,390	2,237	0.92	0.85	1.40	241	363	1.49	1.37	0.74	74	107	4.48	1.20	0.36
2004	2,414	2,603	0.55	1.06	1.39	249	438	1.24	1.77	0.74	92	158	4.26	1.58	0.37
2005	2,425	2,840	0.46	1.20	1.34	246	472	0.82	2.01	0.74	109	196	4.02	1.68	0.35
2006	2,479	3,261	0.30	1.34	1.30	234	564	0.44	2.42	0.67	155	252	3.15	1.67	0.38
2007	2,623	3,485	0.11	1.50	1.26	241	623	0.49	2.82	0.66	244	341	2.79	1.49	0.42
2008	2,676	2,001	-0.13	1.19	1.21	249	410	0.40	2.30	0.61	292	273	2.32	1.15	0.45
2009	2,579	2,485	0.15	0.95	1.21	255	550	0.51	2.10	0.62	312	345	2.24	0.99	0.45
2010	2,451	2,541	0.18	1.13	1.21	238	663	0.92	2.75	0.68	345	417	1.94	1.18	0.45
2011	2,246	2,448	0.14	1.27	1.18	246	686	0.68	3.17	0.67	362	455	0.64	1.37	0.45
2012	2,200	2,621	-0.16	1.30	1.16	251	805	1.10	3.41	0.65	413	582	0.84	1.44	0.43
2013	2,234	3,534	0.48	1.54	1.15	260	1,119	1.46	4.31	0.65	411	890	2.88	1.95	0.42
2014	2,226	3,783	0.26	1.79	1.12	245	1,287	0.98	5.31	0.65	441	1,123	1.83	2.36	0.41
2015	2,262	3,620	-0.05	1.79	1.10	246	1,305	0.39	5.72	0.62	447	1,135	1.11	2.61	0.40
2016	2,233	3,658	-0.50	1.73	1.09	260	1,570	0.60	6.07	0.60	482	1,443	1.43	2.76	0.39
2017	2,189	4,114	-0.32	1.94	1.07	256	1,951	0.10	7.60	0.59	507	1,874	1.49	3.34	0.39

Panel B: The distribution of fund characteristics

Fund Characteristics	Mean	STD	XS STD	TS STD	10%	25%	50%	75%	90%
AMF									
Monthly flow (%)	0.07	5.05	4.99	4.37	-3.22	-1.53	-0.48	0.76	3.48
Quarterly flow (%)	0.77	13.95	13.80	12.28	-9.03	-4.57	-1.49	2.51	11.34
Monthly return (%)	0.68	4.59	1.91	4.34	-5.28	-1.66	1.07	3.46	5.86
Quarterly return (%)	2.01	8.51	3.59	8.63	-9.32	-1.48	3.03	6.81	11.49
Assets ($ millions)	1,427.67	5,739.57			21.50	65.50	244.40	947.20	2,793.50
Age (years)	15.07	12.90			3.50	6.83	12.08	18.92	27.91
Expense (%)	1.19	0.38			0.77	0.95	1.15	1.39	1.66
Management Fee (%)	0.74	0.28			0.42	0.58	0.75	0.90	1.04
Turnover (%)	0.79	0.75			0.17	0.32	0.59	1.00	1.57
IMF									
Monthly flow (%)	0.68	9.38	9.07	6.51	-2.85	-1.03	-0.04	1.07	3.59
Quarterly flow (%)	3.48	22.41	21.62	15.35	-7.29	-2.94	-0.01	3.54	11.51
Monthly return (%)	0.77	4.35	1.46	4.06	-5.12	-1.59	1.17	3.46	5.77
Quarterly return (%)	2.23	8.01	2.78	8.06	-8.78	-1.17	3.22	6.50	11.42
Assets ($ millions)	3,882.01	18,654.32			30.50	103.10	481.30	1,960.70	5,257.00
Age (years)	13.02	8.21			3.83	7.17	12.13	17.33	22.90
Expense (%)	0.65	0.54			0.10	0.21	0.47	0.97	1.53
Management Fee (%)	0.37	0.34			0.05	0.11	0.24	0.59	0.85
Turnover (%)	0.71	1.53			0.04	0.08	0.19	0.54	1.50
ETF									
Monthly flow (%)	1.79	10.68	10.73	9.75	-6.23	-1.45	0.03	3.49	10.59
Quarterly flow (%)	6.11	23.36	23.26	21.31	-12.54	-4.22	1.39	11.15	27.37
Monthly return (%)	0.81	4.96	2.67	4.48	-5.46	-1.69	1.16	3.72	6.40
Quarterly return (%)	2.39	9.00	4.95	7.95	-9.40	-1.29	3.50	7.33	12.26
Assets ($ millions)	2,008.97	8,828.37			20.30	62.40	234.35	941.70	4,004.30
Age (years)	6.80	4.15			1.91	3.40	6.13	9.53	12.52
Expense (%)	0.42	0.20			0.14	0.25	0.40	0.60	0.70
Management Fee (%)	0.34	0.18			0.08	0.20	0.35	0.48	0.55
Turnover (%)	0.37	0.38			0.06	0.11	0.24	0.49	0.90

Table 2

Aggregate flow summary statistics

This table reports summary statistics for the aggregate flows to active mutual funds (AMFs), index mutual funds (IMFs) and exchange-traded funds (ETFs), computed each month as the sum of all dollar flows to the fund type normalized by the lagged market capitalization of the CRSP value-weighted index. Panel A presents the distribution of aggregate flows from January 2005 to December 2017 and Panel B the autocorrelation, contemporaneous correlation, and cross-autocorrelation. Panel C table presents the results of time-series regressions of net flows. t-statistics are presented below the coefficients. The p-value from the LaGrange multiplier test of Godfrey (1978) and Breusch (1978) for first-order autocorrelation of the residuals is shown in the last row (H_0: no autocorrelation). * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

