FLOW

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Abstract

We estimate apples-to-apples comparisons of flows to active mutual funds, index mutual funds, and exchange-traded funds (ETFs). The positive contemporaneous correlations between market returns and aggregate flows that were commonplace for active funds are now only prominent for ETFs. The monthly flow-performance relation of ETFs and index funds is larger than active funds. Annually the relation of active funds and ETFs is similar, while the index fund relation is muted. Category performance drives the relation. Extant theories of fund flows are hapless in explaining our results. Consistent with existing theories, flow-induced fire sales and trading are similar for all vehicles.

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What do we know about investment vehicle flows? For active mutual funds there is a vast literature examining the nuances of this question. However, the massive $22 trillion U.S. asset management industry has undergone a shift to new investment vehicles—index mutual funds and exchange-traded funds (ETFs). Despite the growing relevance of these passive products for investors, asset managers, and markets, little is known about the flows of these vehicles. In this paper, we revisit the literature by conducting an apples-to-apples comparison of flows to equity active mutual funds, index mutual funds and ETFs. This enables us to compare identical empirical specifications over identical periods. We explore if the seminal findings of the active mutual fund literature are applicable to the passive alternatives. In doing so, we re-evaluate the appropriateness of extant theories to explain a broader set of investments.

Our paper investigates three facets of pooled equity vehicles: the relation between aggregate flows and the market, the determinants of fund level flows, and the impact of flows on the underlying portfolio. 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. We re-visit Warther's (1995) classic estimation and find that the unexpected component of aggregate active fund flows and ETF flows drive the positive correlation to market returns over a twelve year period. Using monthly data from the most recent five years we find a stark difference. Warther's result is now non-evident for active funds, although it has continued 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. Both index funds and ETFs have monthly flow standard deviations that are almost twice that of active funds and little to no flow persistence. Because we include all three vehicles we are able to estimate, for the first time, total flow-performance sensitivity, that is attributable to the performance a fund relative to other funds of its category, and the performance of its category relative to other categories At the monthly level, index fund total performance is associated with over twice as much flow as active mutual funds, while ETF total performance is associated with four times as much flow as active mutual funds. We find that category performance flow-sensitivity commands larger slopes than the within-product component.

At the annual frequency, active fund and ETF flow-performance sensitivity is similar, while index fund flow-sensitivity is slight. Our approach of expanding the cross-section to all vehicles uncovers a new perspective on flow. Flow-performance sensitivity for active funds and ETFs is estimated using the full data is four times greater than the within-vehicle sensitivity. Thus, the lion's share of the flow-performance relation occurs when a fund's vehicle group outperforms other vehicle groups, rather than when the fund outperforms other funds within its group. Previous estimates of flow-performance sensitivity, starting with Ippolito (1992), are only the tip of the iceberg.

Next, ETFs' flow-to-performance relation is sharply more convex than active funds, while the relationship for index funds is nearly linear.[1] Finally, we find some evidence that active mutual funds and index funds have a smart-money effect, in that flows predict future vehicle performance over the next month. For ETFs, we are unable to reject the no-smart money null. However, the point estimates are insignificantly different between the three investment vehicles.

The results of this section have important implications for several facets of the theoretical and empirical literature. Since ETFs are not typically included in employee retirement accounts, our finding of little flow persistence for ETFs is consistent with Del Guercio and Tkac (2002) conjecture that retirement account contributions cause persistent flows. Our performance-flow results are inconsistent with the litany of other explanations in the literature, including Berk and Green (2004) and Spiegel and Zhang (2013). Surprisingly, ETFs whose managers are well-known to have zero skill behave most like the rational expectations investors modeled in Berk and Green (2004).

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 methodologies are comparable to the skill chasing of active funds. In untabulated results we find that the magnitude of return chasing remains statistically significant for the products they

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[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.

[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.

categorize as purely passive. Also, like Berk and Green (2004) Easley et al. does not provide an explanation for why the most of the flow to actively-managed funds and ETFs is related to the category's relative performance.

