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Which Factors Matter to Investors? Evidence from Brazilian Mutual Funds

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Abstract

Purpose – We investigate the drivers of investment flows into Brazilian mutual funds.

Design/methodology/approach – The database consists of a panel of Brazilian mutual funds covering the period between January 2001 and April 2019. First, we identify which performance metric is most related to the funds' flows. Then we analyze how the results differ depending on investor sophistication.

Findings – Investors pay more attention to market risk (beta) when evaluating funds, while they attribute returns tied to size, value, momentum, and industry factors to the alpha. These results are consistent with those reported for the United States. Additionally, we document that less sophisticated investors are relatively more sensitive to all past return metrics. However, when fund alphas are broken down into a persistent component and a random component, greater sensitivity is concentrated in the random component of the alphas.

Originality/value – The sensitivity of fund flows to different performance metrics is measured, and this allows us to better understand investors' decision-making processes. Moreover, to the best of our knowledge, this is the first paper to address this issue with data from outside the United States.

Keywords – funds, performance measures, factorial models.

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1. Introduction

This paper finds that the capital asset pricing model (CAPM) best represents the performance evaluation practices used by Brazilian mutual fund investors. Moreover, it concludes that more sophisticated investors use more complex models, in addition to being better at detaching risk from skill when it comes to evaluating funds' past returns.

Whenever investors are choosing between an active management fund and a passive management fund, we expect them to prefer to allocate their assets to a skilled manager, who is able to generate higher returns than those attained with passive management. Investors, therefore, reward skilled managers with new allocations while they punish unskilled managers with withdrawals. As their source of information, investors look at funds' past returns and the historical distribution of risk factors. Within this context, fund alphas, which are defined as the excess return not tied to risk factors, are the metric that is capable of determining skilled managers who are able to attain higher returns than those achieved through exposure to risk factors alone (Barber, Huang, & Odean, 2016; Berk & Binsbergen, 2016, 2017).

Thus, investors only increase their investments in one fund to the detriment of another when it yields a higher alpha. As a result, whenever we compare funds' flows to their return, we expect the flows to be sensitive to their alphas, though not to the components of funds' returns tied to risk factors.

We herein reach our conclusions after evaluating the relationship between data on the fund's flow and past performance. Any given fund's high (low) performance is deemed evidence that its manager is skilled (unskilled), and we presume that investors seek skilled managers. The data used herein relates to Brazilian funds with active management in the time window from January 2001 to April 2019.

Our paper follows a methodology akin to the one proposed by Barber et al. (2016), which looks at conflicting scenarios between fund rankings depending on the method employed to calculate the alphas. These situations are interpreted so that, if the inflow (outflow) is more intense, we conclude that the metric that classifies the fund as good (bad) is the most relevant in decision making. For instance, suppose a scenario where a given fund is ranked as one of the best funds according to the CAPM alpha, though when estimated with the three-factor model (Fama & French, 1992, 1993) the fund is ranked as one of the worst. Also, suppose we verify intense inflows to that fund. In this case, we conclude that the CAPM alpha is best attuned to investors' behaviors. The opposite applies to outflows.

Furthermore, we break down fund returns into alpha and factor-related returns. We define the factor-related returns as the multiplication of the risk factor and the fund's sensitivity (exposure) to said factor. We deem the factor-related returns as the return explained by risk, whereas unexplained returns are a direct result of skilled managers, in other words, funds' alphas. Finally, we look at how these components are related to funds' flows, as well as how proxies for investor sophistication over time (investor sentiment) and between funds (restricted to sophisticated investors and minimum investment requirement) affect the results.

Next, we carry out an additional decomposition of fund alphas into persistent and random components. The persistent component is the proportion related to the alpha's future realization, and the random component is the remaining portion. This decomposition enables us to examine possible alpha imperfections such as potential failures in being able to fully differentiate returns influenced by skilled managers from returns affected by risk or random effects.

We find that investors pay more attention to market risk (beta) and consider returns tied to risk factors, such as size, value, momentum, illiquidity, and exposure to industry sectors, as alphas. Moreover, we find evidence that more sophisticated investors use more sophisticated performance metrics to distinguish between risk and managers' skill. Finally, we conclude that less sophisticated investors are also more sensitive to alphas. However, when breaking down alphas into persistent and random components, we observe that this greater sensitivity comes from the strong sensitivity to the alpha's random component.

Our paper aims to contribute to research produced by Agarwal, Green, and Ren (2018), Barber et al. (2016), Berk and Binsbergen (2016, 2017), and Blocher and Molyboga (2017), all of which report the same investor patterns for the US market. It also describes how less sophisticated investors' enhanced sensitivity to alphas is a direct result of how their investment flows relate to random alpha variations. Nevertheless, we find that the investment flows of less sophisticated investors do not turn out to be more sensitive to the funds' persistent alphas.

The evidence produced by Barber et al. (2016) and Berk and Binsbergen (2016, 2017) is a standard in the underlying literature, applied to the works of Franzoni and Schmalz (2017), Harvey and Liu (2019), and Polkovnichenko, Wei, and Zhao (2019). However, to the best of our knowledge, our paper is the first one to address this behavior not using data from the United States. It therefore helps to support the documented evidence, in addition to contributing to the financial analysis literature with Brazilian data.

2. Methods and data

2.1 Data source

All data used herein is sorted monthly and cover the time window from January 2001 to April 2019. All financial sums are deflated by the Brazilian Consumer Price Index (IPCA) set for May 2018.

The funds' return, inflows, and outflows series are compiled based on data taken from the Economatica® and the Brazilian Securities and Exchange Commission (CVM) online databases. The Brazilian stock market index (Ibovespa) historical rates, as well as the funds' registration information, are collected from the Economatica® online platform. The Brazilian risk factors and industry sector returns are gathered from the Brazilian Center for Research in Financial Economics of the University of São Paulo - NEFIN (www.nefin.com.br).

We remove all funds' observations before said funds' AUM reaches 5.0 million 2018 BRL. Once the funds are included in the dataset, we keep analyzing them until their AUM drops below 1.0 thousand 2018 BRL. Moreover, since the regressions are performed in 30-month rolling windows, funds whose historical performance registers less than 30 months are removed from our evaluation.

Finally, a significant share of the base sample has no information on whether they are open-end or closed-end funds. Thus, to keep only open-end funds in our sample, we dismiss funds with net asset inflows equal to zero in more than 50% of observations.

2.2 Net asset inflows

Our paper's dependent variable, fund flows, entails a fund portfolio's percentage variances resulting from asset inflows and outflows. Consequently, its value for fund p in month t stems from the following equation:

$$Cap_{pt} = \left(\frac{TNA_{p,t}}{TNA_{p,t-1}} - \left(1 + R_{p,t}\right) \right) \times 100 \tag{1}$$

where $TNA_{p,t}$ is the total net assets under management of fund p at the end of month t, and $R_{p,t}$ is the return of fund p in month t. This estimation method follows the standards observed in the literature (Barber et al., 2016; Berk & Binsbergen, 2016; Goldstein, Jiang, & Ng, 2017; Jiang & Yuksel, 2017).

2.3 Return metrics

Investors in actively managed funds are expected to search for funds capable of providing higher returns than anything that can be linked to their exposure to known risk factors (e.g. market risk, size, etc.). That is, they look for funds capable of generating alphas. If investors are only interested in exposing themselves to risk factors, they would only need to allocate their assets to passive management funds (Berk & Binsbergen, 2017).

Even though investors are expected to pursue alphas, how these alphas are measured remains unclear. On the one hand, investors may simply rank funds based on their raw returns. On the other hand, though, they may rank funds based on a multifactor return approach, such as those commonly found in the academic literature on asset pricing.

