FALSE DISCOVERIES AND LUCK IN THE BRAZILIAN EQUITY FUND MARKET

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Abstract

In this study the performance of equity funds in Brazil between January 2001 and January 2021 is assessed. The False Discovery Rate methodology is applied to the entire sample, as well as to sub-samples differentiating bank-affiliated funds from those unaffiliated. The results suggest that some managers are able to generate positive alphas after controlling 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 across the sub-samples, with important academic and practical implications. Lastly, there is evidence that positive and negative performance persist, and that bank-unaffiliated funds are responsible for such phenomenon.

Key Words: (False Discovery Rate, Persistence, Investment Funds)

1. Introduction

Researchers in finance, economics and engineering economics have been historically interested in studying the performance of mutual funds and in answering whether managers actively seeking risk-adjusted returns are able to "beat the market". Since the introduction of Jensen's Alpha by Jensen (1968), academics have studied performance by regressing excess returns on portfolios that mimic risk factors and by counting the number of significant and positive intercepts (alphas) (COCHRANE, 2009).

Studies applying similar methodologies include Carhart (1997), Pástor and Stambaugh (2002) and Wermers (2000), with results generally pointing towards the presence of few positive alphas (positive performance) and many negative ones. These results were subsequently reconciled to economic theory, among others, by Berk and Green (2004), who predict that, in rational markets, positive performance tends to disappear due to fund inflows and decreasing returns to scale.

Carhart (1997) proposes a method to add robustness to the results following the previous methodology and does so through the analysis of performance persistence. The author observes whether funds with higher alphas (t-statistics) obtain, on average, higher out-of-sample alphas (t-statistics). The author forms portfolios with funds in increasing alpha (t-statistic) deciles and observes the portfolio returns in subsequent periods. Skill is observed when funds with higher performance measures are those generating portfolios with higher performance measures out-of-sample.

Although intuitive, this approach is not free of flaws. Kosowski *et al* (2006) show that many statistical features of fund returns and residuals can lead to non-normal alpha distributions, which makes parametric hypothesis testing inappropriate. They propose a non-parametric method to calculate alpha p-values through bootstrapping. They find not only that there are positive alphas, but also that positive performance persists. Similar studies include Cuthbertson, Nitzsche and O'Sullivan (2008), in the UK, Yang and Liu (2017) , in China, and Laes (2010), in Brazil, with mixed conclusions regarding managerial ability.

A similar methodology is proposed by Fama and French (2010), but in which the bootstrap is performed jointly, resulting in the rejection of existing positive alpha funds and, therefore, in accordance to Berk and Green (2004). Applying this to the Brazilian market, Matos, Silva and Silva (2015), Borges and Martelanc (2015) and Laes and da Silva (2014) find similar results, with more negative alphas, and suggestive of size-varying performance.

Such simulation-based methodologies define luck as finding positive alphas due to an inappropriate theoretical alpha distribution, and a different treatment is given by Barras, Scaillet and Wermers (2010). The authors present an extension of the False Discovery Rate (FDR) by Storey (2002), defining luck as the ratio between false rejections and the total number of rejections, but do so while differentiating between positive and negative alphas. Applying the FDR to both cross-sectional alpha tails, they also propose a false discovery robust persistence test which, contrary to Carhart (1997), does account for the probability that portfolios of funds in different alpha deciles are composed by different proportions of positive, negative and zero-alpha funds. The authors find a smaller (greater) proportion of positive (negative) alphas and that positive alphas persist.

The FDR is also applied to investment fund performance by Cuthbertson, Nitzsche and O'Sullivan (2012), in the UK, Cuthbertson and Nitzsche (2013), in Germany and Kim *et al* (2014), in Australia. Augustin, Brenner and Subrahmanyam (2019) apply the method in the context of informed trading and Bajgrowicz and Scaillet (2012), in that of technical trading. Harvey and Liu (2020) present an improvement based on double-bootstrap and Giglio, Liao and Xiu (2020), via machine learning.

A critique of the FDR is made by Andrikogiannopoulou and Papakonstantinou (2019), who suggest that some characteristics of the data may lead the FDR to misestimate the proportions of zero, positive and negative alpha funds. As a reply, Barras, Scaillet and Wermers (2019) replicate the simulation while using arguably more appropriate parameters (for example, they use median instead of mean volatility). They find that the FDR performs well, but indicate that, in some situations, the parameter lambda should be estimated in a more conservative manner (above 0.95).

