CONDITIONAL VOLATILITY IN THE BRAZILIAN MUTUAL FUNDS

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ABSTRACT

This study intends to investigate the (dynamic) behavior of mutual fund managers regarding the variability of the conditional market volatility (analyzed with the support of EGARCH models) in the Brazilian market. The results seem to reveal that managers are able to implement strategies that allow them to respond efficiently to increases of market volatility, by adjusting their exposure to systematic risk.

Keywords: *timing*; conditional volatility; performance; EGARCH, mutual funds.
JEL: G10; G12; G15.

1. Introduction

The investment process involves a vast number of variables and uncertainty, turning it into an extremely complex task, in special, when the portfolio management is considered.

Since the seminal papers of Sharpe (1966) and Jensen (1968), which seek to condense in one single measure the global contribution of active management to the portfolio, many authors have tried to decompose the global performance in specific skills. The ability to anticipate the macromovements of the market, market timing, can contribute to add value to actively managed portfolios.

Traditionally the time concept focus on the market returns; however, the recent development of techniques of volatility modeling brings a new perspective up, once volatility is one of most important concept of modern financial theory, which has been taken as time constant, termed unconditional. In such a manner, the historical volatility, computed as standard deviation of one period, keeps the same in the next period. Nevertheless, the stylized characteristics for the empirical probability distributions for financial asset returns, such as excess kurtosis and clusters, indicate that the volatility is time conditional and nonlinear related to returns.

This study evaluates the ability of fund managers to anticipate the market volatility, the so-called volatility timing. It can be justified, first, because there are still few studies about the extend to which profession management is able to add value to the portfolio in the Brazilian market context and, second, because of the new horizons of this new approach applied in a reality in which predicting the beginning large oscillations moments is a important factor for risk management.

2. Literature Review

The first to analyze empirically the market timing ability of funds managers were Treynor and Mazuy (1966). According to them, funds managers tend, or try, to anticipate the market conditions variations. In consequence of this activity, the characteristic line, which represents the relationship between the excess return on portfolio and the excess market return, is curved. Its inclination changes constantly, indicating that managers answer constantly to the market conditions changes, as described the following equation[1]:

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \gamma_p R_{mt}^2 + \varepsilon_{pt} \quad (1)$$

[1] Some authors qualify this regression as quadratic; however, according to Gujarati (2000), a regression is linear if its parameters are linear, independently of the variables, and that's the case. So in this text, the adjective quadratic is avoided to the Traynor and Mazuy regression.

where R_{pt} is the excess portfolio return on period t, R_{mt} is the excess market return on period t, a_p is the selectivity measure, b_p is the coefficient estimated for a manager without timing, y_p is the timing measure, and e_{pt} is the regression, supposed to be independent, identically distributed (iid). If $\psi_p > 0$, it can be inferred that the portfolio exposition increases as the market risk premium increases. That is what is expected of a manager with timing ability. After examining 57 mutual funds, from 1953 to 1962, the authors concluded that there is no timing evidence, once only one fund showed some timing ability.

Fama (1972) is the first to propose formally a methodology to decompose the observed portfolio return into selectivity and timing; even though, it is hard to implement empirically. Jensen (1972) departs from the correlation between the market expected return and realized return to get a measure of timing. Since expected returns are usually not known, Jensen concludes that is not possible to decompose the global performance. Arguments that would come to be contested by Grant (1977; 1978); by Pfleiderer and Bhattacharya (1983); by Admati and Ross (1985); and by Dybvig and Ross (1985), who demonstrate that the measure of performance could result in inferior performance if the timing activities were ignored.

Merton (1981) defines timing simply as the ability to anticipate if the market return will be greater or smaller than the risk-free return, so that the portfolio return can be taken as the sum of the standard one factor model plus put options on market portfolio with strike price set to risk-free rate. Based on this report, Henriksson and Merton (1981) developed statistical procedures that allow detecting timing activities effects, as shows the following equation:

$$R_{p,t} = \boldsymbol{a}_p + \boldsymbol{b}_p R_{mt} + \boldsymbol{f}_p Max(R_{pt}) + \boldsymbol{e}_{pt} \qquad (2)$$

where $f_p > 0$ means market timing ability and remaining variables as last definition . This measure presumes managers select different levels of systematic risk according to their expectations, increasing the portfolio risk exposition when predicting $R_{mt} > 0$ and decreasing it when predicting $R_{mt} \leq 0$.

