Fundação Getulio Vargas
Escola de Administração de Empresas de São Paulo

Henrique Lamounier Costa

False Discoveries and Luck in the Brazilian Equity Fund Market

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Dissertação apresentada à Escola de Administração de Empresas de São Paulo da Fundação Getulio Vargas (FGV-EAESP), como requisito parcial para a obtenção do grau de Mestre em Administração de Empresas.

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Abstract

In this study I investigate the performance of equity funds in Brazil between January 2001 and January 2021. I do that by applying the False Discovery Rate methodology to the entire sample, as well as to sub-samples separated according to fund administrators being affiliated to commercial banks. I find evidence that some managers are able to generate positive alphas after accounting for luck and that bank-affiliated funds achieve positive (negative) alphas less (more) frequently. The results also show that the location of alphas in the cross-sectional distribution differs according to the sub-samples, which has important academic and practical implications. Lastly, I find evidence of persistence of positive and negative performance when analyzing the entire equity fund sample, but document that non bank-affiliated funds are the responsible for that.

Keywords: False Discovery Rate; Persistence; Mutual Funds.
JEL classification: C10, C13, C14, C50, C51, C52.

Contents

1 Introduction

Finance researchers and practitioners have historically shown interest in studying the matter of mutual fund performance and to answer the question of whether fund managers actively seeking risk-adjusted returns are able to “beat the market”. Since the introduction of Jensen’s Alpha (Jensen, 1968), researchers have studied mutual fund performance by regressing excess returns on factor-mimicking portfolios (Cochrane, 2009) and by observing the number of significant intercepts (i.e. alphas) with positive and negative signs.

Studies applying such general methods to data from the United States have mostly found that few (sometimes no) funds achieve positive alphas and that a larger number generate negative performance (Carhart, 1997; Pástor & Stambaugh, 2002; Wermers, 2000). Such results have been reconciled with a theoretical model by Berk and Green (2004), who predict that, in rational markets, few funds are able to generate positive alphas and, in equilibrium, positive alphas don’t persist due to fund inflows and decreasing returns to scale.

As a way to obtain more robust inferences regarding managerial skill, Carhart (1997) obtains the intercepts through a widely used 4-factor model. The idea behind the methodology is that, if portfolios formed with higher (lower) alphas achieve higher (lower) out-of-sample performance, then it is likely that managers achieving high (low) performance will repeat that in the following period. Therefore, this a first attempt to control for “luck”. The author concludes that, again, empirical evidence supports market efficiency.

Although simple and intuitively appealing, a few flaws of this approach have been pointed out more recently. Kosowski, Timmermann, Wermers, and White (2006), for example, point out that factors such as sample size differences, heterogeneous risk-taking and residual kurtosis and skewness may result in non-normal alphas across funds, thus challenging the traditional approach relying on theoretical distributions. The authors present a residual bootstrapping method that makes it possible to use the empirical alpha distribution, and therefore to obtain bootstrapped *p*-values that account for such non-normality. They generate pseudo-returns with zero alphas by construction and, for each fund, add to its time-series of returns a sample with replacement of the regression residuals. The new pseudo series are then regressed on the factors. Repeating the procedure a number of times yields the data to be used to construct the empirical distributions of fund alphas, as well as *t*-statistics. All in all, the authors do find positive and negative alphas after accounting for the “true” distributions, and by using bootstrapped *p*-values are also able to capture performance persistence among the best funds.

Cuthbertson, Nitzsche, and O’Sullivan (2008) apply this methodology to funds in the United Kingdom and find broadly similar results for “all styles” : a few positive alphas that are attributed to “skill”, since they are rejected as being due to luck, and more negative alphas whose sign is attributed to “bad skill”. Yang and Liu (2017) are unable to find truly positive alphas and infer that the number of unskilled managers is smaller in the 2008-2013 period than in the 2002-2007, in China. In the Brazilian context, Laes (2010) find similar results to Kosowski et al. (2006), meaning few truly positive (attributed to skill) alphas and a large number of truly negative (attributed to “poor management”) ones.

Fama and French (2010) also rely on bootstrap simulations to assess skill in mutual fund management, but their approach is markedly different. Particularly, Kosowski et al. (2006) re-sample residuals from the return series of each fund, therefore maintaining the time-series length of each fund; Fama and French (2010), on the other hand, draw zero-alpha returns from a fixed window (273 months) in each iteration, therefore allowing some funds to be left out of the simulation run after excluding those with fewer than 8 monthly simulated returns. By doing that, they intend to preserve the cross-sectional correlations of fund returns. Overall, they do not find support for the presence of skilled managers.

This methodology has also found applications to the Brazilian investment fund market. Matos, Silva, and Silva (2015) and Borges and Martelanc (2015) find results supporting the existence of a few truly positive alphas (with the latter inferring that larger funds perform better). Laes and da Silva (2014), on the other hand, when investigating equity funds, find results in support of Fama and French (2010), with much more truly negative alphas, but also document that their sample consisting of larger funds showed more (less) cases with truly positive (negative) performance.

The strengths and weaknesses of the two approaches are thoroughly discussed in Fama and French (2010). As advantages, Kosowski et al. (2006) are able to (i) capture autocorrelations by individually re-sampling pseudo-returns for each fund; they also (ii) sample all funds meeting their initial exclusion criteria and to maintain in the simulations the original number of degrees of freedom. However, they (i) are not able to capture cross-correlations, since they re-sample residuals individuals, (ii) do not eliminate survival bias by requiring 60 monthly returns and (iii) do not eliminate incubation bias by allowing small funds to have the same "weight" in their tests.

On the other hand, Fama and French (2010) argue that they are able to (i) capture the cross-sectional correlations by jointly sampling fund returns, (ii) reducing survival bias by requiring shorter series and (iii) eliminating incubation bias by requiring funds to surpass US$ 5 million in assets under management at some point. However, by jointly re-sampling, they also (i) lose autocorrelation effects, (ii) gain a bias towards greater degrees of freedom and (iii) miss time-varying betas. While they discard problem (i) as a serious issue, they do not do so for problem (iii).

A different treatment of "luck" is given in Barras, Scaillet, and Wermers (2010). The authors recognize that in multiple hypothesis testing one should expect to find false discoveries (i.e. observations that have fallen in the rejection region by chance) and propose an extension of the False Discovery Rate (FDR) by Storey (2002) applied to fund performance. Their approach is able to estimate the effect of false discoveries in both tails of the cross-sectional alpha distribution and the proportions of zero, positive and negative alphas. In addition to that, they are able to make inferences on the "location" of positive and negative alphas in the distribution, which has particularly important practical implications, which I discuss in the context of our results. Lastly, they propose a novel method for accounting for false discoveries when assessing performance persistence. Contrary to previous studies, such as Carhart (1997) and Wermers (2003), the authors find that a non negligible number of funds generate positive alphas and that positive alphas persist.

Cuthbertson, Nitzsche, and O'Sullivan (2012) apply their methodology to a sample of UK equity funds, finding (i) few (many) positive (negative) alphas, (ii) higher FDR for positive alphas across a range of significance levels and (iii) no (weak) evidence of persistence of positive (negative) alphas for 10% and 20% FDR target levels. Among applications to other markets, Cuthbertson and Nitzsche (2013) use the methodology to German mutual funds while accounting for market timing and Kim, In, Ji, and Park (2014) investigate how the FDR estimates vary when using a conditional model using a sample of Australian managed funds. Applications of the FDR by Barras et al. (2010) in other contexts include, for example, Augustin, Brenner, and Subrahmanyam (2019) (informed trading), Bajgrowicz and Scaillet (2012) (technical trading), Harvey and Liu (2020) (double-bootstrap improvement) and Giglio, Liao, and Xiu (2020) (combining with machine learning).

In order to foster the debate about "luck" beyond the most common economies using the FDR framework I moved the focus to Brazil. Brazil is an interesting country to study for a number of reasons: (i) by the end 2020 the Brazilian mutual fund industry surpassed 80% of GDP in spite of the 2020/2021 COVID-19 pandemic (Anbima, 2021), (ii) more than doubling the total assets under management (AuM) reported in December 2015. Overall numbers by The International Investment Funds Association (IIFA, 2020), Brazil ranks 11^{th} among the largest mutual fund industries worldwide and 2^{nd} among emerging economies, after China.

An interesting phenomenon regarding the industry's behavior throughout 2020 is the inflow distribution across categories. While total AuM have received a positive US$ 38.89 (R$ 156.40) billion in 2020, the Balanced/Mixed and Equity categories were responsible for 62.40% and 44.47% of that number, with the remaining categories answering for a net outflow. That is in spite of the 2.92% increase of the Ibovespa index in 2020.

All in all, the Brazilian mutual fund market is one of the largest among developing countries and worldwide, and has been able to grow even during a global pandemic. Moreover, funds belonging to the equity category have been the second group with most inflows in 2020 despite the poor stock market performance, which could lead to the conclusion that investors are relying on managerial ability to generate positive performance.

