Fund flows and performance in Brazil

Abstract

This paper analyzes how fund flows react to past performance in the dynamic Brazilian equity fund market from 2001 to 2012. We test for a “smart money” effect (Zheng(1999)), or whether funds that receive more money subsequently outperform those that receive less money. We find that investors' flows chase past performance, and that there are differences in the flow-performance relationship between retail and institutional funds. We do not find evidence of a “smart money” effect for the whole sample. Nonetheless, flows in small and retail funds, which are often seen as populated by less sophisticated investors, do anticipate future performance.

Keywords: Mutual fund flows, performance, smart money effect

Track: Financial Markets, Investment and Risk

1. Introduction and literature review

How fund flows react to past performance has been an issue that has attracted great interest in the literature given the explosive growth of the mutual fund industry around the world in recent years. Moreover, whether historical fund flows convey information on future fund returns has been a topic that has motivated a substantial body of academic research. However, little or no evidence has been provided on these two issues (and especially, the second one) using data of emerging markets funds. Most previous studies have focused in funds operating in the U.S. or developed markets.

This paper is related to two strands of the literature. The first examines the flow-performance relationship and explores the difference in the association of past performance and cash flows among retail and institutional mutual funds. Chevalier and Ellison (1997) examine the flow-performance relationship across subsamples of retail young and old funds. For young funds the association appears steeper (close to linear) than that for old funds (convex).

This steeper relationship provides funds (especially young funds), which their returns fall behind close to those of the market before year's end, a strong incentive to increase risk (at the closing of the year) in order to narrow the return gap to avoid significant cash outflows. Sirri and Tufano (1998) document that funds that belong to a larger fund family, that charge higher fees (usually to increase marketing efforts) and that receive more media attention typically enjoy higher flows and a more pronounced flow-performance relationship.

Mutual fund family size, fees, or marketing efforts, and media attention are then negatively related to search costs that individual investors must absorb when picking a fund, and positively related to fund growth.

Clifford et al. (2011) show that investors chase past raw performance disregarding risk (i.e., standard deviation of monthly returns). They document some differences in terms of the flow-performance relationship between retail and institutional investors. For the former, the relationship appears convex and for the latter is linear implying, among other things, that institutional investors punish bad performance more severely. A similar finding is reported by Del Guercio and Tkac (2002) who provide evidence of a convex flow-performance association in the mutual fund industry and a linear one in the institutional fund segment.

The convex relationship implies a "winner take all" situation in the market for new mutual fund flows that in turn provides managers with an incentive to increase risk to improve the chances to rank among the top of the pack. The same incentive for risk shifting does not appear to be at work in the pension fund segment since sponsors punish large returns' deviations (i.e., a high tracking error) by withdrawing funds.

Our paper is also closely to studies that explore whether investors display selection skills when deciding to buy and sell funds. In the literature the ability of fund flows to correctly anticipate future performance has been labeled the "smart money" effect. On the contrary, when fund flows are detrimental to future performance (e.g., when future underperforming funds receive the lion's share of investor inflows), money is labeled as "dumb".

Previous studies offer mixed evidence on the significance of a "smart" or "dumb" money effect. Zheng (1999) shows that investors make above-average fund selection decisions since various trading strategies that invest in funds with positive flows are able to deliver higher returns than investing in an equally-weighted portfolio of all funds. She also shows that this "smart money" effect is driven by small funds suggesting that investors make shrewder buy and sell decisions when opting for this type of funds. Keswani and Stolin (2008) document a positive association between past net flows and future fund performance in the British as well as in the U.S. equity fund market. In particular, recent positive (or high) net flow funds are shown to perform better (they show less negative risk-adjusted returns) than negative (or low) net flow funds.

Frazzini and Lamont (2008) show that individual investors' mutual fund trading is detrimental to returns since a portfolio of high-flow funds underperformed a portfolio of low-flow funds. This under-performance is especially evident when flows are measured over half a year or longer periods and appears to be related to the value effect. High-flow funds appear to invest heavily in growth stocks with lower returns than value stocks. Furthermore, Cooper et al. (2005) provide evidence that some investors are not particularly smart since they direct flows to funds that (cosmetically) change their names (e.g., without substantially altering their stock holdings) to be associated with the latest hot investment style.

Funds that alter their names experience positive abnormal flows up to a year after the event. Nonetheless, these funds are unable to deliver positive or increasing (with respect to alphas preceding their name changes) risk-adjusted returns after the name shift.