Most studies find little evidence that fund managers possess market timing ability. Henriksson and Merton (1981) find that only 3 funds out of 116 exhibit significant positive market timing. Henriksson (1984) and Chang and Lewllen (1984) observed that the average timing coefficient is negative. Phenomena also observed by Shukla and Trzcinka (1992) and by Lakonishok, Schleifer and Vishny (1992). In the South-African market, Meyer (1998) verifies that, on average, fund managers are not capable of anticipating the market macromovements. In the Italian market, Casarin, Pelizzon and Piva (2002) do not find timing indication. In Brazil, Varga (2001) does not verify statistically significant timing coefficients either.

Another fund performance evaluation approach involves information asymmetry and the portfolio composition information proposed by Cornell (1979) and Grinblatt and Titman (1989; 1993). Regarding the asymmetric information, credit goes to Elton e Gruber (1991) with the development of a set of measures supposed to identify performance, either global or decomposed in timing and selectivity. However, as far as we know, up to the moment, there are only two empirical applications of Elton e Gruber (1991) technique: Hwang (1988) and Machado-Santos (1997). Hwang (1988) analyses five mutual funds and observes significant and positive timing estimates. Machado-Santos (1997), in the Portuguese market, analyses six mutual funds, of which four become evident market timers.

3. Volatility timing

In general, the studies about portfolio managers' timing ability focus exclusively on the market returns, in the attempt to verifying whether the portfolio risk exposition increases before the market is up or whether it decreases before the market drops, in other word, determine the ability of predict the macromovements of markets and act in the proper manner. Nevertheless, Busse (1999) proposes a new evaluation approach. Introducing the conditional volatility concept, he focuses on the manager's ability to anticipate the market volatility, the so-called volatility timing. In contrast to Treynor and Mazuy (1966), Henriksson and Merton (1981), Fama (1972) and Elton e Gruber (1991), Busse investigates if the funds risk exposition is changed properly as the market volatility changes.

The Busse approach is similar, in some aspects, to Brown, Harlow and Starks (1996) and Koski and Pontiff (1999), who also analyze the funds volatility management, but not in relation to the market volatility. Since Busse analyses the managers' response to expected future market conditions, his analyses fits into the conditional literature started by Chen and Knez (1996), Ferson and Schadt (1996) and followed by Ferson and Warther (1996), Chrstopherson, Ferson and Glassman (1998) and Becker *et al*. who use publicly available economic instruments in the context of the conditional market returns.

There are two reasons to focus on volatility: first, because, even though it is difficult to predict market returns, market volatility is predictable (Bollerslev *et al*., 1992); second, because the majority of performance measures are risk-adjusted.

The empirical model is initially based on the one factor model, to which Busse adds terms to detect the volatility timing effects and adjusts it to daily frequency. The factor model is bellow:

$$R_{pt} = \alpha_p + \beta_{mp} R_{mt} + \varepsilon_{pt}\,, \tag{3}$$

where, R_{pt} is the excess portfolio return in the day t; R_{mt} is the excess benchmark return in t; β_{mt} is the beta parameter; α_p is the portfolio abnormal return; and ε_{pt} is the residual component.

In order to deal with potential difficulties due to daily data, described by Scholes and Williams (1977) and Dimson (1979), namely the nonsynchronous trading problem that hampers regression estimates for individual securities, Busse adds a lagged excess market return term $R_{m,t-1}$ to the model, as follows:

$$R_{pt} = \alpha_p + \beta_{mp0} R_{mt} + \beta_{mp1} R_{m,t-1} + \varepsilon_{pt} \tag{4}$$

So to account for the volatility timing, market beta is expressed as a linear function[2] of the difference between market volatility and its mean $(\sigma_{mt} - \bar{\sigma}_m)$:

$$\beta_{mpt} = \beta_{mp0} R_{mt} + \gamma_{mp}(\sigma_{mt} - \bar{\sigma}_m) \tag{5}$$