Panel A: Distribution of aggregate flows

	AMF	IMF	ETF
Mean	-0.05	-0.00	0.02
Std. Dev	0.04	0.02	0.06
10%	-0.10	-0.02	-0.04
25%	-0.07	-0.01	-0.01
50%	-0.04	0.00	0.02
75%	-0.02	0.01	0.05
90%	0.00	0.01	0.08

Panel B: Correlation of aggregate flows

	AMF	IMF	ETF	CRSP
Autocorrelation				
	0.331***	0.492***	0.035	0.128
Contemporaneous correlations				
AMF	1.000			
IMF	0.138*	1.000		
ETF	-0.218***	-0.271***	1.000	
CRSP VW	0.273***	-0.122	0.180**	1.000
Cross-correlations				
AMF(t-1)	0.331***	-0.077	-0.035	0.040
IMF (t-1)	-0.093	0.492***	-0.144*	-0.057
ETF (t-1)	-0.059	0.104	0.035	-0.269***
CRSP VW (t-1)	0.314***	0.002	-0.142*	0.128

Panel C: Time-series regressions of aggregate flows

	One Lag			Two Lags			Three Lags		
	AMF	IMF	ETF	AMF	IMF	ETF	AMF	IMF	ETF
Agg. Flow (t-1)	0.331***	0.493***	0.035	0.282***	0.494***	0.033	0.253***	0.494***	0.036
	4.34	7.00	0.43	3.51	6.07	0.40	3.14	6.03	0.44
Agg. Flow (t-2)				0.114	-0.004	-0.001	0.052	-0.012	-0.004
				1.42	-0.05	-0.02	0.64	-0.13	-0.05
Agg. Flow (t-3)							0.202**	0.015	0.118
							2.55	0.18	1.45
Constant	-0.031***	-0.002	0.022***	-0.029***	-0.002	0.023***	-0.024***	-0.002	0.020***
	-6.65	-1.16	4.56	-5.42	-1.15	4.37	-4.18	-1.15	3.63
Adjusted R-squared	0.104	0.237	-0.005	0.104	0.232	-0.012	0.129	0.226	-0.005
Observations	155	155	155	154	154	154	153	153	153
LM test	0.076	0.966	0.467	0.034	0.853	0.752	0.654	0.962	0.479

Table 3

Time-series regressions with expected and unexpected aggregate flows

This table presents the results of time-series regressions of the CRSP value-weighted index returns in month t on the expected and unexpected components of aggregate flows to active mutual funds (AMFs), index mutual funds (IMFs), and exchange-traded funds (ETFs) from the predictive models of Table 2 Panel C. Also presented are the regressions of unexpected aggregated flows to the investment vehicles on CRSP index returns. Panel A conducts the test for the full sample from January 2005 to December 2017. Panel B limits the sample period to the most recent five years. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

Panel A: Full sample (January 2005 — December 2017)

Dependent Variable:	CRSP value-weighted index return (t)			Unexpected aggregate flows (t)		
	AMF	IMF	ETF	AMF	IMF	ETF
Expected Aggregate Flow	14.176	-23.798	-98.990**			
	0.68	-0.75	-2.06			
Unexpected Aggregate Flow	30.788***	-23.216	15.596***			
	3.56	-1.29	2.63			
CRSP VW (t)				0.002***	-0.001	0.003***
				3.15	-1.35	2.69
CRSP VW (t-1)				0.002***	0.000	-0.001
				2.76	0.32	-0.94
CRSP VW (t-2)				-0.000	-0.000	-0.000
				-0.11	-1.01	-0.38
Constant	1.448	0.700**	3.070***	-0.003	0.001	-0.001
	1.40	1.98	2.66	-1.06	0.37	-0.26
Adjusted R-squared	0.068	0.002	0.057	0.106	-0.002	0.031
Observations	153	153	153	153	153	153

Panel B: Most recent five years (January 2013 — December 2017)

Dependent Variable:	CRSP value-weighted index return (t)			Unexpected aggregate flows (t)		
	AMF	IMF	ETF	AMF	IMF	ETF
Expected Aggregate Flow	-2.383	97.448	-23.261			
	-0.08	1.47	-0.44			
Unexpected Aggregate Flow	15.388	-15.425	23.396***			
	1.29	-0.46	3.61			
CRSP VW (t)				0.001	-0.001	0.009***
				0.99	-0.99	3.99
CRSP VW (t-1)				-0.002	-0.000	0.004*
				-1.30	-0.15	1.87
CRSP VW (t-2)				-0.001	0.000	0.001
				-0.83	0.34	0.40
Constant	1.003	1.490***	1.483	0.003	0.001	-0.006
	0.71	3.53	1.10	0.60	0.45	-0.78
Adjusted R-squared	-0.005	0.020	0.162	0.012	-0.032	0.194
Observations	60	60	60	60	60	60

Table 4

The predictability of fund flows

This table reports regressions of fund flows on past flows and returns for active mutual funds (AMF), index mutual funds (IMF), and exchange-traded funds (ETF) monthly in Panel A and quarterly in Panel B. Newey-West standard errors with twelve lags in the monthly and eight lags in the quarterly are used in Fama MacBeth specifications. Pooled and fund fixed effects regressions use date fixed effects and standard errors clustered at the fund and date level. Panel C shows regressions of monthly flows on the fund's excess return to the average for its type and the average fund type return over the average return of all funds. Panel C standard errors are clustered at the fund level. t-statistics are below the coefficients. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