Based on that in this study I apply the Barras et al. (2010) methodology to the Brazilian equity fund market and seek to answer the following questions: (i) are there skilled (and unskilled) fund managers in Brazil that generate positive (or negative) risk-adjusted and cost-liquid alphas? and (ii) do positive and negative alphas persist?

The sample consists of equity fund monthly returns ranging from January 2001 until January 2001. Additionally, motivated by the evidence (Franzoni & Giannetti, 2019; Hoffmann Junior, 2015) that bank-affiliated funds have lower performance, I also apply the methodology to two sub-samples that separate funds whose fund administrators are among Brazil's largest commercial banks from those who aren't. I therefore add the questions: (iii) have bank-affiliated funds performed better than their unaffiliated counterparts between Jan/2001 and Jan/2021? and (iv) are the positive (or negative) alphas of each sample differently distributed in their respective cross-sectional distributions?

My results support the Berk and Green (2004) hypothesis in that I find that most funds achieve either zero or negative alphas. However, I am able to detect a significant minority of positive alphas. Moreover, I find that the impact of luck is stronger for positive findings and for bank-affiliated funds and that bank-affiliated funds are likely responsible for the positive (negative) alphas located in the extreme right (left) tail of the distribution. Lastly, I show that both positive and negative alphas persist for the entire sample, but unaffiliated funds are responsible for these findings.

The study contributes to the finance literature in roughly three ways. First, I extend the FDR methodology to one of the largest emerging market mutual fund industry and strengthen the argument in favor of the existence of skilled and unskilled managers in Brazil. Second, I suggest that researchers seeking to analyze fund performance should pay attention to other fund characteristics, such as whether the fund administrator is affiliated to a commercial bank. Lastly, I gather more evidence in favor of the under-performance of bank-affiliated funds, now by properly accounting for luck.

The dissertation proceeds as follows. Section 2 presents the asset pricing models and describes the methodology used to analyze the performance of Brazilian equity funds and to test for persistence. Section 3 presents the results and discusses their asset pricing implications. Section 4 shows the robustness tests results and Section 5 concludes.

2 Methodology

In this section I detail the methodology used in order to obtain the results that follow. I begin by presenting the asset pricing models used. I then discuss the implementation of the FDR methodology by Barras et al. (2010) and show how to obtain the bootstrapped *p*-values. Then, I explain the implementation of the performance persistence tests.

2.1 Models

The finance literature has devoted much attention to explaining the cross-section of asset returns, especially given the shortfalls of the Capital Asset Pricing Model (CAPM) by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966). This has led to the introduction of multiple *factors*, or arguably valuable variables to explaining the cross-sectional variations of mean asset returns.

Fama and French (1992) document the size and book-to-market effects, and in Fama and French (1993) introduce the 3-factor model. To the original CAPM, they add as factors long-short portfolios that “mimic” the behavior of size (SMB) and book-to-market (HML). Although lacking theoretical support for the choice of variables, the authors were able to achieve superior performance to the CAPM.

Popular extensions of this approach have ultimately resulted in additional factors. Jegadeesh and Titman (1993) show that a trading strategy - known as momentum - based on buying (selling) stocks with good (bad) performance over 3 to 12 month periods was able to generate abnormal returns, while Jegadeesh and Titman (2001) show that such abnormal returns become negative when the periods are increased to up to 5 years. More recently, Barroso and Santa-Clara (2015) show that such a strategy can generate high (puzzling) returns, and that the predictability of the momentum factor means that crash risk can be managed. Using the momentum by Jegadeesh and Titman (1993), Carhart (1997) introduces the momentum factor (winners minus losers), arguing that it is a further improvement of the Fama and French (1993) 3-factor model in terms of asset pricing errors.

Having considered the literature, I have used two asset pricing specifications in this study, namely the 3-factor model by Fama and French (1993) and the 4-factor model by Carhart (1997). The asset pricing models are, respectively,

$$R^e_{i,t} = \alpha_i + \beta_{1i} R^e_{m,t} + \beta_{2i} SMB_t + \beta_{3i} HML_t + \varepsilon_{i,t} \tag{1}$$

$$R^e_{i,t} = \alpha_i + \beta_{1i} R^e_{m,t} + \beta_{2i} SMB_t + \beta_{3i} HML_t + +\beta_{4i} WML_t + \varepsilon_{i,t} \tag{2}$$

The β terms are slope coefficients and measure *quantity of risk*; the SMB_t, HML_t and WML_t are excess returns mimicking the size, book-to-market and momentum factors (Cochrane, 2009) and $R^e_{m,t}$ is the excess return of the market portfolio on the risk-free rate. These four terms represent

the *prices of risk*. Lastly, α_i is the regression intercept and the standard measure for portfolio performance, i.e abnormal returns.

So there are different dimensions to cover, i.e samples, fund and factors, therefore now I detail how each of these values will be used as inputs of the chosen statistical models.

2.2 Bootstrapped *p*-values

As thoroughly exposed by Kosowski et al. (2006), because of a number of factors, such as kurtosis and skewness of residuals, sample size, risk-taking and cross-sectional dependencies, it may not be appropriate to use the parametric *p*-values directly. The reason is that such factors (and the interaction between those of different funds) can lead the cross-sectional alpha distribution to the non-normal and therefore to weaken the strength of standard hypothesis tests.

In order to account for these issues and following Kosowski et al. (2006), I conduct the following procedure. For each fund, I subtract each monthly return by the fund's $\hat{\alpha}$ estimate obtained above, which results in pseudo-returns achieving zero alphas by construction; I add to those returns a draw with replacement from the fund's residual vector, in such a way that the funds still have zero-alphas on average, but are now subject to luck; then, I regress the pseudo-returns on the same factors and keep the vector of pseudo *t*-statistics. This procedure yields a row of an $B \times M$ matrix, where B is the number of bootstrap iterations (e.g. 1,000) and M is the number of funds in the sample. Doing this 1,000 times completes the matrix.

The idea behind these procedures is that, instead of assuming a theoretical distribution and comparing it to each fund's *t*-statistic, I am now using their empirical distribution to do so. The intuition behind why this is reasonable is that, by subtracting the alphas and adding re-sampled residuals as described above, one imposes the null hypothesis of no performance ($\alpha = 0$). In other words, each fund's *t*-statistic is being compared to an empirical distribution that is able to capture the complexities in each fund's alpha (and *t*-statistic), as well as interactions among funds. I refer to Kosowski et al. (2006) for further details.

Lastly, the $B \times M$ matrix above is used to obtain the new $M \times 1$ vector of bootstrapped p-values, p_i^b. Note that each fund's t-statistic, $\hat{t}_i$, can be now put in perspective against B bootstrapped versions of itself while imposing the null hypothesis of no performance. Like Barras et al. (2010), I follow Davidson and MacKinnon (2004, p. 187) and obtain *p*-values through the equation,

$$p_i^b = 2 \min \left[\frac{1}{B} \sum_{b=1}^{B} \mathbb{I}_{\{t_i^b > \hat{t}_i\}}, \frac{1}{B} \sum_{b=1}^{B} \mathbb{I}_{\{t_i^b < \hat{t}_i\}} \right] \tag{3}$$

Where $\mathbb{I}_{\{t_i^b > \hat{t}_i\}}$ is an indicator function equal to 1 if $\hat{t}_i$ is greater (or less) than each of its bootstrapped version. The vector of bootstrapped *p*-values is then stored. I use the bootstrapped values in the main empirical analysis and defer the results for the parametric ones to the robustness tests section.

2.3 False Discovery Rate

The False Discovery Rate (FDR) by Barras et al. (2010) is a method used in a context of multiple hypotheses testing to account for false discoveries, or rejections that should not have been rejected. It is defined as the rate of estimated false discoveries, $\hat{F}(\gamma)$ to the number of observations, $\hat{R}(\gamma)$ with p-values below the significance level, γ. The model by Storey (2002) is extended to positive and negative false discoveries through the equations,

$$FDR^{+}(\gamma) = \mathbb{E}\left[\frac{F^{+}(\gamma)}{R^{+}(\gamma)} \,|\, R^{+}(\gamma) > 0\right] = \mathbb{E}\left[\frac{\frac{1}{2}F(\gamma)}{R^{+}(\gamma)} \,|\, R^{+}(\gamma) > 0\right] \tag{4}$$

$$FDR^{-}(\gamma) = \mathbb{E}\left[\frac{F^{-}(\gamma)}{R^{-}(\gamma)} \,|\, R^{-}(\gamma) > 0\right] = \mathbb{E}\left[\frac{\frac{1}{2}F(\gamma)}{R^{-}(\gamma)} \,|\, R^{-}(\gamma) > 0\right] \tag{5}$$

Because the positive and negative rejections, $\hat{R}^{+}(\gamma)$ and $\hat{R}^{-}(\gamma)$, at each significance level, are known, the only variables to be estimated are $\hat{F}^{+}(\gamma)$ and $\hat{F}^{-}(\gamma)$. Barras et al. (2010) suggest the use of $\hat{F}^{+}(\gamma) = \hat{F}^{-}(\gamma) = \frac{1}{2}\hat{F}(\gamma) = \frac{1}{2}\hat{\pi}_0\gamma M$, where $\hat{\pi}_0$ is the estimated number of zero-alpha funds (funds that should not be rejected as having performance different from zero).

