Flows and Returns: A New Perspective

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Abstract

The connection between the demand for investments and investment returns has so far been addressed almost exclusively in the context of inflows of money into mutual funds and their return performance. We provide a new perspective on this relationship by exploring a larger set of financial instruments, a set which is more representative of the abundance of investment vehicles currently used in financial markets. In contrast to prior research, we find a much richer structure between flows and returns, a structure that depends on the active vs. passive investment approach which the particular instrument serves.

1 Introduction and Background

In this paper we study the connection between the demand for investments and investment returns. This topic has so far been addressed almost exclusively in the context of inflows of money into mutual funds and their return performance. It has been widely documented that new cash flows into mutual funds are highly correlated with their performance.[1] We provide a new perspective on this relationship by exploring a much broader set of financial instruments, a set which is more representative of the abundance of investment vehicles currently used in financial markets.

We show that once a variety of instruments is considered, the correlation between flows and returns has a much richer structure compared to the one previously documented with the

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[1] The early works on this subject include Ippolito (1992), Warther (1995), Gruber (1996), and Sirri and Tufano (1998). See next few paragraphs for a full review.

mutual funds sector alone. We find that the flow-return correlation structure changes across instruments and within instruments, and depends on a variety of characteristics such as asset class, region, underlying risk exposure, and more. Our results demonstrate that investors are not entirely naive in their investments decisions, as some argue (Cooper, et al. (2005), Sapp and Tiwari (2004)), and indicate how their reactions to returns are closely related to their investment strategy and choice of product.

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), among many others. All of these works documented the same fundamental phenomenon that concurrent flows and returns in the mutual fund sector are highly correlated in a positive way.

However, the interpretation of this phenomenon was less uniform. One group of studies argued that inflows reflect "smart money" effects, which express investors' selection ability of future winning mutual funds or of superior portfolio manager skills (Gruber (1996) and Zheng (1999)). Conversely, another group argued that the positive flow-return correlation simply expresses short-lived price pressures generated by increased demand for assets, price pressures which are reversed in the long run. Among these papers are Edelen and Warner (2001), Coval (2007), Lou (2012), and Ben-Raphael, et al. (2012). A third group of studies provided evidence that inflows merely express "dumb money" movements, where investors naively chase past and current returns. See for example: Jain and Wu (2000), Sapp and Tiwari (2004), Cooper, et al. (2005), and Franzzini and Lamont (2008). Finally, a number of papers focused 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), among others.

As mentioned above, in our work we go beyond the mutual fund sector and analyze the flow-return relationship for a larger set of instruments. In our analysis we include passive mutual funds, long ETFs, inverse ETFs, and leveraged ETFs, in addition to active mutual funds. A priori it is unclear what one should expect the flow-return correlation to be for each of these instruments. For example, if investors indeed have selection capabilities, are these capabilities limited to selecting winning mutual funds and identifying portfolio manager skills, or perhaps they also include the ability to predict market returns and market trends? Under the former scenario we should expect passive investment money flows to have no correlation with returns, whereas under the second scenario we would expect them to have a positive one. Alternatively, if investors are merely naively chasing past returns, is this behavioral pattern exclusive to the active investment sector where returns may be interpreted as superior fund manager skills, or does a similar inclination to naively chase past returns also exist in the passive investment sector? Again, under the former scenario we would expect cash flows into passive investments to have no correlation with returns, whereas under the second scenario we would expect them to have a positive one. Moreover, even within the passive investment sector, are there separate flow-return patterns for tradable instruments, such as ETFs, and non-tradable investments, such as passive mutual funds? Finally, how does the flow-return correlation depend on the instrument's level of risk? Do investors adopt separate investment rules for leveraged and inverse instruments which are separate from those they use for regular ETFs or mutual funds? In this paper we provide empirical evidence to answer these questions.

In our analysis we study the flow-return correlation and causation for each instrument separately. We test for past and current effects in both directions: from flows to returns and from returns to flows. We further apply Granger causality tests to identify causal relationships and to extract potential predictive information that may exist. Finally, we repeat our tests for various sub-sectors within each instrument to test for relations that might cancel out at the aggregate level.

To preview our results, we find that all three types of correlations exist between flows and returns: positive correlations, negative correlations, and no correlation. The highest level of correlation is found for mutual funds, inverse ETFs, and leveraged ETFs; however, their signs vary: mutual funds have a positive correlation between flows and returns, and leveraged and inverse ETFs have a negative one. The next level of correlation is found for regular ETFs (i.e., once long), which experience a much weaker correlation compared to the first group; however, their correlation is always positive. Finally, passive mutual funds show no correlation between flows and returns.