In this study, the FDR is applied to equity funds in Brazil. Motivated by the evidence that funds with administrators affiliated to commercial banks have lower performance, the study also investigates this dimension of the data. Using net monthly returns between January 2001 and January 2021, this study answers the questions: (i) are there skilled (unskilled) managers in Brazil generating positive (negative) alphas? (ii) Do positive (negative) alphas persist? (iii) During the sample period, have funds affiliated to commercial banks performed worse? And (iv) how are positive and negative alphas in the sample (each sub-sample) cross-sectionally distributed? (FRANZONI; GIANNETTI, 2019; HOFFMANN JÚNIOR, 2018)

The results support the theory by Berk and Green (2004), suggesting that most funds have achieved either zero or worse performance, but with a minority of positive alphas. Also, only positive alphas of funds affiliated to commercial banks seem to be concentrated in the extreme right tail of the cross-sectional distribution, and the impact of luck is greater in this sub-sample. Lastly, the results suggest that, for the entire sample, positive and negative alphas persist, indicating that there are truly skilled and unskilled managers. However, unaffiliated funds seem to be responsible for this result.

This study contributes to the engineering economics and finance literature in three ways. First, the FDR is extended to one of the largest emerging markets and strengthens the argument in favor of the existence of a few skilled managers in Brazil. In addition to that, the results suggest that researchers analyzing fund performance should take other individual fund characteristics into account, such as administrator affiliation. Finally, the study gathers evidence in favor of the inferior performance of bank-affiliated funds, now controlling for false discoveries.

The study proceeds as follows. In Section 2, the asset pricing models are presented. Section 3 describes and methodology. Section 4 presents the results and a discussion of their implications and Section 5 concludes.

2. Asset pricing models

Having considered the literature, two asset pricing specifications have been used in the study, the Fama and French (1993) and the Carhart (1997) models. The regressions (Ordinary Least Squares) are,

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

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

The β terms measure the quantity of risk; the SMB_t, HML_t and WML_t are excess returns of portfolios that mimic the size, book-to-market and momentum factors (COCHRANE, 2009) and $R^e_{m,t}$ is the excess return of the market portfolio relative to the risk-free asset. These four terms represent the prices of risk. Lastly, α_i is the regression intercept and the standard measure of performance.

For each sub-sample, fund and model, the following regression results are stored: (i) the $Mx1$ vectors of intercepts and t-statistics; (ii) the $Mx1$ vector of alpha p-values; (iii) the MxF matrices of slope coefficients and corresponding t-statistics (where F is the number of factors, depending on the model) and (iv) the T_i vector of fund i residuals.

3. Methodology

As detailed by Kosowski *et al* (2006), using a theoretical distribution for alphas in order to obtain p-values may be inappropriate and the authors propose a method to deal with this. For each fund, the monthly return is subtracted from the estimated alpha, resulting in pseudo-returns with zero alphas by construction; then, to each pseudo-return vector, a sample with replacement of the residual series is added, in such a way that the pseudo-returns will still have zero alphas on average, but are subject to luck; then, these pseudo-returns are regressed on the factors, and the vector of bootstrapped t-statistics is stored. This procedure gives one line of a BxM matrix, where B is the number of bootstrap iterations (e.g. 1000) and M is the number of funds in the sample. Doing this B times completes the matrix.

The BxM matrix is used to obtain a new $Mx1$ vector of bootstrapped p-values, p_i^b. Note that each fund's t-statistic, t_i^*, may be now compared to simulated versions of itself while imposing the null hypothesis of zero performance. As Barras, Scaillet and Wermers (2010), the formula presented in Davidson and MacKinnon (2004) is used,

$$p_i^b = 2\min\left[\frac{1}{B}\sum_{b=1}^{B} I_{(t_t^b > t_i^*)}, \frac{1}{B}\sum_{b=1}^{B} I_{(t_t^b < t_i^*)}\right] \quad 3$$

Where $I_{(t_t^b > t_i^*)}$ is an indicator function equal to 1 if t_i^* is smaller than each of its bootstrapped versions. The vector of bootstrapped p-values is stored. In the empirical analysis, the simulated p-values are used.