To obtain this value, they rely on the observation of the p-value histogram by noting that, under the null hypothesis, p-values are uniformly distributed between zero and one. Now,

$$\hat{\pi}_0(\lambda) = \frac{W(\lambda)}{(1-\lambda)M} \tag{6}$$

where W is the number of p-values greater than some threshold λ. The estimation procedure consists of choosing a value λ^* that minimizes a mean-squared error (MSE). First, bootstrapped versions of $\hat{\pi}_0$, $\hat{\pi}_0^b$, are formed by drawing with replacement from the p-value vector. Then, λ^* is chosen by minimizing,

$$\widehat{MSE}(\lambda) = \frac{1}{1{,}000}\sum_{b=1}^{1{,}000}\left[\hat{\pi}_0^b(\lambda) - \min_{\lambda}\hat{\pi}_0(\lambda)\right]^2 \tag{7}$$

With λ^*, I obtain $\hat{\pi}_0(\lambda^*)$ according to equation (6), as well as $\widehat{FDR}^{+}(\gamma)$, $\widehat{FDR}^{-}(\gamma)$, $\hat{F}^{+}(\gamma)$ and $\hat{F}^{-}(\gamma)$ for a range of γ levels. Additionally, because $\hat{R}^{+}(\gamma) = \hat{F}^{+}(\gamma) + \hat{T}^{+}(\gamma)$ and $\hat{R}^{-}(\gamma) = \hat{F}^{-}(\gamma) + \hat{T}^{-}(\gamma)$, I additionally obtain vectors for $\hat{T}^{+}(\gamma)$ and $\hat{T}^{-}(\gamma)$, the estimated numbers of true discoveries.

The final step of the FDR application is to obtain estimates for the proportion of funds in the sample with positive ($\hat{\pi}_A^{+}$) and negative ($\hat{\pi}_A^{+}$) performance. That is done through a similar bootstrap approach to that in equation (7). In this case, by obtaining the values of $\hat{F}^{+}(\gamma)$ and $\hat{F}^{-}(\gamma)$ through the FDR procedure, I generate bootstrapped $\hat{\pi}_A^{+}(\gamma)$, called $\hat{\pi}_A^{b+}(\gamma)$ for multiple levels of γ. Then, I choose γ^* that minimizes the MSE,

$$\widehat{MSE}^{+}(\gamma) = \frac{1}{1{,}000}\sum_{b=1}^{1{,}000}\left[\hat{\pi}_A^{b+}(\gamma) - \min_{\gamma}\hat{\pi}_A^{+}(\gamma)\right]^2 \tag{8}$$

I do the same for negative alphas, and choose γ^* to minimize the smallest between the positive and negative MSE. Lastly, if $\text{MSE}^{+} < \text{MSE}^{-}$ I set $\hat{\pi}_A^{+} = \hat{\pi}_A^{+}(\gamma^*)$ and $\hat{\pi}_A^{-} = \hat{\pi}_A - \hat{\pi}_A^{+}$. I do the reciprocal if $\text{MSE}^{+} > \text{MSE}^{-}$.

2.4 Performance Persistence

Barras et al. (2010) note that by obtaining $\widehat{FDR}(\gamma)$ for a wide range of γ, one is able to perform a more robust test of performance persistence than what had been traditionally done. The test consists of establishing FDR targets, $FDR_\tau^+ = FDR_\tau^-$, and choosing funds with p-values below $\gamma_{FDR_\tau^+}$ or $\gamma_{FDR_\tau^-}$ to form a portfolio.

The estimates are obtained using 5 years of data and at the end of a range of years. The portfolio is held for one year, during which weights of dead funds are re-allocated to the remaining ones. The time-series of all years are joined and taken as the time-series of the portfolio formed with the given FDR_τ^+ or FDR_τ^-. The idea behind this approach is that a low FDR_τ^+ (FDR_τ^-) indicates a high proportion of positive (negative) alphas in the portfolio, and therefore this test should give a better idea of whether positive and negative alphas persist.

A caveat that I highlight at this point is that this test is stronger if (as detailed in the results) alphas are found to be concentrated in an extreme of the cross-sectional distribution. Therefore, while I demonstrate the performance analysis for alphas regardless of such behavior, I highlight the samples (or sub-samples) for which positive or negative alphas are concentrated in the extreme right or left tail.

The time-series for positive and negative alphas, and for each target level, are then regressed on the asset pricing factors. I interpret the results as indicating persistence if funds formed with positive (negative) alphas and low FDR_τ^+ (FDR_τ^-) yield significant and higher (lower) alphas than those formed with high targets. Although I have chosen to analyze persistence for positive and negative alphas, I note that when assessing skill one is more interested in the former: it reflects the ability of potentially skilled managers to maintain good performance.

3 Results

I begin this section by describing the data set we have used. I then show the results of applying different asset pricing models and explain the selection criteria. Following that, I present the False Discovery Rate and performance persistence results and discuss the meaning of our findings. I end the section by performing robustness tests.

3.1 Data

I obtain the equity fund and risk factor data from the Economatica and the Brazilian Center for Research in Financial Economics (NEFIN) data bases, respectively. I exclude from the initial data set all funds belonging to the "closed" and "exclusive" categories, and additionally discard fund of funds (*Fundos de Investimento em Cotas* - FIC). The reason for not including FICs is that they may invest in other funds, and including them could potentially lead to "double counting". This procedure results in an initial sample of 3,058 funds.

I use a sample period from Jan/2001 until Jan/2021. After the first filtering, for each fund I match data related to the fund administrator and the class according to the Brazilian Association of Financial and Capital Market Institutions (Anbima), as well as time series of monthly Net Asset Values (NAV). I then build time series of monthly returns (based on NAV) and exclude any fund with fewer than 36 consecutive returns (or three years), which reduces the sample size to 1,463. Note that at no point have I restricted the sample to active funds in order to eliminate survivorship bias.

The last data treatment consists of dividing the sample into bank-affiliated (sub-sample 1) and bank-unaffiliated funds (sub-sample 2). I define bank affiliation similarly to Fantinatti (2008), and therefore only include in this sub-sample funds whose fund administrator is affiliated to one of Brazil's largest banks. This yields sub-samples of size 599 and 864 for bank-affiliated and bank-unaffiliated funds, respectively.

Table 1, Table 2 and Table 3 below show the summary statistics of the equity fund data, as well as the statistics of equal-weighted and value-weighted portfolios formed with all funds in the sample and with sub-samples according to size (small, medium and large). I calculate the mean net assets over the existence period of each fund, and define as small those with mean net assets under BRL 20 million, as medium those between BRL 20 million and BRL 100 million and as large those above BRL 100 million. Panel A shows mean values over the sample and each sub-sample, and Panel B and Panel C, the results for the portfolios.

Intuitively, Panel A of Table 1 shows that larger funds are, on average, older and therefore have a greater number of monthly return observations. Over the entire sample, the mean net assets is around BRL 129 million, with 94.48 observations and slightly under 9 years between inception and end dates (January 01 2021 for active funds).

Table 1: Summary Statistics (All Funds)

	Sample	Small	Medium	Large
Panel A: Fund Characteristics				
	Sample	Small	Medium	Large
Mean Net Assets(Millions of BRL)	128.6562	8.2853	48.5308	423.3059
Mean Number of Observations	94.4819	82.5836	98.3361	108.3660
Mean Fund Age (Days)	3238.7601	2915.0134	3422.7008	3514.1910
Panel B: Equal-Weighted Portfolios				
	Sample	Small	Medium	Large
Portfolio Monthly Return	0.0141	0.0128	0.0132	0.0175
Variance	0.0039	0.0049	0.0037	0.0037
Skewness	-0.4433	0.8320	-0.6286	-0.4240
Kurtosis	2.4749	9.6035	2.2989	3.2441
Panel C: Value-Weighted Portfolios				
	Sample	Small	Medium	Large
Portfolio Monthly Return	0.0140	0.0127	0.0131	0.0174
Variance	0.0039	0.0049	0.0036	0.0036
Skewness	-0.4418	0.8458	-0.6303	-0.4084
Kurtosis	2.4755	9.6871	2.2898	3.1963

As shown on Panel B and Panel C of Table 1, the statistics for the equal-weighted and value-weighted portfolios are fairly similar. In general, portfolios formed with larger funds have, on average, generated greater returns with less variability. Also, while small funds are generally positively skewed, medium and large funds are positively skewed. Lastly, while smaller funds generate portfolios with fatter tails, larger funds generate slightly more kurtosis than medium funds.

I also show the summary statistics for bank-affiliated and bank-unaffiliated funds on Table 2 and Table 3, respectively.