Neither supporting a smart or dumb money effect, Sapp and Tiwari (2004) demonstrate that trading strategies that try to benefit from a "smart money" effect such as described in Zheng (1999) render a zero alpha after controlling for the momentum effect. In all, Sapp and Tiwari (2004) findings are not consistent with a "smart" or "dumb" money effect but with investors making average fund selection decisions. A similar finding is recently reported by Alves and Mendes (2011) who are unable to document a relationship between performance and flows in a small equity fund market (Portugal). Their evidence lends support to the idea that past flows are not capable of predicting either good or bad subsequent performance. Previous evidence on the extent of a “smart money” effect across retail and institutional funds is mixed and thus far prior studies have been focused on developed markets. Clifford et al. (2011) do not find a “smart money” for their overall sample neither for subsamples of retail and institutional funds. On the other hand, Keswani and Stolin (2008) detect that investors’ flows in both individual and institutional funds correctly anticipate future returns. Interestingly, the “smart money” effect is somewhat stronger and more significant (see tables 4 and 5 in their paper) for retail funds. Recently, Salganik (2012) finds that institutional investors do not exhibit superior selection abilities with respect to individual investors. In fact, the opposite seems to occur since a long-short strategy comprising positive and negative net flow retail funds outperforms and equivalent strategy that relies on institutional funds (see table 8 of his paper). He claims that even though retail funds are often populated by less sophisticated investors (when one compares them with their institutional peers), performance persistence and the wide availability of past return information may explain why retail investors, on the whole, do not lag behind institutional investors in terms of risk-adjusted performance, when buying and selling funds.

We contribute to the literature by expanding the evidence on the flow-performance relationship and in particular, by documenting the degree of return chasing and convexity in a sizable and growing market. This paper also contributes to the understanding of the differences in the flow-performance relationship across funds catering to individual and institutional investors. As an additional contribution, we examine the significance of investor selection skills in a mutual fund market in which much of the growth has been fueled by the emergence of institutional funds. We therefore examine whether institutional investors’ net flows are good predictors of future risk-adjusted performance. The extent and significance of a “smart money” effect is also assessed for retail investors as well as large and small funds.

2. Data analysis (sample and descriptive statistics)

This study uses data of net asset value (NAV) per share, total net assets (TNA), investor type, management style, and fund management company from April 2001 to March 2012 of Brazilian open-end funds. The sample consists of equity funds whose geographic focus is Brazil (i.e., domestic funds). The source of this survivorship bias-free data is Bloomberg. To increase comparability with U.S. studies (e.g., Del Guercio and Tkac (2002), p. 531) in terms of distinguishing between equity funds servicing retail or institutional clients, we include in the latter group pension and dedicated funds, and those for “Exclusive”,“ Qualified”, and “Restricted” investors since these mutual funds are often catered to institutions and wealthy investors. After all our data screens (discussed in the full-length paper), the final sample consists of 7,778 quarterly observations of 641 actively managed equity funds from 200 mutual fund families.

The last five columns in the panel A of Table 1[1] report descriptive statistics regarding our dependent variable (quarterly flow growth, “flow”). Mean quarterly flow growth is positive for all years excepting 2012. Median growth is practically zero for all the years considered. The large standard deviation of flow growth and the asymmetric spread between the 10 and 90 percentile are suggestive of a high degree of skewness and kurtosis (indeed, both unreported statistics are positive) in both flow and (by extension) fund assets.

Based on previous studies regarding the flow-performance relationship and data availability, we control for risk using either raw returns’ yearly standard deviation or the variance of the error term (or tracking error) of Carhart four-factor model using a two-year window (Del Guercio and Tkac (2002), Berk and Tonks (2007)). To account for size, we use both fund and fund family (net) assets. We use the latter variable to control for the fact that funds associated with larger fund complexes may attract more flows given their wider scope. Fund age (in months) is also in our set of control variables in line with previous literature (Ferreira et al. (2012) and others).

The middle panel of Table 1 shows descriptive statistics of our independent variables. The mean and median alphas as well as the average excess returns (or the mean annual difference between a fund’s and Ibovespa Index returns) turned out positive in the period. Standard deviations of yearly raw returns (averaged each quarter) amounted to 9.5%. The high levels of standard deviation of both fund and fund family assets are indicative of the considerable differences across funds in terms of assets under management. Further, the average fund in our sample is younger than its peer in the U.S. (Clifford et al. (2011) report a median fund age of 6.5 years far higher than ours (3 years)).