Our Granger causality tests indicate that in most cases where a strong correlation exists, returns cause flows but flows have a much lesser impact on returns. Another difference between flows and returns also exists for their lagged effects. Returns experience a correction process in many cases, where past and current flows affect them in opposite directions. This is not the case for flows - past and current returns affect them in the same direction, indicating a continuous effect over time.

Our results suggest a clear distinction between active and passive investments: active investments are strongly sensitive to returns, whereas more passive ones are much less sensitive.

Also, the more active the investment strategy is, the stronger the correlation and causation structure between flows and returns. This distinction holds both across instruments and within instruments, depending on the specific investment strategy applied. That is, generally mutual funds are more active investments as they apply a dynamic portfolio management. ETFs, on the other hand, simply track a predetermined index or market benchmark, which may be viewed as a more passive approach. Consistent with this initial division, the flow-return structure is much stronger for mutual funds compared to ETFs. However, the strength of the flow-return structure is also more pronounced for more active sub-groups of instruments once further dividing each instrument type into more active and passive investment strategy groups. That is, we find that the flow-return relation is stronger for active mutual funds and inverse, leveraged, strategy, and emerging market ETFs, while for passive mutual funds and broad market ETFs it is either weak or non-existent.

New empirical evidence concerning flow behavior and investors' demand for financial instruments has important implications. Modern financial markets are fast-growing in their diversity of new and innovative financial products. These products continuously increase their market share at the expense of more traditional mutual funds. Data provided by the Investment Company Institute (ICI) shows that ETFs are rapidly growing at an annual rate of around 30% per year, compared to less than 10% for the mutual fund sector. The market share of mutual funds out of the entire investment funds industry dropped from 96% in 2000 to 88% in 2012, whereas the share of ETFs grew from less than 1% to over 9%. These changes demonstrate some of the transitions that current financial markets are going through. The rise of new products facilitates new investment strategies and generates new behavioral patterns. In this respect, the new financial environment provides previously unavailable opportunities to test investor behavior in a more diverse setting and gain insight into new phenomena.

Furthermore, from a regulatory policy point of view, it is important to understand the new challenges that our modern financial environment presents. The surge of new financial products, especially the massively growing market share of ETFs, introduces the need to understand how the demand for these new products behaves and what implications it bears for market stability. Some regulators and official bodies have already expressed growing concerns regarding the consequences of the increasing market share of new investment vehicles to systemic risks, particularly in the case of ETFs. In 2011 the Bank of International Settlements,[2] the IMF,[3] and the Financial Stability Board[4] in the US, all issued reports

[2]See: Ramaswamy (2011)

[3]See: Global Financial Stability Report, April 2011.

[4]See: "Potential financial stability issues arising from recent trends in Exchange-Traded Funds (ETFs)",

addressing systemic risk concerns regarding ETFs, emphasizing risks such as sudden withdrawals, sell-offs, and liquidity shocks.[5] Others dismissed such concerns, referring to them as speculative ideas on liquidity spirals.[6] This paper contributes to this debate by providing empirical evidence on how and when money transits in and out of the market for a diverse set of instruments, and how it inter-depends on returns.

2 Data

We collected data for active mutual funds, passive mutual funds, long ETFs, inverse ETFs, and leveraged 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. Their data is available for the total mutual fund industry and for active and passive mutual funds separately. It includes aggregate month-end information on total Assets Under Management (AUM), gross inflows and outflows, and net flows. The data is also available for various sub-classifications by sector (equities, fixed income, hybrid, etc.) and geographic investment destination (US, 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 a few 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 contained 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 huge heterogeneity in the size and liquidity of ETFs, with AUMs ranging from over 100 billion dollars (e.g. SPY) to less than 100,000 dollars. Since smaller funds have a negligible impact on demand and face greater liquidity frictions, we focused on ETFs with 0.5 billion dollars in AUM or more. Our final list contained the largest 301 ETFs in AUM.

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

12 April 2011.

[5] See "Too Much of a Good Thing", *The Economist*, June 23rd, 2011.

[6] See: "Systemic risk implications of ETFs and impact of ETFs on their underlying markets", *Risk.net*, by Noël Amenc and Frédéric Ducoulombier. February 9, 2012.

3 Variable Construction

Ideally one would like to test the flow-return relationship 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 indicative of new money that flows into the industry. Therefore, we used various classifications to create sub-groups of funds for each instrument, and tested the flow-return relationship per investment group per instrument type. For mutual funds ICI data contains aggregate data for various investment groups such as US and international equities and bonds. For ETFs we created various groups based on similar criteria. Our initial classification for ETFs included the basic cataloging into different asset classes: equities, commodities, and fixed Income. As a second step we took a deeper look into the equity asset class by grouping it separately into various investment categories, styles, and regions. We elaborate on these issues later.