Table 2: Summary Statistics (Bank-affiliated Funds)

	Sample	Small	Medium	Large
Panel A: Fund Characteristics				
	Sample	Small	Medium	Large
Mean Net Assets(Millions of R$)	121.3259	8.0647	50.9853	368.3099
Mean Number of Observations	105.9583	103.3021	106.9952	111.7075
Mean Fund Age (Days)	1852.1133	2135.2604	2144.2512	1915.3333
Panel B: Equal-Weighted Portfolios				
	Sample	Small	Medium	Large
Portfolio Monthly Return	0.0137	0.0136	0.0132	0.0140
Variance	0.0039	0.0039	0.0039	0.0040
Skewness	-0.5633	-0.5795	-0.5616	-0.5154
Kurtosis	2.0490	2.4577	1.8073	1.8194
Panel C: Value-Weighted Portfolios				
	Sample	Small	Medium	Large
Portfolio Monthly Return	0.0137	0.0123	0.0129	0.0154
Variance	0.0039	0.0042	0.0038	0.0036
Skewness	-0.5581	-0.5525	-0.5221	-0.5479
Kurtosis	2.0247	1.9201	1.7336	2.3701

On Table 2, I show that bank-affiliated funds are smaller, on average, than the sample average. The portfolios formed with such funds have also achieved lower returns when compared to those formed with all funds, are negatively skewed and have thinner tails.

Table 3: Summary Statistics (Bank-unaffiliated Funds)

	Sample	Small	Medium	Large
Panel A: Fund Characteristics				
	Sample	Small	Medium	Large
Mean Net Assets(Millions of R$)	116.1477	7.9231	45.7721	500.2949
Mean Number of Observations	86.5255	80.9816	87.3552	99.4471
Mean Fund Age (Days)	1894.4303	1959.6184	2125.2085	1999.9235
Panel B: Equal-Weighted Portfolios				
	Sample	Small	Medium	Large
Portfolio Monthly Return	0.0145	0.0133	0.0135	0.0213
Variance	0.0044	0.0064	0.0035	0.0047
Skewness	0.6348	3.6481	-0.7332	2.0272
Kurtosis	8.7056	38.5385	2.9491	21.9072
Panel C: Value-Weighted Portfolios				
	Sample	Small	Medium	Large
Portfolio Monthly Return	0.0145	0.0132	0.0133	0.0212
Variance	0.0044	0.0064	0.0033	0.0046
Skewness	0.6459	3.6985	-0.8012	2.0798
Kurtosis	8.7516	39.0605	3.2593	22.2193

Table 3 shows the converse for bank-unaffiliated funds. In this case, the portfolios achieve higher returns, have higher variance, fatter tails and are positively skewed. These funds are also smaller than their bank-affiliated pairs.

I also note that, as is the case for all funds, portfolios formed with larger funds achieve higher returns. However, for the bank-affiliated sub-sample, the return variance remains relatively constant, whereas for the bank-unaffiliated sub-sample it is higher for small, large and medium fund portfolios, respectively. Lastly, overall bank-unaffiliated funds generate significantly fatter tails.

3.2 Asset Pricing Models

I now show the results of the asset pricing models applied to the entire sample and sub-samples as well. In order to do that, I apply both the chosen asset pricing models to each fund in each sample (sub-sample). I then keep the statistics (alpha and beta estimates along with their t-statistics, residual skewness and kurtosis, adjusted R-squared values) and present averages over the sample (sub-samples), along with the number of positive and negative alphas. Table 4 shows these values for the entire sample, while Table 5 and Table 6 present those for bank-affiliated and bank-unnafiliated funds, respectively.

The two asset pricing models, when applied to any sample, yield contrasting alpha t-statistics, with the averages being negative and having greater (smaller) magnitude for sub-sample 1 (sub-sample 2), while the t-statistics of the three common betas remain similar. With the exception of sub-sample 2, the Carhart (1997) 4-factor model yields slightly larger adjusted R-squared values.

Table 4: Asset Pricing Models (All Funds)

	4-factor		3-factor	
Parameter	Coefficient	t-statistic	Coefficient	t-statistic
Alpha	0.0001	-0.2390	-0.0014	-0.7113
MKT	0.8467	18.1568	0.8963	18.8300
SMB	0.2011	2.2670	0.1960	2.4213
HML	-0.0386	-0.5696	-0.0164	-0.1756
WML	0.0318	0.5095		
Skewness	0.0364		0.0313	
Kurtosis	2.8295		2.0045	
R-Squared	0.7336		0.7332	
# positive alpha	678		716	
# negative alpha	785		747	

Following Cuthbertson et al. (2012), I also use the Bayesian Information Criterion (BIC) and find that the average over the entire sample is smaller for the Carhart (1997) model. Therefore, from here on I report the main results including the momentum factor.

For the entire sample and not using bootstrapped *p*-values yet, at 5% and 10% significance levels and without accounting for luck, I reject 94 (6.43%) and 122 (8.34%) positive funds (percent of the sample) as having zero performance; I reject 179 (12.24%) and 223 (15.24%) negative funds (percent of the sample) as having zero performance.

For sub-sample 1, 34 (05.68%) and 40 (06.68%) funds (percent of the sample) are found to have significant and positive alphas at 5% and 10% significance levels, respectively. Those values are 77 (12.85%) and 96 (16.03%) for negative alphas.

Table 5: Asset Pricing Models (Bank-affiliated Funds)

	4-factor		3-factor	
Parameter	Coefficient	t-statistic	Coefficient	t-statistic
Alpha	-0.0002	-0.3337	-0.0013	-0.7786
MKT	0.8845	23.4684	0.9337	23.6137
SMB	0.1575	2.1268	0.1500	2.2041
HML	-0.0186	-0.3097	0.0101	0.0538
WML	0.0285	0.5242		
Skewness	0.0484		0.0253	
Kurtosis	2.4963		1.9629	
R-Squared	0.7924		0.7792	
# positive alpha	270		294	
# negative alpha	329		305	

Lastly, using sub-sample 2, with significance levels of 5% and 10%, I reject the null hypothesis of zero performance for 60 (6.94%) and 82 (9.49%) funds (percent of the sample) for positive alphas, respectively, and 102 (11.81%) and 127 (14.70%) of funds (percent of the sample) for negative alphas.

Table 6: Asset Pricing Models (Bank-unaffiliated Funds)

	4-factor		3-factor	
Parameter	Coefficient	t-statistic	Coefficient	t-statistic
Alpha	-0.0000	-0.1734	-0.0015	-0.6800
MKT	0.8205	14.4743	0.8688	15.7177
SMB	0.2314	2.3642	0.2297	2.5760
HML	-0.0525	-0.7498	-0.0359	-0.3481
WML	0.0340	0.4993		
Skewness	0.0280		0.0346	
Kurtosis	3.0605		2.0307	
R-Squared	0.6929		0.6997	
# positive alpha	408		422	
# negative alpha	456		442	

All in all, these results indicate that, regardless of the bank-affiliation status, positive alphas are rare compared to negative alphas and that the majority of the funds have achieved close to zero performance during the sample period. The numbers also suggest that bank-affiliated funds have not performed much worse than their bank-unaffiliated counterparts, which results by comparing positive and negative significant findings.

However, as noted above, these results do not account for luck, in the sense that part, or the entirety of positive and negative findings may be from truly zero-performance funds. Furthermore, it is possible that the proportion of false discoveries varies from sample to sample and across positive and negative alphas, in which case these conclusions regarding the overall and sample-specific performances could be misleading.

3.3 False Discovery Rate

Motivated by the fact some funds may have exhibited positive performance purely by luck, in the this subsection I present the results of the application of the False Discovery Rate (FDR), and discuss their asset pricing implications, as well as how they compare with existing evidence.

In order to obtain the FDR estimates, I follow the bootstrap approach proposed by Barras et al. (2010) and detailed above. For all equity funds, the MSE yields $\lambda^* = 41.15\%$; for bank-affiliated funds, $\lambda^* = 49.50\%$ and $\lambda^* = 43.45\%$ for bank-unaffiliated funds.

On Table 7, Panel A, Panel B and Panel C show the results for the entire sample, sub-sample 1 and sub-sample 2, respectively, using the bootstrapped p-values. I show, for a range of significance levels, the proportion of truly positive and negative significant alphas ($\frac{\hat{R}^+(\gamma)}{M}$ and $\frac{\hat{R}^-(\gamma)}{M}$), as well as the estimated proportion of false ($\frac{\hat{F}^+(\gamma)}{M}$ and $\frac{\hat{F}^-(\gamma)}{M}$) and true ($\frac{\hat{T}^+(\gamma)}{M}$ and $\frac{\hat{T}^-(\gamma)}{M}$) discoveries. For each of these estimates, I also show the standard-errors (Genovese & Wasserman, 2004). Lastly, I also include the FDR estimates for positive ($\widehat{FDR}^+(\gamma)$) and negative ($\widehat{FDR}^-(\gamma)$) alphas.