Therefore, whether the portfolio manager is capable of predicting the market volatility, he must adjust his systematic risk exposition correctly, decreasing it when expecting volatility elevation in order to avoiding possible losses. In such a manner, the γ_{mp} sign is supposed to be negative, reflecting the fact that, in moments the volatility is higher than usual, the portfolio systematic risk exposition level is lower, what can be observed in equation 5. Thus the proposed empirical model is

$$R_{pt} = \alpha_p + \beta_{0mp} R_{mt} + \gamma_{pc}(\sigma_{mt} - \bar{\sigma}_m) R_{mt} + \beta_{1mp} R_{m,t-1} + \varepsilon_{pt} \tag{6}$$

γ_{mp} can be interpreted as the timing market volatility estimator, computed as the product between volatility difference in t, $(\sigma_{mt} - \bar{\sigma}_m) R_{mt}$.

4. Data and Methodology

Sample data consists on daily log returns of 60 open-end mutual funds, in the period from January 2, 2001 to December 31, 2002, in a total of 502 observations for each fund. The database was gently provided by Associação Nacional dos Bancos de Investimentos e Desenvolvimento (ANBID). Three classes are analyzed: Active Bovespa funds, Balanced funds and Other Stocks funds. Active Ibovespa are stock funds that try explicitly to beat

[2] The author uses simplified Taylor series expansion.

the Bovespa Index; Balanced are funds that invest in different classes of assets (stocks, bonds and exchange markets, for instance); and Other Stocks are stock funds that do not fit on the special ANBID classes. The São Paulo stock index is used as the benchmark. Excess returns are defined as

$$R_t = r_t - r_{ft} \tag{7}$$

where, R_t denotes the excess return on portfolio in day t; r_t is the log return and r_{ft} is the Brazilian government bonds rate, Selic interest rate, used as proxy for the riskfree return, obtained in Central Brazilian Bank, daily discounted as follows:

$$r_{f,t} = \left(1 + \frac{i_{ao}}{100}\right)^{\frac{1}{252}} - 1 \tag{8}$$

where i_{ao} is the Selic interest rate per year[3] in day t.

The time horizon was determined, mainly, by the various law revisions in the recent years, which has caused mutual funds and funds classes to extinct, to divide or to merge. Besides, the relatively stable economic scenario, started with the Real Economic Plan, in 1994, has led frequently the local authorities to modernize the fund industry rules[4]. Difficulties in studying long-term in the Brazilian financial market are also found by Martins (2001), when studying mutual funds; by Corrêa *et al*. (2002), studying the stock market; and Cavalcant (2003), on the macroeconomic level.

The motivation for using daily frequency data is due to quantity of additional information about the strategies employed by agents, when actively transacting compared to monthly data, because, as Bollen and Busse (2001) verifies, tests using daily data are more powerful than the monthly tests and funds exhibit timing skills more often.

The empirical model employed considers the conditional volatility is based on equation (6) proposed by Busse (1999). The market conditional volatility (s_{mt}) is estimated using autoregressive conditional heteroskedasticity models introduced by Engle (1982), more specifically, the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model by Nelson (1991), which allows volatility to response non-symetricly to shocks, accounting to a important stylized fact for financial series, the leverage effect. The leverage effect was first observed by Mandelbrold (1963)

3 The Selic interest rate is the interest rate on the overnight inter-bank loans collateralized by government bonds and it is publicized compounded per 252 working days a year.

4 Andrezzo and Lima (1999) and Fortuna (2002) describe in detail the rule changes in Brazilian Fund Industry.

and Black (1976) and describes the fact that negative innovations to returns tend to increase volatility more than positive innovations of the same magnitude. EGARCH model defines the conditional is estimated as follows:

$$
\begin{aligned}
&R_{mt} = c_m + \sum_{j=0}^{p} c_p R_{m,t-p} + \varepsilon_{mt} \\
&\varepsilon_{mt} \mid \varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \ldots \sim N(0, \sigma^2_{mt}) \qquad (9) \\
&\log \sigma^2_{mt} = \omega + \sum_{j=1}^{p} \beta \log \sigma^2_{m,t-1} + \sum_{i=1}^{q} \alpha \left| \frac{\varepsilon_{m,t-i}}{\sigma_{m,t-i}} \right| + \sum_{i=1}^{q} \eta \frac{\varepsilon_{m,t-i}}{\sigma_{m,t-i}}
\end{aligned}
$$