Dollar net flow data for mutual funds was available for various investment groups only at the monthly level. Similar to Sirri and Tufano (1998), Edelen and Warner (2001), and Ben-Raphael et al. (2012), and many others, for each investment group we normalized the month-end dollar net flow data by its previous month-end AUM. In this way we eliminated market growth trends over time and created a more informative percentage net inflow measure. That is,

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

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,

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

For ETFs the variable construction process was a bit 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,

$$Net\ Dollar\ Flow_n^j = \Delta SO_n^j \times P_n^j \tag{3}$$

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

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

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 ETF group J at the end of the previous week,

$$F_t^{ETF} = \frac{Net\ Dollar\ Flow_t}{\sum_{j\in J} AUM_{t-1}^j} \tag{5}$$

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 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,

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

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

4 Methodology

At the preliminary stage of the data analysis, the Pearson correlation coefficient 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 account of 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. The reason is that the correlograms of both flows and returns are almost flat, implying that it is essentially impossible to use lagged variables as good instruments. 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.[7]

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.

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. For brevity, we report only the p-value associated with the test containing 4 lags.

5 Results

We present our estimation results for Equations 8 and 9 in Tables 1-5 for each instrument separately: mutual funds, passive mutual funds, active mutual funds, ETFs by asset class, and inverse and leveraged ETFs, respectively. Each table is divided into two panels: Panel A reports regression results and Granger causality test results for the effect returns have on flows; Panel B reports the same for the effect in the opposite direction, from flows to returns. We start with reproducing the previously documented findings for the mutual fund sector.

[7] 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.

5.1 Mutual Funds

As shown in Table 1, we divided our mutual funds data into various types of funds: equity, bond, and hybrid,[8] for US and world funds separately, in addition to the aggregate total market of mutual funds. Panel A reports our results for the effect returns have on flows. As can be seen, 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, $\overline{R}^2$ values are around 70 percent in most cases indicating high explanatory power.

Panel B reports regression results for returns on flows (Equation 9). Concurrent flows positively affect returns at high significance levels for all fund types. However, this time in many cases lagged flows have a statistically significant negative effect on returns (US bonds and hybrid funds, world equity and bond funds). This result indicates a correction process that returns experience in response to their prior reaction to flows. Finally, $\overline{R}^2$ values are around 20-30 percent, which are much smaller compared to their values in the other direction, yet still indicating substantial explanatory power.

Consistent with these results, our Granger causality tests confirm that returns have a much stronger causal effect on flows compared to the one which flows have on returns. As can be seen in Panel A of Table 1, the p-values for Granger tests for the effect returns have on flows are all around 1 percent or lower, with the exception of world equity funds, which have a p-value of 7 percent. On the other hand, p-values for Granger causality tests in the other direction (Panel B) are 38 percent for US equity funds, 72 percent for US bond funds, and 80 percent for world equity funds, not supporting any evidence for causal effects from flows to returns. World bond and total market also have relatively high p-values of 7 and 10 percent, respectively.

These results are all consistent with the findings previously documented in the literature. (See our introduction for an extensive list of references.)

5.2 Active vs. Passive Mutual Funds

A more refined analysis of the mutual fund industry reveals a new picture with substantial differences between active and passive funds within the industry. Tables 2 and 3 present our estimation results for passive and active funds separately. As can be seen, it is the active

[8] These are mixed equity and bond funds.

sector that accounts for our previous results, while passive funds show very little relation between flows and returns.

Table 2 presents our results for passive mutual funds divided into five different groups: funds that track the S&P index, other US equity indices, global equity indices, a mix of bond and equity indices, and the total market for passive mutual funds. As presented in Panels A and B, funds which passively track US equity indices, whether it is the S&P 500 or other indices, show very little correlation between flows and returns. Further, regression results show that neither returns nor flows have a statistically significant effect on each other. Similarly, $\overline{R}^2$ values are minimal and are below 5 percent, indicating very little explanatory power for our regressions, in both directions. Finally, Granger causality tests show that there are no causal effects from flows to returns and vice versa.[9]

On the other hand, passive mutual funds that track either global indices or hybrid equity and bond indices have a flow-return structure that resembles the one documented above for the entire mutual fund industry. They have higher positive correlations (around 30 percent), and returns have a positive and statistically significant effect on flows. The same holds true in the other direction. $\overline{R}^2$ values are around 50 percent for hybrid funds in both directions, and around 15 and 20 percent for global equity indices in Panel A and B, respectively.