3. Methodology[2]

To analyze the flow-performance relationship in a multivariate setting, we conduct the following panel regression (within estimation), where *i* stands for fund and *t* for quarter:

$$Flow_{i,t} = \beta_1 Excess\ return_{i,t-1} + \beta_2 Excess\ return^2_{i,t-1} + \beta_3 Controls_{i,t-1} + Fixed\ effects_{i,t} + u_{i,t}$$

[1] Please refer to the last section of this document to see Table 1 and the tables cited in this document. Due to space constraints some of the tables of the paper are not shown. We apologize because some text in the tables appears blurry.

[2] We do not include a section describing the objectives of our research. Nonetheless, in our opinion, sections 3 and 4 fill adequately this void.

Excess returni,t−1 is our primary independent variable of interest related to performance. To examine the extent of convexity we include a quadratic term of (one quarter) lagged excess return.

The list of controls includes risk (proxied by the yearly standard deviation of raw returns or by tracking error), fund and fund family assets and fund age. We estimate coefficients standard errors clustering by fund. In addition, our models include fund, year, and month fixed effects. Year and month fixed effects turned out highly significant. Furthermore, we tested for a random- versus fixed-effects estimation applying Hausman (1978) test that clearly favored a fixed effects approach.
For ease of interpretation we standardize our independent and control variables but not the dependent variable. Thus we examine how a one standard deviation change in a explanatory variable affects quarterly flow growth. This standardization allows us to measure the impact of changing (in the same relative scale) one right hand side variable in our dependent variable.

To test for a “smart money” effect we use a portfolio-level approach (Zheng (1999)). Every month we allocate all available funds into two portfolios. The first portfolio comprises funds with positive net flows while the second includes negative net flow funds. Each fund (in either of the two portfolios) is assigned an investment weight directly related to the absolute value of its net flow during the month, i.e., the weight of a particular fund in the positive flow portfolio is just the ratio of its monthly flow over the sum of all flows of the constituent funds in the portfolio. Besides cash-flow weighted portfolios, we also allow for equally-weighted portfolios to gain a clearer perspective on the forecasting power of past flows with respect to future performance.

With the composition of our two portfolios we record their monthly returns in a subsequent (holding or evaluation) period spanning also a month. We then repeat this ranking and evaluation process until the end of the sample. This procedure allows us to construct two stacked time-series of post-ranking returns for our flow portfolios. With the time series of portfolio returns we estimate risk-adjusted returns or alphas (α) from the Carhart (1997) model using Newey and West (1987) standard errors:

$$R_{jt} - Rf_t = a_j + b_j(Rm_t - Rf_t) + s_j R_{SMB,t} + h_j R_{HML,t} + m_j R_{MOM,t} + e_{jt}$$

Alphas for the two portfolios (j= 1, 2) as well as for a long-short portfolio become our measures of “smartness”. The long-short (or spread) portfolio invests in positive flow funds, and takes a short position in the negative flow funds. A positive alpha either for the positive flow or the spread portfolio denotes “smartness”. On the contrary, a negative alpha for the negative flow funds is consistent with wise fund selection decisions (a negative alpha here means that investors aptly moved away resources from laggard funds). To sharpen our conclusions, we will focus on the spread as our preferred and aggregate measure of investor selection skills in line with the previous literature (see Keswani and Stolin (2008) and Salganik (2012)).

4. Results

The flow-performance relationship in Brazil

The first three columns of Table 2 include slight variations of our base model. Clifford et al. (2011) show that investors chase past raw performance disregarding total risk (i.e., standard deviation of monthly returns). To examine whether risk indifference extends to mutual fund investors in Brazil, models 1 through 3 account for risk in various ways (including either returns’ standard deviation or tracking error, or omitting a risk control). Past standard deviation shows a negative (but not significant) coefficient while the coefficient for tracking error is positive (and not significant). The positive loading on volatility is consequent with the idea that fund managers have an incentive to increase risk (Chevalier and Ellison (1997)) to gain market share. Nonetheless, volatility of returns does not appear to be an important determinant of fund flows since omitting a risk control in our regressions barely alters adjusted R^2s and none of the volatility coefficients attained statistical significance.