where the first line is a auxiliary regression, p is the number autoregressive lags and d is the number of values of standard residuals; c_m, c_p, ω, β e η are parameters can take any value, η captures the asymmetry in the returns response to positive and negative chocks, and conditional variance, σ^2_{mt}, is a asymmetric function of residuals, $\varepsilon_{m,t}$. This logarithmic formulation accommodates negative residuals, assuring positive variance. Many reports corroborate the idea the EGARCH describes financial time series better than the GARCH model (Taylor, 1994; Heynen *et al.*, 1994).

The EGARCH specification selection refers to choosing the p and q orders and the decision about inclusion or not the autoregressive term on the auxiliary regression. The information criteria are commonly employed to ARCH models specification (Valls Pereira *et al.*, 1999; Busse, 1999).

The information theory establishes criteria that tradeoff a reduction in the residual sum of squares for a more parsimonious model. Then two most commonly used selection criteria are Akaike Information Criterion (AIC) and Bayesien Information Criterion (BIC). Additionally, if the data is properly modeled, the standardized residuals must be iid.. This is checked by using Ljung-Box Q statistic.

In short, the employed empirical procedure follows four steps:

- To specify the conditional volatility model for Ibovespa returns;
- To generate market volatility series, $(\sigma_{mt} - \bar{\sigma}_m)R_{mt}$;
- To employ regression (6) to each sample mutual fund;
- To infer the statistical significance of volatility timing coefficient, γ_{mp}.

In order to overcome the effects of potential heteroskedasticity and autocorrelation on the regression coefficients, it was constructed bootstrap standard errors, following the procedure described by Freedman e Peters (1984a, 1984b) and used by Bollen e Busse (2001). The bootstrap standard errors and t statistics were computed as follows:

i. To estimate parameters using OLS, according equation (6), over the sample period:

$$\mathbf{Y} = \mathbf{X}\hat{\hat{\mathbf{e}}} + \mathbf{e} \tag{10}$$

where $\mathbf{X}$ is a (t x k) matrix of exogenous variables, $\hat{\hat{\mathbf{e}}}$ is a (k x 1) vector of regression estimated coefficients, $\mathbf{Y}$ is a (t x 1) vector of response variables, and $\hat{\mathbf{e}}$ is a (t x 1) vector of regression residual term, computed as follows:

$$\hat{\mathbf{e}} = \mathbf{Y} - \hat{\mathbf{Y}} \tag{11}$$

where
$$\hat{\mathbf{Y}} = \mathbf{X}\hat{\hat{\mathbf{e}}} \tag{12}$$

ii. The resample of residuals is then drawn randomly with replacement in each t moment in order to generate a bootstrapped residuals vector $\hat{\mathbf{e}}_b{}^*$.

iii. Next, a vector of bootstrapped response variable, by adding the resampled vector of residuals to the vector of fitted response values $\mathbf{Y}$:

$$\mathbf{Y}_b^* = \hat{\mathbf{Y}} + \hat{\mathbf{e}}_b^* \tag{13}$$

iv. These bootstrapped responses, $\mathbf{Y}_b{}^*$, are then regressed casewise on the exogenous variables $\mathbf{X}$ in order to estimate a bootstrapped vector of estimated coefficients ***b*** for this resample:

$$\mathbf{Y}_b^* = \mathbf{X}\hat{\hat{\mathbf{e}}}_b^* + \hat{\mathbf{e}} \tag{14}$$

v. Steps ii to iv are repeated 1000 times, generating (1000 x k) matrix of bootstrapped coefficients $\hat{\hat{\mathbf{e}}}_b^*$. Each column in this matrix can then be converted into an estimate of the sampling distribution of $\hat{\hat{\mathbf{e}}}_k$, by placing probability of 1/1000 on each value of $\hat{\hat{\mathbf{e}}}_b^*$ for a given parameter.

vi. The standard error of each fund's volatility timing coefficient is the bootstrap standard error of the original volatility timing coefficient, which is used to compute empirical t-statistics of the form:

$$t = \frac{\hat{q}_{p,original}}{s(\hat{q}_{p,bootstrap})} \tag{15}$$

Additionally, and for confirmation of the values obtained through the bootstrap method in the regressions that exhibited autocorrelation and/or heteroscedasticity, the Generalized Model of Linear Regression was implemented with the correction for standard errors suggested by Newey and West (1987). The authors proposed an estimate of the matrix of total variance for the parameters of the regression that it is so much consistent in the presence of heteroscedasticity as in the one of unknown autocorrelation. The standard-errors estimated by that method are said heteroscedastic and autocorrelation consistent (HAC).