Based on the scenarios mentioned above, and following the methods suggested by Barber et al. (2016), we proceed to compute six risk-adjusted return metrics (alphas): market adjusted returns (MAR); the capital asset pricing model (CAPM); the Fama-French (1993) three-factor model (M3F), to which size (SMB) and value (HML) factors are added; the Carhart four-factor model (1997), to which the momentum factor (WML) is added; the five-factor model (M5F), to with the Acharya and Pedersen (2005) liquidity factor (IML) is added; and, finally, the eight-factor model (M8F), which also includes three other industry factors measured for the Brazilian market using Nefin industry data, and whose methodology is described by Pástor and Stambaugh (2002a, 2002b).

These models often generate similar rankings for mutual funds. Nevertheless, we choose to examine scenarios where fund rankings established by said measures differ between each other, and we determine which models are best suited to understanding investors' choices based on this discrepancy.

We estimate models with 30-month windows. In the case of the M8F, for instance, we use the following calculation:

$$R^{e}_{p,\tau} = \alpha_{p,t} + \beta_{p,t}\left(R_{m,\tau} - R_{f,\tau}\right) + s_{p,t}SMB_{\tau} + h_{p,t}HML_{\tau} + w_{p,t}WML_{\tau} + l_{p,t}IML_{\tau} + \sum\nolimits_{k=1}^{3} i^{k}_{p,t}IND^{k}_{\tau} + \epsilon_{p,\tau} \quad (2)$$

where $\tau \in [t-1, t-30]$; $R^{e}_{p,\tau}$ stands for excess returns of fund p; $R_{m,\tau}$ is the market return; $R_{f,\tau}$is the risk-free return; and SMB_{τ}, HML_{τ} , WML_{τ}, IML_{τ}, and IND^{k}_{τ} are, respectively, size, value, moment, liquidity, and the *k-th* industry factor.

Equation (2) leads to $\hat{\beta}_{p,t}$, $\hat{s}_{p,t}$, $\hat{h}_{p,t}$, $\hat{w}_{p,t}$, $\hat{l}_{p,t}$, and $\hat{i}_{p,t}$, which we use to calculate the risk-adjusted return (alpha) in month t:

$$\hat{\alpha}_{p,t} = R^{e}_{p,\tau} - \begin{bmatrix} \hat{\beta}_{p,t}\left(R_{m,t} - R_{f,t}\right) + \hat{s}_{p,t}SMB_{t} + \hat{h}_{p,t}HML_{t} + \\ \hat{w}_{p,t}WML_{t} + \hat{l}_{p,t}IML_{t} + \sum\nolimits_{k=1}^{3} \hat{i}_{p,t}IND^{k}_{t} \end{bmatrix} \quad (3)$$

We apply the same procedure for each month as well as for each fund. This enables us to achieve a historical series ($\hat{\alpha}_{p,t}$) for each fund sample. The procedure is the same for every additional model that we examine. In regards to the CAPM, for instance, we compute alphas by regressing fund returns solely against excess market returns. The MAR alpha concerns the difference between the fund return and market return.

Alphas are appraised as metrics used to evaluate manager skill. High alphas signal skilled managers; thus, we expect net flows to be positively related to alphas.

However, examining investor behavior also entails defining the analysis time horizon as well as the relative significance of each of these time horizons. One option is to presume that all alphas share the same importance in investors' decision-making processes, so we therefore estimate past alpha averages. Another option is to assume that the latest alphas carry a higher relative weight.

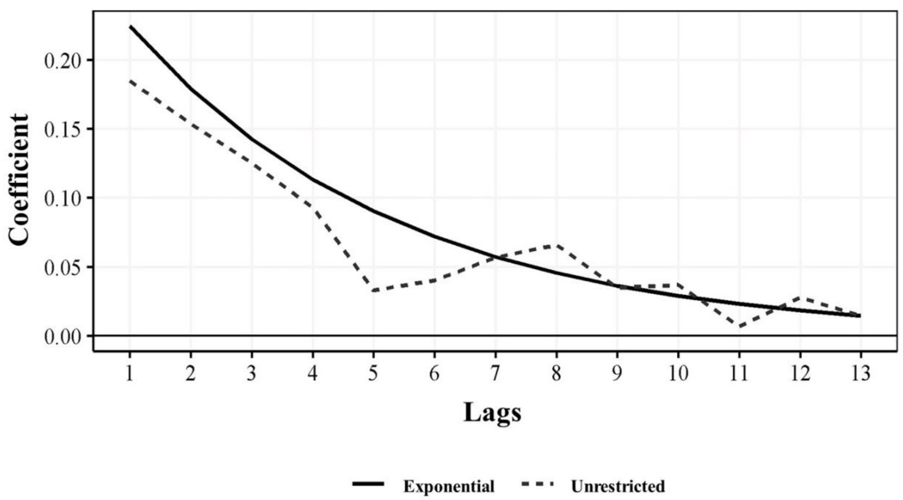
Again, following the paper of Barber et al. (2016), we compute exponential averages of the last alphas observed for the fund:

$$Cap_{p,t} = a + \sum\nolimits_{s=1}^{13} b_{s}MAR_{p,t-s} + \mu_{t} + cX_{p,t} + e_{p,t} \quad (4)$$

where, $Cap_{p,t}$ represents the number of funds captured by fund p in month t; $MAR_{p,t-s}$ means adjusted market returns for fund p in month t-s, such that $s \in (1,2,\ldots,13)$; μ_{t} is the fixed time effect; and $X_{(p,t)}$ is the control variable matrix used, namely: the log of the fund's age in *t-1*; the standard deviation of excess returns of the fund in the past 12 months; the log of the fund's TNA in month *t-1*; and lagged fund flows from the past 14 months (we evaluate time horizons ranging from one to 24 months, and define the number of lags based on the Akaike information criterion – AIC).

The regression leads to the coefficients b_{s}, which are represented by the dotted line in Figure 1. These coefficients denote the relationship between past returns and current asset inflows. As we can see in the graph, there is an evident decay in the relationship between past returns and fund flows.

To parsimoniously capture this decay in the flow-return relationship, we estimate the relationship between asset inflows and an exponential average of returns in the past 13 months. These averages are computed using the rate of decay λ, which can be expressed as:



[1]**Figure 1**: Relationship between net inflows and past returns

$$Cap_{p,t} = a + b\sum_{s=1}^{T} e^{-\lambda(s-1)} MAR_{p,t-s} + \mu_t + cX_{p,t} + e_{p,t} \tag{5}$$

The exponential decay relationship is also illustrated in Figure 1. In this case, we only estimate one parameter, although the relationship between net inflows and past returns can be assessed by multiplying the estimated parameter b by weights $e^{-\lambda(s-1)}$.

The method allows us to determine the number of lags assessed (13), in addition to estimating the exponential decay parameter λ. We use these two fixed parameters to compute the risk-adjusted return metrics evaluated here for each fund p and month t, based on the following calculation:

$$ALPHA_{p,t} = \frac{\sum_{s=1}^{13} e^{-\hat{\lambda}(s-1)} \hat{\alpha}_{p,t-s}}{\sum_{s=1}^{13} e^{-\hat{\lambda}(s-1)}} \tag{6}$$

Therefore, each model's risk-adjusted return metric is composed of an exponential average of each fund's $\alpha_{p,t-s}$ for the last $s = 13$ lags.

2.4 Competition between models

This paper aims to verify which risk types are taken into account by investors when they evaluate a fund's performance. The findings obtained with the method employed herein come from examining investors' capital allocation decisions for investment fund options, as well as from how said decisions relate to a fund's past performance. High performing funds signal that they are administered by skilled managers and should therefore attract assets, whereas a bad performance suggests an unskilled manager, thereby yielding a more significant volume of redemption orders.