At this point we do not expand on the fundamental differences between passive mutual funds that track US equity indices and other hybrid funds or global ones. Our ICI data indicates that, at their peak, hybrid and global passive mutual funds accounted for no more than 30 percent of the passive mutual fund industry, and therefore are less representative of this sector. However, we elaborate on this issue later on. These differences are consistent with similar findings we later document within the ETF industry, another passive instrument. We thus dedicate a whole section for discussing the regional impact on the flow-return structure within the passive instruments industry.

Table 3 presents our results for the active mutual fund sector alone. Interestingly, once we exclude passive funds from the mutual fund industry, the characteristics of the flow-return relation for the remaining active funds becomes more distinct. All our regression results in both directions, estimates, statistical significance, and $\overline{R}^2$ values, are maintained and remain very similar to those obtained from analyzing the entire mutual funds industry, as reported in the previous section. However, Granger causality tests for the effect returns

[9] These results stand in contrast to Goetzmann and Massa (2003), who documented daily correlations between flows and returns for passive mutual funds. However, they used only 2 years of daily and intraday data for only 3 index funds (Fidelity) in the mid 1990's.

have on flows are all highly significant, whereas in the other direction none are statistically significant. This property was less uniform when we previously considered the entire mutual fund industry as a whole, passive and active fund combined. We conclude that this one-directional causal effect from returns to flows becomes clearer for active mutual funds once the set of passive instruments is removed - a set that has a fundamentally different correlation structure between flows and returns.

5.3 Long ETFs

We next describe our estimation results for the ETF industry. We divided the long ETF industry into three sub-sectors: equities, commodities, and fixed income. Panel A in Table 4 reports our results for the effects returns have on flows. The correlation between flows and returns is 30 percent for equities and commodities, and only 5 percent for the fixed income sector. Consistent with these numbers, concurrent returns have a statistically significant positive effect on flows for equities and commodities, but not for the fixed income sector. Returns do not have a statistically significant lagged effect on flows in all sectors. Adjusted $\overline{R}^2$ values are 12 and 21 percent for equities and commodities, respectively, but 0 for fixed income. These are substantially lower levels of explanatory power compared to those found for active mutual funds. A similar picture arises for the regression of returns on flows, as reported in Panel B. Finally, the weak relation between flows and returns is also reflected in their Granger causality tests in both directions. There is evidence for causal effects only in two cases, from flows to returns for equities and from returns to flows for fixed income.

As a final comment we point out that when regressing flows on returns (Panel A) there is a statistically significant positive constant in all sectors. This result indicates a positive growth of these funds over time, which is consistent with the massive growth of these instruments over the past decade.

5.4 Inverse & Leveraged ETFs

The last two instruments we analyze are leveraged and inverse ETFs. Their results are reported in Table 5. In contrast to all previous instruments, the correlation between flows and returns is negative in this case. Further, Panel A reports regression results for flows on returns which confirm that concurrent returns have a statistically significant negative effect on flows with p-values equal to zero in all cases. Moreover, their coefficients are the highest among all instruments (in absolute values): -30 and -40 percent for inverse and leveraged ETFs, respectively, compared to less than 10 percent in most previous cases, and often even less than 1 percent. There are also no lagged effects. Finally, adjusted $\overline{R}^2$ values are 25 and

48 percent for inverse and leveraged ETFs, respectively, indicating high explanatory power for our model.

Similar results are obtained in the other direction when regressing returns on flows, as reported in Panel B. However, one noticeable difference is that lagged flows are statistically significant and have a positive effect on returns. This result is consistent with the correction effect we previously found for returns in all other instruments that similarly experience a strong correlation between flows and returns.

Last, Granger causality tests do not indicate any statistically significant causal effects between flows and returns in both direction, with p-values above 50 percent.

The unique negative correlation between flows and returns implies that investors in leveraged and inverse ETFs are contrarian, who buy when ETF prices are declining and sell when they are increasing. This trading strategy should also imply that these investors do not buy and hold for long terms, but are rather more short term investors. To check this prediction 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 9 and 10.

As can be seen in Figure 1, between 2005-2012 the turnover time for US equity ETFs is mostly above the 20-day level, and at 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. Also, their turnover times are very close to one another. Annual averages reported in Table 9 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.

These results are also consistent with the data for institutional holdings for these three groups of ETFs. Data for institutional holdings was available on Bloomberg only from 2010 and on, yet it presents a clear difference between US equity and inverse and leveraged ETFs during this period. 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 10, indicating similar results.

[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.

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 short term market contrarians trades.