Panel A: Monthly

	Fama MacBeth			Pooled			Fund Fixed Effects		
Variable:	AMF	IMF	ETF	AMF	IMF	ETF	AMF	IMF	ETF
Flow (t-1)	0.191***	0.057**	-0.013	0.199***	-0.003	0.029	0.181***	-0.036	0.008
	24.85	2.04	-0.46	22.62	-0.11	1.64	20.16	-1.24	0.42
Flow (t-2)	0.105***	0.063**	0.018	0.108***	0.041	0.038***	0.094***	0.007	0.017*
	19.45	2.48	1.51	21.58	1.64	3.68	19.01	0.30	1.73
Flow (t-3)	0.077***	0.023	0.055***	0.080***	0.029	0.056***	0.069***	-0.002	0.037***
	16.03	1.23	4.76	16.82	1.36	4.98	14.49	-0.09	3.20
Flow (t-4)	0.053***	0.051***	0.031***	0.054***	0.005	0.023*	0.044***	-0.025	0.005
	15.73	2.99	3.11	11.82	0.23	1.85	9.66	-1.18	0.44
Flow (t-5)	0.044***	0.034**	0.026*	0.041***	0.037*	0.017	0.033***	0.006	-0.001
	8.31	2.42	1.86	9.29	1.92	1.60	7.39	0.28	-0.07
Flow (t-6)	0.038***	0.074***	0.021**	0.035***	0.055***	0.023***	0.028***	0.025	0.006
	9.41	4.17	2.11	7.98	2.92	2.72	6.30	1.26	0.75
Flow (t-7)	0.023***	0.038**	0.026**	0.021***	0.020	0.009	0.014***	-0.011	-0.007
	6.82	2.15	2.36	5.10	1.33	1.13	3.42	-0.78	-0.88
Flow (t-8)	0.028***	0.038**	0.030***	0.028***	0.056***	0.017*	0.021***	0.025	0.001
	8.33	2.57	3.33	6.32	3.44	1.83	4.76	1.56	0.13
Flow (t-9)	0.019***	0.019	0.023***	0.019***	0.034**	0.017*	0.013***	0.007	0.002
	4.66	1.23	3.29	4.97	1.98	1.87	3.36	0.44	0.24
Flow (t-10)	0.021***	0.034*	0.016**	0.019***	0.021	0.007	0.013***	-0.006	-0.008
	4.60	1.82	2.03	5.17	1.11	0.77	3.61	-0.32	-0.89
Flow (t-11)	0.014***	0.018	0.013*	0.017***	0.014	0.016**	0.010***	-0.012	0.000
	2.78	1.28	1.67	4.26	0.70	2.20	2.62	-0.63	0.02
Flow (t-12)	0.029***	0.042***	0.019**	0.030***	0.056***	0.014	0.023***	0.031	-0.001
	8.76	2.90	2.17	7.84	2.69	1.63	6.15	1.48	-0.11
Return (t-1)	0.276***	0.297***	0.814***	0.207***	0.238***	0.561***	0.206***	0.233***	0.567***
	14.11	7.06	9.95	16.38	4.09	12.03	16.36	3.86	12.28
Return (t-2)	0.157***	0.115*	0.384***	0.107***	0.059	0.249***	0.110***	0.062	0.267***
	11.05	1.97	7.65	9.84	1.47	6.52	10.29	1.58	7.02
Return (t-3)	0.110***	0.140**	0.151***	0.078***	0.049	0.063*	0.083***	0.053	0.086***
	11.90	2.30	3.92	7.63	1.15	1.86	8.31	1.25	2.66
Return (t-4)	0.083***	0.164**	0.080	0.048***	0.031	0.007	0.054***	0.037	0.031
	10.58	2.49	1.52	5.65	0.82	0.22	6.54	0.96	0.91
Return (t-5)	0.066***	0.179***	-0.022	0.037***	0.046	-0.058*	0.044***	0.055	-0.035
	7.40	2.67	-0.49	3.70	1.12	-1.78	4.57	1.32	-1.03
Return (t-6)	0.079***	0.124**	0.090	0.046***	-0.002	0.017	0.054***	0.006	0.038
	8.58	2.19	1.24	4.64	-0.06	0.56	5.65	0.19	1.24
Return (t-7)	0.058***	0.105*	-0.002	0.049***	0.004	-0.039	0.057***	0.012	-0.017
	8.29	1.95	-0.04	5.10	0.12	-1.43	6.08	0.34	-0.63
Return (t-8)	0.044***	0.167***	0.016	0.029***	0.095***	-0.003	0.038***	0.103***	0.020
	4.71	3.45	0.34	3.24	2.84	-0.09	4.47	3.06	0.69
Return (t-9)	0.048***	0.079	0.030	0.020**	-0.019	-0.014	0.029***	-0.008	0.008
	5.84	1.61	0.59	2.19	-0.52	-0.48	3.30	-0.22	0.27
Return (t-10)	0.025***	0.002	0.011	0.008	-0.005	-0.025	0.018*	0.007	-0.004
	2.76	0.04	0.23	0.90	-0.18	-0.72	1.91	0.27	-0.11
Return (t-11)	0.026**	0.145***	-0.098*	0.031***	0.061**	-0.023	0.040***	0.074**	-0.001
	2.52	2.82	-1.91	3.47	2.04	-0.81	4.79	2.46	-0.05
Return (t-12)	0.028***	0.027	-0.036	0.010	0.015	-0.003	0.021***	0.029	0.018
	3.90	0.51	-1.09	1.39	0.47	-0.09	2.90	0.87	0.60
R-squared				0.195	0.038	0.073	0.210	0.069	0.093
Observations	301,157	30,802	41,563	301,157	30,802	41,563	301,087	30,795	41,552
Flow Sum	0.642***	0.491***	0.265***	0.651***	0.365***	0.266***	0.543***	0.009	0.059*
Return Sum	1.000***	1.544***	1.418***	0.670***	0.572***	0.732***	0.754***	0.663***	0.978***