We consequently expect to observe a positive relationship between past performance and subsequent net inflows of investment. Additionally, we expect to see more robust relationships in regards to the specific risk model most widely used by investors. For instance, if an investor's sole concern is market risk, then fund flows should show a more pronounced reaction to CAPM alphas than to alphas resulting from more intricate models. On the other hand, if investors also choose to consider more complex risk components, it would only be natural for fund flows to have stronger reactions to alphas of models in which said components are considered.

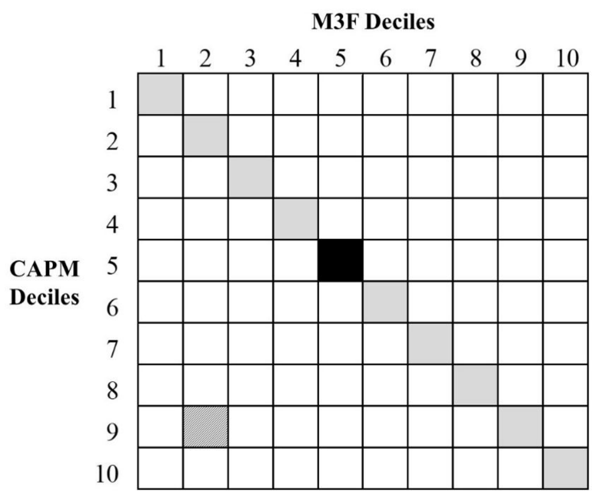
Thus, our methodology follows that of Barber et al. (2016). It suggests competition between models. For each month of the sample and using each model, the risk-adjusted return metrics are divided into deciles, enabling the worst performing funds of a given month to be ranked in the 1st decile, whereas the top performing funds are placed in the 10th decile.

Based on this ranking, we compare two models at a time according to the dummies D_{ijpt}, which denote the relationship between two models' rankings. If we use the comparison between the CAPM and the M3F, for instance, the dummy D_{ijpt} takes the value one when fund p is ranked in decile j in month t, according to the CAPM; and in decile j, according to the M3F. We are therefore able to estimate:

$$Cap_{pt} = a + \sum_i \sum_j b_{ij} D_{ijpt} + cX_{pt} + \mu_t + e_{pt}. \tag{7}$$

The parameters of interest for (7) are the values of b_{ij}, which can be sorted as shown in Figure 2. In it, the diagonal coefficients represent scenarios in which the models assessed yield the same ranking. Non-diagonal coefficients, in turn, denote scenarios in which there are differences in regards to the model rankings. The numbers displayed in the lower (upper) triangle of the matrix refer to scenarios in which the CAPM decile ranking for the funds is better (worse) than the M3F ranking.

This enables us to evaluate differences between the lower triangle and upper triangle coefficients. All scenarios in which the sum of the lower triangle coefficients is greater than the sum of the upper triangle coefficients mean that whenever the CAPM yields a better return ranking than the M3F, there are consequently higher net inflows than the other way around. In other words, investors tend to monitor CAPM-estimated risk-adjusted returns more intensely than those of M3F.



[2]**Figure 2**: Competition between models

To assess the sensitivity differences in net asset inflows between the CAPM and M3F metrics, we estimate regression (7), reaching the following hypothesis test:

$$\sum_{i>j}\left(b_{ijpt}\right)-\sum_{i<j}\left(b_{ijpt}\right)=0 \tag{8}$$

In other words, we proceed to test whether the sum of b_{ij} in the lower triangle of Figure 2 is greater than the sum in the upper triangle. If the hypothesis is not dismissed, then we are unable to state that there actually are differences between investor reactions and model results. However, if the hypothesis is rejected, then there is evidence that investors react differently to each model, in which case if the difference is positive (negative), the reaction to the CAPM is greater (lower) than the reaction to the M3F. We apply the same procedure to every combination of models, always using two models at a time.

2.5 Return decomposition

The fact that a specific model is more compliant with the investment flows observed does not necessarily mean that investors are entirely insensitive to returns tied to factors included in that same model. With that said, Barber et al. (2016) suggest a test to measure the investment flow sensitivity of funds in each component that comprises their returns. First, the method consists of breaking down fund alpha returns as well as returns tied to risk factors to which the funds are exposed, while in its second stage it carries out a regression of the investment flows against these components of the fund's return.

To break down fund returns, we use the following calculation:

$$R_{pt}^{e}=\hat{\alpha}_{pt}+\begin{bmatrix}\hat{\beta}_{p,t}\left(R_{m,t}-R_{f,t}\right)+\hat{s}_{p,t}SMB_t+\hat{h}_{p,t}HML_t+\\ \hat{w}_{p,t}WML_t+\hat{l}_{p,t}IML_t+\sum_{k=1}^{3}\hat{i}_{p,t}^{k}IND_t^{k}\end{bmatrix} \tag{9}$$

Next, we estimate the exponential averages of each component's past 13 months for each month *t*. Thus, to calculate the component of the fund return tied to the fund market risk, for instance, we have:

$$RMARKET_{p,t}=\frac{\sum_{s=1}^{13}e^{-\hat{\lambda}(s-1)}\hat{\beta}_{p,t-s}\left(R_{m,t-s}-R_{f,t-s}\right)}{\sum_{s=1}^{13}e^{-\hat{\lambda}(s-1)}} \tag{10}$$

This same method is applied to all components, which we herein denominate as: RMARKET; RSIZE; RVALUE; RMOMENT; RLIQUIDITY; RIND1, RIND2; and RIND3.

We then use this return decomposition to determine whether investors react differently to each component, estimating the following regression:

$$Cap_{p,t}=b_0+b_1ALPHA_{p,t}+b_2RMARKET_{p,t}+b_3RSIZE_{p,t} \tag{11}$$

$$+b_4RVALUE_{p,t}+b_5RMOMENTUM_{p,t}+b_5RLIQUIDITY_{p,t}$$

$$+\sum_{k=1}^{3}b_{5+k}RINDk_t+\mu_t+cX_{p,t}+\varepsilon_{p,t}$$

The parameters of interest are the coefficients b_j so that $j\in\{1,\ldots,9\}$. If the value of the coefficient is positive and significant, we are able to conclude that investors are sensitive to returns stemming from the factor at hand. We verify whether, for instance, investors fully consider market risk $b_1=0$, in addition to whether returns resulting from this factor entail changes to the fund's investment flow. On the other hand, though, a positive coefficient means that investors relate observed returns to skilled managers, consequently changing the fund's investment flow due to returns stemming from exposure to this factor.

3. Descriptive analysis

The purpose of this section is to introduce the database used herein, in addition to explaining the filters we applied and their impacts on the base sample. The full database includes both active and passive management funds. We define passive management funds as funds whose performance is tied to a market index, and which claim not to charge performance fees. All remaining funds are dubbed active management funds.

Table 1 shows fund distribution per management type and performance category, in accordance with the Anbima ranking. Each group includes information on the number of funds assessed, the number of observations made, and the average total net assets under management (TNA) in BRL millions.

As we can see in the table, the base sample is composed of 3,071 active management and 185 passive management funds. The funds are spread over time, amounting to an overall number of 188,671 active fund observations and 14,008 passive fund observations. The active management group is composed of 15 categories with significant numbers of "free funds" and "active index funds." Furthermore, since they collect performance fees from investors, they are deemed active management funds despite their performance being tied to a market index.

