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Active Flows and Passive Returns

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Abstract. The positive relationship between money flows into investment products and their return performance is an important market indicator for market practitioners and academics. This paper studies the impact that active versus passive investment styles have on this relationship. We further evaluate the effects of a passive approach in two crucial stages: portfolio selection and asset allocation. We find that a passive investment style in either stage weakens the relationship between flows and returns compared to an active style. However, the investment style in the asset allocation stage has a greater effect than in the portfolio selection stage, on the relationship between flows and returns.

JEL Classification: G10, G11, G23

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Keywords: ETF, flows, passive, active, investment products

1. Introduction

It has been widely documented that new cash flows into investment products are highly positively correlated with the products' return performance. Some of the early works on this topic include Ippolito (1992), Warther (1995), Gruber (1996), and Sirri and Tufano (1998), among many other more recent works. In this paper we explore the extent to which this relationship depends on an active versus passive investment style. That is, we explore the sensitivity to returns of flows into and out of passive investment products versus actively-managed products.

This issue has become particularly timely given the increasingly dominant role that passive investment products have been playing in current financial markets. Over the past decade financial instruments such as Exchange Traded Funds (ETFs) and index mutual funds,[1] which passively track a predetermined market benchmark, have been steadily

[1] A passive investment product, or an index fund, is a financial vehicle designed to replicate the performance of a predetermined financial benchmark, or specifies a set of investment rules that are held constant, regardless of market conditions. Passive products may take the form of mutual funds or of Exchange Traded Funds (ETFs). Under the former structure, buying and selling the fund is executed exclusively with the fund manager, and purchasing prices or selling proceeds are determined according to end-of-day Net Asset Values (NAV). On the other hand, ETFs are continuously traded in the secondary market. Therefore, they can be purchased or sold in two channels, on the exchange or directly with the ETF sponsor. When ETFs are traded directly with the fund sponsor, new share-units

increasing their market share at the expense of more traditional actively-managed mutual funds.[2]

In the context of this trend, we study how "passive" passive investing really is. Is passive investing comprehensive enough to be indifferent even to return performance? Passive investors may view index tracking products as effectively fulfilling their investment purpose as long as they continue to successfully follow their underlying index, regardless of its particular price behavior. If this is the case, money flows into and out of passive funds should experience less sensitivity to their return performance than the flows of active funds.

Furthermore, the traditional characterization of investment products on the whole as either "passive" or "active" is too general and misguiding, considering that products in fact include two elements—asset allocation and portfolio selection—each of which may be passive or active independently. For example, an ETF that replicates a market index can be characterized in that respect as applying a passive portfolio selection. However, there is a substantial difference if it replicates an exotic index or a broad market index. Investing in an ETF that tracks an emerging market index (e.g., EEM), oil prices (e.g., USO), or a high yield bond index (e.g., HYG), may indicate quite an active investment strategy in

can be created and existing units can be redeemed, consequently changing the outstanding number of circulated share units.

[2] Data provided by the Investment Company Institute (ICI) shows that since 2004, ETFs and index mutual funds have been rapidly growing at an annual rate of around 20% per year, compared to 5% for the active mutual fund sector. Their market share of the entire investment products industry increased from about 8% in 2004 to almost 18% in 2012. In terms of Assets Under Management (AUM), their combined value in 2004 was less than 800 billion dollars, whereas in 2012 they surpassed 2.5 trillion dollars.

its asset allocation. Conversely, investing in a broad market index such as the S&P 500 (e.g., SPY) may imply a passive asset allocation, as this approach simply buys the market portfolio as a whole, reflecting no opinion as to future performance of individual classes. Similarly, investing in a specific asset class can be executed using an active "stock picking" approach indicating an active portfolio selection, or by passively buying a relevant index which corresponds to the chosen asset class (for example, the S&P 500 Index for large cap equities, the S&P Financial Select Sector Index for the financial sector, or the iBoxx Investment Grade Index for corporate bonds).

Therefore, investment products that are traditionally viewed as passive investments may in fact represent hybrid approaches where a passive portfolio selection is used to carry out an active investment strategy.

Here we study the impact of these two components of investment—determining and executing strategy—on the relation between flows and returns. We explore the implications of a passive strategy (asset allocation) and of a passive execution (portfolio selection). If indeed a passive investment approach has consequences for the sensitivity of flows to returns, this distinction allows for a more meaningful and subtle analysis that identifies the specific components in the investment structure that account for it, whether they are the strategic, executional, or both.

In our analysis we classify products by their level of activeness or passiveness both in their portfolio selection and asset allocation styles. We then test for past and current effects from returns to flows to identify different patterns that correspond to the different classifications we defined. We further apply Granger causality tests to identify causal relationships and to extract potential predictive information for each group of products.

Finally, we repeat our tests in the opposite direction from flows to returns, to identify any potential effects of demand on prices.

To preview our results, we find that the relationship between flows and returns is much weaker when a passive component exists. We find a clear impact for both components, the portfolio selection and the asset allocation. However, the investment strategy (asset allocation) plays a more dominant role in determining the connection between flows and returns compared to the more technical component, the portfolio selection. Passive investment products with a more specialized asset allocation, such as ETFs that track emerging markets, inverse and leveraged ETFs and others, still exhibit a strong relationship between flows and returns, despite their passive portfolio selection structure. Nevertheless, the overall relationship remains weaker compared to actively-managed mutual funds. On the other hand, passive products that invest in a non-specialized strategy or the market portfolio, such as US large cap equities and the S&P 500 index, hardly exhibit any relation between flows and returns.

Interestingly, we also find that despite the relative lack of sensitivity of flows to returns for passive products, their relative performance does matter. When active mutual funds outperform passive products money flows to the winning industry, and vice versa in the opposite case.

To account for our results we only note at this stage that the unique setting of passive products in addition to the heterogeneous relations we found between flows and returns help differentiate between the main competing theories as to the driving force behind the flow-return correlation. Our findings suggest that investors' motivation to outperform the market plays a role in determining the flow-return relation, and that adopting an active or a passive investment style has implications for this motivation. We discuss this in further detail in Section 10.

The remainder of this paper is organized as follows. In the next section we review related literature. Sections 3, 4 and 5 describe our data, discuss our variable construction and definitions and present our econometric methodology, respectively. We then introduce our results. The discussion of our results is divided into two parts. In the first part we discuss the phenomenon of our main interest—the sensitivity of flows to returns. In the second part we discuss the effect in the opposite direction—the sensitivity of returns to flows. In each part we first present the impact of a passive portfolio selection on the relationship between flows and returns. That is, we compare the results across active mutual funds, index mutual funds, and ETFs. In the next step we present the results for adopting a passive investment strategy (asset allocation), by using various criteria for characterizing the level of activeness versus passiveness for a given instrument. In Section 10 we interpret our findings in the context of the existing theories that account for the flow-return relation. We summarize our conclusions in the last section.

2. Related Literature

As mentioned before, the study of the flow-return correlation in the mutual fund sector started over 20 years ago with the early works of Ippolito (1992), Warther (1995), Gruber (1996), and Sirri and Tufano (1998). More recent works include those of Sapp and Tiwari (2004), Franzzini and Lamont (2008), Ivkovic and Weisbenner (2009), and Ben-Raphael, et al. (2012). All of these works document the same fundamental phenomenon that concurrent flows and returns in the mutual fund sector are highly positively correlated.

However, the interpretation of the phenomenon was less uniform. One group of studies argues that inflows reflect "smart money" effects, which express investors' abilities to select winning mutual funds or superior portfolio managers (Gruber (1996) and Zheng (1999)). Another group argues that inflows merely express "dumb money" movements, where investors naively chase past and current returns (Jain and Wu (2000), Sapp and Tiwari (2004), Cooper, et al. (2005), and Franzzini and Lamont (2008)). Both of these interpretations attribute the correlation to investors' expectations of future returns and their motivation to outperform the market, whether justifiably or not. Conversely, a third group of studies provides evidence that the positive flow-return correlation simply reflects short-lived price pressures generated by increased demand for assets—price pressures which are reversed in the long run. That is, the correlation is a result of temporary supply and demand imbalances which are unrelated to expectation of future performance (Edelen and Warner (2001), Coval and Stafford (2007), Lou (2012), and Ben-Raphael, et al. (2012)).

Finally, a number of papers focuses on different factors that affect the strength of the positive flow-return correlation. Some of these factors include search costs, management fees, taxes, and advertisement efforts. For more on this topic see: Sirri and Tufano (1998), Jain and Wu (2000), Bergstresser Poterba (2002), Cooper, et al. (2005), Ivkovic and Weisbenner (2009).

Despite the growing importance of passive products in financial markets, very little attention has been dedicated to studying their flow-return relationship. To the best of our knowledge only three papers address an initial analysis of this issue in the context of passive investment products. Goetzmann and Massa (2002) study the trading behavior of individual investors in a single passive mutual fund that tracks the S&P 500 over two years, 1998–1999. They find evidence for the existence of some momentum and contrarian behavior among investors. Goetzmann and Massa (2003) use daily flow data for three passive mutual funds that track the S&P 500 index using two years of data in the 1990's. They find evidence for a positive correlation between flows and returns. Last, Elton, Gruber and Busse (2004) study the sensitivity of index mutual fund flows to their tracking error. They study passive funds that track the S&P 500 between 1997 and 2002, and explore the impact of the deviation of their performance from their underlying index on flows.