The importance of past returns in generating flows to passive vehicles is a critical consideration for 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] The results here support the latter findings, since managers are compensated by increased assets under management which is most significantly related to past returns they are incentivized to actively participate in value enhancing corporate decisions following the logic of Lewellen and Lewellen (2018).

Our third set of results document the relation between flow and the underlying securities in the investment vehicle. In sharp contrast to the flow-performance results, these results are generally consistent with the active mutual fund 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 relation between flows and trading in a near proportional level. The sensitivity of index mutual fund trading to flows is consistent with cash management strategies. Following Coval and Stafford (2007) we find that ETFs induce "fire sales"

[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.

in the stock positions in their portfolios to a greater extent than do active funds. Thus, stocks that are held in vehicles that experience dramatic net outflows have contemporaneous negative returns, followed by long-run positive returns. So, price pressure is just as important for ETFs as it is for active mutual funds. Despite the similarity of the coefficients, accounting for the extreme volatility of passive fund flows suggests that their actual impact on the underlying may be much larger. Our 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 mutual fund flows, suggesting that our results portend ETF flows playing an outsized role contributing to equity returns.

1. Background on investment vehicle structures

Over time, pooled investment vehicles have evolved. This evolution has an impact on capital flows between investors and vehicle and the extent to which vehicles are passive. In this section we provide details on the transformation of the asset management industry and distinguishing features of the fund types considered.

We study pooled equity investment vehicles offering pro-rata ownership to an underlying portfolio of assets. 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 between the fund and investors

[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/

occur only during the initial public offering and liquidation. At periods in between, investors trade closed-end fund shares with other investors on an exchange.

In 1924 the industry transitioned to a new era with 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 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."

A new era in the industry began in 1993 when State Street introduced the SPDR S&P 500 ETF.[8] Like closed-end funds, ETFs are traded by individuals on stock exchanges. Unlike closed-end funds, ETF flow is a daily occurrence. Like index mutual funds, the majority of ETFs are passive products. Unlike index mutual funds, the secondary ETF market has enhanced investors' passive trading capabilities by allowing them to not only buy and sell, but also to trade on

[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.

leverage and sell short. Due to these features ETFs have become popular vehicles to speculate and hedge. 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 structural difference yield distinct interpretations of fund flows. Measured mutual fund flows are the result of the net activities from all investors for cash exchanges. In contrast, ETF flows are a consequence of APs activity in the primary market. Despite this nuance, it is the activity of these secondary market investors that translate into primary market flows. For example, buy orders that push an ETF price above the net asset value (NAV) result in an AP buying the underlying basket and delivering them to the ETF sponsor in exchange for a creation unit of ETF shares, 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

[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 received compensation from commissions from their clients or from any arbitrage profits. See Antoniewicz and Heinrichs (2014) for further details.

mutual funds, and ETFs 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

[Insert Figure 1]

Indicative of the broader trend towards passive investing is the total new flows into the various investment vehicles plotted Panel B. Early in the sample period cash flows to active mutual funds dominated those of passive products, but beginning in 2006 the 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 the time period plotted.

The role of active mutual fund flows in financial markets has been and continues to be widely studied as summarized by 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 broadly 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 the yield spread of corporate bond 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 also 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*.

To identify fund type we rely on data from CRSP. 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 product.[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 funds 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] Vanguard utilizes a structure in which ETFs and mutual funds are distinct share classes of the same portfolio. To address this issue, we create two portfolios for these funds. 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. To address the issue of outliers 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.

[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.*

[Insert Table 1]

Table 1 documents that many of the trends that we discussed in the previous section using ICI data are reflected in our sample. 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 reaching 507 funds. The Table shows that the average fund of all types has experienced expense ratio compression as a result of the passive investment trend. 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, for our flow analysis we elect to begin the data in 2005. Panel B of the table presents the distribution of fund characteristics for the investment vehicles over the 2005 to 2017 period confirming the claims regarding the benefits of ETFs – lower turnover and lower expense ratios. 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 initial result suggests that while passive in name and mandate, the underlying investors may be more active.