Table 1
Fund Distribution per Category

Anbima Ranking	Number of Funds	Number Assessed	Average TNA (Million BRL)
Active Management Funds			
Dividend Funds	90	7,800	181.90
IBOVESPA Active Funds	367	15,061	53.09
IBOVESPA Active Funds with Leverage	111	3,019	42.36
IBOVESPA Index Funds**	2	58	188.12
IBrX Active Funds	75	3,587	117.87
IBrX Active Funds with Leverage	5	185	187.53
IBrX Index Funds**	2	105	91.43
Index Funds**	5	332	70.73
Active Index Funds	340	33,235	123.60
Free Funds	1764	102,221	128.64
Free Funds with Leverage	65	1,366	47.49
Small-Cap Funds	53	5,201	114.24
Sustainability/Governance Funds	30	3,622	113.14
Value/Growth Funds	159	12,751	111.61
Closed-end Stocks	3	128	58.66
Overall Active Management	3,071	188,671	108.69
Passive Management Funds			
IBOVESPA Index Funds	60	3,002	50.48
IBrX Index Funds	14	761	47.54
Index Funds	71	8,222	126.97
Dividend ETFs	40	2,023	425.66
Overall Passive Management	185	14,008	162.66

Note: *The table shows fund distribution per management type and performance category. In regards to management type, they are split into active and passive management funds. The performance category follows Anbima-set standards. For each month, the table reports the number of funds, the number of observations made pursuant to the number of funds, and the months analyzed, as well as the TNA in BRL 5 million. **Funds deemed active since they charge performance fees.

The classification of funds in terms of open-end or closed-end funds is also relevant to the article. Closed-end fund investors are only able to place redemption orders according to previously defined rates. Thus, these funds' investment flows are not expected to be sensitive to their past performance, at least in short and medium-range time horizons. As a result, this limits an investor's interest in open-end funds.

The fund distribution according to whether they are open-end or closed-end funds is shown in Table 2. As we can see, the volumes of open-end-ranked funds are vastly superior to those of closed-end-ranked funds. Nevertheless, the unranked fund volumes are also significant.

Instead of selecting funds by their classification as open-end or closed-end funds, we select them based on the rates of non-zero inflows or redemptions. As a result, we only choose funds with non-zero net inflows in more than 50% of the months we looked at (this number is close to the minimum rate observed across all open-end-ranked funds).

Funds of funds are maintained in the database, as we expect their inflows to also be sensitive to their past returns.

Table 3 shows a descriptive analysis of the database we used. Panel A shows data for the full sample. Panel B refers to the subsample attained using filters required to adequately appraise fund net inflows. The filters used aim to select: (i) active funds; (ii) those with at least 30 observations over time (number of months needed to perform the rolling-window regressions in section 4); and (iii) non-zero net asset inflows in more than 50% of the observations made.

Looking at Table 3, we can see that the filters we applied to determine the base sample used herein, described in Panel B of the table, fail to generate significant distortions in the statistics for the variables when it comes to the averages, standard deviation, and

Table 2
Fund Distribution per Fund Type

	Active	Passive	Overall
Number of Funds	3,071	185	3,256
Open-end	2,016	82	2,098
Closed-end	31	-	31
Unranked fund	1,024	103	1,127
Number of months (Jan/2000 - Apr/19)	**220**	**220**	**220**
Overall number of observations	188,671	651	202,679

Note: *The table shows fund distribution pursuant to the fund type. The first column reports the funds' ranking type: open-end; closed-end; or unranked. The last three columns show the volume of data assessed for active and passive funds, as well as the sum of both groups.

percentages assessed. Furthermore, it is worth pointing out that the use of the filters mentioned above results in nearly 40% of active fund observations being removed from our evaluation. This drop is mostly a result of the 30-month window requirement. This filter brings somewhat of a survivorship bias to our assessment, although it is important for applying the methodology we suggest. In the papers using US data, such as that of Berk and Binsbergen (2015), a 60-month window filter is used. We can see, in the table, the occurrence of highly dissident TNA values, which also distort the variable means compared to their median. This, however, does not call for additional adjustments, and our conclusions are not included in these observations.

Table 3
Descriptive Analysis

Variable	Average	Standard Deviation	Min.	p05	Median	p95	Max.
Panel A: Full Sample Base							
Active Funds (N = 3,071; Obs = 188,671)							
Net inflows (%)	0.34	9.35	-35.76	-9.71	0.00	12.62	51.74
Age (months)	103.86	58.00	1.00	23.00	94.00	220.00	220.00
TNA (BRL million)	119.81	265.91	0.10	3.31	39.90	499.02	5,390.11
Return (%)	0.02	5.67	-16.37	-9.58	-0.01	9.53	15.31
Cumulative return (%)	7.43	61.49	-99.63	-63.19	-2.88	116.74	538.05
Trading activity rate (%)	64.49	36.12	0.00	3.83	79.22	100.00	100.00
Management fee (%)	0.104	0.094	0.00	0.00	0.088	0.249	0.799
Performance fee (%)	0.48	0.79	0.00	0.00	0.26	1.46	11.12
Passive Funds (N = 185; Obs = 14,008)							
Net inflows (%)	-0.02	9.87	-35.76	-11.79	-0.12	13.75	51.74
Age (months)	129.88	64.90	7.00	28.00	137.00	220.00	220.00
TNA (BRL million)	149.40	433.29	0.17	3.17	45.32	509.92	6,664.69
Return (%)	0.04	6.48	-16.37	-11.29	-0.13	10.22	15.31
Cumulative return (%)	-14.53	31.88	-94.49	-58.40	-15.73	35.88	139.78
Trading activity rate (%)	79.46	30.52	1.85	10.19	98.89	100.00	100.00
Management fee (%)	0.08	0.10	0.00	0.00	0.02	0.29	0.55
Performance fee (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Net Inflow Sample Base Analysis							
Active Funds (N =1,193; Obs =112,388)							
Net inflows (%)	0.48	9.68	-35.76	-10.28	-0.12	14.92	51.74
Age (months)	121.80	55.83	30.00	43.00	113.00	220.00	220.00
TNA (BRL million)	144.00	304.68	0.10	3.32	46.25	594.63	5,390.11
Return (%)	0.12	5.61	-16.37	-9.37	0.07	9.51	15.31
Cumulative return (%)	14.65	69.21	-94.80	-62.74	1.66	137.00	538.05
Trading activity rate (%)	89.31	13.90	50.00	57.41	96.59	100.00	100.00
Management fee (%)	0.12	0.10	0.00	0.00	0.12	0.29	0.73
Performance fee (%)	0.31	0.43	0.00	0.00	0.18	0.93	4.70

Note: *The table provides a descriptive analysis of the variables. Panel A refers to the full base sample, while panel B shows numbers related to the sub-sample used to assess inflows obtained after we applied filters only to active funds with at least 30 observations, in addition to non-zero net inflows in at least 50% of the months we appraised. We analyzed the following variables: fund net inflow percentage (Net inflows); fund age in months (Age); average total net assets under management of fund throughout fund's history (TNA); excess monthly returns (Return); cumulative excess return (Cumulative return); the percentage of months when the fund had non-zero net inflows (Trading activity rate); management fee (Management fee); and the performance fee (Performance fee). The statistics displayed include: average; standard deviation; minimum (Min.); 5th percentile (p05); median; 95th percentile (p95); and maximum (Max.).

Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), Brown, Goetzmann, Hiraki, Shirishi, and Watanabe (2003), and Chiu and Kini (2013) discuss using net asset inflows for investment funds to measure the so-called "investor sentiment." To achieve this, and following Barber et al. (2016), we use the variation of this variable over time to signal high sentiment in the market. High sentiment periods are deemed to be periods when aggregate inflows exceed the value of their 75th historical percentile. We apply the same reasoning to the percentage variances in the mutual fund market share numbers. Both of these high sentiment metrics are required for section 2.5, in which we break down returns into alpha and risk.