Panel B: Quarterly

Variable	Fama MacBeth AMF	Fama MacBeth IMF	Fama MacBeth ETF	Pooled AMF	Pooled IMF	Pooled ETF	Fund Fixed Effects AMF	Fund Fixed Effects IMF	Fund Fixed Effects ETF
Flow (q-1)	0.210***	0.140***	0.023	0.213***	0.104***	0.052**	0.167***	0.036	-0.007
	23.64	5.27	1.34	20.66	3.18	2.44	14.93	1.01	-0.34
Flow (q-2)	0.105***	0.081**	0.076***	0.104***	0.020	0.057**	0.072***	-0.043	0.004
	8.45	2.32	4.49	12.32	0.51	2.54	7.83	-1.02	0.20
Flow (q-3)	0.066***	0.034	0.073***	0.067***	0.058	0.051**	0.042***	-0.008	0.003
	8.62	0.54	3.98	12.51	1.66	2.40	7.03	-0.23	0.11
Flow (q-4)	0.057***	0.091***	0.021**	0.061***	0.098**	0.022	0.040***	0.037	-0.019
	11.93	2.99	2.21	8.15	2.19	1.31	5.43	0.87	-1.19
Flow (q-5)	0.024***	0.035*	0.047**	0.027***	0.026	0.025*	0.011	-0.035	-0.009
	3.62	1.77	2.13	3.97	0.93	1.75	1.60	-1.38	-0.62
Flow (q-6)	0.024***	0.080***	0.034**	0.026***	0.056*	0.021	0.011*	-0.004	-0.008
	3.51	3.27	2.30	4.28	1.86	1.49	1.75	-0.11	-0.55
Flow (q-7)	0.017***	0.020	0.007	0.015**	0.080**	0.014	0.001	0.037	-0.013
	3.39	1.13	0.48	2.39	2.31	1.02	0.22	1.29	-1.08
Flow (q-8)	0.025***	0.041**	0.011	0.027***	0.073***	0.004	0.014**	0.033*	-0.023**
	4.65	2.42	1.01	4.43	3.92	0.49	2.34	1.91	-2.02
Return (q-1)	0.479***	0.243*	0.676***	0.335***	0.134	0.490***	0.341***	0.143	0.465***
	11.29	1.70	10.91	8.29	1.18	5.57	8.68	1.34	5.38
Return (q-2)	0.261***	0.370***	-0.073	0.194***	0.003	-0.066	0.214***	0.016	-0.059
	10.67	2.90	-0.83	5.98	0.04	-1.00	6.48	0.21	-0.88
Return (q-3)	0.192***	0.214**	-0.074	0.146***	0.099	-0.029	0.174***	0.117	-0.033
	6.81	2.28	-0.65	5.20	1.52	-0.46	6.81	1.63	-0.51
Return (q-4)	0.103***	0.209**	-0.111	0.072***	0.075	-0.069	0.104***	0.093	-0.076
	4.72	2.04	-1.12	2.71	1.12	-1.24	4.06	1.37	-1.37
Return (q-5)	0.046**	0.062	-0.156	0.008	-0.079	-0.130**	0.042	-0.048	-0.144**
	2.65	0.57	-1.42	0.31	-1.29	-2.23	1.67	-0.81	-2.30
Return (q-6)	0.003	0.077	-0.329**	-0.001	-0.001	-0.063	0.035	0.032	-0.081
	0.08	0.79	-2.58	-0.03	-0.03	-0.99	1.09	0.72	-1.25
Return (q-7)	0.044**	-0.114*	0.070	0.026	0.017	0.036	0.062**	0.046	0.016
	2.31	-1.77	0.81	0.87	0.21	0.54	2.11	0.58	0.23
Return (q-8)	0.034**	-0.036	0.066	0.029	0.047	-0.037	0.068***	0.071	-0.045
	2.33	-0.52	0.84	1.33	0.97	-0.59	2.80	1.37	-0.70
R-squared				0.164	0.094	0.067	0.205	0.153	0.126
Observations	92,517	9,498	12,011	92,517	9,498	12,011	92,400	9,487	12,000
Flow Sum	0.528***	0.522***	0.292***	0.540***	0.515***	0.246***	0.358***	0.053	-0.072
Return Sum	1.162***	1.025***	0.069	0.809***	0.295	0.132	1.040***	0.470	0.043