Holdings level data is also obtained from CRSP for securities with share codes 10 or 11. While Thomson Reuters is widely used for this data, we elect to follow Shive and Yun (2013) and rely only on CRSP holdings data for reports between June 2008 and December 2017 to address the Thomson Reuters data integrity issues detailed by Ben-David, Franzoni, and Moussawi (2018) and Zhu (2017). While ETFs report holdings monthly, our holdings data is collected quarterly to have comparable information for all mutual funds and ETFs. 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 of the paper details the empirical results of our paper. We first begin with studying the aggregate flows to the different investment vehicles. The paper then continues by examining the determinants of flows to individual funds and concludes with the impact of these 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 sector returns, while unexpected flows display a strong positive correlation with sector returns. The literature has yet to disentangle whether this relation is the result of active flows causing price pressure, or whether flows and price pressure are the result of the same primary market forces. In this section, we expand upon Warther and study aggregate flows of actively managed funds, index funds, and ETFs. To compute aggregate flows we sum total dollar flows to all funds of a certain type normalized by the lagged market capitalization of the CRSP value-weighted index.[16]

[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

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 autocorrelation of aggregate flows. For both active and index mutual funds there is positive and significant monthly autocorrelation suggestive of the 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 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. This relation supports the information hypothesis of Warther that suggests news about the market moves flows and the market in the same direction. Lagged aggregate ETF flows are negatively related to the CRSP index supporting the temporary price pressure hypothesis rejected by Warther for active mutual funds at the monthly level, but supported at the daily level by Ben-Rephael, Kandel, and Wohl (2011) and Edelen and Warner (2001). Finally, aggregate active fund flows are positively related to lagged returns of the CRSP index suggestive of return chasing behavior.

[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 moderately significant, but the third lag is strongly significant. 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. In fact, the coefficients are both negative. 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 are 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 coefficient on expected flows is positive, but not significant.

[Insert Table 3]

Columns (5)—(7) look for evidence of a lag in the other direction by regressing unexpected flows on concurrent and lagged market returns. This setting examines Warther's (1995) feedback-trader hypothesis that predicts that flows must lag returns. Over the full sample period there is positive and statistically significant coefficients on contemporaneous and one-month lagged CRSP index returns, suggesting that active mutual fund flows in aggregate may lag 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. This change implies that as ETF investors have become more prominent market participants they may follow a positive feedback trading strategy.

Warther (1995) documents that active mutual funds influenced market returns in stocks, bonds, and even gold. 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. However, the relationship for index mutual funds is muted in all periods as 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. In the next subsection, we seek to understand the flow dynamics for individual funds.

3.2. *Persistence and flow-to-performance relationship of 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 general 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 12 monthly or 8 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 12 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. 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).

[Insert Table 4]

For the passive vehicles, the evidence of flow persistence is mixed. Fama-MacBeth and pooled estimations produce sum of flow coefficients 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. These findings are consistent with Del Guercio and Tkac's (2002) linking of flow persistence to 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 fund participants. In the 2018 Fact Book, the ICI documents that index funds account for just 21% of the 401(k) assets.[17] Unlike mutual funds, ETFs have not generally been adopted in 401(k) retirement plans.[18]

For all three investment vehicles, for all three specifications, for both measurement frequencies, last period's returns are significantly positively related to flows. Similarly, the sum of monthly return coefficients is positive and statistically significant. Over a year, the sum of monthly coefficients tells us that ETF flows have a higher response to relative performance than actively managed funds in most specifications. Comparisons of index fund 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.