6 Additional Classifications and Sub-Groups

In order to take a deeper look into the correlation structure we used additional sub-classifications to refine our within-instrument analysis. We focus on the equities asset class, which constitutes the largest asset class for both ETFs and mutual funds. Aggregate market data provided by ICI indicates that pure equity funds' market share ranged in 2005-2012 from 95 to 85 percent for ETFs, from 77 to 89 percent for passive mutual funds, and from 54 to 72 percent for active mutual funds. We therefore start with grouping individual equity funds into different investment categories, and then add additional cataloging into investment style-and-size and geographic regions.

6.1 Classification by Category

We first divided the equities asset class into different investment categories. Unfortunately this classification is available in our data only for ETFs. However, as we immediately show, it provides insightful information which supports our previous results.

We defined three groups for our sample of long ETFs: sector investments, size-and-style investments, and strategy investments. Sector ETFs track single sector indices such as financial, technology, and so on. The size-and-style classification includes ETFs that track broad market indices such 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, asset allocation strategies, etc.

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 one that adopts an active dynamic managerial approach. Therefore, this group of ETFs could serve as an indication to 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 6 reports regression results for our three different investment categories. Panel A reports our results for regressing flows on returns. For the size-and-style and sector 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 sector ETFs, and lowest for size and style ETFs, with 24, 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 group the Granger causality test statistic is highly non-significant with a p-value of 74 percent. This is consistent with their $\overline{R}^2$ values.

Panel B in Table 6 reports the results in the opposite direction, from flows to returns, which reflect a mirror image. Flows have the most significant effect on returns for the size-and-style group, then for the sector group, and last for the strategy group. This holds true in terms of coefficient size, statistical significance, and $\overline{R}^2$ values. Coefficients are 0.54 and 0.50 for size and style and sector ETFs, respectively, and both are highly statistically significant. $\overline{R}^2$ values are 8 percent and 11 percent, respectively. On the other hand, for strategy ETFs the flow coefficient is not statistically significant and $\overline{R}^2$ is almost zero.

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

The opposite is true for the effect flows have on returns. The most active ETF groups experience the weakest effect, while the most active ones show the highest effect.

In summary, these results support our previous findings when we examined the flow-return structure at the instrument level. Returns for more active instruments (active mutual funds, leveraged and inverse ETFs) had a much stronger effect on flows compared to passive instruments (passive mutual funds and long ETFs). The opposite tended to be true for the effect flows have on returns. Our findings in this section suggest that the implications of the separation between active and passive approaches translate into similar results within the ETF industry as well.

6.2 Classification by Size and Style

To further support our previous results, we focus in this section on the size-and-style group and divide it into additional three 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 7 reports our regression results for these three cases. Panel A reports the results for the effect returns have on flows. Coefficient estimates are all positive and statistically significant. However, $\overline{R}^2$ values are very low and around 4 percent for large and medium caps, which indicate very limited explanatory power. For small caps $\overline{R}^2$ is around 12 percent, indicating higher explanatory power. Panel B reports similar results on the whole for the effects in the other direction. These findings are consistent with our previous results in the last sub-section for the style-and-size group of ETFs and fortify our division between passive and active investment approaches.

6.3 Classification by Region

Our last sub-classification divides our sample of instruments into geographic regions. ICI data for active and passive mutual funds provides only a basic classification into international and US funds. However, for ETFs a richer classification is available into different geographic regions and levels of economic development. Tables 2 and 3 report our results for passive and active mutual funds with additional breakdown of the equity sector into US and international investment exposures. Similarly, Table 8 reports our results for ETFs grouped for various international regions (North America, Europe, global, Asia and Latin America) and economic development (Developed and Emerging Markets). The overall picture that arises across all instruments is that the less developed the region is, the stronger the relation between flows and returns.

Panels A in Tables 2 and 3 report our results for the effect returns have on flows for passive and active mutual funds, respectively. As can be seen, returns have a stronger effect on flows for both active and passive global mutual funds compared to those of the US. For active global mutual funds (Table 3 Panel A) the return coefficient and adjusted $\overline{R}^2$ values are of the order of two-fold their size for domestic funds: returns and lagged returns have a combined effect of almost 70 percent on flows, compared to less than 30 percent for US equity funds. Similarly $\overline{R}^2$ values are 72 percent compared to 43 percent for global and US equity funds, respectively. This difference is even more pronounced for passive mutual funds (Table 2 Panel A). The return coefficient is not statistically significant for passive US funds (S&P and other indices), and their $\overline{R}^2$ values are 6 percent for S&P index funds and 0 for other US index funds, indicating very minimal explanatory power. However, for passive global equity funds the return coefficient is statistically highly significant, and $\overline{R}^2$ is around 15 percent, indicating substantial explanatory value.