Panel C: Monthly flow and relative returns

Variable:	AMF (1)	AMF (2)	IMF (3)	IMF (4)	ETF (5)	ETF (6)
Fund Ret - Type Ret (t-1)	0.239***	0.214***	0.268***	0.238***	0.577***	0.565***
	26.04	23.09	4.71	4.48	16.62	15.29
Fund Ret - Type Ret (t-2)		0.158***		0.067*		0.279***
		20.91		1.70		9.28
Fund Ret - Type Ret (t-3)		0.137***		0.069		0.115***
		19.09		1.42		5.12
Fund Ret - Type Ret (t-4)		0.111***		0.049		0.060**
		17.53		1.14		2.45
Fund Ret - Type Ret (t-5)		0.096***		0.058		-0.019
		13.15		1.51		-0.97
Fund Ret - Type Ret (t-6)		0.104***		0.017		0.047**
		13.66		0.51		2.47
Fund Ret - Type Ret (t-7)		0.107***		0.034		-0.010
		18.58		0.99		-0.60
Fund Ret - Type Ret (t-8)		0.094***		0.120***		0.016
		15.22		2.95		0.89
Fund Ret - Type Ret (t-9)		0.084***		0.017		0.014
		13.99		0.41		0.70
Fund Ret - Type Ret (t-10)		0.071***		0.040		-0.002
		12.74		1.47		-0.09
Fund Ret - Type Ret (t-11)		0.091***		0.086**		0.002
		17.33		2.46		0.09
Fund Ret - Type Ret (t-12)		0.077***		0.051		0.016
		14.76		1.55		0.85
Type Ret - All Funds Ret (t-1)	0.069	-0.076	0.364**	0.313*	0.725***	0.669***
	0.51	-0.54	2.23	1.78	4.80	3.95
Type Ret - All Funds Ret (t-2)		1.346***		-0.214		0.256*
		10.55		-1.65		1.65
Type Ret - All Funds Ret (t-3)		0.528***		-0.151		0.309**
		4.18		-1.04		1.98
Type Ret - All Funds Ret (t-4)		0.847***		0.141		-0.273*
		6.76		1.08		-1.84
Type Ret - All Funds Ret (t-5)		0.651***		0.038		0.039
		5.24		0.25		0.26
Type Ret - All Funds Ret (t-6)		-0.050		-0.138		0.102
		-0.41		-0.97		0.74
Type Ret - All Funds Ret (t-7)		0.043		0.065		0.722***
		0.36		0.49		4.58
Type Ret - All Funds Ret (t-8)		0.890***		0.005		0.517***
		6.85		0.04		3.69
Type Ret - All Funds Ret (t-9)		-0.107		-0.071		0.662***
		-0.86		-0.55		4.59
Type Ret - All Funds Ret (t-10)		-0.490***		0.333**		0.264*
		-3.89		2.30		1.76
Type Ret - All Funds Ret (t-11)		0.439***		-0.031		0.403***
		3.43		-0.25		2.93
Type Ret - All Funds Ret (t-12)		-0.039		-0.248**		0.229*
		-0.29		-2.12		1.70
Constant	0.036	-0.177***	0.579***	0.334***	1.729***	1.244***
	1.60	-8.15	6.23	3.85	36.55	18.28
R-squared	0.009	0.036	0.268***	0.238***	0.024	0.038
Observations	329,091	276,684	34,011	28,461	48,446	40,625
Sum of all coefficients	0.307	5.328	0.631	0.886	1.303	4.982
p-value	0.020	0.000	0.000	0.152	0.000	0.000
Sum (Type Ret-All Funds Ret)		3.983		0.043		3.899
p-value		0.000		0.939		0.000

Table 5

The flow-performance relation

This table presents the results of panel regressions examining the flow-return relation for active mutual funds (AMFs), index mutual funds (IMFs), exchange-traded funds (ETFs). The dependent variable is percentage fund flows and the independent variables are lagged performance and fund characteristics. A piecewise linear regression is used to define three linear segments of the flow-return relationship. Each month funds are ranked relative to funds of the same type according to their return in excess of the CRSP equal weighted index, CRSP value weighted index, the average performance of other funds of the same type in the same Lipper objective, and raw returns. This procedure produces three performance variables for fund j of investment vehicle type f in month t: $Low_{j,f,t-1} = \min(0.2, Rank_{j,f,t-1})$, $Mid_{j,f,t-1} = \min(0.6, Rank_{j,f,t-1} - Low_{j,f,t-1})$, and $High_{j,f,t-1} = Rank_{j,f,t-1} - (Low_{j,f,t-1} + Mid_{j,f,t-1})$. Control variables include the lag of logged fund age in years, the lag of logged fund assets in millions, lagged expense ratio, lagged flow, lagged volatility of 12 month returns, and the monthly dollar flow to all funds of the same type and Lipper category divided by lagged aggregate assets ($Cat\ Flow$). The regression also uses date and style fixed effects. t-statistics computed using standard errors clustered at the fund and date are presented below the coefficients. p-values from a Wald test of the equality of the top and bottom performance coefficients are reported in the last row of the table. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

	Return relative to											
	CRSP equal weight			CRSP value weight			Lipper objective			Raw returns		
	AMF	IMF	ETF	AMF	IMF	ETF	AMF	IMF	ETF	AMF	IMF	ETF
Low(t-1)	2.516***	2.702**	3.347**	2.541***	2.727**	3.616**	2.936***	2.457	6.078***	2.530***	2.736**	3.805**
	7.14	2.07	2.01	7.21	2.09	2.15	8.82	1.53	4.13	7.19	2.11	2.26
Mid(t-1)	0.440***	0.423	3.245***	0.438***	0.422	3.214***	0.417***	0.431	2.417***	0.457***	0.409	3.141***
	5.84	1.53	9.17	5.80	1.50	9.10	5.88	1.46	7.14	6.05	1.50	8.83
High(t-1)	6.312***	2.644	17.332***	6.304***	2.627	17.341***	6.145***	1.924	14.428***	6.158***	2.700	17.323***
	13.78	1.60	7.88	13.78	1.58	7.91	14.09	1.15	7.01	13.25	1.57	7.73
Log Age (t-1)	-0.705***	-0.944***	-1.256***	-0.705***	-0.944***	-1.256***	-0.702***	-0.945***	-1.269***	-0.704***	-0.945***	-1.256***
	-18.08	-5.42	-7.29	-18.08	-5.42	-7.29	-18.07	-5.41	-7.28	-18.07	-5.42	-7.29
Log Assets (t-1)	0.079***	-0.011	-0.175***	0.079***	-0.011	-0.175***	0.078***	-0.011	-0.158***	0.079***	-0.011	-0.175***
	5.54	-0.16	-3.08	5.54	-0.16	-3.08	5.49	-0.16	-2.77	5.53	-0.16	-3.08
Expense Ratio (t-1)	-0.307***	-0.294	-3.648***	-0.307***	-0.293	-3.647***	-0.311***	-0.281	-3.670***	-0.306***	-0.294	-3.645***
	-4.37	-0.96	-6.26	-4.37	-0.96	-6.26	-4.46	-0.89	-6.28	-4.37	-0.96	-6.26
12M Return Volatility (t-1)	-0.244***	-0.053	-0.147**	-0.244***	-0.053	-0.145**	-0.244***	-0.056	-0.101	-0.243***	-0.052	-0.143**
	-7.38	-0.44	-2.12	-7.38	-0.44	-2.08	-7.46	-0.46	-1.45	-7.38	-0.44	-2.03
Category Flows (%)	0.678***	0.757***	0.511***	0.678***	0.757***	0.511***	0.743***	0.767***	0.548***	0.679***	0.757***	0.511***
	12.28	7.13	11.30	12.28	7.13	11.30	12.22	7.34	11.99	12.27	7.13	11.30
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.049	0.055	0.123	0.049	0.055	0.123	0.049	0.054	0.117	0.049	0.055	0.123
Observations	301,092	30,802	41,563	301,092	30,802	41,563	301,092	30,802	41,563	301,092	30,802	41,563
Difference High-Low	3.796	-0.058	13.985	3.764	-0.100	13.724	3.209	-0.534	8.350	3.627	-0.036	13.518
Wald test (p-value)	0.000	0.975	0.000	0.000	0.956	0.000	0.000	0.828	0.000	0.000	0.985	0.000