None of these works addresses the distinction between the two components of the investment process, asset allocation and portfolio selection, as they focus only on S&P 500 funds. Part of the reason is the limited available data and very thin markets that existed for passive investment products at the time. Only over the past decade have markets for these instruments matured in their volume, data availability, and diversity of products, allowing for a meaningful empirical study. Thus, in our study we explicitly address the effect of both passive components. Additionally, we build on a much richer and diverse data set, which includes a number of products that track various underlying indices with AUMs that dwarf those that existed over a decade ago.

3. Data

We collected data for active mutual funds, passive mutual funds, and ETFs in the US from multiple sources. The data for mutual funds was obtained from ICI and contained information on all funds that reported to the investment company institution from 2005–2012. This data is available for the total mutual fund industry, and for active and passive mutual funds separately. It includes aggregate month-end information on AUM, gross inflows, outflows, and net flows. The data is also available for various sub-classifications by sectors (e.g., equities, fixed income, hybrid) and geographic investment destination (US or international). For passive mutual funds there are additional sub-classifications for funds that track the S&P 500, single indices, and other passive strategies.

The data for ETFs was collected in several stages. In the first stage, we downloaded from ETFdb, a leading comprehensive online database for ETFs, a complete list of ETFs listed in the US at the end of 2012, sorted by AUM. This list included about 1,400 ETFs with detailed characteristics for each ETF, such as associated sector, underlying market benchmark, asset class, investment region, exposure (inverse, long, leveraged), and more.

There is a huge heterogeneity in the size and liquidity of ETFs with AUMs ranging from more than 100 billion dollars (e.g., SPY) to less than 100,000 dollars. Because smaller funds have a negligible impact on demand and face greater liquidity frictions, we focused on ETFs with at least 500 million dollars in AUM. Our final list contained the largest 301 ETFs in AUM.

From Bloomberg we downloaded daily data on end-of-day prices and shares-outstanding from 2005 to 2012 for this list of ETFs. Based on this data we calculated weekly returns and net flows for each ETF. We elaborate on this process in the next section.

The relationship between flows and returns ideally would be tested for each fund separately. However, since many funds are substitutes for one another, inflows and outflows to individual funds partially represent within-sector money movements. In other words, flows at the individual fund level are not necessarily representative of new money that flows into the industry. Therefore, we used various classifications to create sub-groups of funds per investment product and tested the flow-return relationship per investment group per product type.

For mutual funds, ICI data contains aggregate data by various classification groups such as geographic regions (US and international) and asset class (equities and bonds). ETFs data is much richer in information and allows for a richer cataloging. Thus, we classified ETFs by geographic investment destination, by investment category (size and style, sector, strategy, and commodities), by investment size (large cap, medium cap, small cap), and by other specialized ETFs (inverse and leveraged).

These classifications serve two purposes in our study. First, they are used for creating groups of products that allow for measuring flows in a consistent way, as explained above. Second, they allow for characterizing the level of specialization in the product's investment strategy and consequently the degree of activeness in its asset allocation, as discussed in the previous section. We further elaborate on these classifications later.

4. Variable Construction

We constructed our variables for flows and returns for mutual funds and ETFs in the following way, a procedure which was to some extent dictated by the structure of our data. For mutual funds, both active and passive, dollar net flow data was available from ICI only at the monthly level. We summarized net flows across all funds for a given group to calculate total monthly net flows in dollars per group. Then, similar to Sirri and Tufano (1998), Edelen and Warner (2001), Ben-Raphael et al. (2012), and many others, we normalized the month-end dollar net flow by its previous month-end AUM.[3] In this way we eliminated market growth trends over time and created a more informative percentage

[3] The construction of our variables relies on the following definition: AUM_t is equal to AUM_{t-1}, plus the return on AUM_{t-1}, plus the net flow from $t-1$ to t, that is: $AUM_t = \text{ Net Dollar Flow}_t + AUM_{t-1} + r_t \times AUM_{t-1}$.

net inflow measure. That is,

$$F_t^{MF} = \frac{\text{Net Dollar Flow}_t}{AUM_{t-1}} \tag{1}$$

Monthly return data for mutual funds was calculated using AUM data per investment group. We calculated returns as monthly growth in AUM after deducting net cash inflows. That is,

$$R_t^{MF} = \frac{AUM_t - \text{Net Dollar Flow}_t}{AUM_{t-1}} \tag{2}$$

For ETFs the variable construction process was more delicate. In our analysis we focused on the weekly horizon for ETFs; therefore, our raw daily data for prices and shares outstanding had to be translated carefully to construct weekly flows and returns.

Let P_n^j and SO_n^j be the end-of-day price and shares outstanding for ETF j on day n, respectively. Net cash inflows for a single ETF j on day n can be easily calculated by multiplying the daily change in shares outstanding by end-of-day price. That is,[4]

$$\text{Net Dollar Flow}_n^j = \Delta SO_n^j \times P_n^j \tag{3}$$

Therefore, net cash flow during week t for ETF group J is,

$$\text{Net Dollar Flow}_t = \sum_{j \in J} \sum_{n \in t} \Delta SO_n^j \times P_n^j \tag{4}$$

where the right-hand side is the sum of all net cash flows during week t across all ETFs included in group J. Finally, we normalized our weekly net cash flows by total AUM for

[4] The number of net new shares issued on day n for ETF j is equal to the difference in shares outstanding (SO) for ETF j from end of day $n-1$ to the end of day n, i.e., $\Delta SO_n^j = SO_n^j - SO_{n-1}^j$. In order to measure net money flows, we need to value this net change of shares. Since all ΔSO_n^j shares were issued on day n they should also be valued with day n prices. Otherwise, valuing SO_n^j with day n prices and SO_{n-1}^j with day $n-1$ prices would measure changes in AUM from day $n-1$ to day n ($AUM_n^j - AUM_{n-1}^j$).

ETF group J at the end of the previous week,

$$F_t^{ETF} = \frac{\text{Net Dollar Flow}_t}{\sum\limits_{j \in J} AUM_{t-1}^j} \tag{5}$$

where,

$$AUM_t^j = SO_t^j \times P_t^j \tag{6}$$

and SO_t^j and P_t^j are the end-of-day shares outstanding and price for ETF j at the end of week t, respectively. Thus F_t^{ETF} represents the percentage share of net flows during week t out of a total AUM per group, similar to F_t^{MF} for mutual funds as described in Equation (1) above.

Weekly returns for ETF group J were calculated as the weighted average of weekly returns for all single ETFs included in group J, scaled by AUM. That is,

$$R_t^{ETF} = \sum_{j \in J} \frac{R_t^j \times AUM_t^j}{\sum\limits_{j \in J} AUM_t^j} \tag{7}$$

where R_t^j is the return of ETF j during week t.

5. Methodology

At the preliminary stage of the data analysis, the Pearson and Spearman correlation coefficients as well as the cross correlogram between F_t and R_t were computed. Consequently, the model under consideration is,

$$F_t = \beta_0 + \sum_{j=1}^{p} \beta_j F_{t-j} + \sum_{j=1}^{q+1} \beta_{j+p} R_{t+1-j} + u_t \tag{8}$$

$$R_t = \gamma_0 + \sum_{j=1}^{p} \gamma_j R_{t-j} + \sum_{j=1}^{q+1} \gamma_{j+p} F_{t+1-j} + \varepsilon_t, \tag{9}$$

where u_t and ε_t are disturbance terms. In theory, the model should be estimated by two-stage least squares, three-stage least squares, GMM, or any reasonable alternative which takes into account the possible endogeneity of a right-hand side variable. However, the use of these estimators necessitates the specification of suitable instrumental variables and these are almost impossible to find in this setting. This is because the correlograms of both flows and returns, as well as the cross-correlograms between the two, are almost flat, implying that it is essentially and practically impossible to use lagged variables as good instruments. Indeed, the use of lagged variables as instruments can only be justified as long as they are highly correlated with the design matrix and uncorrelated with the error term, but the first of these conditions clearly does not hold, given the preliminary analysis on the correlograms and the cross-correlograms. Other instrumental variables which are highly correlated with the endogenous variables and not with the equation-error term are extremely difficult to obtain in the present setting.[5]

For this reason, each equation was estimated by ols, with p and q ranging from 0 to 2. This means that in the equation for flows, the explanatory variables include up to two lags of flows and up to two lags of returns as well as the present value of returns. The converse holds true for the regression in the other direction: of returns on their past and on present and past values of flows. We remark that in the preliminary analysis of the data we attempted to fit models with higher order lags, but again, given that the correlograms of flows and returns, as well as the cross-correlograms between the two, are almost flat, the higher-order lags turned out to be insignificant and were dropped from the model, because over-specification leads to inefficient estimators. For this reason, we have abandoned the

[5] These methods were implemented in the preliminary empirical work but were consequently abandoned, when the standard errors of estimates were found to be too large compared with ols estimates and as a result, the estimated coefficient signs and sizes varied considerably.

idea to fit the Almon lag model or the Koyck model and proceeded using model selection criteria, as described next.

In practical terms, we recorded the AIC, SC and $\bar{R}^2$ values for each lag-specification. For each data set, the selected model was the one which was best, by a majority rule, of the three criteria. Consequently, a variety of statistical tests were performed on the selected model's residuals, including an inspection of their correlogram for autocorrelation. The conclusion of these tests provides an indication for remaining model misspecification.