For passive mutual funds a similar difference holds from flows to returns (Table 2 Panel B). However, our regression results indicate that the effect concurrent flows have on returns for passive global mutual funds is almost completely reversed within a week, as the coefficients for flows and lagged flows sum up to nearly zero. Also note that Granger causality tests indicate that flows have a statistically significant causal effect on returns for global funds, unlike for US funds.

For ETFs we use a more detailed breakdown into different regions and levels of market development, as reported in Table 8. 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 (Panel A). Return coefficient estimates are 16, 6, and 4 percent for North American, 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 significance levels. Finally, Global ETFs are somewhat an average case, probably as they contain a blend of both developed and non-developed regions in their portfolio.

Similar differences also exist for the effect in the opposite direction, from flows to returns, as reported in Panel B. However, just like in the case for passive global mutual funds, lagged flows tend to be more statistically significant for non-developed countries and emerging markets. They also tend to have more negative coefficients, which indicate a stronger price reversal process within a week. Interestingly, Granger causality tests indicate causal effects from flows to returns only in two cases: for the US and emerging markets. We are not sure how to interpret this result.

In summary, on the whole we find that the flow-return connection is more pronounced for less developed regions and much weaker for more developed countries. This finding holds true across all instruments: active and passive mutual funds and ETFs. This result further supports the general trend we have identified so far. Similar to sector ETFs or strategy ETFs, investments in less developed countries are more particular in their investment exposure, and thus their flow-return structure resembles more closely that of other active investment approaches, such as active mutual funds, inverse and leveraged ETFs. Conversely, ETFs that track US markets and other developed countries are less specialized in their investment exposure and are more similar to broad market ETFs. Thus, they resemble other truly passive investment approaches, such as passive mutual funds and size-and-style ETFs.

7 Conclusions

In contrast to prior research that documented almost unanimously a statistically strong and positive relationship between flows and performance, we find a much richer structure between these two variables. Instead of focusing on the mutual sector alone, we explore a richer set of instruments and include passive and active mutual funds, long ETFs, and inverse and leveraged ETFs. Moreover, we create sub-groups per family of instruments by using various classification criteria to test the flow-returns structure at the within-instrument level as well.

Our main finding is a strong distinction between active and passive investment approaches both across instruments and within instruments. Active mutual funds, and inverse and leveraged ETFs, show a strong connection between flows and returns. The effect is typically stronger from returns to flows and often expressed in more pronounced causal effects. On the other hand, more passive investments strategies, such as passive mutual funds and long ETFs, show a weaker to no connection between flows and returns.

Interestingly, inverse and leveraged ETFs show a statistically strong yet negative relation between flows and returns. This finding is consistent with the function that these instruments are designed to fulfil, to serve market contrarians and those seeking increased risk. Their increased risk and contrarian properties may also imply two other unique characteristics. First, their increased risk may imply that the average holding period or turnover time for these instruments is much shorter. Second, institutional investors might be less inclined to use them, either because they have cheaper ways to exercise such trades, or because they are less inclined to take very short term positions in the market. Indeed, our data for turnover and institutional holdings supports a clear distinction between regular equity ETFs and inverse and leveraged ETFs consistent with the two characteristics described above, a result which fortifies the more active investment approach taken by their users.

The distinction between instruments that are used for more active vs. passive investment approaches also manifests itself within instruments. More active ETFs, such as strategy ETFs, and ETFs that track specific market segments, such as emerging markets, less developed countries, or sector ETFs, experience a stronger relation between flows and returns. Again, the effect is more dominant from returns to flows for both correlations and causal effects. On the other hand, broad market ETFs, which may be viewed as tracking the pure market portfolio in the CAPM sense, and thus adopt a truly passive investment approach, show very little relation between flows and returns.

Finally, a similar pattern was also found within the passive mutual funds sector. Passive funds that track the S&P 500 or other single US equity indices show no relation between flows and returns, whereas hybrid and global passive funds show a stronger connection.

References

Ben-Rephael A., Kandel S., Wohl A. 2012. Measuring investor sentiment with mutual fund flows. Journal of Financial Economics 104:363–382.

Bergstressera D., Poterba J. 2002. Do after-tax returns affect mutual fund inflows? Journal of Financial Economics 63:381–414.

Cooper M. J., Gulen H., Rau P. R. 2005. Changing Names with Style: Mutual Fund Name Changes and Their Effects on Fund Flows. The Journal of Finance 60:2825–2858.

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

Dong L. 2012. A Flow-Based Explanation for Return Predictability. Review of Financial Studies 25: 3457-3489.

Edelen, R. M., and J. B. Warner. 2001. Aggregate price effects of institutional trading: A study of mutual fund flow and market returns. Journal of Financial Economics 59:195–220.

Frazzini, A., and O. A. Lamont. 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88:299–322.