Table 4 provides an analysis of risk measures computed for funds pursuant to the eight-factor model resulting from equation (11), in addition to a descriptive analysis of the components of the funds' return according to equation (2). An examination of Panel A of the table allows us to observe significant variations in the estimation results between funds, thereby evidencing a fund's variability to risk exposure. Moreover, Panel B of the table suggests that differences in a fund's risk exposure entail significant variations in fund returns since, as we can see, the distribution observed differs for each component of the fund's return.

Finally, table 5 shows the results of a correlation analysis of fund returns, in addition to an evaluation of performance measures expressed by the alphas estimated across all the models that we assessed. As expected, the correlation between the components of the funds' return is low, as a result of these being broken down by the orthogonal relationship estimated with equation (2). On the other hand, when it comes to the alphas estimated with the different models, we notice that the measures are highly correlated. This high correlation emphasizes the significance of the proposed competition between models since the method is not limited to linear relationships, therefore being more suited to address issues resulting from the strong linear relationship among the measures.

Table 4
Descriptive analysis of funds and components of the funds' return

Variable	Mean	Standard Deviation	Min.	p05	Median	p95	Max.
Panel A: Fund analysis (1,193 funds)							
alpha coefficient ($\hat{\alpha}$)	0.085	0.479	-3.046	-0.716	0.104	0.772	2.337
market coefficient($\hat{\beta}$)	0.703	0.242	-0.475	0.246	0.751	0.964	1.881
size coefficient ($\hat{s}$)	0.110	0.258	-1.200	-0.262	0.095	0.539	1.350
value coefficient ($\hat{h}$)	-0.032	0.188	-0.895	-0.314	-0.037	0.294	0.970
moment coefficient ($\hat{w}$)	0.061	0.142	-1.117	-0.195	0.065	0.279	0.524
liquidity coefficient ($\hat{l}$)	0.097	0.242	-0.889	-0.273	0.086	0.486	1.411
industry coefficient 1 ($\hat{i}^1$)	-0.010	0.098	-0.500	-0.139	-0.013	0.145	0.532
industry coefficient 2 ($\hat{i}^2$)	0.090	0.393	-2.534	-0.165	-0.017	0.801	3.668
industry coefficient 3 ($\hat{i}^3$)	-0.025	0.133	-0.663	-0.241	-0.016	0.137	1.118
Panel B: Analysis over time (220 months)							
$ALPHA_{M8F}$	0.114	1.162	-2.768	-1.657	0.091	1.727	6.961
RMARKET	0.058	5.270	-21.064	-8.350	-0.097	8.415	12.096
RSIZE	0.080	1.335	-4.778	-1.952	0.030	2.031	6.035
RVALUE	0.116	0.896	-3.762	-1.033	0.013	1.485	3.956
RMOMENTUM	0.005	0.761	-3.843	-1.361	0.024	1.065	3.175
RLIQUIDITY	-0.080	0.797	-3.253	-1.438	0.010	1.082	3.222
RIND1	-0.024	0.346	-2.023	-0.598	-0.007	0.522	1.633
RIND2	-0.063	1.821	-10.444	-3.074	0.008	2.467	6.429
RIND3	0.075	0.687	-2.403	-0.602	0.000	1.066	5.004

Note: *Panel A of the table shows fund distribution in regards to the funds' risk coefficients using the eight-factor model equation (11). Panel B displays the descriptive analysis of the components of the funds' return broken down by the eight-factor model, following equation (2). The statistics shown include: average; standard deviation; minimum (Min.); percentile 5 (p05); median; percentile 95 (p95); and maximum (Max.).

Table 5
Correlation analysis of components of the funds' return and alphas

Panel A: Correlation between components of the funds' return								
	$ALPHA_{M8F}$	**RMARKET**	**RSIZE**	**RMOMENT**	**RLIQUIDITY**	**RIND1**	**RIND2**	**RIND3**
$ALPHA_{M8F}$	1.000							
RMARKET	-0.048	1.000						
RSIZE	-0.046	0.103	1.000					
RVALUE	-0.089	-0.101	0.036	1.000				
RMOMENT	-0.066	-0.097	-0.164	0.077	1.000			
RLIQUIDITY	-0.045	0.032	-0.510	-0.170	-0.029	1.000		
RIND1	-0.101	-0.060	-0.051	-0.036	-0.006	0.022	1.000	
RIND2	-0.097	-0.033	-0.329	-0.322	-0.131	0.096	-0.081	1.000
RIND3	-0.102	0.059	0.037	-0.028	-0.135	-0.004	-0.020	-0.189

Panel B: Correlation between alphas						
	$ALPHA_{MAR}$	$ALPHA_{CAPM}$	$ALPHA_{M3F}$	$ALPHA_{M4F}$	$ALPHA_{M5F}$	$ALPHA_{M8F}$
$ALPHA_{MAR}$	1.000					
$ALPHA_{CAPM}$	0.738	1.000				
$ALPHA_{M3F}$	0.674	0.916	1.000			
$ALPHA_{M4F}$	0.652	0.865	0.944	1.000		
$ALPHA_{M5F}$	0.637	0.837	0.913	0.970	1.000	
$ALPHA_{M8F}$	0.578	0.750	0.820	0.867	0.893	1.000

Note: *Panel A of the table shows results of the correlation between components of the funds' return, while Panel B displays results of the correlation between the different alpha metrics assessed.

4. Results

4.1 Which factors are significant to investors?

There are numerous options available to adjust fund returns based on the risk that these returns are exposed to, ranging from basic methods such as making comparisons between funds' returns and market returns, to sophisticated methods such as the CAPM or multifactor models. This wide range of alternatives makes it difficult to determine which method best represents an investor's decision-making process. In this section we seek to recognize which model best fits investors' decisions.

Table 6 summarizes results attained with the method described in section 2.4, in which we suggest a comparison between models, always two models at a time, and which is based on the funds' monthly performance data in deciles.

As we can see, the CAPM-measured performances suggest an enhanced ability to explain fund inflows. The CAPM model performs well against every other metric assessed, including in regards to both more straightforward measures such as MAR and increasingly complex ones such as multifactor models. We also observe a pattern of loss of explanatory power as the model takes in more risk factors. Despite this, we fail to see any significant differences between said models after comparing the M3F and M4F results.

4.2 Return decomposition

In this section, we look at the relationship between funds' net asset inflows and their past returns broken down into alphas and returns tied to risk factors. As described in section 2.5, returns are broken down into alphas with the eight-factor model (M8F) used as a performance measure, as well as different returns linked to the risk factors. This enables us to examine regressions in which the dependent variable is the funds' investment flow, while the independent variable relates to the funds' return components.

An investor is not expected to increase the volume of resources in one fund at the expense of another, whenever the differences in returns between them are only related to their exposure to risk factors. We would only expect investors to increase the volume of resources in one fund if it presents a higher alpha. For instance, a fund whose high performance stems solely from its high exposure

Table 6
Competition between models

	MAR	CAPM	M3F	M4F	M5F	M8F
MAR		-8.532	7.377	13.008	16.754	20.363
p-value		(0.019)	(0.006)	(0.000)	(0.000)	(0.000)
CAPM	8.532		22.379	25.029	28.048	26.344
p-value	(0.019)		(0.000)	(0.000)	(0.000)	(0.000)
M3F	-7.377	-22.379		11.799	16.153	18.811
p-value	(0.006)	(0.000)		(0.132)	(0.019)	(0.000)
M4F	-13.008	-25.029	-11.799		30.938	18.173
p-value	(0.000)	(0.000)	(0.132)		(0.005)	(0.000)
M5F	-16.754	-28.048	-16.153	-30.938		14.922
p-value	(0.000)	(0.000)	(0.019)	(0.005)		(0.000)
M8F	-20.363	-26.344	-18.811	-18.173	-14.922	
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: *The table summarizes the results of the competition between models – always two models at a time. The results refer to the hypothesis test in equation (8). The row results provide a comparison between row models and column models. Positive results mean that the row performance metric outperforms the column model in regards to its ability to explain net asset inflows. All numbers are displayed in percentages, where 1 means that whenever a row model ranks a fund better than a column model, then fund net inflows tend to be 1% positive.

to the momentum risk factor should theoretically not be able to obtain more inflows than other funds. Thus, when we regress net inflows against the components of the fund's return, we expect the inflows to be sensitive to the alpha. However, we do not expect them to have any kind of relationship with any risk factor.