To supplement the analysis, causal relations in both directions were investigated using the Granger causality test, with 1, 2, and 4 lags.[6] For brevity, we report only the p-value associated with the test containing 4 lags.

In the specifications in Equations (8) and (9) we did not include the effects of other factors, such as liquidity or informational frictions, in the relation between flows and returns, since we tested for aggregate effects as opposed to individual fund effects.[7] Consequently, our variables are aggregate flows and returns for families of funds, grouped by various classifications. Frictions in general, and liquidity and informational frictions in particular, measure properties of individual funds; it is conceptually unclear how to apply these properties to the aggregate level. Liquidity measures the ease at which trades can be placed for an individual security, but it is unclear what objects should be measured at the aggregate level. One option is to simply take averages of individual funds per group, but this creates problematic biases in measures and estimates. Similarly, informational frictions, such as private knowledge about fund manager skills, the investment strategy, or "off the radar" funds that require a special effort to locate (e.g. limited marketing efforts), are all relevant

[6] We used an embedded feature in Eviews to run the test and not equations (8) and (9).

[7] On this issue we followed Warther (1995), Ben-Raphael, et al. (2012), and others. See additional references therein.

only at the individual fund level. It is unclear how to apply these characteristics to a group of funds. Moreover, at the aggregate level these factors should cancel out on average.

Furthermore, the liquidity of ETFs and other tracking products should not be confused with that of stocks, bonds, or other basic securities, which are simply derived from their trading volume on the exchange. Trading volume measures how many shares have been traded, whereas liquidity should measure how many shares potentially could be traded. Normally these measures coincide (e.g., for stocks and bonds), but not for ETFs. The unique creation and redemption mechanism for ETFs allows for increasing their share unit amounts anytime. Therefore, sizable trades can still be easily executed even for ETFs that experience very thin trading volumes, since they are placed directly with the market maker by creating new share units, or redeeming existing ones. The true level of liquidity for ETFs is determined by the implied liquidity derived from all assets available for hedging the ETF, which the market maker uses to hedge his position when creating (redeeming) new (existing) ETF share units. These assets include the underlying securities, underlying index derivatives or futures, correlated trading vehicles, all in addition to the average daily volume of the ETF. Consequently, it is very rare to find ETFs which experience meaningful liquidity frictions, as the implied liquidity of the underlying indices is very deep. For more on this see an informative discussion in Abner (2013).[8]

Last, we further enhanced our analysis by testing the effects the relative returns of actively-managed mutual funds to those of passive products have on the transition of

[8] We thank our referee for emphasizing these issues. Further, when we used an extended specification that included the Amihud (2002) illiquidity measure, coefficient estimates for illiquidity proved to be non-significant.

money from active products to passive ones. Therefore, we used the following model,

$$\Delta F_t = \lambda_0 + \sum_{j=1}^{p} \lambda_j \Delta F_{t-j} + \sum_{j=1}^{q+1} \lambda_{j+p} \Delta R_{t+1-j} + \sum_{j=1}^{s+1} \lambda_{j+p+q} R_{t+1-j}^{active} + v_t \qquad (10)$$

where,

$$\Delta F_t = F_t^{active} - F_t^{passive}$$

is the difference in flows between the active sector and the passive sector. Similarly,

$$\Delta R_t = R_t^{active} - R_t^{passive}$$

is their difference in returns. The number of lags p, q and s ranges from 0 to 2 with an optimal model selection criterion similar to the one described above.

In our analysis we applied the framework described in Equations (8)–(10) to each group of funds. In the first step we cataloged our groups of funds by product type; that is, we focused on the product classification as an active mutual fund, passive mutual fund or ETF. This allowed for a comparison between products based on their portfolio selection style. In the next step, we applied additional classifications per product type that characterized their strategic investment style by various criteria such as region, size and style as elaborated on below. These additional classifications allow for comparison between products based on their asset allocation strategy and their degree of specialized investment exposure versus a non-specialized broad market investment exposure.

6. Results

We divide the discussion on our econometric results into two parts. In the first part we present the results which are related to our central question, the effect returns have on flows, as captured by Equations (8) and (10). In the second part we present additional results that are related to the effect in the opposite direction, from flows to returns, as captured by Equation (9). Each part is divided into two discussions: one addresses the effect the product type has as a passive or active one on the relationship between flows and returns, which corresponds to the portfolio selection component. The other discussion addresses the effect the asset allocation and investment exposure have as a passive or active one on the flow return relationship. This corresponds to the more strategic component of the investment.

Tables 1–10 present the results for the effect returns have on flows. We start with reproducing the previously documented findings for the aggregate mutual fund sector. Then, we continue with our testing for additional classifications by product types and investment strategy styles.

7. Mutual Funds

As shown in Table 1, we divided our mutual funds data into various types of funds: equity, bond, and hybrid,[9] for US and world funds separately, in addition to the aggregate total market of mutual funds. Flows and returns are positively correlated. Our estimates for regressing flows on returns (Equation (8)) confirm that concurrent returns positively affect flows for all types of funds, as all current return coefficients are positive and statistically significant. There is very little evidence that past returns affect flows. Finally, Adjusted $\overline{R}^2$ values are around 60 percent in most cases, indicating high explanatory power.

Consistent with these results, our Granger causality tests confirm that returns have a strong causal effect on flows. The p-values for Granger tests are all around 1 percent or

[9] These are mixed equity and bond funds.

lower, with the exception of world equity funds group, which has a p-value of 7 percent. These results are all consistent with the findings previously documented in the literature.

8. Product Type—Portfolio Selection

Dividing the investment product universe into actively managed products and index tracking products reveals a new picture with substantial differences between them. Table 2 presents our estimation results for the total market for each product type separately: active mutual funds, passive mutual funds, and ETFs. As can be seen, once removing passive mutual funds from the mutual fund industry and focusing exclusively on active mutual funds, the effect returns have on flows becomes even more distinct. Comparing our estimation results for the total mutual funds industry in Table 1 and the active mutual fund industry in Table 2 shows that the return coefficient increases from 0.044 to 0.051; Adjusted $\overline{R}^2$ increases from 64% to 70%; the Granger test statistic increases as well. These results indicate that the effect returns have in the case of active mutual funds is stronger, explains flows better, and experiences a stronger causal effect.

On the other hand, the opposite holds true for passively managed products. Return coefficients for passive mutual funds and ETFs are still positive and statistically significant, however their $\overline{R}^2$ values, Pearson correlation, and Granger causality test statistics are all much lower compared to actively managed ones. Adjusted $\overline{R}^2$ values dropped to 12% and 11% for passive mutual funds and ETFs, respectively; Pearson correlations are around 35%; Granger test statistics are less significant for passive mutual funds and non-significant for ETFs.

Notably the constant coefficients in all three types of products are positive and significant. However, the coefficient size for passive mutual funds and ETFs is of a different order of magnitude compared to active funds: 0.47% and 0.22% on a weekly basis compared to 0.05% on a monthly basis, respectively. This result is consistent with the massive growth rate of the passive market compared to the active one, as mentioned earlier.

Overall, these results present the difference in sensitivity of flows to returns as a result of the product management style. The passive management style implies much less sensitivity of flows to returns compared to an actively managed style. In the next subsection we address the effect the strategic style of investing has on flows.

9. Investment Strategy—Asset Allocation

In the following subsections we use four different criteria for the classification of funds by their investment strategy: geographic region, investment category, size, and special ETFs. For each criterion we provide a corresponding breakdown per investment product, as much as our data allows. Then, for each group we examine how the effect returns have on flow changes with the level of specialization of the investment strategy. If indeed the more passive an investment strategy is the weaker the effect returns have on flows, we would expect to find that more specialized asset allocations exhibit a stronger connection between flows and returns, with non-specialized asset allocations (i.e., broad market investing or the "market portfolio") showing a weaker connection.

Unless otherwise mentioned, we focus in our analysis on equities only, a constraint dictated by the structure of ICI data, which provides data per family of funds and various sub-classifications only for equities. However, equities constitute the largest asset class for both ETFs and mutual funds by far. ICI aggregate market data indicates that the market share of equity funds ranged from 95% to 85% for ETFs, from 77% to 89% for passive mutual funds, and from 54% to 72% for active mutual funds, between 2005 and 2012.

9.1 Classification by Region

Our first classification divides our sample of investment products into geographic regions. ICI data for active and passive mutual funds provides only a basic cataloging into international and US funds. However, for ETFs a richer cataloging into different geographic regions and levels of economic development is available.

Table 3 shows the results for passive and active mutual funds with additional breakdown of the equity sector into US and international investment exposures. Similarly, Table 4 shows our results for ETFs grouped by international region (North America, Europe, global, Asia and Latin America) and economic development (Developed and Emerging Markets).

As Table 2 shows, for both active and passive mutual funds, returns have a stronger effect on flows for funds that invest internationally compared to those which invest domestically in the US. For active mutual funds that invest in non-US equity, the return coefficient is 0.045 which is approximately double the size for funds that invest domestically in US-equity, 0.029. A similar pattern exists for their adjusted $\overline{R}^2$ values: 43% and 72% respectively, again, almost double the size.

This difference is even more pronounced for passive mutual funds. The return coefficient is not statistically significant for passive US funds that track the S&P 500 index and other US-equity indices; their adjusted $\overline{R}^2$ values drop to 6% and 0%, respectively, indicating minimal explanatory power. However, for passive non-US equity funds the return coefficient is positive and highly statistically significant, with $\overline{R}^2$ of around 15 percent, indicating substantial explanatory value.