3.2. False discovery rate

The False Discovery Rate proposed by Barras, Scaillet and Wermers (2010) is a method used in multiple hypothesis testing in order to control the inference for type I errors. It is defined as the ratio of the expected number of false discoveries, $E[F(\gamma)]$, to the number of observations, $R(\gamma)$, with p-values below the significance level, γ. The model is extended to positive and negative discoveries through,

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

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

Because positive and negative rejections, $R^+(\gamma)$ and $R^-(\gamma)$, in each significance level, are known, the variables to be estimated are $F^+(\gamma)$ and $F^-(\gamma)$. Barras, Scaillet and Wermers (2010) suggest the estimators $E[F^+(\gamma)] = E[F^-(\gamma)] = \frac{1}{2}E[\pi_0]\gamma M$, where $E[\pi_0]$ is the estimated number of zero-alpha funds. In order to obtain this value, the authors use the fact that, under the zero-performance hypothesis, the p-values follow a uniform distribution between 0 and 1. Now,

$$E[\pi_0(\lambda)] = \frac{W(\lambda)}{(1-\lambda)M} \quad 6$$

Where $W(\lambda)$ is the number of p-values greater than a given threshold λ. The estimation consists of choosing a value, λ^* that minimizes a mean-squared error (MSE). First, simulated versions of $E[\pi_0]$, $E[\pi_0^b]$, are formed by choosing with replacement from the p-value vector. Then, λ^* is chosen to minimize:

$$E[MSE(\lambda)] = \frac{1}{1000}\sum_{b=1}^{1000}\{\mathrm{E}[\pi_0^b(\lambda) - \min E[\pi_0(\lambda)]]\}^2 \quad 7$$

With λ^*, $E[\pi_0(\lambda^*)]$ is obtained through Equation 6, as well as $E[FDR^+(\gamma)]$, $E[FDR^-(\gamma)]$, $E[F^+(\gamma)]$ and $E[F^-(\gamma)]$ or a range of values of γ. In addition to that, since $R^+(\gamma) = E[F^+(\gamma)] + E[T^+(\gamma)]$ and $R^-(\gamma) = E[F^-(\gamma)] + E[T^-(\gamma)]$, the estimated numbers of truly positive and negative discoveries, are also obtained.

The final step of the FDR consists of obtaining estimated values for the proportions of funds with positive and negative performances, $E[\pi_A^+]$ and $E[\pi_A^-]$. In order to do that, the MSE is used,

$$E[MSE^+(\gamma)] = \frac{1}{1000}\sum_{b=1}^{1000}\{\mathrm{E}[\pi_0^{b+}(\gamma) - min\mathrm{E}[\pi_A^+(\gamma)]\,]\}^2 \quad 8$$

Where $min\mathrm{E}[\pi_A^+(\gamma)]$ is the smallest value of $\mathrm{E}[\pi_A^+(\gamma)]$. The same is done for negative alphas and γ^* to minimize the minimum between $E[MSE^+(\gamma)]$ and $E[MSE^-(\gamma)]$. If $E[MSE^+(\gamma)] < E[MSE^-(\gamma)]$, then $E[\pi_A^+] = E[\pi_A^+(\gamma^*)]$ and $E[\pi_A^-] = (1 - E[\pi_0])$ - $E[\pi_A^+]$. The reciprocal is done if $E[MSE^+(\gamma)] > E[MSE^-(\gamma)]$.

3.3. Performance persistence

Barras, Scaillet and Wermers (2010) note that, when $E[FDR^+(\gamma)]$ and $E[FDR^-(\gamma)]$ are obtained for many values of γ, it is possible to implement a test of performance persistent that is robust to false discoveries. The test consists of choosing FDR targets, $FDR_\tau^+ = FDR_\tau^-$, and to choose funds with p-values below $\gamma_{FDR_\tau^+}$ or $\gamma_{FDR_\tau^-}$ to form equal-weighted portfolios.

The necessary estimates are obtained using 5 years of monthly returns and the portfolios are formed at the end of each year. The portfolio is held for one year, during which the weights of extinct funds are reallocated to the remaining ones. The time-series of all years are gathered and taken as the time-series of the portfolio for each level of FDR_τ^+ or FDR_τ^-.

Lastly, the monthly returns of the portfolios with positive and negative alphas for each FDR target are regressed on the factors. Persistence is observed when funds formed with positive (negative) alphas and low levels of FDR_τ^+ (of FDR_τ^-) obtain higher (lower) alphas. Because the literature is more concerned with managerial skill, rather than lack of skill, the results for positive alphas are more relevant. Nonetheless, results for positive and negative alphas are presented, in such a way that both skill and lack of skill are analyzed.

4. Results

First, the database is described. Then, the results of the asset pricing applications are presented. Lastly, the FDR and persistence results are shown and the empirical evidence is discussed.

4.1. Data

Data on funds and factors are obtained through the Economatica and Nefin (Brazilian Center for Research in Financial Economics) databases, respectively. Exclusive, closed and quote funds are excluded. The initial sample consists of 3,058 funds.