Goetzmann, W. N. and M. Massa. 2003. Index Funds and Stock Market Growth. The Journal of Business 76: 1-28.

Gruber, M. J. 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51:783–810.

Ippolito, R. A. 1992. Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. Journal of Law and Economics 35:45–70.

Ivkovic Z. , and Weisbenner S. 2009. Individual investor mutual fund flows. Journal of Financial Economics 92:223–237.

Jain P. C., Wu J. S. 2000. Truth in Mutual Fund Advertising: Evidence on Future Performance and Fund Flows. The Journal of Finance 55:937–958.

Ramaswamy S. 2011. Market structures and systemic risks of exchange-traded funds. BIS Working Papers No. 343. April 2011.

Sapp,T., andA.Tiwari. 2004. Does stock return momentum explain the “smart money” effect? Journal of Finance 59:2605–22.

Sirri, E. R., and P. Tufano. 1998. Costly search and mutual fund flows. Journal of Finance 53:1589–622.

Warther, V.A. 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39:209–35.

Zheng, L. 1999. Is money smart? A study of mutual fund investors’ fund selection ability. Journal of Finance 54:901–33.

TABLE 1

ALL MUTUAL FUNDS

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for monthly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Return (-1)	Flow (-1)	Flow (-2)	$\bar{R}^2$	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*				*0.0142*	
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	0.0724	0.0272	0.3955	0.1477	0.6555	0.5578	3.2951	93
	0.0479	*0.0000*	*0.0323*	*0.0003*	*0.0967*			*0.0146*	
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*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Flow (-2)	Return (-1)	Return (-2)	$\bar{R}^2$	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*	

TABLE 2

PASSIVE MUTUAL FUNDS

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for monthly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Flow (-1)	$\bar{R}^2$	Corr	Granger	# Obs.
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 Indexs	0.0072	-0.0034		-0.0099	-0.0329	1.2494	93
	0.0000	*0.7522*				*0.2968*	
Global Equity Index	0.0068	0.1029	0.2544	0.1491	0.3310	0.6094	92
	0.0052	*0.0001*	*0.0136*			*0.6571*	
Hybrid	0.0013	0.3524	0.6826	0.5282	0.3702	0.3546	92
	0.2601	*0.0000*	*0.0000*			*0.8402*	
Total	0.0048	0.0305		0.1126	0.3495	2.6644	93
	0.0000	*0.0006*				*0.0382*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Return (-1)	Return (-2)	$\bar{R}^2$	Corr	Granger	# Obs.
S&P Index	0.0031	-0.0354		0.2335		0.0334	-0.0195	1.0325	92
	0.5155	*0.9783*		*0.0263*				*0.3956*	
Other US Equity Indexs	0.0076	-0.4374		0.2111		0.0246	-0.0329	0.1504	92
	0.4029	*0.6697*		*0.0444*				*0.9623*	
Global Equity Index	0.0094	1.4820	-1.3675			0.2100	0.3310	3.7393	92
	0.3174	*0.0001*	*0.0004*					*0.0077*	
Hybrid	0.0067	1.1572	-1.1488	0.1384	-0.2426	0.5569	0.3702	6.6508	91
	0.0010	*0.0000*	*0.0000*	*0.0715*	*0.0012*			*0.0001*	
Total	-0.0142	3.7056		0.1491		0.1238	0.3495	0.9343	92
	0.0435	*0.0017*		*0.1376*				*0.4484*	

TABLE 3

ACTIVE MUTUAL FUNDS

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for monthly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Return (-1)	Flow (-1)	Flow (-2)	$\bar{R}^2$	Corr	Granger	# Obs.
US Equity	-0.0015	0.0291		0.4454		0.4352	0.4913	3.5589	92
	0.0000	*0.0000*		*0.0000*				*0.0100*	
Global 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*	
Hybrid and Bond	0.0013	0.1497	0.0513	0.5815		0.8265	0.6071	6.8038	92
	0.0004	*0.0000*	*0.0059*	*0.0000*				*0.0001*	
Total	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*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Return (-1)	Return (-2)	$\bar{R}^2$	Corr	Granger	# Obs.
US Equity	0.0195	9.5407	-3.3267			0.2659	0.4913	1.0458	92
	0.0013	*0.0000*	*0.0433*					*0.3889*	
Global Equity	-0.0009	6.4958	-4.0274			0.2987	0.4417	0.3539	92
	0.8664	*0.0000*	*0.0002*					*0.8406*	
Hybrid and Bond	-0.0027	3.6450	-2.2999			0.5914	0.6071	0.3421	92
	0.1149	*0.0000*	*0.0000*					*0.8488*	
Total	-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*	