For ETFs we use a more detailed breakdown into different regions and levels of market development, as reported in Table 4. On the whole, our regression results show that for the US and other developed regions the effect returns have on flows is smaller compared to those for less developed regions or emerging markets. Return coefficient estimates are 16, 6, and 4 percent for North America, Europe and developed countries, respectively, and all are highly statistically significant. For Asia, Latin America and emerging markets, return coefficients are 11, 18, and 25 percent, respectively, all highly statistically significant. This difference also holds true for $\overline{R}^2$ values, with 9, 16 and 17 percent for the US, Europe and developed markets, compared to 37, 36 and 29 percent for Latin America, Asia, and emerging markets, respectively. This is also reflected in Granger causality tests where less developed countries achieve much higher test statistics. Finally, Global ETFs are somewhat an average case, most likely because they contain a blend of both developed and non-developed regions in their portfolio.

In summary, we find that the farther the investment strategy is from the aggregate US broad market the stronger the effect returns have on flows. Investments in less developed countries and emerging markets are considered alternative asset classes to the US market, and indeed they experience much higher sensitivity to returns. European, developed and global markets are more similar asset classes to US markets and experience less sensitivity between flows and returns. This finding holds true across all investment products: active mutual funds, passive mutual funds, and ETFs. It is consistent with the hypothesis that adopting a more active investment strategy, one that is farther from an aggregate US broad market index in its characteristic (from a US perspective) also implies more sensitivity of flows to returns, regardless of the management style of the products (i.e., a tracking product or an actively managed product).

9.2 Classification by Investment Category

We next divided our investment product sample by investment category. Unfortunately this classification is available only for our ETF data. However, it provides insightful information consistent with our previous results.

We defined four categories for our sample of ETFs: sector investments, size-and-style investments, strategy investments, and commodities. Sector ETFs track single sector indices such as financial, technology, utilities, and so on. The size-and-style classification includes ETFs that track broad market indices such as large cap, small cap, medium cap stocks, etc. Last, the strategy classification includes ETFs that follow a predetermined strategy, such as US IPOs, merger arbitrage, alternative assets, and asset allocation strategies.

Notice that the strategy group of ETFs is conceptually very close to an active mutual fund: it is not a passive investment strategy but rather a strategy that adopts an active dynamic approach, as its title suggests. Therefore, this group of ETFs could serve as a special indication of the extent to which the flow-return correlation structure depends on the investment approach as opposed to a pure instrumental division between mutual funds and ETFs.

Table 5 reports regression results for our four different investment categories. For the size-and-style, sector and commodities categories concurrent return coefficients are positive and highly statistically significant. For the strategy category only lagged returns are significant and positive, with p-values of 6 percent and 2 percent, respectively, indicating a delay in the effect returns have on flows. Adjusted $\overline{R}^2$ values are the highest for strategy ETFs, then for commodities, sector ETFs, and lowest for size and style ETFs, with 24, 21, 15, and 7 percent, respectively. Finally, Granger tests also confirm that only for the strategy and sector groups returns have a causal effect on flows at a 1 percent significance level; for the size-and-style and commodities groups Granger causality test statistics are non-significant.

These results are consistent with our previous findings, only this time within the ETF industry. Returns have very little effect on flows for truly passive investment strategies or asset allocation styles that simply follow broad market indices, such as large cap or total market. On the other hand, ETFs with the most specialized investment approaches, that is, those that adopt investment strategies, or commodities, indicate the highest sensitivity of flows to returns. Last, the middle ground case, where some level of pro-activity in the investment strategy is taken but is limited to choosing a specific sector rather than following a dynamic strategy, also indicates medium sensitivity of flows to returns.

9.2.1 Classification by Size and Style

Next we focus on the size-and-style group from the previous section, but this time further divide it into three additional sub-groups: large cap, medium cap, and small cap ETFs. If indeed broad market ETFs have a weaker connection between their flows and returns, we would expect this finding to translate into all three sub-groups.

Table 6 reports our regression results for these three cases. Return coefficient estimates are all positive and statistically significant. However, $\overline{R}^2$ values are very low and around 4% for large and medium caps, which indicate very limited explanatory power. For small caps $\overline{R}^2$ is around 12%, indicating higher explanatory power. These findings therefore are consistent with our main hypothesis: the farther the asset allocation is from a broad market index the stronger the effect returns have on flows, as indicated by small caps compared to large and medium caps. This fortifies our division between passive and active investment strategies.

9.3 Inverse and Leveraged

The last group of passive investment products we analyze are the classes of inverse and leveraged ETFs, where the first class shorts an index and the other amplifies the returns of an index by a pre-specified multiplier. The nature of their performance exposure implies that they are financial instruments that are very specialized in their investment strategy and may require strong active beliefs. Table 7 shows regression results and further supporting evidence follows.

Return coefficients are all statistically significant and obtain the highest values among all our previous tests and investment products: 0.3 and 0.4 for inverse and leveraged ETFs in absolute values, respectively, compared to less than 0.1 in most previous cases, and often even less than 0.01. Additionally adjusted $\overline{R}^2$ values are 25% and 48% for inverse and leveraged ETFs, respectively, indicating very high explanatory power for our model, in fact, among the highest achieved thus far in our tests.

Notice that in contrast to all previous cases, the correlation between flows and returns is negative for inverse and leveraged passive products. This implies that investors in leveraged and inverse ETFs are contrarians, who buy when ETF prices are declining and sell when they are increasing. In this respect, they behave like profit-takers, as they are frequently described in the financial press. Such a trading strategy supports their characterization as specialized investments which require a specific belief on future market behavior, far from a passive investment strategy. Again, despite the fact that these are passively managed ETFs, they experience a strong relationship between flows and returns since their investment strategy is more active, as all our previous results indicate.

Further, if investors in inverse and leveraged products are indeed contrarian, one could expect them to be more speculative compared to the average ETF investor. This implies that they are likely to be short-term investors and that their share of institutional holdings is smaller than that of other regular long ETFs. In order to explore these predictions we downloaded from Bloomberg historical data for turnover time and institutional holdings for US equity ETFs and leveraged and inverse ETFs. The time series for this data are presented in Figures 1 and 2 and Tables 8 and 9.

As can be seen in Figure 1, between 2005 and 2012 the turnover time for US equity ETFs is for the most part above the 20-day level; its highest values reached levels of beyond 60 days. In sharp contrast leveraged and inverse ETFs turnover times are mostly below 5 days, especially after 2007,[10] and rarely crossed the 10-day threshold. Annual averages reported in Table 8 indicate annual average turnover time for US equity ETFs between 15 and 35 days, compared to averages of 2 and 6 days for inverse and leveraged ETFs, respectively, with some variation between the years. These findings imply that investors in inverse and leveraged ETFs are very short-term investors and do not hold their positions for more than a few days.

Data for institutional holdings was available on Bloomberg only from 2010 onwards, yet it presents a clear difference between US equity and inverse and leveraged ETFs. As seen in Figure 2, institutional holdings for US equity ETFs mostly range between 50–60 percent, whereas for inverse ETFs levels are mostly between 20 and 30 percent, and for leveraged ETFs between 10 and 20 percent. Annual averages are reported in Table 9, conveying the same pattern.

These characteristics fortify the unique role and function that inverse and leveraged ETFs play for investors. They mostly serve non-institutional investors to carry out very

[10] Inverse and leveraged ETFs started trading in mid-2006; therefore, their initial relatively high turnover times were probably due to low liquidity around their introduction.

short-term market contrarian trades. Consistent with our previous results, we find that flows into these products are very sensitive to returns despite the fact they are passively managed in their portfolio selection.

10. Discussion

Evaluating our results in the context of the competing theories as to the driving cause behind the flow return correlation, we find support for the existence of "smart" or "dumb" money effects. As mentioned before, three theories have been proposed to explain the correlation between flows and returns. The first is the information hypothesis, which argues that the correlation is an expression of "smart" money flows, where investors increase or decrease investments based on information that is relevant to future performance. These types of information could include available news that is relevant to forming predictions or rational evaluations of fund-manager skills. The flow-return correlation arises because this information impacts returns and flow-decisions jointly. The second theory is the return chasing hypothesis, which argues that the correlation is an expression of "dumb" money flows, where uninformed investors simply chase returns under the (unjustified) assumption that mere returns signal future returns (i.e., momentum) or express fund-manager capabilities. Under this hypothesis, the correlation arises from the very nature of the strategy adopted by investors who interpret positive returns as a sign to invest (and vice versa for negative returns).

Both "smart" and "dumb" money hypotheses do not assume any causal effects from flows to returns, but rather describe a return-seeking investment behavior (whether rational or not) that is correlated with returns. Therefore, we have referred to these two theories as profit-seeking behavioral hypotheses. The third theory is the price pressure hypothesis, which argues that flows are not only correlated with security prices but also affect them. If demand for equity is not fully elastic, a large flow into investment funds will push security prices up, and conversely, a large flow out will push them down.