The period is from January 2001 until January 2021. After the initial filtering, for each fund the data on administrator and asset class, according to the Brazilian Association for Financial and Capital Market Entities are obtained. Also, the monthly Net Asset Value series are obtained in order to construct the return series. Funds with fewer than 36 consecutive returns are discarded, resulting in 1,463 funds.

Two sub-samples are constructed. Sub-sample 1 (SS1) consists of funds whose administrators are affiliated to banks, and sub-sample 2 (SS2), of those who are not. The definition of affiliation is that used by Fantinatti (2008), considering only the 5 largest commercial Banks in Brazil. SS1 and SS2 contain 599 and 864 funds, respectively.

4.2. Asset pricing models

The results for the asset pricing models applied to the sample and sub-samples are shown. Table 1 presents the mean (across funds) values of the alpha, beta, residual skewness and kurtosis, as well as adjusted R-squared. Panels A-C correspond to the complete sample and to SS1 and SS2, respectively.

As in Cuthbertson, Nitzsche and O'Sullivan (2012), the Bayesian Information Criterion (BIC) is used, which, for the entire sample, is smaller for the C4FM, which is chosen.

Although the numbers of positive and negative alphas seem close, this changes when only significant values are considered. Significantly positive alphas vary between 05.68% for SS1 and 06.94% for SS2. Significantly negative alphas, in their turn, vary between 11.81% for SS1 and 14.70% for SS2.

Table 1 - Asset pricing model result

Panel A: All equity 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	
Adjusted R-squared	0.7336		0.7332	
# positive alphas	678		716	
# negative alphas	785		747	
Panel B: 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	
Adjusted R-squared	0.7924		0.7792	
# positive alphas	270		294	
# negative alphas	329		305	
Panel C: 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	2.0605		2.0346	
Adjusted R-squared	0.6929		0.6997	
# positive alphas	408		422	
# negative alphas	456		442	

Source: Estimates by the authors

The results suggest that positive alphas are rare compared to negative ones in all samples. However, as discussed before, this is without taking false discoveries into account, which is addressed as follows.

4.3. False discovery rate

The FDR results are shown on Table 2. Panels A-C show the results for the entire sample, SS1 and SS2, respectively. The application suggests that 14.68% (40.94%) of the funds achieved positive (negative) alphas. Although these results are higher than in Barras, Scaillet and Wermers (2010), Cuthbertson, Nitzsche and O'Sullivan (2012) and Cuthbertson and Nitzsche (2013), the conclusion is the same: as predicted by Berk and Green (2004), most of the managers are unable to generate net profit.

Table 2 - FDR results and proportions

Panel A: All equity funds									
$E[\pi_A^+]$ = 14.68%				$E[\pi_0]$= 44.38%			$E[\pi_A^-]$= 40.94%		
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$E[R^+(\gamma)]/M$	0.12	0.16	0.18	0.20	0.26	0.24	0.22	0.18	$E[R^-(\gamma)]/M$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
$E[FDR^+(\gamma)]$	0.09	0.14	0.18	0.22	0.17	0.14	0.10	0.06	$E[FDR^-(\gamma)]$
$E[F^+(\gamma)]/M$	0.01	0.02	0.03	0.04	0.04	0.03	0.02	0.01	$E[F^-(\gamma)]/M$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
$E[T^+(\gamma)]/M$	0.11	0.14	0.15	0.16	0.22	0.21	0.19	0.17	$E[T^-(\gamma)]/M$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
Panel B: Affiliated equity funds									
$E[\pi_A^+]$ + = 12.17%				$E[\pi_0]$= 46.48%			$E[\pi_A^-]$ = 41.35%		
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$E[R^+(\gamma)]/M$	0.11	0.14	0.16	0.17	0.27	0.26	0.23	0.20	$E[R^-(\gamma)]/M$
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
$E[FDR^+(\gamma)]$	0.10	0.17	0.22	0.27	0.17	0.14	0.10	0.06	$E[FDR^-(\gamma)]$
$E[F^+(\gamma)]/M$	0.01	0.02	0.03	0.05	0.05	0.03	0.02	0.01	$E[F^-(\gamma)]/M$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
$E[T^+(\gamma)]/M$	0.10	0.11	0.12	0.12	0.22	0.22	0.21	0.19	$E[T^-(\gamma)]/M$
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Panel C: FDR Unaffiliated equity funds									
$E[\pi_A^+]$ + = 16.50%				$E[\pi_0]$= 42.07%			$E[\pi_A^-]$ = 41.43%		
γ	0.05	0.1	0.15	0.2	0.2	0.15	0.1	0.05	
$E[R^+(\gamma)]/M$	0.13	0.17	0.20	0.02	0.26	0.23	0.20	0.17	$E[R^-(\gamma)]/M$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
$E[FDR^+(\gamma)]$	0.08	0.12	0.16	0.19	0.16	0.14	0.10	0.06	$E[FDR^-(\gamma)]$
$E[F^+(\gamma)]/M$	0.01	0.02	0.03	0.04	0.04	0.03	0.02	0.01	$E[F^-(\gamma)]/M$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
$E[T^+(\gamma)]/M$	0.12	0.15	0.17	0.17	0.22	0.20	0.18	0.16	$E[T^-(\gamma)]/M$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	