Coupled with the scenario mentioned, and taking into account evidence pointing to the fact that CAPM best represents investor performance, we expect the inflows to be less sensitive to market risk exposure (RMARKET) than to the components of the fund's return tied to additional risk factors.

Furthermore, given that sophisticated investors should better segregate skill-related returns from risk-related returns, we additionally predict the sensitivity of investment flows for returns tied to risk components to be lower for sophisticated investors. We do that based on the interaction with proxies to determine the investor's sophistication level.

This leads to the pattern observed in Table 7. It helps us to compare regression results between net asset inflows and the components of the fund's return, in accordance with four different scenarios. The first one, illustrated by column (1), shows the coefficient of the relationship between net inflows and the components of the fund's return with no interaction with proxies used for investor sophistication. The scenarios shown in the next columns, in turn, entail results for the same correlation, although they take into account a number of interactions with the purpose of capturing the variable effect prevalent in investors sophisticated over time and across funds. The columns marked as "Dif" always denote differences in the estimated relationship between unsophisticated and sophisticated investors.

Thus, columns (2) and (3) sort the results into low and high sentiment behavioral time windows. Column (2) defines high sentiment periods based on the aggregate net inflows observed, while column (3) carries out the same assessment, although it is based on varying aggregate share numbers. We expect high sentiment periods to have a greater volume of less sophisticated investors.

On the other hand, columns (4) and (5) examine the observed variable effect on investor sophistication across funds. Column (4) looks at relationship differences between both restricted and unrestricted funds for sophisticated investors. Column (5), in turn, assesses relationship differences between funds whose minimum investment requirement is BRL 100,000 and less demanding funds.

The regression results without interactions verify the expected behavior. While asset inflows show a strong reaction to the alpha, they also exhibit a weaker relationship with the RMARKET component. The table also shows us that the dependent variable is sensitive to every other component of the fund's return, thereby suggesting that investors tend to allocate their assets in funds with stronger past performances, regardless of this

Table 7
Return decomposition and relationship with investor sophistication

	Without interactions	High and Low Sentiment Periods (Inflows)			High and Low Sentiment Periods (Shares)			Restricted to sophisticated Investors			Minimum Investment Requirement		
	(1)	(2)			(3)			(4)			(5)		
		Low	High	Dif.	Low	High	Dif.	Restricted	Unrestricted	Dif.	≥100 k	<100 k	Dif.
$ALPHA_{M8F}$	0.688	0.483	1.008	**0.526**	0.623	0.722	**0.099**	0.519	0.845	**0.326**	0.207	0.701	**0.495**
	(0.041)*	(0.040)*	(0.096)*	**(0.104)***	(0.047)*	(0.094)*	**(0.108)**	(0.043)*	(0.063)*	**(0.071)***	(0.161)	(0.041)*	**(0.163)***
RMARKET	0.246	0.090	0.592	**0.502**	0.189	0.472	**0.282**	0.121	0.329	**0.208**	-0.029	0.254	**0.282**
	(0.040)*	(0.037)*	(0.095)*	**(0.103)***	(0.047)*	(0.074)*	**(0.088)***	(0.040)*	(0.048)*	**(0.042)***	(0.108)	(0.040)*	**(0.099)***
RSIZE	0.784	0.633	1.120	**0.487**	0.785	0.688	**-0.097**	0.636	0.915	**0.280**	0.530	0.784	**0.254**
	(0.068)*	(0.060)*	(0.179)*	**(0.190)***	(0.081)*	(0.158)*	**(0.179)**	(0.078)*	(0.090)*	**(0.104)***	(0.288)	(0.069)*	**(0.291)**
RVALUE	0.454	0.263	1.014	**0.752**	0.306	0.915	**0.610**	0.133	0.720	**0.587**	-0.437	0.488	**0.925**
	(0.103)*	(0.111)*	(0.239)*	**(0.262)***	(0.118)*	(0.200)*	**(0.232)***	(0.119)	(0.145)*	**(0.167)***	(0.392)	(0.107)*	**(0.416)***
RMOMENTUM	0.648	0.408	1.348	**0.939**	0.548	1.348	**0.800**	0.355	0.867	**0.512**	0.575	0.645	**0.070**
	(0.077)*	(0.074)*	(0.215)*	**(0.229)***	(0.087)*	(0.222)*	**(0.239)***	(0.091)*	(0.113)*	**(0.140)***	(0.356)	(0.080)*	**(0.374)**
RLIQUIDITY	1.047	0.884	1.068	**0.184**	1.042	0.818	**-0.224**	0.824	1.213	**0.388**	1.020	1.046	**0.026**
	(0.094)*	(0.092)*	(0.260)*	**(0.279)**	(0.105)*	(0.216)*	**(0.241)**	(0.105)*	(0.120)*	**(0.134)***	(0.402)*	(0.095)*	**(0.398)**
RIND1	0.612	0.282	1.660	**1.378**	0.445	0.905	**0.461**	-0.049	1.188	**1.237**	-0.267	0.636	**0.904**
	(0.132)*	(0.133)*	(0.296)*	**(0.324)***	(0.164)*	(0.201)*	**(0.259)**	(0.164)	(0.201)*	**(0.262)***	(0.479)	(0.133)*	**(0.469)**
RIND2	0.859	0.662	1.394	**0.732**	0.470	0.698	**0.228**	0.619	1.043	**0.424**	0.619	0.867	**0.248**
	(0.096)*	(0.096)*	(0.181)*	**(0.204)***	(0.173)*	(0.257)*	**(0.310)**	(0.106)*	(0.123)*	**(0.127)***	(0.422)	(0.097)*	**(0.422)**
RIND3	0.857	0.648	1.166	**0.517**	0.852	0.984	**0.132**	0.524	1.161	**0.637**	0.342	0.875	**0.534**
	(0.127)*	(0.116)*	(0.358)*	**(0.378)**	(0.175)*	(0.273)*	**(0.322)**	(0.154)*	(0.166)*	**(0.194)***	(0.515)	(0.128)*	**(0.512)**
Controls	Yes		Yes			Yes			Yes			Yes	
Fixed time effect	Yes		Yes			Yes			Yes			Yes	
Observations	92,793		92,793			87,129			92,793			92,793	
R^2-Adjus,	0.120		0.127			0.127			0.122			0.120	
*p<0,05													

Note: *The table shows the regression results between net asset inflows and components of the funds' return. Column (1) displays the coefficients of the relationship between net inflows and components of the funds' return without interactions. Column (2) shows high sentiment periods based on observed aggregate net inflows. Column (3) carries out the same assessment; however, it is based on variations of aggregate share numbers instead. Column (4) looks at differences in the relationships between both restricted and unrestricted funds for sophisticated investors. Column (5) examines relationship differences between funds with a minimum required investment of BRL 100,000 and less demanding funds. The columns marked as "Dif" refer to differences in the estimated relationships between unsophisticated and sophisticated investors.

performance being influenced by the fund's exposure to the risk components well documented in the literature, and not by skilled managers.