[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

Table 4, Panels A and B, follows the literature and considers vehicle-specific performance. Thus, the performance of a particular index fund is relative to other index funds. Panel C broadens the estimation of the flow-return relation by partitioning return performance into performance relative to the average performance of same type vehicles and the average performance of the fund's vehicle type relative to the average performance of all funds. 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 product type in response to the product type's relative performance. Estimations that only include return performance for the last month are reported in columns 1, 3, and 5. Both index funds and ETF display more elevated flow performance sensitivity for both performance relative to the fund's category and for the fund's category's performance relative to the all funds. For both index funds and ETFs, the coefficient for category performance is larger than that of performance relative to category.

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 category performance sums and the total performance sums is dramatic. The within-category return-flow sensitivity that is featured in the vast mutual fund literature only accounts for about a fifth of the total flow-sensitivity.

Although Panels A and B estimate flow-performance sensitivity that is higher for index funds and ETFs than active mutual funds, the cross-sectional nature of the estimation masks the more drastic impact of vehicle-specific 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. We are unfamiliar of any theory in the extant literature that make sense of performance based flows to types of vehicles.

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 category (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 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 now 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.

In a similar vein, our findings of passive fund flow-performance and vehicle-based flow-performance are a challenge for research that conducts horse races between proxies for how investors assess managerial ability. Examples include, Barber, Huang, and Odean (2016), Ben-David et al. (2019) and Berk and Van Binsbergen (2016).

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. Goetzmann and Peles (1997) claim this phenomena is the result of behavior biases while Sirri and Tufano (1998) suggest it is a byproduct of fund family marketing. 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:

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

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, a nearly symmetric to the effect for high performing funds. 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 Spiegel 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).

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).

We are unable to reconcile these results with current explanations for mutual fund liquidity. Goetzmann and Peles' (1997) behavioral-bias convexity explanation does not fit the ETF—active mutual fund comparison. Sophisticated traders are more present in ETFs than mutual funds because of the ability 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.[19] 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. Although relevant to hedge funds, 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) recommend an optimal 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:

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

[19] 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.

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 with absolute performance negative and significant for all alpha measures for all vehicles. Comparing the performance of the portfolios to the average fund, there is some evidence that positive cash flow funds outperform the average fund of the same type, particularly on a three-factor basis. 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. ETF equally-weighted positive and negative and all are 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). In contrast, there is 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 mixed evidence that mutual fund investors make smart allocation decisions, as do their index fund peers. In contrast, there is no evidence that ETF investors despite their hyperactivity 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. Brown, Davies, and Ringgenberg (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.

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 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. The results so far demonstrate that the underlying investors driving flows to and from active mutual funds, index mutual funds, and ETFs have distinct motivations, biases, and abilities. For these flows to translate into material impacts for 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. For instance, mutual fund managers have the discretion to maintain a cash buffer to mitigate the impact of flow-related trading. ETFs rarely trade on the funds behalf 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 fund managers 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

$$Net\ Trading\ Activity_{j,q} = \frac{Trading\ Buy_{j,q} - Trading\ Sell_{j,q}}{Total\ Assets_{j,q-1}}, \tag{2}$$

where

$$Trading\ Buy_{j,q} = \sum_{i=1}^{N} prc_{i,q} * \Delta shares_{i,g,q} if\ \Delta shares_{i,g,q} > 0 \quad (3)$$

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

We regress this proxy on flows and, in some specifications, the portion of fund assets held in cash since 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. As the least likely to transact in response to flows, 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. Since the investment vehicles all show evidence of flow-induced trading, 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,

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

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. The 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 previously 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 apples-to-apples comparison of active mutual fund, index mutual funds and exchange traded fund investment flows. Our estimation emulates the premier empirical studies of active mutual fund flows.

At the aggregate level, passive flows appear to play the role that active flows played in the past. We find that Warther's finding of a contemporaneous, positive relation between market returns and aggregate inflows to equity funds has subsided. Recently, this correlation is apparent with ETFs.

Index fund and ETF flows are nearly twice as volatile, at both the monthly and quarterly frequency, as active mutual fund flows. The passive vehicles demonstrate much less flow-persistence than active funds, which is consistent with Del Guercio's and Tkac's (2002) contention that investment products that are placed in defined contribution plans illicit slower investor reactions to performance.