Source: Estimates by the authors

The FDR values suggest that the proportion of false discoveries in the right tail of the cross-sectional distribution is approximately twice that in the left tail, and that they are smaller than those found by Barras, Scaillet and Wermers (2010), Cuthbertson, Nitzsche and O'Sullivan (2010), Cuthbertson and Nitzsche (2013) and Kim *et al* (2014). However, the difference is significant.

Table 2 also reveals the location of the alphas. For the entire sample, because the estimated proportion of true discoveries (line 6) raises with γ, positive (negative) alphas are spread in the right (left) tails. However, the results for SS1 and SS2 show that positive alphas are concentrated in the extreme right tail, whereas only negative alphas of bank-affiliated funds are concentrated in the extreme right tail. In practice, managers could form portfolios of funds with positive performance by choosing low significance levels but could only avoid those with bad performance in the case of affiliated funds.

4.3. Performance persistence

Having noted the FDR results and their implications, the investigation now turns to the performance persistence tests. Table 3 shows the results obtained by regressing equal-weighted portfolio returns on risk factors using positive (panels A-C) and negative (panels D-F) alphas while allowing increasing levels of false discoveries.

The results show that the performance of positive and negative alphas persist. The out-of-sample performance of all portfolios using positive alphas are significant, but the alpha decreases with FDR_{τ}^{+}. Using negative alphas, only the portfolio formed with $FDR_{\tau}^{-} = 10\%$ is significant, while the others are negative, but with smaller in absolute value and significant at increasing levels.

Table 3 - Performance persistence

Panel A: Performance persistence with FDR_{τ}^{+}= 10%				
	Estimate	Standard error	t-statistic	p-value
Alpha	0.0045	0.0016	2.8100	0.0063
MKT	0.7825	0.0281	27.8200	0.0000
SMB	0.3158	0.0427	7.4000	0.0000
HML	-0.1243	0.0419	-2.9700	0.0040
WML	0.1607	0.0314	5.1200	0.0000
Panel B: Performance persistence with FDR_{τ}^{+}= 20%				
	Estimate	Standard error	t-statistic	p-value
Alpha	0.0041	0.0017	2.4300	0.0173

	Estimate	Standard error	t-statistic	p-value
MKT	0.7703	0.0298	25.8700	0.0000
SMB	0.3358	0.0452	7.4400	0.0000
HML	-0.1208	0.0443	-2.7300	0.0079
WML	0.1557	0.0332	4.6900	0.0000
Panel C: Performance persistence with FDR_{τ}^{+} = 40%				
	Estimate	Standard error	t-statistic	p-value
Alpha	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_{τ}^{-} = 10%				
	Estimate	Standard error	t-statistic	p-value
Alpha	-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_{τ}^{-} = 20%				
	Estimate	Standard error	t-statistic	p-value
Alpha	-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_{τ}^{-} = 40%				
	Estimate	Standard error	t-statistic	p-value
Alpha	-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

Source: Estimates by the authors

Overall, the results suggest that investors may select (avoid) the best (worst) funds by looking at past performance. The conclusions of this study are stronger than those found by Cuthbertson, Nitzsche and O'Sullivan (2012) and contrast with the traditional literature.

5. Conclusion

In this study the FDR methodology by Barras, Scaillet and Wermers (2010) was applied to equity funds in Brazil. A sample of 1463 funds was used, as well as sub-samples containing 599 (864) funds whose administrators are (aren't) affiliated to the largest commercial banks in the country.

The FDR results suggest that: (i) less affiliated funds have achieved positive performance; (ii) false discoveries are more common in the case of bank-affiliated funds and in the right tail of the cross-sectional alpha distribution; (iii) positive alphas are concentrated in the extreme right tail, but only those of affiliated funds.

By performing a robust performance persistence test, this study suggests that positive and negative performance persist. This conclusion is stronger for positive alphas and indicates that investors may be able to avoid (seek) the worst (best) funds.

Lastly, the results suggest that a minority of fund managers in Brazil have shown skill during the sample period and that this proportion is high when compared to that observed in studies applied to other countries.

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