For the entire sample (Panel A), the FDR implementation suggests that 14.68% of the funds in

the sample were able to generate truly positive alphas, 40.94% generated truly negative and 44.38% did not achieve differential positive or negative alphas. Therefore, it supports the Berk and Green (2004) hypothesis in the sense that the vast majority of managers are unable to generate long term positive performance, although the $\hat{\pi}_A^+$ is higher than has been found in previous studies (Barras et al., 2010; Cuthbertson & Nitzsche, 2013; Cuthbertson et al., 2012). In the robustness tests below, I find significantly less truly positive alphas when using parametric, instead of bootstrapped p-values.

Looking at sub-sample 1 and sub-sample 2 (Panel B and Panel C), my results suggest that funds unaffiliated to banks have achieved higher performance than the entire sample. Also, proportionately less bank-affiliated funds were found to achieve truly positive alphas, but also achieved negative performance slightly less frequently. This is in line with the international (Ferreira, Matos, & Pires, 2018; Franzoni & Giannetti, 2019) and Brazilian (Hoffmann Junior, 2015) literature on bank-affiliation and management performance. Interestingly, I find that the estimated proportions of negative alpha funds are similar in the two sub-samples.

The bootstrapped p-values also yield relatively low levels of false discoveries, with the $\widehat{FDR}^+(\gamma)$ ($\widehat{FDR}^-(\gamma)$) reaching a maximum of 22% (17%) for the entire sample at $\gamma = 20\%$. By looking at the first row on Panels A through Panel C, I also note that, before accounting for luck, relatively many funds are rejected as having differential performance, and that the negative rejections are indeed more frequent than the positive ones. The close FDR levels for positive and negative alphas, therefore, does not change the no-luck interpretation that positive alphas are less frequent. The FDR estimates for positive alphas are close to those by Kim et al. (2014) when they use an unconditional model like mine, but for negative ones, mine are smaller; compared to Barras et al. (2010) and Cuthbertson et al. (2012), on the other hand, I find smaller FDR estimates for positive alphas and similar estimates for negative ones.

Turning to a comparison of samples, I note that the FDR appears as a more serious issue for bank-affiliated funds than for their unaffiliated counterparts across all significance levels considered, although that is more evident for positive discoveries. For positive alphas, the difference in the impact of false discoveries ranges from 2% at $\gamma = 5\%$ until 8% at $\gamma = 20\%$. As I show below, the robustness tests suggest a greater differential impact of false discoveries for each sub-sample when using parametric p-values.

Finally, I turn to the location of positive and negative alphas in the cross-sectional distribution. I do that by looking at the estimates for positive and negative true discoveries ($\frac{\hat{T}^+(\gamma)}{M}$ and $\frac{\hat{T}^-(\gamma)}{M}$) and by seeing whether these values increase with γ or whether they become constant. If the estimates increase with γ, alphas are taken to be spread in the respective tail of the cross-sectional distribution, whereas if they become constant I interpret that the alphas are concentrated in the extreme of the respective tail.

Table 7: False Discoveries in Right and Left Tails (Bootstrapped p-values)

Panel A: FDR Results for All Equity Funds									
$\hat{\pi}_A^+ = 14.68\%$ $\hat{\pi}_0 = 44.38\%$ $\hat{\pi}_A^- = 40.94\%$									
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$\frac{\hat{R}^+(\gamma)}{M}$ (rejected)	0.12	0.16	0.18	0.20	0.26	0.24	0.22	0.18	(rejected) $\frac{\hat{R}^-(\gamma)}{M}$
$SD_{\frac{\hat{R}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$SD_{\frac{\hat{R}^-(\gamma)}{M}}$
$\widehat{FDR}^+(\gamma)$	0.09	0.14	0.18	0.22	0.17	0.14	0.10	0.06	$\widehat{FDR}^-(\gamma)$
$\frac{\hat{F}^+(\gamma)}{M}$ (lucky)	0.01	0.02	0.03	0.04	0.04	0.03	0.02	0.01	(unlucky) $\frac{\hat{F}^-(\gamma)}{M}$
$SD_{\frac{\hat{F}^+(\gamma)}{M}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	$SD_{\frac{\hat{F}^-(\gamma)}{M}}$
$\frac{\hat{T}^+(\gamma)}{M}$ (skilled)	0.11	0.14	0.15	0.16	0.22	0.21	0.19	0.17	(unskilled) $\frac{\hat{T}^-(\gamma)}{M}$
$SD_{\frac{\hat{T}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$SD_{\frac{\hat{T}^-(\gamma)}{M}}$
Panel B: FDR Results for Bank-affiliated Equity Funds									
$\hat{\pi}_A^+ = 12.17\%$ $\hat{\pi}_0 = 46.48\%$ $\hat{\pi}_A^- = 41.35\%$									
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$\frac{\hat{R}^+(\gamma)}{M}$ (rejected)	0.11	0.14	0.16	0.17	0.27	0.26	0.23	0.20	(rejected) $\frac{\hat{R}^-(\gamma)}{M}$
$SD_{\frac{\hat{R}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	$SD_{\frac{\hat{R}^-(\gamma)}{M}}$
$\widehat{FDR}^+(\gamma)$	0.10	0.17	0.22	0.27	0.17	0.14	0.10	0.06	$\widehat{FDR}^-(\gamma)$
$\frac{\hat{F}^+(\gamma)}{M}$ (lucky)	0.01	0.02	0.03	0.05	0.05	0.03	0.02	0.01	(unlucky) $\frac{\hat{F}^-(\gamma)}{M}$
$SD_{\frac{\hat{F}^+(\gamma)}{M}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	$SD_{\frac{\hat{F}^-(\gamma)}{M}}$
$\frac{\hat{T}^+(\gamma)}{M}$ (skilled)	0.10	0.11	0.12	0.12	0.22	0.22	0.21	0.19	(unskilled) $\frac{\hat{T}^-(\gamma)}{M}$
$SD_{\frac{\hat{T}^+(\gamma)}{M}}$	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	$SD_{\frac{\hat{T}^-(\gamma)}{M}}$
Panel C: FDR Results for Bank-unaffiliated Equity Funds									
$\hat{\pi}_A^+ = 16.50\%$ $\hat{\pi}_0 = 42.07\%$ $\hat{\pi}_A^- = 41.43\%$									
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$\frac{\hat{R}^+(\gamma)}{M}$ (rejected)	0.13	0.17	0.20	0.22	0.26	0.23	0.20	0.17	(rejected) $\frac{\hat{R}^-(\gamma)}{M}$
$SD_{\frac{\hat{R}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$SD_{\frac{\hat{R}^-(\gamma)}{M}}$
$\widehat{FDR}^+(\gamma)$	0.08	0.12	0.16	0.19	0.16	0.14	0.10	0.06	$\widehat{FDR}^-(\gamma)$
$\frac{\hat{F}^+(\gamma)}{M}$ (lucky)	0.01	0.02	0.03	0.04	0.04	0.03	0.02	0.01	(unlucky) $\frac{\hat{F}^-(\gamma)}{M}$
$SD_{\frac{\hat{F}^+(\gamma)}{M}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	$SD_{\frac{\hat{F}^-(\gamma)}{M}}$
$\frac{\hat{T}^+(\gamma)}{M}$ (skilled)	0.12	0.15	0.17	0.17	0.22	0.20	0.18	0.16	(unskilled) $\frac{\hat{T}^-(\gamma)}{M}$
$SD_{\frac{\hat{T}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	$SD_{\frac{\hat{T}^-(\gamma)}{M}}$

By only looking at the entire sample (Panel A), one would conclude that positive and negative alphas are spread in the right and left tails, respectively. However, the fourth rows of Panel B (bank-affiliated) and Panel C (bank-unaffiliated) show that such is not the case, as positive alpha funds in sub-samples 1 and 2 become constant after 10%, leading to the conclusion that they are concentrated in the extreme right tails, which is not the case for negative alpha funds. This is in agreement with the international literature (Barras et al., 2010; Cuthbertson & Nitzsche, 2013;

Cuthbertson et al., 2012) and will be further discussed in the context of performance persistence.

3.4 Performance Persistence

I again follow Barras et al. (2010), now to evaluate performance persistence. As the idea in Carhart (1997), if managers achieving positive performance are able to generate positive alphas subsequently, there is stronger evidence that they are skilled. However, without accounting for luck, one cannot say whether portfolios formed with *t*-statistic (or alpha) in high quantiles are indeed positive, or they can be lucky.

Because I have found that positive alphas in both sub-samples are concentrated in the extreme right tail, I expect that by targeting a low FDR (as detailed above) it is possible to form portfolios that are mostly composed of positive alpha funds. The same idea applies to negative alphas. I therefore expect that as the FDR target rises, performance becomes weaker (or disappears), as a greater proportion of the portfolio is likely to consist of zero-alpha (lucky and unlucky) funds.

My first formation date is Dec/2014 using 60 months of data, and that portfolio is held throughout 2015. I do the same until I have obtained the return series for 2021. I then regress the portfolio series on the factors to obtain the performance results. The analysis is shown on Table 8. The parameters in the first column of each panel correspond to the intercept and slope coefficient of the asset pricing model regression, respectively.