Fund assets show a negative coefficient implying that as funds grow larger, clients start to switch to smaller funds. Age has a negative effect on flow growth, and along fund size, is one of the most important controls from an economic significance stance. In all, we find that larger and older funds get less flow consistent with findings by Chevalier and Ellison (1997) and recently by Clifford et al. (2011).

Flow growth and fund family size are positive related since a one standard deviation increase in fund family assets makes quarterly flows to grow by 1.5% percent (see model 3). Sirri and Tufano (1998) find that funds that belong to large mutual fund families typically enjoy higher flows. Search costs that individual investors must absorb when screening for mutual funds tend to be lower when a fund is a member of a large family of funds. The reduction in search costs brought about by the wider breadth (e.g., more advertising or media attention) of large fund complexes can then account for the positive association between flows and family size.

Past excess return has an important and significant positive effect on fund flows. A one standard deviation move in excess return (in model 3) translates into a 1.9% increase in quarterly flows. This evidence is consistent with fund investors chasing past performance perhaps as they expect good performance to persist. The coefficient on squared excess return is positive and significant indicating a convex relationship between flow growth and past performance. Nonetheless, the coefficient is relatively small economically. Convexity implies that investors respond asymmetrically to bad and good performance. Investors appear not to withdraw resources from laggard funds but they flock to recent "star" funds.

Berk and Tonks (2007) argue that reluctance by some investors to pull out money from under-performing funds is one of the reasons behind the convex flow-performance relationship. Possible explanations for this unwillingness or inability to pull out funds are tax considerations, switching costs, back-end loads, and further market frictions. The higher these market frictions the more the reluctance to punish bad performing funds that shows up in a greater asymmetry of the response of flows to past performance.

Using a panel of 28 countries (excluding Brazil), Ferreira et al. (2012) reach a similar conclusion as they are able to empirically link higher investment costs (therefore making a fund switch more difficult) to an increasing degree of convexity across countries. Furthermore, Huang et al. (2007) demonstrate that participation costs (information gathering and transaction costs) affect the strength of the flow-performance relationship. The higher the participation costs, the higher the return threshold an investor demands or expects to purchase a fund. All of these factors cause fund flows to be gradually more sensitive to past performance as participation costs rise.

Given the recent emergence of the Brazilian equity fund market (mind that funds here are far younger than those included in U.S. studies), one would reasonably expect participation costs to surpass those faced by investors in more established markets thus providing support for our finding of an asymmetric relation between fund flows and past performance.

In the fourth model we allow for non-linearities in our control variables. Non-linear effects (besides those for performance related variables) are rather weak since only the coefficient for squared age turned out significant. The positive and negative coefficient for age and age squared respectively, imply a concave relationship between flow growth and age.

Thus far our models have documented an overall convex relationship between performance and flows for our sample of funds. The last two models test for any differential effect in the extent of past performance chasing, and convexity across institutional and retail funds. We create an institutional fund dummy variable that takes the value of one if the fund is directed to institutions or wealthy investors and zero if the fund is directed to individuals.

In all, 448 funds are classified as institutional and 193 as retail. In model 5 we expand model 1 with an interaction variable of lagged excess return and our institutional dummy.

The coefficient on the interaction variable is negative and highly significant consistent with the idea that return chasing is a stronger phenomenon for retail investors. Indeed, the sensitivity of institutional investors to past performance is small (0.008 = 0.041 - 0.033) but statistically significant (using a Wald test) at a 1% level. Furthermore, in model 6 we add an interaction variable of past squared alphas and the institutional dummy to test for convexity differences in two segments of the equity fund market. The interaction variable carries a negative sign suggesting that convexity is weaker in the institutional segment.

Besides, the coefficient is highly significant. Importantly, after controlling for differences in return chasing and departures from linearity, we no longer find convexity to be statistically significant for institutional clients (0.002 = 0.010 - 0.008, p-value of 0.358). Models 5 and 6 imply a symmetric (linear) response by institutional investors to good and bad past performance.

“Smart money” effect in Brazil

In panel A of Table 4 we start by analyzing performance of cash-flow weighted portfolios. One of the advantages of these portfolios is to put a greater emphasis on funds with larger absolute net flows. The positive cash flow portfolio delivers an alpha of 0.004 (0.4% or 40 basis points per month). As expected, the market beta is positive (close to 1) and highly significant. We also find a positive and significant loading on the SMB factor. A similar finding is described by Sapp and Tiwari (2004) in the U.S.. The positive loading on the size factor suggests that managers in flow-attracting funds tend to favor small stocks.