Regressions with interactions to determine an investor's sophistication levels denote that as behaviors of potentially more-sophisticated investors are assessed, the inflow sensitivity to past returns tied to risk tends to decrease. For instance, there is a noticeable positive difference in the relationship between the investment flow and the RMARKET between low and high sentiment periods. This suggests that asset inflows tend to react more strongly to past returns tied to the market risk during high sentiment periods. The same pattern repeats for most risk factors.

There is only one scenario where the estimated difference is negative; nevertheless, the sum is statistically different to zero.

We come across the same pattern when we examine the differences between funds restricted to sophisticated investors and unrestricted funds. Restricted funds tend to behave similarly to what is expected for investors who know how to separate return on risk from manager skill. The same can be said when it comes to evaluating minimum investment requirements. Funds with restrictions always entail weaker relationships between net inflows and returns tied to risk factors in relation to the behavior of restricted funds.

However, the question of why the relationship between the alpha and investment flows is also higher for less sophisticated investors remains unanswered. When analyzing the differences between these relationships and the different sophistication levels, with the exception of column (3), which looks at the investor sentiment effect estimated with share variances, the difference for all the others is positive and significant. In spite of this pattern being attuned to the behavior described by Barber et al. (2016), we do not expect unsophisticated investors to have a higher sensitivity to the alpha than the sensitivity perceived for sophisticated investors.

This reversal in the expected relationship may stem either from proxy noise derived from qualifying investors or from the fact that the estimated performance measure fails to fully separate the part a skilled manager plays in the returns, from the part resulting from risk or random effects. We base our next section on this second assumption.

4.2.1 *Alpha decomposition*

Based on the previous section's results, we conclude that unsophisticated investors demonstrate a higher sensitivity not only when it comes to returns tied to risk factors, but also to increases in the fund alpha. Nevertheless, the expected behavior is for unsophisticated investors to have equal or lower sensitivities to alphas in relation to what we verified for sophisticated investors. We therefore proceed to take a more in-depth look at this question in this section.

We conduct our analysis based on the assumption that the estimated alpha used as a performance metric fails do fully distinguish the returns influenced by skilled managers from a random term. To this end, we break down the alpha into a persistent and a random component. The persistent part is defined as the portion of the alpha related to the future alpha. The random term, on the other hand, is defined as the remaining portion. The persistent component is defined as the contemporary alpha related to the future alpha. We understand that the persistent term, despite not being observed by the investor, is a better measure for the manager's ability and, therefore, sophisticated investors should be more sensitive to this measure than less sophisticated investors

The alpha decomposition is obtained by regressing the current alpha ($ALPHA_{M8F,p,t}$) with the following month's alpha ($ALPHA_{M8F,p,t}$), as expressed in equation (12). It is worth pointing out that while the current alpha is estimated as the alpha's weighted average in the past 13 months as according to section 2.3, the following month's alpha involves only one month's observations.

$$ALPHA_{M8F,p,t} = \theta_p \alpha_{p,t+1} + u_{p,t} \quad (12)$$

Based on the estimated equation (12), we proceed to break down the current alpha into a persistent alpha and a random alpha, as follows:

$$ALPHA_{Persistent,p,t} = \theta_p \alpha_{p,t+1} \quad (13)$$

$$ALPHA_{Random,p,t} = u_{p,t} \quad (14)$$

The regression results for the decomposition of the fund alphas are summarized in Table 8, which displays estimated value percentiles for the relationship between the current alpha and the future alpha ($\hat{\theta}$), in addition to t statistics for these estimates and the distribution of the

Table 8
Summary of Alpha Decomposition

	0%	1%	5%	10%	50%	90%	95%	99%	100%
$\hat{\theta}$	0.0468	0.1682	0.1913	0.2021	0.2538	0.3297	0.3630	0.4677	0.8306
t-value	0.2981	3.1447	3.9092	4.5680	6.9228	10.6821	11.7704	12.2603	13.4452
R^2	0.0816	0.3522	0.3895	0.4037	0.4217	0.4798	0.5124	0.6380	0.7947

Note: *The table summarizes the results obtained with regressions performed for all funds between their current alpha ($ALFA_{M8F_{p,t}}$) and the following month's alpha ($\alpha_{i,t+1}$). The table displays specific percentile values for estimated values concerning the relationship between the current alpha and the future alpha ($\hat{\theta}$), in addition to t statistics of these estimates and the distribution of the R^2 regressions.

R^2 regressions. As we can see, every relationship estimated is either positive or non-significant, of which 99% of the estimates are positive and significant. Something else that stands out is how the regression captures over 35% of the dependent variables for the vast majority of funds.

Finally, we repeat the analysis of the relationship between a fund's investment flows and its components of return based on breaking down the alpha into a persistent and random component. The results are displayed in Table 9. The table shows regression results between net asset inflows and the components of the funds' return, which are sorted according to the exact same four scenarios already used. As a result, we have a column for results without interactions, as well as four additional columns for results obtained with interactions with the proxy for investor sophistication, to enable differentiation between unsophisticated and sophisticated investors. The columns marked as "Dif." always refer to differences in the estimations for unsophisticated investors as opposed to sophisticated investors. The difference is that they include the alpha's persistent and random components in the first two rows of the table results.

An examination of the table enables us to conclude that the estimates measured for risk factors remain the same, in other words: (i) investment flows are less sensitive in relation to returns resulting from exposure to market risk measured by the RMARKET variable; (ii) risk factor sensitivity increases as less sophisticated investors are assessed. However, we notice that less sophisticated investors refrain from showing a higher sensitivity to the alpha's persistent component. The significant difference concerning sophisticated and unsophisticated investor sensitivity remains only for the random component.

5. Comparison to literature results

The Brazilian database used for this paper features particular traits that distinguishes it from studies that document evidence in the US market (Agarwal et al., 2018; Barber et al., 2016; Berk & Binsbergen, 2016, 2017). We therefore discuss some of these differences below, in addition to pointing out the adjustments made as well as potential impacts on the results submitted herein.

First, we must acknowledge the size of the database in regards to time windows. The US-based results are attained using data comprising 17-year to 34-year windows, which our paper does not significantly stray from since its results entail a 17-year window.

Furthermore, a shorter data time window requires rolling window regressions to be carried out with only 30 years of data. Papers based on US data usually use 60-month windows. On one hand, the impact of this adjustment lowers the survivorship bias as well as the accuracy of the estimated alphas, while on the other it hinders the robustness of the evidence found. Collectively, however, these adjustments give greater robustness to the data since they have a lower survivorship bias and are statistically significant, in spite of the occurrence of noise in the variables estimated.

Another discrepancy refers to the number of funds available. Our paper looks at a set of 1,193 funds, whereas international research studies base their conclusions on approximately 5,000 funds. Again, these differences may hinder the evidence we submit, as well as hampering the statistical significances. Nevertheless, the robust results observed here will hopefully make them more significant as we proceed to assess databases that comprise a greater number of funds. Thus, we expect the recent trend seen in the increase in numbers of funds in Brazil to benefit future papers using Brazilian mutual fund market data.