Regarding return-flow sensitivity, our comparisons allow us to bifurcate return performance into the vehicle's performance relative to its category, and the fund's category performance relative to all funds. At the annual level, flow-performance sensitivity is similar for active mutual funds and ETFs, but the category specific component is four times as large as the within-category performance. Thus, the previous literature's estimate of flow-performance sensitivity that focuses on active funds neglect 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.

Individuals generate mutual fund flows while authorized participants generate ETF flows. Although the agents are different, the associations between flows and underlying portfolio effects are similar across vehicles. Smart-money effects, fire-sales, and flow-induced trading are similar regardless of whether the vehicle is an active mutual fund or ETF. Although these associations are similar per unit of flow, elevated flow volatility for ETFs over mutual funds leads to more turgid total impact.

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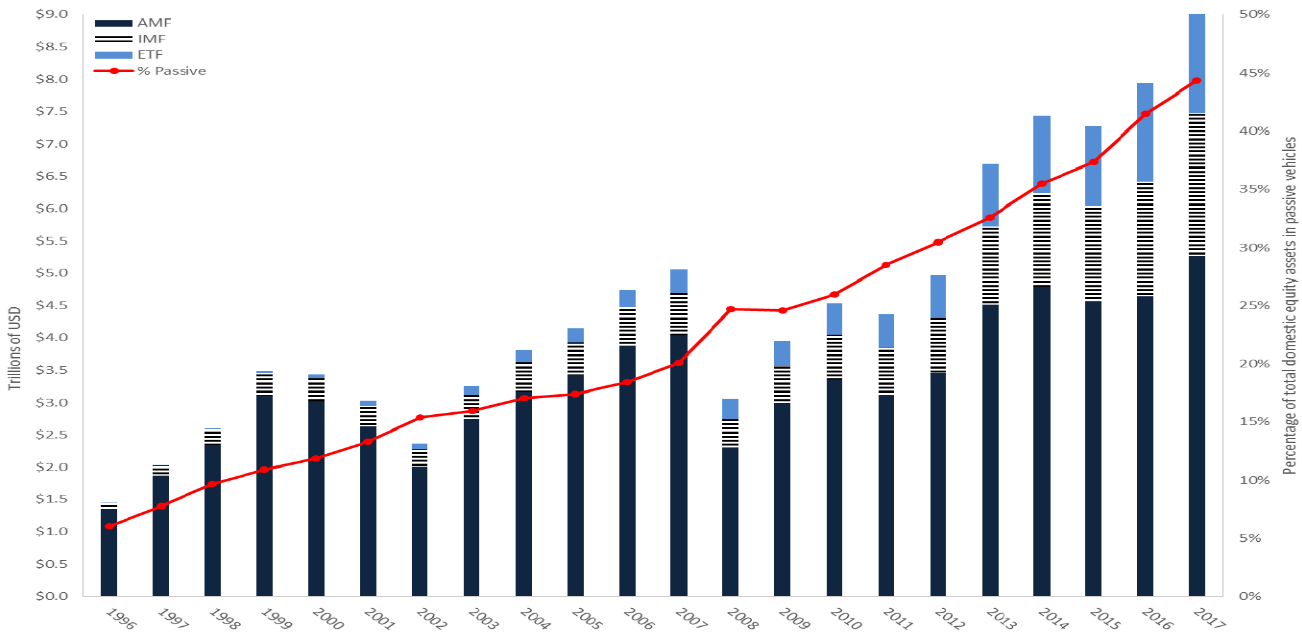
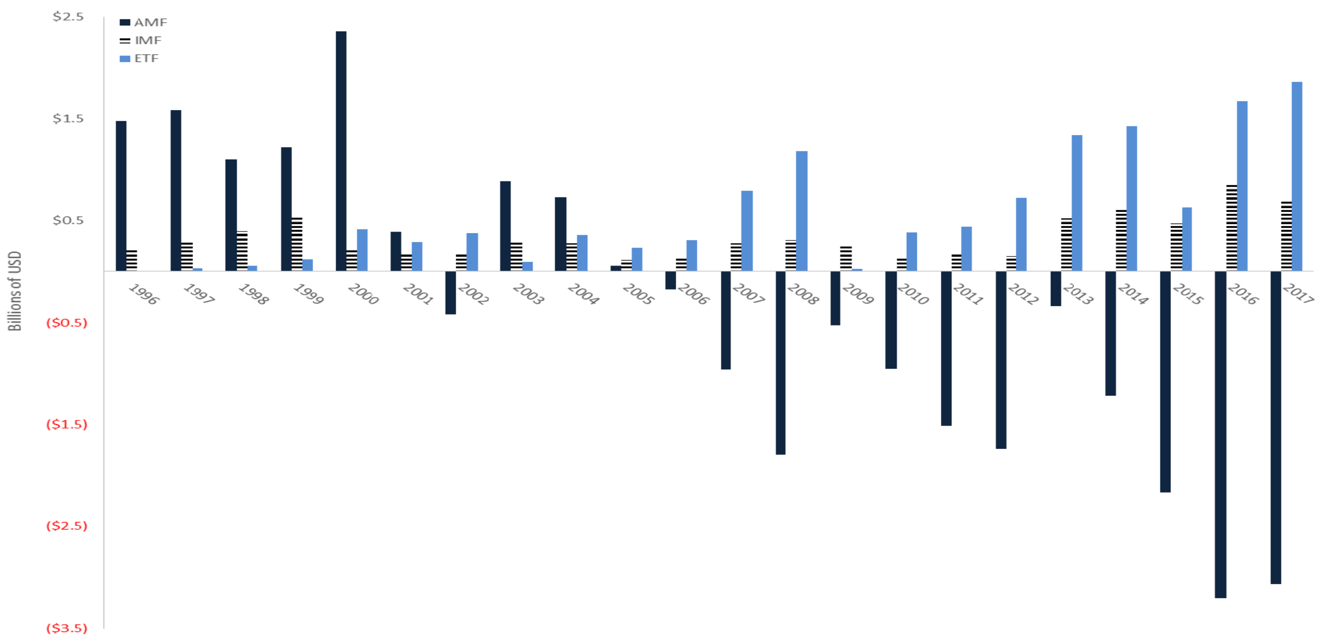
Figure 1