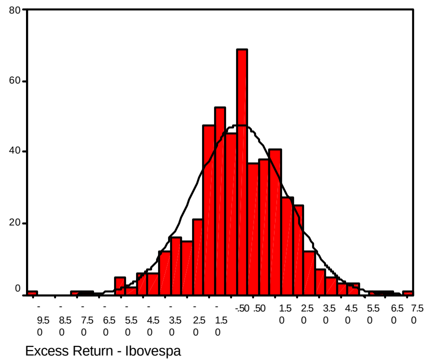
On the other hand, the model of Busse evaluates the timing through a different perspective, that is to say, presumes that the managers are able to anticipate the market volatility based on its own predictability, once, according to the author, the market volatility tends to persist, while the returns alone are not easily predictable and reliable.

5. The Results

The study was preceded firstly to the analysis of the Ibovespa's returns characteristics, in order to determine the most appropriate method to be used in implementing the conditional volatility model.

Figure 1 shows the histograms of the daily raw returns and excess returns, respectively, of Ibovespa together with the curve of the normal distribution. The chart analysis allows us to verify that, in both situations, a lot of observations are placed out of the area expected for the standardized (theoretical) normal distribution. In general, the empiric distributions are narrower, longer and with higher concentration of observations in the extremities. A distribution with these characteristics is said leptokurtic, displaying more density in the extremities, which denotes that the probability of extreme events is larger than the expected for a normal density function.

Figure 1
Empirical distribution of the Ibovespa excess returns

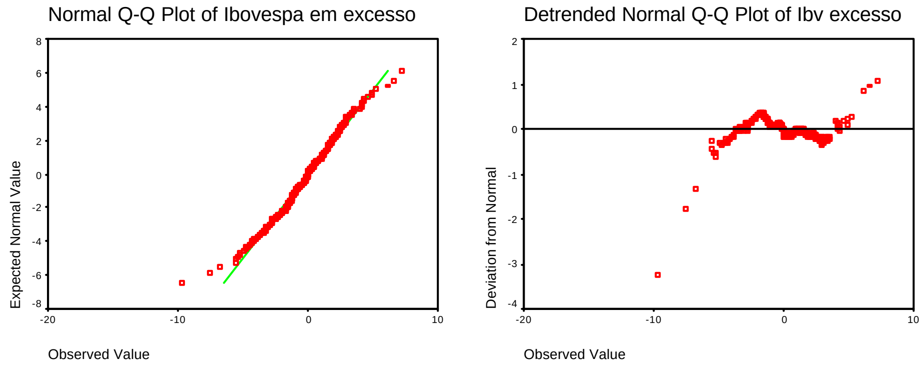


It is also possible to observe deviations of the normality from Figure 2a (*Normal Quantile-Quantile plot).* In case the distribution was normal, the dots should locate randomly around the ascending line, which is not verified. The phenomena of the heavy tails is exhibited by the negative deviations of the inferior dots, which denote the smallest quartiles of the distribution, and for the positive deviations of the superior dots, that denote the largest quartiles of the distribution, indicating the existence of negative and positive extreme values, respectively.

Figure 2

Q-Q plot and Detrended Q-Q plot of the empiric Ibovespa excess returns distribution

(a) **(b)**



A better idea of the intensity with that the observed points deviate from normality is given by Figure 2b (*Detrend Normal Quantile-Quantile plot)*, in which the difference among the values standardized for each observation and the corresponding normalized values is represented in the vertical axis, against the values observed in the horizontal axis. For a normal distribution, the points would locate randomly around the horizontal line (zero). However, it is not the observed behavior and the probability of extreme values becomes still more evident.