The HML factor is positive (as reported by Keswani and Stolin (2008) for the U.K.) but not significant. Further, the momentum factor is positive and significant consistent with the idea that flow-receiving funds tend to invest in the best recent performing stocks.

A bit surprisingly, the negative cash flow portfolio also shows a positive and significant alpha. In contrast, flow-shedding funds tend to subsequently under-perform in U.S. studies. The loadings related to the market and size are about the same size and significance as the ones for the positive cash flow portfolio. The distress factor is negative while the momentum factor is positive. Nonetheless both coefficients are not statistically significant. Adjusted R^2s for both positive and negative cash flow portfolios are rather high and of the same magnitude highlighting the satisfactory explanatory power of the pricing model.

When we focus in the last column of the upper panel of Table 4, the spread between positive and negative flow funds is positive but rather small (0.001). Importantly, the difference in alpha between inflow and outflow funds turned statistically insignificant. The evidence shown is not conducent to the idea that investors allocate resources in a “smart” or “dumb” way across funds. Investor selection skills appear as average since the risk-adjusted performance of flow-receiving funds appears to be of the same magnitude of that of flow-shedding funds. By and large, the difference in adjusted performance between the two portfolios is shown to cancel out. To put this result into context, if one hypothetically assumes that investors that pulled their resources (from negative flow funds) poured all their resources into positive flow funds, the zero alpha result implies that these investors would have done as good by leaving their assets intact rather than moving them within funds.

In untabulated results we examine whether the choice of pricing model has an impact in our results. Sapp and Tiwari (2004) shows that using a different pricing model (three factor vs. four factor) can have a significant effect in the tenor of our inferences. To this end, we resort both to one-factor (CAPM) and three-factor (Fama and French (1993)) models.
In short, the difference in alphas between positive and negative flow funds remains small and insignificant. For example, the three-factor model renders an alpha of 0.001 (p-value of 0.601). In panel B of Table 4 we use equally-weighted portfolios and reach identical conclusions. Both the positive and negative cash flow portfolios deliver positive and significant alphas. Equal-weighting does not appear to substantially shrink or stretch the magnitude of risk-adjusted performance. As before, the difference in alphas is not material and does not attain statistical significance.

Taken together, our findings are consistent with the idea that investor fund selection decisions in a large emerging market like Brazil neither create nor destruct value by shifting resources across funds. Money in Brazil appears neither “smart” nor “dumb”.

“Smart money” effect for institutional and retail funds

Panel A in Table 6 shows risk-adjusted returns for our subsample of retail funds using cash-flow weighted portfolios. The alpha for the positive cash-flow portfolio is positive and highly significant while abnormal returns for our negative flow portfolio are positive although not statistically significant. The difference in alphas between the two portfolios is positive and statistically significant indicating the existence of a “smart money” effect in the retail segment in Brazil. A closer look indicates then that this “smart money” effect is driven by buying decisions rather than selling decisions of retail investors.

In panel B of Table 6 we examine alphas for portfolios that include only institutional funds. A positive cash flow portfolio of institutional funds does not deliver significant risk adjusted returns. The portfolio comprising outflow funds presents a positive and significant alpha. Importantly, the return spread between a positive and negative cash flow portfolio is not statistically significant. Similar to our findings for the entire sample (bear in mind that institutional funds comprise 70% of the overall sample), we do not find that, on an aggregate level, that institutional flows correctly foretell future returns.

In conclusion, our results indicate that a “smart money” effect does not hold for institutional investors. This implies that institutional investors help as much with their buying and selling decisions, as in Clifford et al. (2011). Perhaps as in Gruber (1996), some institutional investors face hurdles (e.g., taxes) to move capital from average to top performing funds thus accounting for the zero alpha for the positive cash flow portfolio. A freer movement of capital would probably boost the weighting of outperforming funds in the positive cash flow portfolio improving its performance. On the other hand, we document a “smart money” effect for the retail segment. This result resembles those of Keswani and Stolin (2008) and Salganik (2012) for the U.K. and U.S. respectively that tend to favor stronger selection abilities within the retail fund sector.

“Smart money” effect for large and small funds

In panel A of Table 7 we find that the spread between popular and unpopular large funds is nil and statistically insignificant. Investors in large funds do not show outstanding selection skills. When we focus in panel B of the table we verify a strong “smart money” effect for small funds. The alpha for the positive cash flow portfolio is far larger than its equivalent for the negative flow portfolio. In all, the difference in alpha is quite high (0.005) and statistically significant at a 1% level.