Discriminating among the three competing hypotheses in order to test for their empirical validity is a challenging task. Inflows, price movements, and new information about future security prospects, typically occur simultaneously, which makes it difficult to disentangle a single effect that takes place. One way to address this problem is to locate special settings where only a single hypothesis can take effect. Several studies followed this approach and focused on cases where isolated price pressure effects exist in the absence of “smart” and “dumb” money effects. For example, Shleifer (1986) and Harris and Gurel (1986) document price pressure effects for changes in the composition of Standard and Poor’s list of 500 stocks. They document that the inclusion of a new stock in the S&P 500 index increases demand for that stock, primarily by institutional investors, and pushes its price up. These exogenous events isolate price effects since they convey no new information to the market about potential future returns. Similarly, Coval and Stafford (2007) examine price pressures in mutual fund transactions caused by large fire sales. Again, these events are uncorrelated with new information and allow for examining an isolated price pressure effect. Moreover, they show that the price impact is stronger for large flows and non-existent for small flows. Additional works on mutual funds include Edelen and Warner (2001), and Ben-Rephael, Kandel and Wohl (2011).

Our setting of passive investment products provides a special case of the opposite circumstances, where price pressure effects are absent and only “smart” or “dumb” money effects can play a role. As we elaborate below, there are three main facts that make this case hard to reconcile with the existence of price pressures effects, but can accommodate the profit-seeking hypotheses. This provides support for the existence of independent behavioral effects which contribute to the flow-return correlation.

First, under the price pressure theory, large flows are required to shift the demand for securities and affect prices.[11] In our setting of passive investment products, despite their recent high growth rates, they still constitute a relatively small share of the total investment product industry, both in AUMs and total inflows/outflows. Therefore, it is unlikely that they would have a significant impact on the demand for securities that could impact prices. Table 18 and Figure 3 present historical year-end AUMs for ETFs and mutual funds in 1996–2012 based on ICI data. As can be seen, AUMs for ETFs are much smaller in magnitude compared to those of mutual funds. Despite their continuously growing share of the industry, in 2012 AUMs for ETFs were still only \$1.3 trillion compared to \$13 trillion for mutual funds, i.e., less than 10%. A similar picture arises when examining total inflows and outflows per year as reported in Table 19 and Figure 4. Annual total new issuances and redemptions for ETFs ranged from \$0.7 to \$1.3 trillion in 2007–2012, compared to a range of \$16 to \$25 trillion for mutual funds. In 2011 new issuances and redemptions for ETFs constituted around 7% of those for mutual funds. Similar evidence is brought by Stambaugh (2014). We refer the reader to his review for a supplementary comprehensive analysis of recent market trends.

These figures indicate that the passive industry is still relatively small and is unlikely to affect demand and push prices. Therefore, the flow-return correlation we find for passive products in a number of cases cannot be driven by price pressures. On the other hand, the correlation can still be explained by the alternative hypotheses of profit-seeking behavior.

[11] See Shleifer (1986), Harris and Gurel (1986), and Coval and Stafford (2007).

Second, the price pressure theory does not discriminate between different types of financial vehicles—that is, as long as flows are large enough they will shift demand and push prices regardless of the particular vehicle at stake. Particularly, in the case of investment products, we would expect to find the same impact for flows across all products regardless of their classification as passive or active. On the other hand, the profit-seeking hypotheses allow for heterogeneity in the flow-return relation, especially when investors' strategy is not driven by active profit-seeking. Indeed, as mentioned before, in our case passive investors may view index-tracking products as effectively fulfilling their investment aims as long as they continue to follow their underlying index, regardless of returns. Expectations of future returns, interpreting manager skills, and outperforming the market are a priori irrelevant for such an investment goal. They only become relevant for active investors who seek out signals of superior performance or future performance. A similar distinction between active and passive management strategies is adopted by Stambaugh (2014) to develop an equilibrium model, where only active management corrects most of the noise-trader induced mispricing, while index investing does not. As described above, we find various levels of correlation between flows and returns, depending on the level of passive or active investment style. This result is inconsistent with the price pressure explanation, but can be accommodated by the "smart" or "dumb" money hypotheses that allow for this flexibility.

Third, as mentioned before, under the price pressure theory it is more likely that large flows rather than small flows would impact prices. However, in our estimation results for tracking products we find the opposite, that the flow-return correlation is strong and more significant for smaller families of funds, and weak or non-existent for the largest families of funds. That is, the largest families of funds such as S&P index mutual funds, North

American ETFs, and size and style ETFs, experience very weak relations between flows and returns if any (see Tables 3, 4, and 5, respectively), whereas much smaller families of funds, such as non-US equity index mutual funds, Emerging Markets, Asia, Latin America, strategy, inverse and leveraged ETFs, all experience very strong flow-return relations (see Tables 3, 4, 5 and 7). Table 20 compares year-end AUMs for these large and small families of funds in 2000–2012. Substantial differences in AUMs are evident for these groups. For example, in 2011, AUMs for S&P passive mutual funds, North American ETFs, and size and style ETFs, were $376, $650 and $543 billion, respectively; compared to $121, $86, $33, $13, $36, $13 and $7 billion for non-US equity passive mutual funds, Emerging Markets, Asia and Latin America ETFs, strategy ETFs, and inverse and leveraged ETFs, respectively. The fact that substantially smaller families of funds exhibit a much stronger relation between flows and returns is inconsistent with the price pressure theory. On the other hand, under the alternative return-seeking hypotheses, it is reasonable to expect that investors would utilize more specialized vehicles (such as strategy or inverse ETFs) to execute active investment strategies, regardless of their minimal market share.

Last, we recognize that our findings cannot differentiate between "smart" and "dumb" money effects. Nevertheless, the ability to distinguish between effects generated by investors' motivation to outperform the market (profit-seeking hypotheses) from those caused by price pressures is significant in itself.

11. Relative Flows and Returns

Up to this point we tested for the impact that absolute returns for each product have on their own flows. In this section we extend our framework and address the impact that relative returns in the active sector compared to those in the passive sector have on the transition of money from one sector to the other. It may be the case that when actively-managed mutual funds outperform passive products, money flows to the winning industry despite the fact that both industries experience absolute positive returns. The model in Equation (10) is designed to capture such effects and its regression results are displayed in Table 10.

We estimated Equation (10) twice, once for flows from passive mutual funds to actively managed mutual funds, and again for flows from ETFs to actively managed mutual funds. The first block of results in Table 10 reports the former test, and the second block reports the latter. Each case is also split into total and US-domestic markets.

As can be seen the coefficient for the excess return variable in the total market for active mutual funds (premium) over passive ones is positive and highly significant. In fact, its coefficient size is as much as five times larger than the one for its absolute return, 0.24 compared to 0.05, respectively. Also, the $\overline{R}^2$ value is 54% indicating high explanatory power. Similar qualitative results are obtained for the transition of money from US passive mutual funds and from total ETFs into active mutual funds. Only US ETFs do not indicate much sensitivity to their relative performance compared to active mutual funds.

Notice that the constant coefficient in all regression is negative and statistically significant. This is consistent with the overall trend of the massive growth of the passive industry at the expense of more traditional actively-managed funds.

In summary, these results supplement our previous findings. They suggest that while passive products are less sensitive in their flows to their own absolute performance they are very sensitive to their relative performance in the competing industry of actively managed mutual funds. Put differently, when portfolio managers show superior (inferior) performance, new money is transferred to (withdrawn from) their management at the expense of (to the benefit of) passively-managed products.

12. Effect of Flows on Returns

To complete our analysis of the relationship between flows and returns, we tested for effects in the opposite direction. We repeated all our regressions, this time testing for effects from flows to returns following the same classifications and groups of products. Tables 11–17 present our results. Overall we find a statistically significant correlation coefficient between flows and returns, as expected given our previous regressions. However, the effect flows have on returns is much weaker across all groups of products and classification criteria. Adjusted $\overline{R}^2$ values are much weaker, especially for passive products, and Granger tests statistics are rarely significant. These facts indicate that flows are less successful in explaining the heterogeneity in returns and display no causal effects.

Table 11 presents our results for the aggregate mutual fund sector. The estimates for the flow coefficients are statistically significant; however, $\overline{R}^2$ values are lower compared to the effect in the opposite direction (between 20%–40% compared to 60%–70%, respectively). Similarly, none of the Granger causality test statistics are significant, as opposed to all of them being statistically significant for the effect in the opposite direction (see Table 1).

Table 12 presents our results per product type. The separation between active and passive mutual funds does not yield any new results. However, ETFs indicate causal effects from flows to returns as their Granger test statistics are statistically significant at the 1% significance level.

This pattern is generally maintained when further dividing each investment product into various classification groups by region, category, and size and style investment strategies.

As displayed in Tables 13–17, Granger test statistics are statistically significant for US and emerging markets equity ETFs (Table 14); for all categories of size and style, sector, and strategy (Table 15); and for large and medium caps (Table 16). On the other hand, causal effects cannot be detected for active nor passive mutual funds as seen in Table 13, with the exception of non-US equity passive mutual funds. Moreover, the only two cases where the flow coefficient is not even statistically significant are passive US-equity mutual funds, indicating no effect from flows to returns.

In summary, flows explain returns much less successfully than returns explain flows, despite a statistically significant relationship between the two. One exception is the case of US equity ETFs which display some predictability from flows to returns.

13. Conclusions

The strong relationship between inflows of money into investment products and their return performance is widely discussed in both academic and professional platforms. However, despite the massive growth in passive products, the distinction between the flow behavior for passive and active funds has received very little attention so far.

Moreover, the term “passive products” is almost unanimously used to describe funds that passively track a predetermined market index, such as ETFs or index mutual funds. We argue that a more refined description of a product as passive or active should take into account two underlying components that determine its overall characterization. One is the asset allocation which determines the investment strategy, and the other is the portfolio selection which relates to the executional aspect of the portfolio and its managerial style. Each one of these components may take a passive or active form. Thus, many investment products that are traditionally viewed as passive—as they passively track an index—in fact apply a fairly active asset allocation strategy, which makes them hybrid structures in their passive and active overall characterization.