Table 1 exhibits the values for asymmetry and the statistics tests for normality of Jarque-Bera and Kolmogorov-Smirnov. The asymmetry is considered to be the third standardized moment of a distribution and the Kurtosis the fourth standardized moment.

Table 1

Distribution Statistics and test for normality of the empiric distribution of Ibovespa

	Excess Return (**R**)
Mean	-0.1292
Maximum	7.2771
Minimum	-9.7035
Standard Deviation	2.0885
Skewness	-0.2254
Kurtosis	4.3495 **
Jarque-Bera	42.34 **
D	0.0506 **

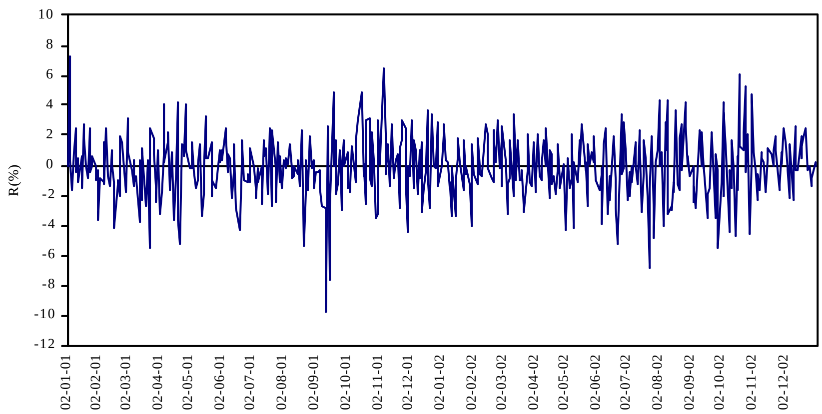
Statistical JB tests the null hypothesis for normality of the sample distribution. The non-parametric statistics D tests the null hypothesis for normality of the sample distribution with significance according to the Lilliefors' correction. The asymmetry of a standardized normal distribution is 0 and the kurtosis is 3.

The Ibovespa excess return presents a slight negative asymmetry and large kurtosis, significant at 1% level. The negative asymmetry is associated to the fact that extreme negatives values might reflect autocorrelation of the squared returns. It is also important to mention that leptokurtic distributions are related with non-linear time series. The non-linearity may be defined as the tendency of the series in reacting more intensively to positive or negative values[5], what will be verified further on. Finally, the formal Jarque-Bera and Kolmogorov-Smirnov tests confirm, categorically, the deviation from the normality.

Figure 3 exhibits the daily excess returns of Ibovespa and Figure 4 the Ibovespa against the square of its excess returns (also known as instantaneous volatility), which allow to observe volatility conglomerates (denominated as persistence) and that the volatility shocks occur in the moments that precede the market falls, pursued by strong fluctuations that arise in moments of crisis, with the simultaneous fall of the index. Black (1976) and Nelson (1991) denominate this asymmetric behavior as leverage effect, where such oscillations last long for some time until that market comes back to its previous behavior.

Figure 3

Daily excess returns of Ibovespa



From the figures above we can observe that some special and specific events resulted in moments of high volatility. Firstly, in September 11, as a consequence of the terrorist attack to the twin towers in the USA. Later, in June 2002, Ibovespa (and the Brasilian Market) was strongly influenced by the investors' risk perception in face of the electoral campaign (with the possibility of a victory of a historical leftist candidate) and for the pressures of the American stock markets, influenced negatively by Iraq and for the negative performance of the American companies. The Brazilian market stabilized in

[5] For a more detailed discussion see Campbel, Lo and MacKinlay (1997, ch.12).

August 2002 when the elected President Lula reaffirmed the commitment in keeping the fiscal discipline and the prices stability.