In all, our results are more aligned with those of Zheng (1999) and Salganik (2012) for the U.S. than those of Keswani and Stolin (2008) for the U.K.. Investors in small funds display greater (and significant) fund picking skills than their peers in large funds. Since investing in small funds usually entails higher participation costs, one would reasonably expect to see more selective investors in below-median size funds. Selectivity appears quite evident in our sample of small flow-attracting funds.

5. Conclusions

We contribute to the literature by examining the flow-performance relationship in a large, young, and dynamic equity fund market. We find a convex flow-performance relationship for the overall sample of funds. One of the implications of a convex flow-performance relationship is that investors in Brazil strongly chase past good past performance. Consequently, we observe that top performing funds receive a large fraction of inflows. Distinguishing between institutional and retail funds, we find that institutional funds display a linear (symmetric) flow-performance relationship while retail funds show a convex one. Nonetheless, departures from linearity for both the whole sample and our subsample of retail funds are not large.

We also document that flow persistence (herding) is stronger for individuals rather than institutions. Perhaps institutional investors are likely to be more vigilant of fund managers (rebalancing their portfolios more swiftly if necessary), and are less prone to invest automatically in a fund than retail investors, thus accounting for a lower degree of herding.
We then examine whether investors display significant fund selection skills. For the entire sample, we do not find evidence of a "smart money" effect. Next, we study whether fund flows are good predictors of future performance across institutional and retail funds.

In the institutional segment, we do not find significant risk-adjusted performance (alpha) for a portfolio long on popular funds and short on unpopular ones. This implies that institutional investors make "average" fund selection decisions after adjusting for systematic risk. Interestingly, in the retail market, we notice that alphas for our long-short cash flow portfolio are positive and significant. The "smart money" effect in retail funds is propelled by the out-performance of flow-attracting funds. Then, the paper tests the existence of investor selection skills in large and small funds. Previous literature (Zheng (1999)) is supportive of the idea that investors in small funds make smarter fund selection decisions. Our results (in line with those of Zheng (1999) and Salganik (2012) for the U.S.) show that investors in small funds display greater (and significant) fund picking skills than their peers in large funds. Since investing in small funds usually entails higher participation costs, one would reasonably expect to see more selective investors in below-median size funds. The out-performance of small flow-attracting funds appears to drive the "smart money" effect of this market segment.

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Tables

Table 1: Descriptive statistics

This table presents descriptive statistics of the sample of Brazilian actively managed equity funds. The data covers the period from April 2001 to March 2012. In panel A, the number (Nr.) of funds is as of the end of the year (except for 2012) and the number of months refers to how long an average fund survived during each year. In the last five columns, the mean, median, standard deviation (SD.), and 10 and 90 percentiles are calculated from net flows in U.S. dollars. In panel B, alpha refers to the intercept of Carhart four-factor model while tracking error corresponds to the variance of the error term of the same model. Both variables are estimated with a two-year (rolling) window of monthly returns. Excess returns correspond to the mean annual difference between a fund's and Ibovespa Index returns. SD stands for the standard deviation of yearly raw returns. Fund and fund family (or fund management company) net assets are both expressed in U.S. millions. Age is denoted in months. In panel C, p-values of the null hypothesis of zero correlation are reported in brackets below correlation estimates.

Panel A. Number of funds and summary statistics of quarterly net flow growth

Year	Nr. of funds	Dead funds	Nr. of months	Mean	Median	SD.	10%	90%
2001	76	0	8.368	0.010	-0.000	0.164	-0.110	0.101
2002	114	0	10.596	0.030	0.000	0.184	-0.092	0.190
2003	133	0	11.158	0.020	-0.000	0.256	-0.167	0.206
2004	155	2	11.127	0.028	-0.000	0.258	-0.180	0.300
2005	199	5	10.578	0.008	-0.000	0.218	-0.180	0.208
2006	252	3	10.693	0.039	-0.000	0.209	-0.116	0.237
2007	350	5	10.321	0.099	0.000	0.259	-0.074	0.445
2008	471	10	10.255	0.025	-0.000	0.173	-0.097	0.167
2009	568	8	10.845	0.036	0.000	0.215	-0.111	0.213
2010	588	20	11.709	0.027	0.000	0.171	-0.085	0.154
2011	561	27	11.766	0.002	-0.000	0.123	-0.087	0.087
2012	545	16	2.971	-0.015	-0.000	0.145	-0.131	0.069