Panel A, Panel B and Panel C show the regression results for the portfolios formed with FDR_τ^+ = 10%, 20% and 40%, respectively. Panel D, Panel E and Panel F show the results for FDR_τ^- = 10%, 20% and 40%, respectively. I am mainly concerned with the α estimates and their t-statistics. These values reflect how periodically re-balanced portfolios with different proportions of zero-alpha funds perform. Under the assumption that there are skilled managers and that performance persists, the α estimates should decrease with the FDR target in the case of positive alphas (Panel A, Panel B and Panel C), and increase in the case of negative alphas (Panel D, Panel E and Panel F).

The results strongly support performance persistence presented in studies using the FDR, like Barras et al. (2010) and studies using only the empirical distributions of alphas, as in Kosowski et al. (2006). However, for studies outside of the United States, my results oppose those by Cuthbertson et al. (2012), using the FDR, and by Laes and da Silva (2014), using the bootstrap approach.

Looking at Panels A through C, I note that, as FDR_τ^+ increases, the out-of-sample performance of the portfolio decreases. Also, the alpha results become significant at increasing levels and for FDR_τ^+, performance becomes negative and insignificant at $\gamma = 40\%$. Panels D to F show a similar, but weaker phenomenon for negative alpha portfolios. For $FDR_\tau^- = 10\%$, the portfolio achieves a significantly negative out-of-sample performance, but for 20% and 40% it is not significant at a 10% level, although the sign remains negative. Because the three α estimates are significant in Panels A through C, I conclude that there is strong evidence of performance persistence in the case of positive alphas. Conversely, because the α significance in Panels D through F disappears with increasing FDR targets, I conclude that there is weak evidence of that for negative alphas.

Table 8: Performance Persistence (Bootstrapped p-values)

Panel A: Performance persistence with $FDR^+_\tau = 10\%$

	Estimate	Sd. Error	t-stat	p-value
α	0.0045	0.0016	2.81	0.0063
MKT	0.7825	0.0281	27.82	0.0000
SMB	0.3158	0.0427	7.40	0.0000
HML	-0.1243	0.0419	-2.97	0.0040
WML	0.1607	0.0314	5.12	0.0000

Panel B: Performance persistence with $FDR^+_\tau = 20\%$

	Estimate	Sd. Error	t-stat	p-value
α	0.0041	0.0017	2.43	0.0173
MKT	0.7703	0.0298	25.87	0.0000
SMB	0.3358	0.0452	7.44	0.0000
HML	-0.1208	0.0443	-2.73	0.0079
WML	0.1557	0.0332	4.69	0.0000

Panel C: Performance persistence with $FDR^+_\tau = 40\%$

	Estimate	Sd. Error	t-stat	p-value
α	0.0028	0.0016	1.78	0.0796
MKT	0.7831	0.0275	28.43	0.0000
SMB	0.3176	0.0418	7.60	0.0000
HML	-0.1168	0.0410	-2.85	0.0056
WML	0.1595	0.0307	5.19	0.0000

Panel D: Performance persistence with $FDR^-_\tau = 10\%$

	Estimate	Sd. Error	t-stat	p-value
α	-0.0030	0.0011	-2.63	0.0103
MKT	0.9760	0.0199	49.11	0.0000
SMB	0.1042	0.0301	3.46	0.0009
HML	0.0157	0.0296	0.53	0.5969
WML	0.0310	0.0222	1.40	0.1651

Panel E: Performance persistence with $FDR^-_\tau = 20\%$

	Estimate	Sd. Error	t-stat	p-value
α	-0.0020	0.0012	-1.62	0.1084
MKT	0.9684	0.0212	45.58	0.0000
SMB	0.1080	0.0322	3.35	0.0012
HML	0.0216	0.0316	0.68	0.4964
WML	0.0046	0.0237	0.19	0.8460

Panel F: Performance persistence with $FDR^-_\tau = 40\%$

	Estimate	Sd. Error	t-stat	p-value
α	-0.0016	0.0012	-1.26	0.2099
MKT	0.9559	0.0215	44.38	0.0000
SMB	0.1111	0.0327	3.40	0.0011
HML	0.0365	0.0321	1.14	0.2579
WML	-0.0027	0.0240	-0.11	0.9107

The factor coefficients are markedly different across positive and negative alpha portfolios. First, portfolios formed with positive alphas are less (more) exposed to the market (size) factor, and have negative value coefficients, contrary to negative alpha portfolios. Also, while the momentum factor coefficient for the positive alpha portfolios remain relatively constant, positive and significant, it decreases consistently with the FDR target in the case of negative alphas, although losing statistical significance.

Using the bootstrapped *p*-values, I have not encountered empirical issues in obtaining the targeted FDR, as Barras et al. (2010) and Cuthbertson et al. (2012). To make that clear, I present that on Table 9. For each year, I compare our FDR targets (first line) to our achieved FDR estimates. By doing that, I verify whether I was able to achieve our FDR targets by following the methodology. In order words, I check if I am confident that the low (high) FDR portfolios are indeed composed of a low (high) number of zero-alpha funds.

Table 9: Target vs Achieved FDR

Panel A: FDR_τ^+ versus $\widehat{FDR}^+(\gamma)$							
year/target	0.10	0.15	0.20	0.25	0.30	0.35	0.40
2015	0.09	0.15	0.20	0.25	0.30	0.35	0.40
2016	0.10	0.15	0.20	0.25	0.30	0.35	0.40
2017	0.10	0.15	0.20	0.25	0.30	0.35	0.40
2018	0.10	0.15	0.20	0.25	0.30	0.35	0.36
2019	0.10	0.15	0.20	0.25	0.30	0.35	0.35
2020	0.10	0.15	0.20	0.25	0.28	0.28	0.28
2021	0.10	0.15	0.20	0.25	0.26	0.26	0.26
Panel B: FDR_τ^- versus $\widehat{FDR}^-(\gamma)$							
year/target	0.10	0.15	0.20	0.25	0.30	0.35	0.40
2015	0.10	0.15	0.20	0.24	0.24	0.24	0.24
2016	0.10	0.15	0.20	0.24	0.24	0.24	0.24
2017	0.10	0.15	0.20	0.25	0.27	0.27	0.27
2018	0.10	0.15	0.20	0.25	0.30	0.30	0.30
2019	0.10	0.15	0.20	0.25	0.30	0.30	0.30
2020	0.10	0.15	0.20	0.25	0.30	0.34	0.34
2021	0.10	0.15	0.20	0.25	0.30	0.35	0.40

Because the FDR estimates are relatively low, it is possible to achieve even targets as low as 10%. Therefore, I only encounter empirical difficulties in this sense for high targets, above 30%. The practical implication of this is that, unlike prior studies, I am more confident that the low-target portfolios are indeed composed proportionately less zero-alpha funds than high-target ones.

4 Robustness

In the main results, I have restricted the analyses to a single asset pricing model (Carhart, 1997), to a single *p*-value estimation method (Kosowski et al., 2006) and to a single sample for testing persistence (all equity funds). In order to strengthen my findings, in this section I generate the same results using parametric *p*-values. I also re-assess performance persistence using each of the sub-samples.

4.1 Parametric *p*-values

I obtain the *p*-value vectors for the entire sample, for bank-affiliated and for bank-unaffiliated equity funds. I then perform the FDR and persistence tests identically. Table 10 shows the results. As before, Panel A, Panel B and Panel C present the results for all equity funds, for bank affiliate (sub-sample 1) and for bank unaffiliated (sub-sample 2).

The results obtained with parametric *p*-values contrast with those using the bootstrap approach in a number of ways. For all funds, I find that false discoveries account for 23% (12%) of positive (negative) rejections at a 5% significance level, and for 46% (31%) at 20%. Those ranges are 28%-54% (12%-31%) for sub-sample 1 and 21%-42% (12%-31%) for sub-sample 2. Therefore, not only do I find that false discoveries appear as a more serious issue with parametric *p*-values, but also that the difference in severity between bank and bank-unaffiliated funds increases.

I identify significantly less truly positive alphas and more zero-alpha funds using this approach. For the entire sample, I estimate that 6.27% are positive alpha funds, 59.49% are zero-alpha funds and 34.24% as negative alpha funds. For sub-sample 1 (sub-sample 2), I find 4.21% (7.40%), 63.09% (59.21%) and 32.70% (35.39%). Therefore, these results suggest that not only are positive alphas almost twice as frequent for bank-affiliated funds in the sample, but that negative alphas are less frequent.

I also find interesting results regarding the location of funds. By looking at the results for all funds only, one would infer that positive alphas are spread in the right tail. However, by looking at the results for the sub-samples, one would in fact conclude that positive and negative alphas of bank-affiliated funds are concentrated in the extreme of the tails, and that the driver of the spread shown for the entire sample is sub-sample 2. If taken as the correct results, these findings would lead the finance practitioner to confidently seek (avoid) funds with positive (negative) alphas beyond an approximate (10%) significance level. The possibility of doing this would not be apparent without looking at the sub-samples separately.