We tested for differences in the flow return relation for passive and active funds, while controlling for each component separately. Using a rich set of classifications, we find that while a passive approach in both components weakens the connection, the investment strategy has a stronger effect. ETFs and index mutual funds that are passive in their portfolio selection, as they simply track an index, still exhibit a strong effect from returns to flows when their asset allocation style is active. This was found to be expressed through a variety of measures, such as correlations, model explanatory power, and causal effects. On the other hand, index products that track a broad market index exhibit minimal effects from flows to returns.

Our results indicate a fundamental difference in attitude between investors in each product type. Users of passive products indeed adopt a more comprehensive passive investment approach, one that is less dependent on market performance and does not attempt to outperform it. Their investment decisions indeed display relative indifference to returns, as a broad passive approach implies. However, this is conditional on investors' adoption of a truly passive attitude. If their investment approach is merely passive in its management style of selecting securities, but is active in its strategic style, they resemble other more active investors in their flow behavior.

Finally, despite the weak sensitivity of passive investors to their own absolute performance, they are not indifferent to the competing industry's performance. Once active mutual funds outperform the passive sector, money flows to the winning sector at the expense of the losing one, and vice versa. This result emphasizes the competitiveness level of the financial service industry. When active fund managers display differential ability to generate abnormal returns, or, alternatively, display inferior ability and underperform passive benchmarks, investors respond by re-allocating their investments accordingly. The response of fund flows to the better performing industry can be interpreted, as in Berk and Green (2004), as evidence that capital is channeled to investments in which it is most productive.

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Table 1 ALL MUTUAL FUNDS

Return Effect on Flows 2005–2012

Name	Const.	Return	Return (-1)	Flow (-1)	Flow (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
US Equity	-0.0003	0.0242	0.0140	0.4308		0.4818	0.4593	3.3169	93
	0.2045	*0.0000*	*0.0242*	*0.0000*				*0.142*	
US Bonds	0.0012	0.2310	0.1553	0.4363	0.1198	0.7677	0.5609	5.8812	93
	0.0145	*0.0000*	*0.0003*	*0.0000*	*0.1520*			*0.0003*	
US Hybrid	0.0007	0.074	0.0272	0.3955	0.1477	0.6555	0.5578	3.2951	93
	0.0479	*0.0000*	*0.0323*	*0.0003*	*0.0967*			*0.1146*	
World Equity	0.0005	0.0371	0.0209	0.4448	0.2835	0.7129	0.4093	2.2089	93
	0.2887	*0.0000*	*0.0198*	*0.0000*	*0.0027*			*0.0748*	
World Bond	-0.0007	0.3103	0.2093	0.4485	0.3425	0.8242	0.3434	5.3123	93
	0.5285	*0.0000*	*0.0000*	*0.0000*	*0.0002*			*0.0007*	
Total Market	0.0008	0.0447	0.0292	0.2213	0.1450	0.6483	0.6196	5.1902	93
	0.0041	*0.0000*	*0.0004*	*0.0285*	*0.0746*			*0.0009*	

This table reports regression results for the optimal number of lags for each group of funds. For more details, see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly changes (all in percentage points where 100% = 1).

Table 2 PRODUCT TYPE

Return Effect on Flows 2005–2012

Name	Const.	Return	Return (-1)	Flow (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
ETF	0.0022	0.1407			0.12896	0.3616	1.3880	409
	0.0000	*0.0000*					*0.2373*	
Passive MF	0.0048	0.0305			0.1126	0.3495	2.6644	93
	0.0000	*0.0006*					*0.0382*	
Active MF	0.0005	0.0519	0.0273	0.3542	0.7062	0.6464	5.4311	92
	0.0271	*0.0000*	*0.0007*	*0.0000*			*0.0006*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly changes (all in percentage points where 100% = 1).

Table 3 GEOGRAPHIC REGION: MUTUAL FUNDS

Return Effect on Flows 2005–2012

Name	Const.	Return	Return (-1)	Flow (-1)	Flow (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
				Active:					
US Equity	-0.0015	0.0291		0.4454		0.4352	0.4913	3.5589	92
	0.0000	*0.0000*		*0.0000*				*0.0100*	
Non-US Equity	0.0003	0.0450	0.0223	0.3837	0.3078	0.7254	0.4417	2.9877	91
	0.5054	*0.0000*	*0.0115*	*0.0002*	*0.0008*			*0.0236*	
				Passive:					
S&P Index	0.0001	-0.0032		0.2868		0.0616	-0.0195	1.2494	92
	0.8178	*0.6912*		*0.0060*				*0.2968*	
Other US Equity Indexes	0.0072	-0.0034				-0.0099	-0.0329	1.2494	93
	0.0000	*0.7522*						*0.2968*	
Non-US Equity Index	0.0068	0.1029		0.2544		0.1491	0.3310	0.6094	92
	0.0052	*0.0001*		*0.0136*				*0.6571*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly and weekly changes for mutual funds and ETFs, respectively (all in percentage points where 100% = 1).

Table 4 GEOGRAPHIC REGION: ETFs

Return Effect on Flows 2005–2012

Name	Const.	Return	Return (-1)	Flow (-1)	Flow (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
North America	0.0015	0.1653				0.0914	0.3061	1.3797	410
	0.0405	*0.0000*						*0.2402*	
Europe	0.0031	0.0649	0.0510	0.3317		0.1690	0.1788	1.9815	415
	0.0000	*0.0002*	*0.0040*	*0.0000*				*0.0965*	
Developed Markets	0.0034	0.0432				0.0174	0.1405	0.8574	414
	0.0000	*0.0042*						*0.4896*	
Global	0.0037	0.0783	0.0411	0.2301	0.1641	0.1540	0.1958	2.5110	415
	0.0000	*0.0000*	*0.0170*	*0.0000*	*0.0006*			*0.0413*	
Asia Pacific	0.0010	0.1143	0.0353	0.3593		0.3721	0.3380	2.1082	406
	0.0196	*0.0000*	*0.0076*	*0.0000*				*0.0791*	
Latin America	0.0019	0.1839	0.1169	0.2220	0.1635	0.3660	0.3776	6.5844	414
	0.0388	*0.0000*	*0.0000*	*0.0000*	*0.0001*			*0.0000*	
Emerging Markets	0.0046	0.2499		0.2684		0.2983	0.4801	1.8785	415
	0.0000	*0.0000*		*0.0000*				*0.1133*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where 100% = 1).

Table 5 CLASSIFICATION BY CATEGORY

ETFs—Return Effect on Flows 2005–2012

Name	Const.	Return	Return (-1)	Return (-2)	Flow (-1)	Flow (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
Size and Style	0.0027	0.1268					0.0693	0.2674	0.4922	415
	0.0001	*0.0000*							*0.7415*	
Sector	0.0040	0.2141	-0.0812		-0.1184		0.1513	0.3417	3.6873	410
	0.0000	*0.0000*	*0.0110*		*0.0096*				*0.0058*	
Strategy	0.0029	0.0177	0.0266	0.0339	0.2414	0.2590	0.2416	0.0715	4.2152	412
	0.0000	*0.2200*	*0.0678*	*0.0199*	*0.0000*	*0.0000*			*0.0024*	
Commodities	0.0038	0.1731			0.2197		0.2161	0.3575	0.3631	406
	0.0000	*0.0000*			*0.0000*				*0.8349*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where $100\% = 1$).

Table 6 CLASSIFICATION BY SIZE: ETFs

Return Effect on Flows 2005–2012

Name	Const.	Return	Flow (-1)	Flow (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
Large Cap.	0.0009	0.1352	-0.0911		0.0436	0.1955	0.5098	410
	0.3476	*0.0002*	*0.0384*				*0.7286*	
Mid-Cap	0.0016	0.0751			0.0409	0.2079	2.4410	412
	0.0045	*0.0000*					*0.0463*	
Small Cap	0.0033	0.2613	-0.2255	-0.1895	0.1292	0.2194	1.0337	407
	0.0874	*0.0000*	*0.0000*	*0.0000*			*0.3895*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where $100\% = 1$).

Table 7 INVERSE AND LEVERAGED ETFs

Return Effect on Flows 2005–2012

Name	Const.	Return	Flow (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
Inverse	0.0088	-0.3062	0.3824	0.2535	-0.2771	0.7438	334
	0.0001	*0.0000*	*0.0000*			*0.5627*	
Leveraged	0.0090	-0.4943	0.3566	0.4809	-0.5647	0.1850	336
	0.0006	*0.0000*	*0.0000*			*0.9461*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where 100% = 1).