Panel B. Descriptive statistics of explanatory variables

	N	Mean	Median	SD.	10%	90%
Alpha	7778	0.002	0.001	0.008	-0.005	0.010
Excess returns	7778	0.040	0.022	0.229	-0.141	0.229
SD. of returns	7778	0.095	0.084	0.058	0.056	0.151
Tracking error	7778	0.002	0.000	0.087	0.000	0.001
Assets	7778	60.319	21.534	134.361	4.889	143.488
Family assets	7778	996.693	331.016	1411.786	15.993	3298.108
Age	7778	43.868	36.000	31.261	10.000	93.000

Panel C. Correlation matrix of explanatory variables

	Alpha	Excess returns	SD. of returns	Tracking error	Assets	Family assets	Age
Alpha	1						
Excess returns	0.478	1					
	[0.000]						
SD. of returns	-0.062	-0.091	1				
	[0.000]	[0.000]					
Tracking error	0.334	0.012	0.064	1			
	[0.000]	[0.163]	[0.000]				
Assets	0.099	0.034	-0.064	0.091	1		
	[0.000]	[0.000]	[0.000]	[0.000]			
Family assets	-0.061	-0.059	-0.051	-0.001	0.166	1	
	[0.000]	[0.000]	[0.000]	[0.934]	[0.000]		
Age	-0.130	-0.070	-0.002	-0.014	0.160	0.263	1

Table 2: Panel regressions of the flow-performance relationship

This table reports results of panel regressions that examine the flow-performance relationship. The dependent variable in all models is the net flow growth for quarter t. The explanatory variables (defined in Table 1) are standardized (or expressed as z-scores, i.e., we divide de-meaned variables by their standard deviation). A coefficient measures the change in the dependent variable based on a one standard deviation move in the independent variable. Excess annual return (fund return minus Ibovespa index return) is our measure of performance. The institutional (inst.) dummy variable takes the value of one if a fund is classified as so and 0 otherwise. We include fund, year, and month fixed effects. p-values based on standard errors clustering by fund are reported in brackets below coefficient estimates. R^2 is the adjusted R^2 of each model. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	1	2	3	4	5	6
Exc. Returns$_{t-1}$	0.019***	0.021***	0.019***	0.020***	0.041***	0.040***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exc. Returns$^2_{t-1}$	0.006***	0.006***	0.006***	0.006***	0.004**	0.010**
	[0.002]	[0.008]	[0.002]	[0.001]	[0.022]	[0.017]
STD$_{t-1}$	−0.002			−0.002	−0.003	−0.003
	[0.553]			[0.584]	[0.401]	[0.391]
Assets$_{t-1}$	−0.043***	−0.042***	−0.043***	−0.049***	−0.042***	−0.042***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
F. Assets$_{t-1}$	0.015***	0.014***	0.015***	−0.001	0.014***	0.014***
	[0.001]	[0.005]	[0.001]	[0.962]	[0.002]	[0.002]
Age$_{t-1}$	−0.031***	−0.055***	−0.031***	0.045*	−0.027***	−0.028***
	[0.001]	[0.000]	[0.001]	[0.054]	[0.002]	[0.002]
Tracking Error$_{t-1}$		0.003				
		[0.266]				
Assets$^2_{t-1}$				0.004		
				[0.672]		
F. Assets$^2_{t-1}$				0.013		
				[0.209]		
Age$^2_{t-1}$				−0.080***		
				[0.000]		
Exc. Returns$_{t-1}$*$inst.dummy$					−0.033***	−0.032***
					[0.000]	[0.000]
Exc. Returns$^2_{t-1}$*$inst.dummy$						−0.008*
						[0.073]
R^2	0.065	0.071	0.065	0.068	0.074	0.074

Table 4: Performance of positive and negative net flow funds

This table reports coefficients from Carhart four-factor model for positive and negative net flow funds. In panel A funds are weighted in each of the two portfolios according to their net cash flows in the formation period while in panel B funds are equally-weighted. The last column (difference) shows the risk-adjusted spread or alpha of a portfolio long on positive and short on negative flow funds. P-values using Newey-West (heteroskedasticity and autocorrelation) standard errors computed with floor($4(N/100)^{2/9}$) lags are reported in brackets (N is the sample length). Adj. R^2 stands for the adjusted R^2 of the regression. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Panel A. Cash flow-weighted portfolios