Table 6

Performance of new money portfolios using fund-level approach

This table presents the returns of portfolios of active mutual funds (AMFs), index mutual funds (IMFs), and exchange-traded funds (ETFs) from January 2005 to December 2017 formed on the basis of the prior month's flows. Individual fund excess return, Excess, is computed as $R_{j,t} - R_{m,t}$ where $R_{j,t}$ is the return of fund j in month t and $R_{m,t}$ is the return on the CRSP value-weighted index. The alphas are based on the CAPM, the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). Factor loadings for month t are estimated using a 36 month rolling window prior to the month of analysis. For each month, the portfolio performance is computed as either the value-weighted (VW), equal-weighted (EW), or dollar cash flow-weighted (CW) average of the measure for the funds comprising the portfolio. Panel A presents the time-series average performance of each portfolio is presented in the first row with the t-statistic for its difference from zero below. Panel B presents the results for the performance difference between portfolios. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

Panel A: Portfolio Returns

	AMF				IMF				ETF			
	Excess	1 Factor	3 Factor	4 Factor	Excess	1 Factor	3 Factor	4 Factor	Excess	1 Factor	3 Factor	4 Factor
1. All Funds (EW)	-0.047	-0.100**	-0.093***	-0.098***	0.010	-0.064*	-0.044**	-0.049**	-0.032	-0.119**	-0.103***	-0.092***
	-1.11	-2.14	-2.98	-3.18	0.25	-1.80	-2.11	-2.38	-0.74	-2.58	-2.93	-2.85
2. All Funds (VW)	-0.024	-0.053	-0.061*	-0.071**	0.016	-0.035**	-0.022	-0.025	-0.007	-0.050*	-0.029	-0.036
	-0.83	-1.46	-1.85	-2.16	0.56	-2.04	-1.44	-1.60	-0.25	-1.90	-1.19	-1.47
3. Positive cash flow (EW)	-0.047	-0.076	-0.065*	-0.077**	0.025	-0.051	-0.029	-0.034	-0.028	-0.117**	-0.083**	-0.083**
	-1.06	-1.55	-1.87	-2.40	0.57	-1.34	-1.28	-1.57	-0.63	-2.27	-1.99	-2.20
4. Negative cash flow (EW)	-0.049	-0.114**	-0.107***	-0.108***	-0.008	-0.081**	-0.059***	-0.064***	-0.035	-0.110**	-0.111**	-0.092**
	-1.10	-2.41	-3.44	-3.42	-0.21	-2.25	-2.73	-2.89	-0.64	-2.01	-2.57	-2.25
5. Positive cash flow (CW)	-0.080	-0.079	-0.013	-0.054	-0.020	-0.058	0.016	0.002	-0.101	-0.140***	-0.107**	-0.082**
	-1.28	-1.21	-0.21	-0.95	-0.22	-0.72	0.36	0.04	-1.63	-2.74	-2.54	-2.10
6. Negative cash flow (CW)	-0.066*	-0.118***	-0.111***	-0.109***	-0.013	-0.073**	-0.045*	-0.037	-0.000	-0.006	-0.016	-0.021
	-1.73	-2.83	-3.07	-3.04	-0.30	-2.14	-1.82	-1.56	-0.01	-0.10	-0.34	-0.43

Panel B: Difference in positive and negative portfolio returns

	AMF				IMF				ETF			
	Excess	1 Factor	3 Factor	4 Factor	Excess	1 Factor	3 Factor	4 Factor	Excess	1 Factor	3 Factor	4 Factor
Portfolio 2-Portfolio 1	0.023	0.047	0.032**	0.027*	0.005	0.029	0.021*	0.024**	0.025	0.069*	0.074***	0.056**
	0.74	1.65	2.27	1.83	0.18	1.07	1.74	2.01	0.60	1.95	2.83	2.59
Portfolio 3-Portfolio 4	0.002	0.038	0.042**	0.031*	0.033	0.030	0.031**	0.030**	0.007	-0.007	0.029	0.010
	0.09	1.57	2.10	1.76	1.52	1.51	2.12	2.06	0.13	-0.14	0.66	0.23
Portfolio 5-Portfolio 6	-0.013	0.039	0.098	0.055	-0.007	0.015	0.061	0.039	-0.100	-0.134*	-0.090	-0.061
	-0.19	0.63	1.61	0.96	-0.08	0.18	1.27	0.84	-1.07	-1.67	-1.55	-1.03