As with the bootstrapped *p*-value approach, I now test performance persistence. Note that, contrary to before, one would now expect the portfolio with low FDR_{τ}^{-} to show persistence (if we expect persistence in the first place). The reason is that the methodology was proposed precisely to capture the extreme funds, which were not apparent on Panel A of the bootstrapped FDR results.

As opposed to the previous analysis, I now find no evidence of persistence of positive alphas and strong evidence in favor of persistence of negative alphas. Although the ex-post performance

of the portfolio with $FDR^+_\tau = 20\%$ is numerically less than with $FDR^+_\tau = 10\%$, neither is significant. However, the alphas of the portfolios formed with negative alpha funds does decrease in magnitude as FDR^-_τ increases, remain negative and are significant.

Table 10: False Discoveries in Right and Left Tails (Parametric p-values)

Panel A: FDR Results for All Equity Funds									
$\hat{\pi}^+_A = 06.27\%$ $\hat{\pi}_0 = 59.49\%$ $\hat{\pi}^-_A = 34.24\%$									
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$\frac{\hat{R}^+(\gamma)}{M}$ (rejected)	0.06	0.08	0.11	0.13	0.19	0.17	0.15	0.12	(rejected) $\frac{\hat{R}^-(\gamma)}{M}$
$SD_{\frac{\hat{R}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$SD_{\frac{\hat{R}^-(\gamma)}{M}}$
$\widehat{FDR}^+(\gamma)$	0.23	0.36	0.42	0.46	0.31	0.26	0.20	0.12	$\widehat{FDR}^-(\gamma)$
$\frac{\hat{F}^+(\gamma)}{M}$ (lucky)	0.01	0.03	0.04	0.06	0.06	0.04	0.03	0.01	(unlucky) $\frac{\hat{F}^-(\gamma)}{M}$
$SD_{\frac{\hat{F}^+(\gamma)}{M}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	$SD_{\frac{\hat{F}^-(\gamma)}{M}}$
$\frac{\hat{T}^+(\gamma)}{M}$ (skilled)	0.05	0.05	0.06	0.07	0.13	0.13	0.12	0.11	(unskilled) $\frac{\hat{T}^-(\gamma)}{M}$
$SD_{\frac{\hat{T}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$SD_{\frac{\hat{T}^-(\gamma)}{M}}$
Panel B: FDR Results for Bank-affiliated Equity Funds									
$\hat{\pi}^+_A = 04.21\%$ $\hat{\pi}_0 = 63.09\%$ $\hat{\pi}^-_A = 32.70\%$									
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$\frac{\hat{R}^+(\gamma)}{M}$ (rejected)	0.06	0.07	0.09	0.12	0.20	0.19	0.16	0.13	(rejected) $\frac{\hat{R}^-(\gamma)}{M}$
$SD_{\frac{\hat{R}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	$SD_{\frac{\hat{R}^-(\gamma)}{M}}$
$\widehat{FDR}^+(\gamma)$	0.28	0.47	0.51	0.54	0.31	0.25	0.20	0.12	$\widehat{FDR}^-(\gamma)$
$\frac{\hat{F}^+(\gamma)}{M}$ (lucky)	0.02	0.03	0.05	0.06	0.06	0.05	0.03	0.02	(unlucky) $\frac{\hat{F}^-(\gamma)}{M}$
$SD_{\frac{\hat{F}^+(\gamma)}{M}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	$SD_{\frac{\hat{F}^-(\gamma)}{M}}$
$\frac{\hat{T}^+(\gamma)}{M}$ (skilled)	0.04	0.04	0.05	0.05	0.14	0.14	0.13	0.11	(unskilled) $\frac{\hat{T}^-(\gamma)}{M}$
$SD_{\frac{\hat{T}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	$SD_{\frac{\hat{T}^-(\gamma)}{M}}$
Panel C: FDR Results for Bank-unaffiliated Equity Funds									
$\hat{\pi}^+_A = 07.40\%$ $\hat{\pi}_0 = 57.21\%$ $\hat{\pi}^-_A = 35.39\%$									
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$\frac{\hat{R}^+(\gamma)}{M}$ (rejected)	0.07	0.09	0.12	0.14	0.19	0.16	0.15	0.12	(rejected) $\frac{\hat{R}^-(\gamma)}{M}$
$SD_{\frac{\hat{R}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	$SD_{\frac{\hat{R}^-(\gamma)}{M}}$
$\widehat{FDR}^+(\gamma)$	0.21	0.30	0.37	0.42	0.31	0.26	0.19	0.12	$\widehat{FDR}^-(\gamma)$
$\frac{\hat{F}^+(\gamma)}{M}$ (lucky)	0.01	0.03	0.04	0.06	0.06	0.04	0.03	0.01	(unlucky) $\frac{\hat{F}^-(\gamma)}{M}$
$SD_{\frac{\hat{F}^+(\gamma)}{M}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	$SD_{\frac{\hat{F}^-(\gamma)}{M}}$
$\frac{\hat{T}^+(\gamma)}{M}$ (skilled)	0.06	0.07	0.07	0.08	0.13	0.12	0.12	0.10	(unskilled) $\frac{\hat{T}^-(\gamma)}{M}$
$SD_{\frac{\hat{T}^+(\gamma)}{M}}$	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	$SD_{\frac{\hat{T}^-(\gamma)}{M}}$

Table 11: Performance Persistence (Parametric p-values)

Panel A: Performance persistence with FDR^+_τ = 10%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	0.0044	0.0033	1.30	0.1976
MKT	0.7449	0.0688	10.83	0.0000
SMB	0.2635	0.0974	2.70	0.0091
HML	-0.0842	0.0856	-0.98	0.3300
WML	0.0589	0.0666	0.88	0.3809

Panel B: Performance persistence with FDR^+_τ = 20%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	0.0024	0.0017	1.42	0.1610
MKT	0.6060	0.0353	17.16	0.0000
SMB	0.1608	0.0500	3.21	0.0022
HML	-0.0374	0.0440	-0.85	0.3986
WML	0.0563	0.0342	1.64	0.1059

Panel C: Performance persistence with FDR^+_τ = 40%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	0.0030	0.0018	1.70	0.0935
MKT	0.7790	0.0307	25.37	0.0000
SMB	0.3086	0.0466	6.62	0.0000
HML	-0.1417	0.0457	-3.10	0.0027
WML	0.2020	0.0342	5.90	0.0000

Panel D: Performance persistence with FDR^-_τ = 10%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	-0.0070	0.0027	-2.58	0.0117
MKT	0.9991	0.0474	21.09	0.0000
SMB	-0.0268	0.0718	-0.37	0.7104
HML	-0.0303	0.0705	-0.43	0.6682
WML	-0.0638	0.0528	-1.21	0.2306

Panel E: Performance persistence with FDR^-_τ = 20%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	-0.0066	0.0023	-2.82	0.0060
MKT	0.9974	0.0410	24.33	0.0000
SMB	-0.0013	0.0622	-0.02	0.9834
HML	-0.0398	0.0610	-0.65	0.5164
WML	-0.0378	0.0457	-0.83	0.4113

Panel F: Performance persistence with FDR^-_τ = 40%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	-0.0032	0.0011	-2.99	0.0037
MKT	0.9771	0.0190	51.37	0.0000
SMB	0.0706	0.0289	2.45	0.0167
HML	0.0158	0.0283	0.56	0.5788
WML	0.0406	0.0212	1.91	0.0592

Contrary to the persistence analysis using bootstrapped p-values, I now find that the exposure of the negative alpha portfolios to the momentum factor increases significantly with the FDR target. For 10% and 20% targets, the WML beta for the positive alpha portfolio is negative and not significant, while for the 40% target it becomes positive and significant at a 10% level. Also, in the case of the positive alpha portfolios, only a 40% target yields a significant (and negative) HML coefficient, while for negative alphas the HML coefficients are consistently insignificant (consistent with the analysis using bootstrapped p-values).

All in all, the results in this section support the previous evidence in the following points: (i) proportionally less bank-affiliated funds are found to achieve positive alphas; (ii) the FDR is larger for bank-affiliated funds; (iii) the FDR is larger for positive alphas and (iv) negative performance persists. They challenge our previous findings because: (i) they result in higher positive alpha estimates; (ii) they result in overall much lower FDR for all samples and any alpha sign; (iii) positive alphas are now found to only weakly persist.

4.2 Persistence With Different Sub-Samples

As mentioned before, the motivation of Barras et al. (2010) to perform tests of persistence lies in the findings that positive alphas are in the extreme right tail of the cross-sectional distribution.

However, the FDR analyses with bootstrapped p-values suggest that such is not the case for positive or negative alphas. I have also found that bank affiliated (sub-sample 1) presents alpha spread over both tails while bank unaffiliated (sub-sample 2) shows positive alphas in the extreme right tail. Motivated by this, I performed tests of performance persistence for each sub-sample separately. I expect that the results are robust for positive alphas independently of the sample.

Table 12 repeats the persistence tests for bank-affiliated funds, and Table 13, for bank-unaffiliated ones. As before, panels A through C represent the results for FDR_{τ}^{+} = 10%, 20% and 40%, respectively, and panels D through F, for FDR_{τ}^{-} = 10%, 20% and 40%.