	Positive Cash Flow Portfolio						Negative Cash Flow Portfolio						
	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Difference
Coefficient	0.004**	0.860***	0.093**	0.022	0.058**	0.957	0.004**	0.853***	0.082***	−0.002	0.029	0.967	0.001
	[0.012]	[0.000]	[0.020]	[0.465]	[0.027]		[0.018]	[0.000]	[0.001]	[0.934]	[0.194]		[0.635]

Panel B. Equally-weighted portfolios

	Positive Cash Flow Portfolio						Negative Cash Flow Portfolio						
	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Difference
Coefficient	0.004***	0.852***	0.081***	0.012	0.028	0.972	0.003**	0.860***	0.074***	0.012	0.043**	0.975	0.001
	[0.002]	[0.000]	[0.005]	[0.619]	[0.103]		[0.016]	[0.000]	[0.001]	[0.584]	[0.038]		[0.175]

Table 6: Performance of positive and negative net flow funds: Retail vs. Institutional funds

This table reports coefficients from Carhart four-factor model for positive and negative net flow funds. In panel A we include only funds catering to individual investors while in panel B the sample is restricted to funds aimed at institutional investors. Both in panel A and B funds are weighted in each of the two portfolios according to their net cash flows in the formation period. The last column (difference) shows the risk-adjusted spread or alpha of a portfolio long on positive and short on negative flow funds. P-values using Newey-West (heteroskedasticity and autocorrelation) standard errors computed with floor($4(N/100)^{2/9}$) lags are reported in brackets (N is the sample length). Adj. R^2 stands for the adjusted R^2 of the regression. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Panel A. Retail funds

	Positive Cash Flow Portfolio						Negative Cash Flow Portfolio						
	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Difference
Coefficient	0.006***	0.876***	0.122***	0.033	0.034	0.951	0.003	0.872***	0.100***	0.014	0.036	0.959	0.003***
	[0.000]	[0.000]	[0.002]	[0.305]	[0.237]		[0.100]	[0.000]	[0.000]	[0.547]	[0.125]		[0.002]

Panel B. Institutional funds

	Positive Cash Flow Portfolio						Negative Cash Flow Portfolio						
	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Difference
Coefficient	0.003	0.818***	0.068*	0.008	0.064**	0.952	0.005***	0.824***	0.072***	0.007	0.022	0.964	−0.002
	[0.137]	[0.000]	[0.069]	[0.784]	[0.014]		[0.003]	[0.000]	[0.002]	[0.783]	[0.351]		[0.322]

Table 7: Performance of positive and negative net flow funds: Large vs. Small funds

This table reports coefficients from Carhart four-factor model for positive and negative net flow funds. Large funds are those in the top 50% of all funds each month according to their total net assets. Small funds are those in the bottom 50% of all funds each month according to their total net assets. In both panels funds are weighted in each of the two portfolios according to their net cash flows in the formation period. The last column (difference) shows the risk-adjusted spread or alpha of a portfolio long on positive and short on negative flow funds. P-values using Newey-West (heteroskedasticity and autocorrelation) standard errors computed with floor($4(N/100)^{2/9}$) lags are reported in brackets (N is the sample length). Adj. R^2 stands for the adjusted R^2 of the regression. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Panel A. Large funds

	Positive Cash Flow Portfolio						Negative Cash Flow Portfolio						
	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Difference
Coefficient	0.003*	0.883***	0.098**	0.031	0.058**	0.951	0.004**	0.852***	0.074***	−0.006	0.030	0.966	−0.001
	[0.072]	[0.000]	[0.029]	[0.351]	[0.035]		[0.019]	[0.000]	[0.002]	[0.812]	[0.184]		[0.734]

Panel B. Small funds

	Positive Cash Flow Portfolio						Negative Cash Flow Portfolio						
	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Alpha	RMRF	SMB	HML	MOM	Adj. R^2	Difference
Coefficient	0.008***	0.858***	0.063**	0.011	0.038	0.933	0.004**	0.863***	0.109***	0.013	0.026	0.968	0.005***
	[0.000]	[0.000]	[0.016]	[0.656]	[0.101]		[0.016]	[0.000]	[0.000]	[0.581]	[0.179]		[0.000]