Table 7

Relation between trading activity and flow

This table presents the results of regressions of proxies for net trading activity, $Net\ Trading\ Activity_{j,q}$ on quarterly fund flows, $Flows_{j,q}$. Following Fang, Peress, and Zhang we use quarterly fund holdings reports to proxy for fund $j's$ trading activity using the end of quarter price of fund holding i, with

$$Net\ Trading\ Activity_{j,q} = \frac{Trading\ Buy_{j,q} - Trading\ Sell_{j,q}}{Total\ Assets_{j,q-1}},$$

where

$$Trading\ Buy_{j,q} = \sum_{i=1}^{N} prc_{i,q} * \Delta shares_{i,g,q} if\ \Delta shares_{i,g,q} > 0$$

$$Trading\ Sell_{j,q} = \sum_{i=1}^{N} -prc_{i,q} * \Delta shares_{i,g,q} if\ \Delta shares_{i,g,q} < 0.$$

The regressions include date fixed effects and t-statistics computed with standard errors clustered at the date and fund level are presented below the coefficients. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

	AMF		IMF		ETF	
Quarterly Flow	0.652***	0.652***	0.561***	0.582***	0.780***	0.781***
	33.95	33.98	7.19	7.94	26.27	26.25
% Cash		-0.017		-0.336***		0.221
		-1.17		-3.82		0.98
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.435	0.435	0.141	0.148	0.571	0.571
Observations	72,788	72,788	7,543	7,543	12,529	12,529

Table 8

Fund response to flows

This table reports regression analyses of mutual fund trading in response to flows. The dependent variable in all specifications is $trade_{j,s,q}$, which measures the percentage change in split-adjusted shares held by fund j in stock s from quarters $q-1$ to q. The main covariate of interest is $flow_{j,q}$, the percentage capital flow to the fund. Other control variables include the portion of stock s shares outstanding help by fund j in the previous quarter, $own_{j,s,q-1}$, and a proxy for the illiquidity of the stock, $Amihud_{s,q-1}$, which measures the price impact of a trade. The regression also uses date fixed effects. t-statistics computed with standard errors clustered at the fund and date level are presented below the coefficients. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

	Outflow						Inflow					
	AMF		IMF		ETF		AMF		IMF		ETF	
Flow (t)	1.098***	1.144***	0.695***	0.903***	1.086***	1.121***	0.849***	0.948***	0.529***	0.630***	0.965***	0.986***
	35.69	36.46	6.83	6.19	22.93	22.69	17.37	16.75	7.13	4.84	19.26	20.17
Own (t-1)		0.066		-4.579**		1.312		1.314***		-10.431**		1.783
		0.36		-2.31		1.52		5.26		-2.49		1.24
Flow (t) * Own (t-1)		-0.027		-0.969		0.003		-0.416***		-0.877***		-0.429
		-1.26		-1.20		0.05		-7.68		-5.24		-1.50
Amihud (t-1)		-0.470		0.889**		-0.830		0.174		0.524**		0.511
		-0.88		1.98		-1.47		0.65		2.04		1.29
Flow (t) * Amihud (t-1)		0.019		0.050		-0.131		0.022***		-0.002		-0.048*
		0.12		0.84		-0.96		3.51		-0.08		-1.66
R-squared	0.011	0.012	0.025	0.033	0.074	0.119	0.042	0.051	0.120	0.160	0.267	0.317
Observations	5,027,429	4,072,317	2,202,948	1,582,153	1,337,855	1,240,481	3,184,382	2,208,413	2,516,482	1,856,989	1,960,539	1,829,134

Table 9

Flow induced price pressure

This table presents the results of the impact of fire sales and forced buys by active mutual funds (AMFs), index mutual funds (IMFs) and exchange-traded funds (ETFs) on monthly stock returns Panel A and quarterly in Panel B for holdings between January 2009 and December 2017. Excess return is computed as the percentage stock return above that of the average stock held by funds at the beginning of the month. A stock is identified as a fire sale if the pressure measure, computed as difference between the stock purchased by funds in the top decile of quarterly flows minus the stock sold by funds in the bottom decile of quarterly flows as a percentage of lagged shares outstanding, is negative and in the bottom ten percent of all stocks that quarter. A stock is a forced buy if the measure is positive and in the top 10%. Average abnormal returns are calculated each month, then the time-series of mean abnormal returns is used to control for potential cross-sectional dependence in the monthly abnormal returns. We require at least 25 firms in a quarter for the firm average return to be included as an observation. t-statistics are presented next to the mean return. * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.