Considering the database compiled, we can now point to how the results we achieved are very similar to those reported in the United States. We basically reproduce the model relevance whereby the CAPM model proves to be the most significant, followed by the remaining models

Table 9
Alpha decomposition and relationship to investor sophistication

	Without interactions	High and Low Sentiment Periods (Inflows)			High and Low Sentiment Periods (Shares)			Restricted to sophisticated investors			Minimum Investment Requirement		
	(1)	(2)			(3)			(4)			(5)		
		Low	High	Dif.	Low	High	Dif.	Restricted	Unrestricted	Dif.	≥100 k	<100 k	Dif.
$ALPHA_{Persistent}$	0.515	0.357	0.623	**0.267**	0.491	0.316	**-0.175**	0.420	0.603	**0.183**	0.326	0.520	**0.193**
	(0.061)*	(0.058)*	(0.143)*	**(0.154)**	(0.068)*	(0.133)*	**(0.149)**	(0.063)*	(0.091)*	**(0.101)**	(0.243)	(0.062)*	**(0.243)**
$ALPHA_{Random}$	0.824	0.586	1.291	**0.705**	0.732	1.019	**0.287**	0.600	1.034	**0.434**	0.117	0.845	**0.729**
	(0.052)*	(0.050)*	(0.130)*	**(0.139)***	(0.057)*	(0.121)*	**(0.138)***	(0.057)*	(0.075)*	**(0.085)***	(0.212)	(0.052)*	**(0.212)***
RMARKET	0.249	0.091	0.601	**0.510**	0.191	0.486	**0.295**	0.123	0.333	**0.210**	-0.031	0.257	**0.288**
	(0.040)*	(0.037)*	(0.093)*	**(0.101)***	(0.047)*	(0.073)*	**(0.087)***	(0.040)*	(0.047)*	**(0.041)***	(0.108)	(0.040)*	**(0.099)***
RSIZE	0.776	0.631	1.068	**0.437**	0.783	0.664	**-0.119**	0.631	0.907	**0.276**	0.526	0.776	**0.250**
	(0.069)*	(0.060)*	(0.185)*	**(0.196)***	(0.081)*	(0.169)*	**(0.188)**	(0.079)*	(0.089)*	**(0.103)***	(0.291)	(0.070)*	**(0.294)**
RVALUE	0.465	0.274	1.005	**0.731**	0.321	0.873	**0.552**	0.137	0.741	**0.604**	-0.436	0.501	**0.937**
	(0.101)*	(0.109)*	(0.238)*	**(0.260)***	(0.116)*	(0.189)*	**(0.221)***	(0.119)	(0.141)*	**(0.165)***	(0.390)	(0.104)*	**(0.415)***
RMOMENTUM	0.647	0.408	1.351	**0.943**	0.551	1.293	**0.742**	0.356	0.864	**0.508**	0.569	0.643	**0.074**
	(0.077)*	(0.074)*	(0.216)*	**(0.229)***	(0.087)*	(0.241)*	**(0.256)***	(0.091)*	(0.111)*	**(0.136)***	(0.356)	(0.080)*	**(0.376)**
RLIQUIDITY	1.032	0.877	0.999	**0.122**	1.037	0.733	**-0.304**	0.818	1.189	**0.371**	1.037	1.031	**-0.005**
	(0.093)*	(0.091)*	(0.263)*	**(0.281)**	(0.103)*	(0.220)*	**(0.244)**	(0.106)*	(0.117)*	**(0.134)***	(0.402)*	(0.093)*	**(0.398)**
RIP1	0.595	0.267	1.673	**1.407**	0.430	0.882	**0.452**	-0.060	1.167	**1.226**	-0.276	0.617	**0.893**
	(0.134)*	(0.135)*	(0.307)*	**(0.335)***	(0.168)*	(0.205)*	**(0.265)**	(0.165)	(0.200)*	**(0.258)***	(0.480)	(0.135)*	**(0.471)**
RIP2	0.853	0.662	1.352	**0.690**	0.479	0.610	**0.131**	0.616	1.037	**0.421**	0.657	0.862	**0.204**
	(0.098)*	(0.097)*	(0.192)*	**(0.214)***	(0.176)*	(0.276)*	**(0.327)**	(0.107)*	(0.124)*	**(0.126)***	(0.425)	(0.098)*	**(0.427)**
RIP3	0.850	0.641	1.178	**0.537**	0.842	0.900	**0.059**	0.524	1.144	**0.621**	0.355	0.868	**0.513**
	(0.128)*	(0.117)*	(0.344)*	**(0.364)**	(0.177)*	(0.291)*	**(0.340)**	(0.154)*	(0.166)*	**(0.194)***	(0.519)	(0.129)*	**(0.519)**
Controls	Yes		Yes			Yes			Yes			Yes	
Fixed time effect	Yes		Yes			Yes			Yes			Yes	
Observations	92,793		87,129			92,793			92,793			92,793	
R^2-Adjus,	0.120		0.127			0.128			0.122			0.121	

Note: *The table shows the regression results between net asset inflows and components of the funds' return, as well as those of persistent and random alphas. Column (1) displays the coefficients of the relationship between net inflows and components of the funds' return without interactions. Column (2) establishes high sentiment periods based on observed aggregate net inflows. Column (3) conducts the same assessment, based, however, on the variation in aggregate share numbers. Column (4) looks at differences in the relationships either between restricted or unrestricted funds for sophisticated investors. Column (5) analyzes differences in the relationship between funds with a minimum BRL 100,000 investment requirement and less demanding funds. The columns marked as "Dif." denote differences in the estimated relationship for unsophisticated investors as opposed to sophisticated investors.

sorted in accordance with their sophistication level, from the most basic to the most sophisticated.

Similarly, it is clear how fund inflow sensitivity differs according to the level of sophistication of the approach used by the investor. Just as what we see in the United States market, we find that the theory that sophisticated investors use more sophisticated evaluation measures also stands.

6. Conclusion

The finance literature widely recognizes that the patterns observed for asset returns depend on specific traits, such as: company size; the relationship between book value and market value; liquidity; past asset performance; among other factors. Additionally, a significant number of passive funds devise their investment profiles based on these traits.

However, investors tend to reward managers who reproduce patterns relating to two factors. For instance, for every 1% of excess returns attributed to one of the factors assessed here (size, value, liquidity, and industry risk), fund inflows tend to go up by between 0.6% and 1%. These effects are more pronounced and reach percentages of up to 1.7% when we take into account less sophisticated investors.

Our paper shows how investors are capable of distinguishing the market risk effect from fund returns. They credit skilled managers for returns stemming from the exposure to additional risk factors. On the other hand, we verify that sophisticated investors are more efficient in making the distinction between risk and skill while assessing a fund's past performance.

The CAPM proves to be the model best suited to explaining mutual fund investors' behaviors, outperforming multifactor models as well as direct comparisons to market returns. The results underscore the evidence documented in the US market, while also broadening their scope to an emerging market such as Brazil.

Moreover, we find that less sophisticated investors prove to be more sensitive not only in regards to returns tied to risk, but also to fund alphas. For every alpha yielding 1% excess return, fund inflows tend to rise by 0.7%; furthermore, inflows are 0.5% higher for less sophisticated investors than for sophisticated investors.

However, when we break down fund alphas into both persistent and random components, it becomes clear that this enhanced sensitivity is centered on the random alpha component. While persistent alphas fail to yield significant differences when it comes to asset inflows across all sophistication levels; for every 1% random return, less sophisticated investors' asset inflows tend to be up to 0.7% higher than those of sophisticated investors.

Notas

1 The figure above illustrates the relationship between net inflows and risk-adjusted returns with a lag of up to T=13 months ($MAR_{p,t}$). The dotted line illustrates b_s measured by unrestricted model (4). The continuous line, in turn, denotes the exponential decay function l ($b \times e^{-\lambda(s-1)}$) computed by restricted model (5).

2 The figure represents a comparison between the CAPM and the M3F deciles. The rows illustrate deciles according to the CAPM, whereas the columns show deciles ranked by the M3F. Numbers in the lower (upper) triangle denote scenarios in which funds are considered to have received a better (worse) ranking by the CAPM than by the M3F. For example, the cross-hatched cell signals that the CAPM ranked the funds in the 9th decile, while the M3F ranked the same funds in the 2nd decile. Consequently, the CAPM ranking is somewhat better than the M3F ranking.

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