The tests strongly support the idea that there is persistence in positive and negative performance of funds in sub-sample 2, but not so much in sub-sample 1. While the portfolios formed with bank-affiliated funds generate alphas with the same sign achieved in-sample, only that for $FDR_{\tau}^{+} = 10\%$ is significant at a 10% level. Funds in sub-sample 2, on the other hand, generate significant ex-post performance for all FDR_{τ}^{+} and FDR_{τ}^{-} levels, except for $FDR_{\tau}^{-} = 40\%$. Moreover, in absolute value, the ex-post performance decreases with the FDR target level, which might be due to the greater proportion of zero-alpha funds allowed in the portfolio.

An interesting thing to note regards the portfolio exposures to the HML factor. When analyzing the entire sample, I found that positive (negative) alpha portfolios had significant (insignificant) and negative HML, and constant and significant WML coefficients. Now, I note that the HML coefficients for sub-sample 1 (sub-sample 2) and negative alphas are positive (negative) and significant (insignificant).

Table 12: Performance Persistence (Bootstrapped p-values, sub-sample 1)

Panel A: Performance persistence with FDR^{+}_{τ} = 10%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	0.0029	0.0015	1.91	0.0600
MKT	0.8651	0.0263	32.87	0.0000
SMB	0.3218	0.0399	8.06	0.0000
HML	-0.1224	0.0392	-3.12	0.0025
WML	0.1764	0.0293	6.01	0.0000

Panel B: Performance persistence with FDR^{+}_{τ} = 20%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	0.0016	0.0015	1.04	0.3009
MKT	0.7746	0.0268	28.86	0.0000
SMB	0.3041	0.0407	7.47	0.0000
HML	-0.1438	0.0399	-3.60	0.0006
WML	0.1690	0.0299	5.65	0.0000

Panel C: Performance persistence with FDR^{+}_{τ} = 40%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	0.0009	0.0014	0.61	0.5416
MKT	0.7966	0.0249	31.94	0.0000
SMB	0.3021	0.0378	7.99	0.0000
HML	-0.1515	0.0371	-4.08	0.0001
WML	0.1629	0.0278	5.86	0.0000

Panel D: Performance persistence with FDR^{-}_{τ} = 10%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	-0.0015	0.0012	-1.34	0.1830
MKT	1.0163	0.0202	50.24	0.0000
SMB	0.0251	0.0307	0.82	0.4159
HML	0.0662	0.0301	2.20	0.0308
WML	0.0014	0.0226	0.06	0.9502

Panel E: Performance persistence with FDR^{-}_{τ} = 20%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	-0.0010	0.0013	-0.74	0.4635
MKT	1.0032	0.0229	43.77	0.0000
SMB	0.0249	0.0348	0.72	0.4761
HML	0.0814	0.0341	2.39	0.0194
WML	-0.0215	0.0256	-0.84	0.4035

Panel F: Performance persistence with FDR^{-}_{τ} = 40%

	Estimate	Sd. Error	t-stat	p-value
(Intercept)	-0.0010	0.0012	-0.85	0.3993
MKT	0.9922	0.0206	48.14	0.0000
SMB	0.0393	0.0313	1.26	0.2126
HML	0.0782	0.0307	2.55	0.0128
WML	-0.0091	0.0230	-0.40	0.6937

Table 13: Performance Persistence (Bootstrapped p-values, sub-sample 2)

Panel A: Performance persistence with FDR^{+}_{τ} = 10%

	Estimate	Sd. Error	t-state	p-value
(Intercept)	0.0065	0.0021	3.03	0.0033
MKT	0.7366	0.0376	19.60	0.0000
SMB	0.3736	0.0570	6.56	0.0000
HML	-0.1060	0.0559	-1.90	0.0617
WML	0.1575	0.0419	3.76	0.0003

Panel B: Performance persistence with FDR^{+}_{τ} = 20%

	Estimate	Sd. Error	t-state	p-value
(Intercept)	0.0057	0.0020	2.89	0.0049
MKT	0.7613	0.0345	22.07	0.0000
SMB	0.3524	0.0523	6.74	0.0000
HML	-0.1070	0.0513	-2.08	0.0403
WML	0.1525	0.0384	3.97	0.0002

Panel C: Performance persistence with FDR^{+}_{τ} = 40%

	Estimate	Sd. Error	t-state	p-value
(Intercept)	0.0045	0.0019	2.36	0.0207
MKT	0.7726	0.0336	23.01	0.0000
SMB	0.3479	0.0509	6.83	0.0000
HML	-0.0991	0.0500	-1.98	0.0509
WML	0.1584	0.0374	4.23	0.0001

Panel D: Performance persistence with FDR^{-}_{τ} = 10%

	Estimate	Sd. Error	t-state	p-value
(Intercept)	-0.0047	0.0013	-3.68	0.0004
MKT	0.9325	0.0224	41.58	0.0000
SMB	0.1396	0.0340	4.10	0.0001
HML	-0.0189	0.0334	-0.57	0.5733
WML	0.0226	0.0250	0.90	0.3687

Panel E: Performance persistence with FDR^{-}_{τ} = 20%

	Estimate	Sd. Error	t-state	p-value
(Intercept)	-0.0027	0.0016	-1.76	0.0826
MKT	0.9184	0.0273	33.61	0.0000
SMB	0.2042	0.0415	4.93	0.0000
HML	-0.0536	0.0407	-1.32	0.1918
WML	0.0265	0.0305	0.87	0.3870

Panel F: Performance persistence with FDR^{-}_{τ} = 40%

	Estimate	Sd. Error	t-state	p-value
(Intercept)	-0.0023	0.0016	-1.50	0.1376
MKT	0.9084	0.0273	33.31	0.0000
SMB	0.2137	0.0414	5.17	0.0000
HML	-0.0415	0.0406	-1.02	0.3101
WML	0.0272	0.0304	0.89	0.3742

These robustness tests support the idea that while there are skilled (unskilled) managers able to repeat positive (negative) performance, they do not represent all the discoveries even controlling for luck. Otherwise, one would expect greater evidence of persistence for bank-affiliated funds.

For the investor, this section suggests that bank-affiliated fund managers achieve positive alphas less frequently and the ex-ante performance is weakly indicative of the ex-post performance. Along with the FDR results (bootstrapped p-values), this suggests that holding bank-unaffiliated funds with positive alphas that are significant at a threshold close to 10% could result in ex-post profits, as long as the results generalize in time.

5 Conclusions

In order to assess the existence of skilled mutual fund managers, the finance literature has turned to econometric methods that are able to capture the effect of luck in multiple hypothesis testing. While most of the studies in this field focus on developed economies such methods have not been thoroughly explored in emerging markets.

Therefore, I apply the False Discovery Rate methodology proposed by Barras et al. (2010) to the Brazilian equity fund market. The goal is to shed some light on (i) the proportions of positive, negative and zero alpha funds in the Brazilian equity fund market; (ii) the location of positive and negative alphas in the cross-sectional distribution and (iii) the impact of luck in the right and left tails of the distribution. Additionally, I determine whether positive and negative alphas persist. I do this for our entire equity fund sample and extend it to sub-samples of bank and bank-unaffiliated funds.

Regarding the proportions, I infer that the majority of funds achieve either zero or negative performance during the sample period (between 83.65% and 88.06% depending on the sub-sample). I also find that less (more) bank-affiliated funds have achieved positive (negative) performance. Overall, these results are consistent with the Berk and Green (2004) hypotheses in that few funds are able to generate alphas, although I find that these proportions are larger than previous studies have found.

With respect to the location of alphas, I find that dividing the funds into two sub-samples according to bank affiliation uncovers an interesting aspect of the asset management industry: while bank-affiliated funds seem to generate positive and negative alphas that are concentrated in the tails of the cross-sectional distribution, bank-unaffiliated ones only exhibit this for positive alphas. The practical importance of this finding is that, by choosing a small enough significance level, investors could have been able to avoid bad bank-affiliated funds. This is not evident when ignoring the sub-samples.

Where it concerns the impact of luck, I also find that false discoveries are a more serious issue for bank-affiliated funds, although the difference is smaller when using bootstrapped *p*-values than parametric *p*-values. In the latter case, as much as 28% (12%) of positive (negative) rejections at a 5% significance levels are estimated to be false discoveries. Using parametric *p*-values also results in smaller estimated proportions of positive alphas, although the conclusions regarding the sub-samples remains the same.

Lastly, in tests of performance persistence I find an interesting pattern across the sub-samples. For all equity funds, I document that both positive and negative alphas persist out-of-sample, which could lead to the conclusion that there are both skilled and unskilled managers spread across the sub-samples. However, I also document that bank-unaffiliated funds show strong evidence of persistence, whereas their bank-affiliated counterparts show only weak evidence. Therefore, this paper was intended to shed some light on whether positive and negative alphas can result from skill or from some other non skill-related factor, depending on the ownership status of the fund administrator.

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