TABLE 4

LONG ETFS: BY ASSET CLASS

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for weekly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Flow (-1)	$\bar{R}^2$	Corr	Granger	# Obs.
Equity	0.0022	0.1407		0.1286	0.3616	1.3880	409
	0.0000	*0.0000*				*0.2373*	
Commodities	0.0038	0.1731	0.2197	0.2161	0.3575	0.3631	406
	0.0000	*0.0000*	*0.0000*			*0.8349*	
Fixed Income	0.0075	0.0661		-0.0001	0.0484	2.9903	411
	0.0000	*0.3285*				*0.0188*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	$\bar{R}^2$	Corr	Granger	# Obs.
Equity	-0.0004	0.8845	-0.2580	0.1387	0.3616	4.9033	409
	0.7911	*0.0000*	*0.0169*			*0.0007*	
Commodities	-0.0005	0.7433	-0.0919	0.1272	0.3575	0.5120	406
	0.7507	*0.0000*	*0.1876*			*0.7260*	
Fixed Income	0.0003	0.0399	-0.0377	0.0010	0.0484	0.4568	411
	0.4716	*0.2715*	*0.2267*			*0.7675*	

TABLE 5

INVERSE AND LEVERAGED ETFS

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for weekly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Flow (-1)	$\bar{R}^2$	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*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Return (-1)	$\bar{R}^2$	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*	

TABLE 6

EQUITY ETFS: BY CATEGORY

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for weekly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Return (-1)	Return (-2)	Flow (-1)	Flow (-2)	$\bar{R}^2$	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*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Return (-1)	$\bar{R}^2$	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*				*0.0048*	
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*	

TABLE 7

EQUITY ETFS: BY SIZE AND STYLE

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for weekly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Flow (-1)	Flow (-2)	$\bar{R}^2$	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*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Return (-1)	$\bar{R}^2$	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*	

TABLE 8

EQUITY ETFS: BY REGION

Flows and Returns 2005-2012

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. Panel A reports results for the effect returns have on flows, and Panel B reports the same results for the effect flows have on returns (all in percentage points where 100%=1). Coefficient estimates are reported in the first row for each regression, and *p*-vlaues below. Flows and returns are measured for weekly changes.

Panel A: Regressing Flows on Returns

Name	Const.	Return	Return (-1)	Flow (-1)	Flow (-2)	$\bar{R}^2$	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*	

Panel B: Regressing Returns on Flows

Name	Const.	Flow	Flow (-1)	Return (-1)	$\bar{R}^2$	Corr	Granger	# Obs.
North America	0.0004	0.5397	-0.1593		0.0983	0.3061	3.8150	410
	0.7803	*0.0000*	*0.0430*				*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*	

TABLE 9

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	13.4	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 10

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

FIGURE 1

TURNOVER TIME: US EQUITY, INVERSE, AND LEVERAGED ETFS

2005-2012 (days)

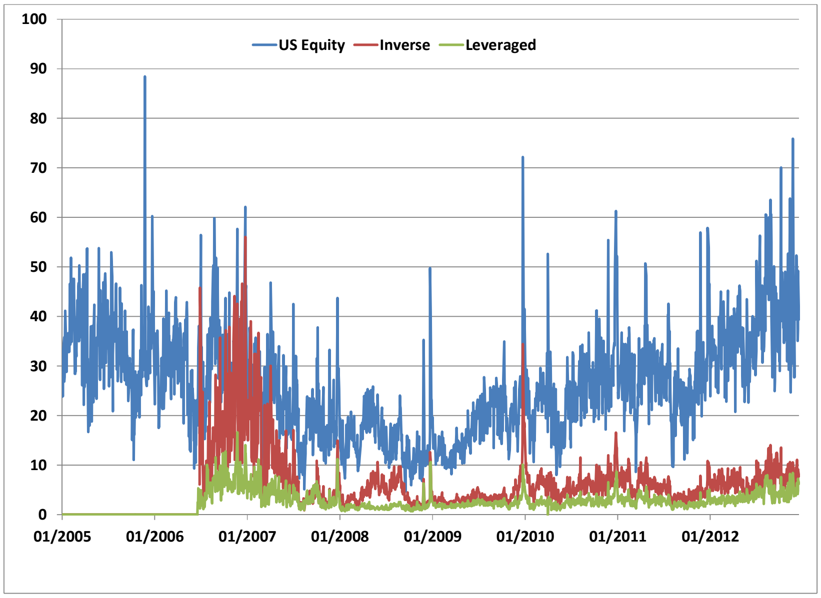

FIGURE 2

INSTITUTIOINAL HOLDINGS: US EQUITY, INVERSE, AND LEVERAGED ETFS

2010-2012 (percent)