Panel A: Monthly

	Fire Sales						Forced Buys					
	AMF		IMF		ETF		AMF		IMF		ETF	
Event Month	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic
-6	0.111	0.76	0.225	1.58	0.809***	4.33	0.703***	5.30	0.458***	2.79	0.233	1.27
-5	-0.024	-0.17	0.236	1.59	0.602***	3.28	0.849***	6.39	0.331*	1.87	0.585***	3.25
-4	-0.172	-1.28	0.191	1.43	0.337**	2.05	0.875***	6.93	0.200	1.11	0.793***	4.34
-3	-0.353**	-2.55	0.019	0.14	-0.100	-0.56	0.822***	6.40	0.203	1.14	0.927***	5.49
-2	-0.505***	-3.20	-0.077	-0.59	-0.574***	-2.85	0.757***	6.11	0.340*	1.95	1.064***	6.04
-1	-0.461***	-3.01	-0.104	-0.77	-0.737***	-4.15	0.616***	4.84	0.298	1.53	1.176***	6.68
Event 1	-0.388**	-2.62	0.014	0.10	-0.565***	-3.32	0.516***	4.44	0.235	1.22	0.984***	5.29
Event 2	0.046	0.36	0.280**	2.14	-0.035	-0.25	0.258**	2.03	0.203	1.11	0.490***	2.88
Event 3	0.228*	1.82	0.345**	2.63	0.182	1.20	0.198	1.53	0.221	1.40	0.100	0.69
1	0.324***	2.65	0.331***	2.88	0.156	0.94	0.038	0.31	0.073	0.49	-0.026	-0.17
2	0.222**	2.03	0.121	0.99	0.302*	1.85	0.116	0.95	0.033	0.21	-0.076	-0.48
3	0.182*	1.75	0.156	1.29	0.270*	1.71	0.154	1.27	0.029	0.19	-0.037	-0.22
4	0.197*	1.87	0.147	1.17	0.383***	2.67	0.078	0.65	0.027	0.17	-0.059	-0.38
5	0.158	1.53	0.189	1.47	0.197	1.37	0.107	0.89	-0.039	-0.26	0.225	1.37
6	0.218*	1.93	0.172	1.39	0.286*	1.94	0.072	0.61	0.049	0.32	0.197	1.22
7	0.138	1.25	0.276**	2.29	0.244	1.57	0.074	0.64	0.047	0.32	0.229	1.42
8	0.168	1.52	0.369***	3.04	0.265	1.65	0.085	0.68	0.116	0.86	0.104	0.76
9	0.143	1.33	0.281**	2.31	0.293*	1.90	0.005	0.04	0.070	0.50	0.083	0.62
10	0.159	1.46	0.223*	1.86	0.418***	2.95	0.018	0.15	0.081	0.52	0.042	0.28
11	0.166	1.54	0.179	1.48	0.243*	1.80	-0.014	-0.13	0.128	0.82	0.126	0.84
12	0.088	0.82	0.261**	2.24	0.122	0.92	0.049	0.49	0.097	0.63	0.208	1.33
13	0.096	0.93	0.206*	1.78	-0.020	-0.14	0.048	0.47	0.221	1.56	0.326**	2.26
14	0.119	1.20	0.253**	2.34	0.162	1.17	0.112	1.01	0.215	1.46	0.221	1.35
15	0.231**	2.39	0.300***	2.67	0.127	0.96	0.065	0.57	0.187	1.32	0.234	1.43
16	0.252***	2.64	0.263**	2.26	0.150	1.21	0.052	0.48	0.168	1.32	0.102	0.63
17	0.276***	2.77	0.222*	1.97	0.153	1.20	0.016	0.16	0.156	1.20	0.178	1.11
18	0.188*	1.80	0.118	1.03	0.176	1.34	0.083	0.85	0.268**	2.10	0.141	0.84
Sum of												
Event Months	-0.168	-0.78	0.633**	2.58	-0.441	-1.48	0.949***	4.66	0.651*	1.98	1.556***	5.75
Months 1-6	1.121***	3.76	0.978***	4.58	1.484***	4.95	0.266	1.20	-0.025	-0.08	0.071	0.24
Months 1-12	1.752***	4.18	2.303***	7.20	2.678***	5.51	-0.037	-0.13	0.384	0.93	0.580	1.25
Months 1-18	2.634***	5.24	3.522***	9.65	3.214***	5.87	0.098	0.27	1.374***	2.70	1.718***	2.96

Panel B: Quarterly

	Fire Sales						Forced Buys					
	AMF		IMF		ETF		AMF		IMF		ETF	
Event Quarter	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic	Excess Return	t-statistic
-2	0.380	0.75	0.595	1.20	2.417***	3.79	1.991***	4.23	1.335**	2.18	0.578	1.01
-1	-1.148**	-2.55	0.063	0.11	-0.429	-0.62	2.452***	5.65	0.511	0.78	2.876***	5.70
Event 1	-1.198**	-2.69	-0.078	-0.19	-1.817***	-3.05	1.626***	5.03	0.676	1.02	3.046***	5.19
1	1.114**	2.48	0.941***	2.78	0.425	0.67	0.064	0.17	0.115	0.27	-0.231	-0.45
2	0.660*	1.78	0.405	0.95	1.081**	2.38	0.223	0.55	-0.029	-0.06	-0.264	-0.56
3	0.487	1.48	0.800*	1.84	0.698	1.29	0.233	0.55	0.019	0.04	0.568	1.07
4	0.560	1.54	0.661	1.66	1.231***	3.08	0.095	0.21	0.107	0.21	0.008	0.02
5	0.337	0.93	0.572	1.45	-0.081	-0.17	0.226	0.73	0.565	1.23	0.929*	1.76
6	0.871**	2.60	0.718*	1.84	0.382	0.87	0.195	0.45	0.407	1.00	0.328	0.52
7	0.637*	1.85	0.264	0.73	0.127	0.34	0.383	1.31	0.666	1.24	0.668	1.16
8	0.456	1.50	0.927**	2.74	0.446	0.76	0.235	0.59	0.847*	1.76	0.089	0.24
Sum of Returns												
Event Q	-1.198**	-2.69	-0.078	-0.19	-1.817***	-3.05	1.626***	5.03	0.676	1.02	3.046***	5.19
Quarters 1-2	1.645**	2.63	1.182**	2.57	1.432**	2.21	-0.000	-0.00	-0.059	-0.12	-0.629	-1.10
Quarters 1-4	2.444***	2.89	2.393***	3.87	2.985***	3.09	-0.170	-0.33	-0.097	-0.14	-0.349	-0.45
Quarters 1-8	4.318***	3.97	4.619***	5.90	3.373**	2.64	0.358	0.50	2.444**	2.56	1.763	1.45