Table 8 TURNOVER TIME: US EQUITY, INVERSE AND LEVERAGED ETFs
Annual Averages 2005–2012 (Days)

Year	US Equity	Inverse	Leveraged
2005	31.6	NA	NA
2006	27.5	132.4	4.6
2007	18.8	4.6	2.9
2008	13.2	3.2	1.4
2009	16.2	3.2	2.0
2010	22.2	5.3	2.2
2011	24.8	4.6	2.3
2012	36.1	6.5	3.5

Table 9 INSTITUTIONAL HOLDINGS: US EQUITY, INVERSE AND LEVERAGED ETFs

Annual Averages 2010–2012 (Percent)

Year	US Equity	Inverse	Leveraged
2010	51	20	12
2011	53	21	10
2012	55	25	16

Table 10 RELATIVE FLOWS AND RELATIVE RETURNS

Relative Return Effect on Relative Flows 2005–2012

Type	Const.	ΔReturn	ΔReturn (-1)	ΔReturn (-2)	Return	Return (-1)	Return (-2)	$\overline{R}^2$	#Obs.
Passive MFs to Active MFs:									
Total Market	-0.001	0.242			0.052			0.54	94
	0.0000	*0.0000*			*0.0000*				
US Market	-0.001	0.239			0.015			0.60	93
	0.0285	*0.0000*			*0.0225*				
ETFs to Active MFs:									
Total Market	-0.019	0.706	0.297	0.946	0.050	0.213	0.528	0.20	93
	0.0000	*0.0060*	*0.2419*	*0.0002*	*0.0440*	*0.0972*	*0.0000*		
US Market	-0.014	0.572			0.003			0.00	95
	0.0003	*0.2438*			*0.9720*				

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly changes (all in percentage points where 100% = 1).

Table 11 ALL MUTUAL FUNDS

Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Flow (-2)	Return (-1)	Return (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
US Equity	0.0062	7.5858	-1.9790				0.2058	0.4593	1.0463	93
	0.1800	*0.0000*	*0.2225*						*0.3883*	
US Bonds	-0.0004	1.6089	-0.8867				0.4285	0.5609	0.5192	93
	0.7410	*0.0000*	*0.0000*						*0.7218*	
US Hybrid	-0.0011	4.8454	-0.9250	-1.7681			0.4048	0.5578	4.7692	93
	0.7146	*0.0000*	*0.2684*	*0.0102*					*0.0016*	
World Equity	-0.0026	5.2445	-2.8595				0.2106	0.4093	0.4065	93
	0.6602	*0.0000*	*0.0098*						*0.8035*	
World Bond	0.0058	1.5148	-0.5208	-0.7563	-0.3183		0.4722	0.3434	2.2533	93
	0.0114	*0.0000*	*0.0236*	*0.0002*	*0.0031*				*0.0700*	
Total Market	-0.0076	7.7804			-0.1437	-0.1933	0.4180	0.6196	2.0317	93
	0.0246	*0.0000*			*0.1525*	*0.0229*			*0.0972*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly changes (all in percentage points where $100\% = 1$).

Table 12 PRODUCT TYPE

Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Return (-1)	Return (-2)	$\overline{R}^2$	Corr	Granger	#Obs.
ETF	-0.0004	0.8845	-0.2580			0.1387	0.3616	4.9033	409
	0.7911	*0.0000*	*0.0169*					*0.0007*	
Passive MF	-0.0142	3.7056		0.1491		0.1238	0.3495	0.9343	92
	0.0435	*0.0017*		*0.1376*				*0.4484*	
Active MF	-0.0049	8.4072		-0.2073	-0.2744	0.5072	0.6464	1.1679	91
	0.1063	*0.0000*		*0.0318*	*0.0007*			*0.3312*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly and weekly changes (all in percentage points where 100% = 1).

Table 13 GEOGRAPHIC REGION: MUTUAL FUNDS

Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Return (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
				Active:				
US Equity	0.0195	9.5407	-3.3267		0.2659	0.4913	1.0458	92
	0.0013	*0.0000*	*0.0433*				*0.3889*	
Non-US Equity	-0.0009	6.4958	-4.0274		0.2987	0.4417	0.3539	92
	0.8664	*0.0000*	*0.0002*				*0.8406*	
				Passive:				
S&P Index	0.0031	-0.0354		0.2335	0.0344	-0.0195	1.0325	92
	0.5155	*0.9783*		*0.0263*			*0.3956*	
Other US Equity Indexes	0.0076	-0.4374		0.2111	0.0246	-0.0329	0.1504	92
	0.4029	*0.6697*		*0.0444*			*0.9623*	
Non-US Equity Index	0.0094	1.4820	-1.3675		0.2100	0.3310	3.7393	92
	0.3174	*0.0001*	*0.0004*				*0.0077*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for monthly and weekly changes for mutual funds and ETFs, respectively (all in percentage points where $100\% = 1$).

Table 14 GEOGRAPHIC REGION: ETFs
Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Return (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
North America	0.0004	0.5397	-0.1593		0.0983	0.3061	3.8150	410
	0.7803	*0.0000*	*0.430*				*0.0047*	
Europe	-0.0015	0.4985		-0.0746	0.0327	0.1788	0.3753	415
	0.4259	*0.0001*		*0.1305*			*0.8263*	
Developed Markets	-0.0008	0.4627	-0.0036		0.0169	0.1405	0.6160	414
	0.6166	*0.0038*	*0.3731*				*0.6514*	
Global	-0.0010	0.5979	-0.2330		0.0405	0.1958	0.0976	415
	0.6093	*0.0000*	*0.0867*				*0.9832*	
Asia Pacific	-0.0003	1.4598	-0.6314		0.1609	0.3380	0.5442	406
	0.8419	*0.0000*	*0.0000*				*0.7034*	
Latin America	0.0012	1.1306	-0.3678	-0.1940	0.2152	0.3776	0.3892	414
	0.5957	*0.0000*	*0.0005*	*0.0001*			*0.8164*	
Emerging Markets	-0.0018	1.0738	-0.4488		0.2733	0.4801	2.8067	415
	0.3462	*0.0000*	*0.0000*				*0.0254*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where 100% = 1).

Table 15 CLASSIFICATION BY CATEGORY: ETFs

Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Return (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
Size and Style	0.0003	0.5469	-0.3009		0.0874	0.2674	3.8039	415
	0.8317	*0.0000*	*0.0026*				*0.048*	
Sector	-0.0009	0.5135		-0.0114	0.1126	0.3417	2.4876	410
	0.5397	*0.0000*		*0.8090*			*0.0430*	
Strategy	-0.0015	0.2486		-0.1083	0.0118	0.0715	2.3562	412
	0.3593	*0.0954*		*0.0296*			*0.0532*	
Commodities	-0.0005	0.7433	-0.0919		0.1272	0.3575	0.5120	406
	0.7507	*0.0000*	*0.1876*				*0.7260*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where 100% = 1).

Table 16 CLASSIFICATION BY SIZE: ETFs

Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Return (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
Large Cap.	0.0009	0.2413	-0.1441		0.0477	0.1955	3.0054	410
	0.4858	*0.0002*	*0.0142*				*0.0183*	
Mid-Cap	0.0004	0.5933		-0.0756	0.0442	0.2079	2.8490	412
	0.8207	*0.0000*		*0.1183*			*0.0237*	
Small Cap	0.0008	0.1872	0.0147		0.0439	0.2194	1.1568	407
	0.6288	*0.0000*	*0.6670*				*0.3295*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where 100% = 1).

Table 17 INVERSE AND LEVERAGED ETFs

Flow Effect on Return 2005–2012

Name	Const.	Flow	Flow (-1)	Return (-1)	$\overline{R}^2$	Corr	Granger	#Obs.
Inverse	-0.0001	-0.2972	0.1064		0.0856	-0.2771	0.3224	334
	0.9580	*0.0000*	*0.0223*				*0.8629*	
Leveraged	0.0091	-0.7749	0.2199	-0.1177	0.3887	-0.5647	0.8642	336
	0.0065	*0.0000*	*0.0000*	*0.0178*			*0.4857*	

This table reports regression results for the optimal number of lags for each group of funds. For more details see Section 3 on the specification and optimal model criteria. Coefficient estimates are reported in the first row for each regression, and p-values below. Flows and returns are measured for weekly changes (all in percentage points where $100\% = 1$).

Table 18 TOTAL ASSETS UNDER MANAGEMENT

Billions of Dollars, Year End (1996–2012)

Year	Mutual Funds Total	Mutual Funds Passive	ETFs	ETFs Share
1996	$3,526	-	$2	0.1%
1997	4,468	-	7	0.2%
1998	5,525	-	16	0.3%
1999	6,846	-	34	0.5%
2000	6,965	-	66	0.9%
2001	6,975	-	83	1.2%
2002	6,383	-	102	1.6%
2003	7,402	-	151	2.0%
2004	8,095	-	228	2.7%
2005	8,891	619	301	3.3%
2006	10,398	747	423	3.9%
2007	12,000	855	608	4.8%
2008	9,603	602	531	5.2%
2009	11,113	835	777	6.5%
2010	11,831	1,017	992	7.7%
2011	11,626	1,094	1,048	8.3%
2012	13,044	1,297	1,337	9.3%

Source: ICI Data

Table 19 CREATIONS AND REDEMPTIONS—MUTUAL FUNDS and ETFs
Billions of Dollars, Annual (2001–2012)

Year	Mutual Funds		ETFs		ETFs Share	
	New Sales	Redemptions	Issuance	Redemptions	Issuance	Redemptions
2001	12,748	12,242	76	45	0.6%	0.4%
2002	13,084	13,011	98	52	0.7%	0.4%
2003	12,315	12,362	97	81	0.8%	0.7%
2004	12,101	12,039	158	102	1.3%	0.8%
2005	13,812	13,547	271	214	1.9%	1.6%
2006	17,229	16,752	457	383	2.6%	2.2%
2007	23,236	22,352	1,056	905	4.3%	3.9%
2008	26,133	25,725	1,318	1,141	4.8%	4.2%
2009	20,528	20,680	868	752	4.1%	3.5%
2010	18,050	18,319	1,106	988	5.8%	5.1%
2011	17,657	17,737	1,320	1,203	7.0%	6.4%
2012*	16,826	16,618	846	716	4.8%	4.1%