Assets and flows to domestic equity funds



Panel A: Total assets to domestic equity funds

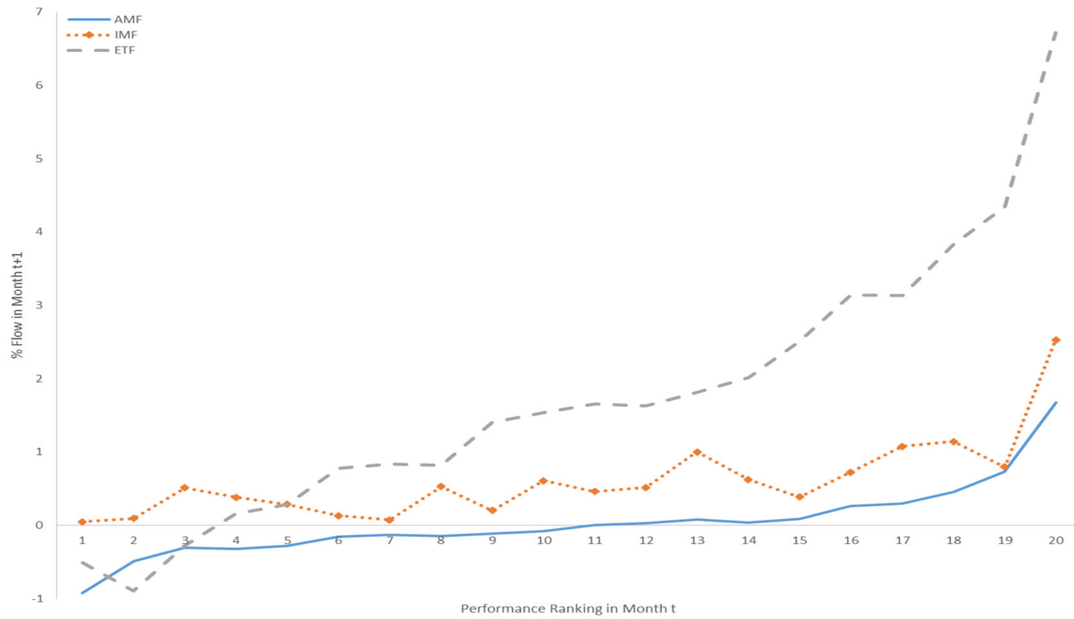


Panel B: New cash flows annually

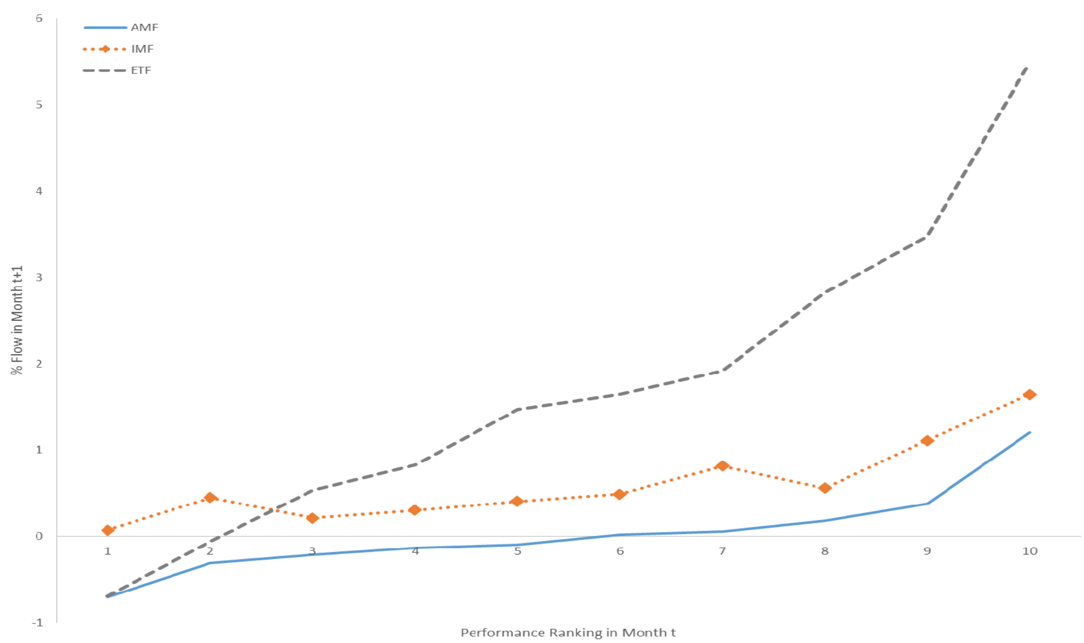
This figures plots the total assets in Panel A and new cash flows in Panel B to active mutual funds (AMF), index mutual funds (IMF), and exchange-traded funds (ETFs) using data from the Investment Company Institution (ICI) Factbook. The annual data sample is from 1996 to 2017.

Figure 2
The flow to performance relationship

Panel A: Groups of Twenty



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



Panel B: Flow-to-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

	AMF		IMF		ETF	
Variable:	(1)	(2)	(3)	(4)	(5)	(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.

	AMF				IMF				ETF			
	Excess	*1 Factor*	*3 Factor*	*4 Factor*	*Excess*	*1 Factor*	*3 Factor*	*4 Factor*	*Excess*	*1 Factor*	*3 Factor*	*4 Factor*
Panel A: Portfolio Returns												
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												
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						Fire 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