*ETF data as of September 2012. Source: ICI Data

Table 20 ASSETS UNDER MANAGEMENT—BY FAMILY FUND

Billions of Dollars, Year-End (2000–2012)

	Passive Mutual Funds		ETFs								
			Region				Category			Special	
Year	S&P Index	Non-US Equity Index	North America	Emerging Markets	Asia Pacific	Latin America	Size and Style	Sector	Strategy	Inverse	Leveraged
2000	0.00	0.00	60.79	0.00	1.02	0.05	60.25	2.34	0.00	0.00	0.00
2001	0.00	0.00	77.92	0.00	0.99	0.07	75.81	4.94	0.00	0.00	0.00
2002	0.00	0.00	95.11	0.00	1.29	0.11	90.39	5.59	0.00	0.00	0.00
2003	0.00	0.00	132.30	1.09	4.93	0.49	129.44	11.01	0.93	0.00	0.00
2004	0.00	0.00	184.45	3.92	10.82	0.81	184.15	19.37	5.51	0.00	0.00
2005	334.01	42.79	223.08	10.79	21.16	2.94	237.13	27.72	7.85	0.00	0.00
2006	379.77	66.65	280.46	17.80	30.63	5.86	317.93	40.37	9.29	0.43	0.46
2007	394.59	95.67	374.69	34.79	38.31	11.82	440.88	57.42	9.27	2.03	1.98
2008	252.96	50.13	358.68	25.08	21.89	5.33	350.19	50.96	6.42	4.68	8.20
2009	328.65	92.51	460.83	62.03	37.86	16.63	459.11	75.62	9.09	14.53	7.15
2010	375.95	122.75	576.40	101.01	42.57	19.72	566.47	100.68	20.26	13.40	7.77
2011	376.58	121.45	650.12	86.13	33.34	13.68	543.28	111.05	36.88	13.83	7.19
2012	*426.498	*153.844	823.32	128.63	39.89	14.28	693.55	146.78	51.12	10.80	8.28

*Data as of November 2012. Source: ICI Data

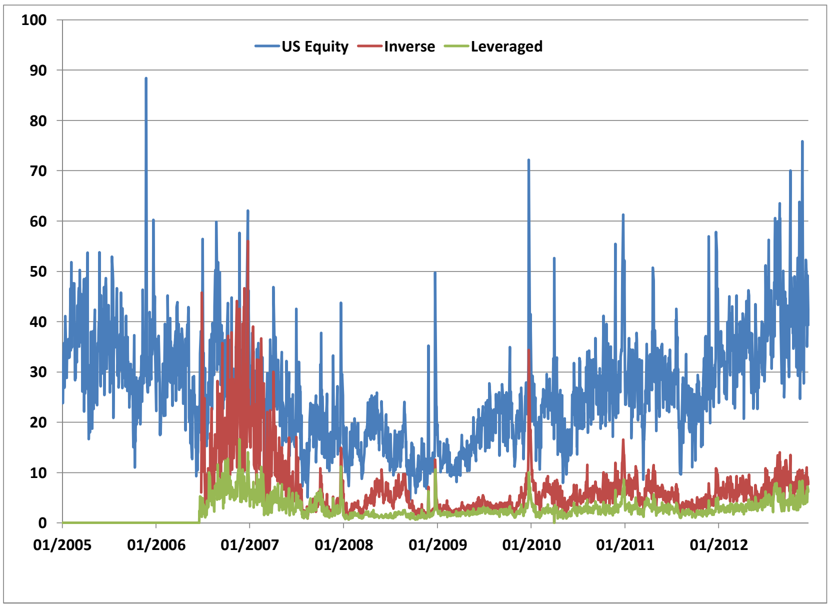

Fig. 1. TURNOVER TIME: US EQUITY, INVERSE and LEVERAGED ETFs For years 2005–2012 (Days)

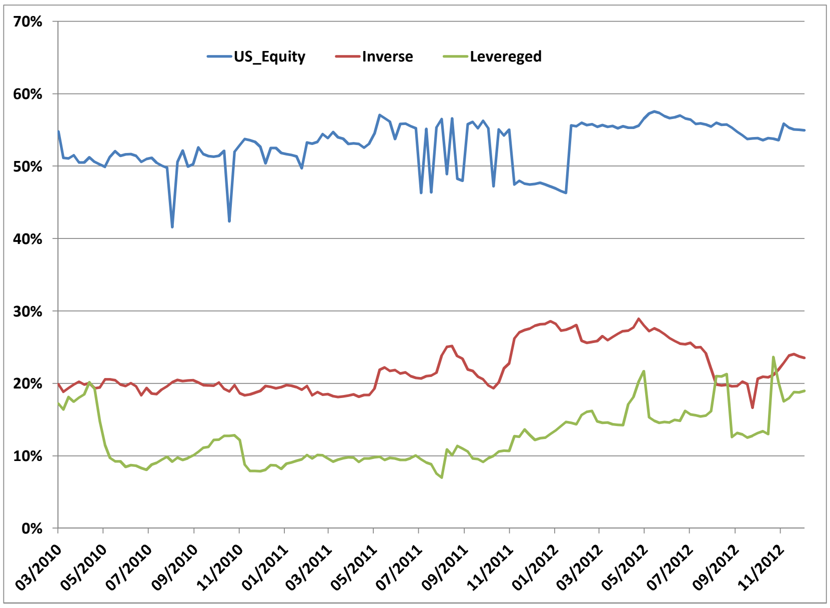

Fig. 2. INSTITUTIONAL HOLDINGS: US EQUITY, INVERSE and LEVERAGED ETFs

For Years 2010–2012 (Percent)

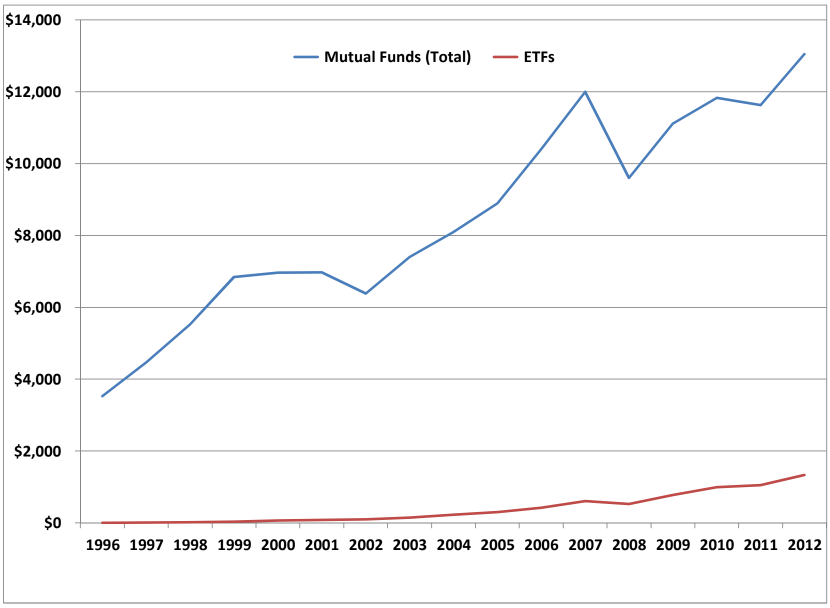

Fig. 3. TOTAL ASSETS UNDER MANAGEMENT

Billions of Dollars, Year-End Values (1996–2012)

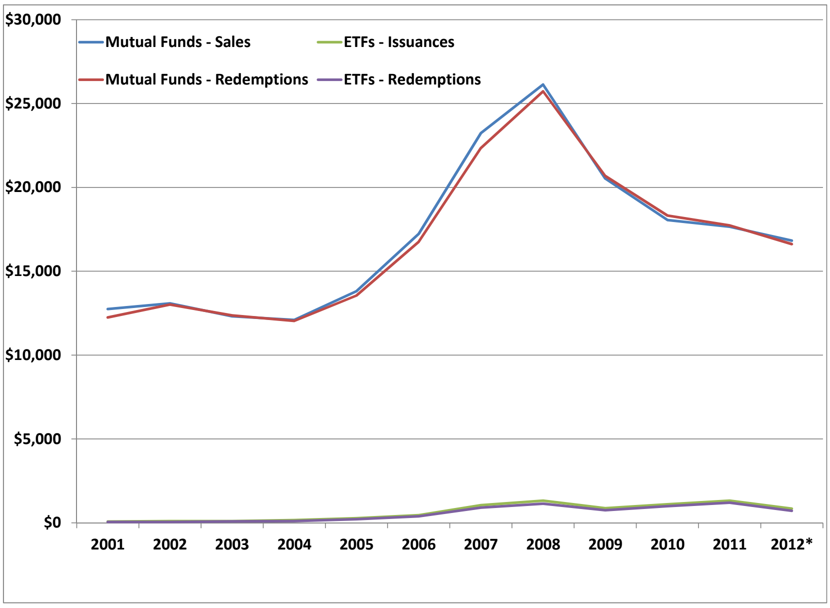

Fig. 4. CREATION and REDEMPTIONS—MUTUAL FUNDS and ETFs

Billions of Dollars, Total Annual Values (2001–2012)