Figure 4

Ibovespa index and the square of its excess returns

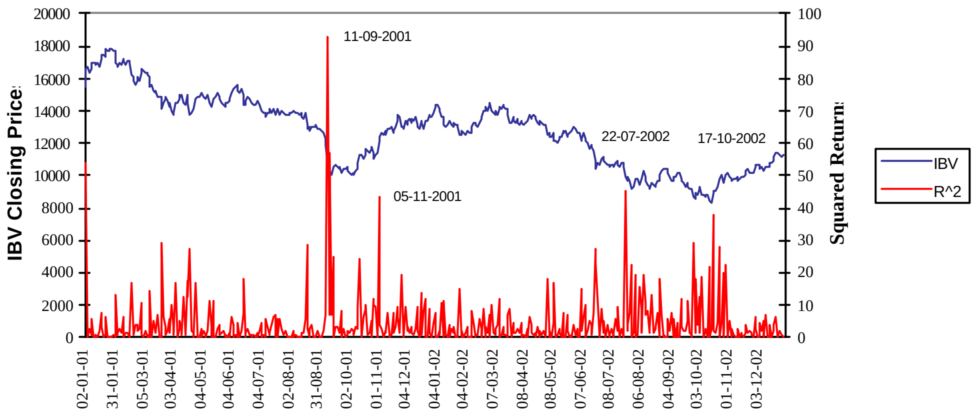


Table 2

Autocorrelation tests for the excess returns and for the square of the excess returns of Ibovespa

P	R		R^2	
	Q	P(Q)	Q	P(Q)
1	0.1480	0.700	0.1176	0.732
2	0.4816	0.786	20.492	0.000
3	0.7846	0.853	22.884	0.000
4	1.1456	0.887	30.515	0.000
5	1.1688	0.948	30.730	0.000
6	1.2332	0.975	30.736	0.000
7	1.9758	0.961	30.825	0.000
8	2.0552	0.979	31.367	0.000
9	2.7648	0.973	31.509	0.000
10	3.9053	0.952	32.873	0.000
11	3.9092	0.972	33.385	0.000
12	4.0312	0.983	33.521	0.001
13	4.1876	0.989	34.598	0.001
14	10.477	0.727	35.539	0.001
15	12.679	0.627	38.291	0.001
16	13.267	0.653	38.298	0.001
17	13.453	0.705	38.322	0.002
18	19.873	0.340	38.361	0.003
19	19.989	0.395	38.392	0.005
20	20.792	0.409	38.432	0.008

Q is the statistic Ljung-Box for the series autocorrelation with p lags and P(Q) is the P value for the Q statistic.

However, concentrating our attention on the presence of such volatility conglomerates, and according to Campbel, Lo and Macinlay (1997), we pursue with the analysis of the autocorrelation of the time series of excess returns and the square of excess returns. Serial autocorrelation was not detected in the Ibovespa returns alone, though, tests for the square of the excess returns reveal the presence of strong serial autocorrelation starting from the second to the twentieth lag. In the second lag, the Q statistic for the square of returns (20.492) it is 43 times higher than the one estimated for the excess returns (0.1480), confirming that the market volatility tends to form conglomerates, in which relatively calm periods of low returns are cut out by volatile periods with high returns, such as those observed by Mandelbrot (1963) and Engle (1982). This way, and as revealed by Busse (1999), given that the volatility is not homocedastic, its values can be accurately predicted.

Thus, we identify two more characteristics in the time series of returns and excess returns of Ibovespa - volatility conglomerates and asymmetric behavior - already revealed by the heavy tails of its distribution. Bollerslev et al. (1992) affirm that the asymmetry and heavy tails are some of the main characteristics of the financial series. Herencia et al. (1995) confirm the presence of such characteristics in the Brazilian series.

Finally, with the purpose of confirming the existence of conditional heteroscedasticity, the Lagrange's Multiplier test (LM ARCH) of Engle (1982) is implemented for the order 10, 15 and 20 in the Ibovespa series of the excess returns (see Table 3), which allows verifying strong evidence of heteroscedasticity, or ARCH effect, in the series.

Table 3

Tests for heteroscedasticity in the series of the excess returns of Ibovespa

Ordem	LM ARCH	Valor crítico	Valor P
10	32.8725	18.3070	0.0003
15	38.2912	24.9958	0.0008
20	38.4325	31.4104	0.0078

The statistic LM ARCH tests the null hypothesis that the series is homocedastic.

As we may verify, the series present the characteristics stylized by the literature: leptokurtosis, persistence and asymmetry. These way, the most appropriate models seem to be those that replicate such characteristics. In fact, the ARCH models, said conditional heteroscedastics models, are broadly used when modeling the volatility of financial series for which they take into account that the return's variance in a given moment of time depends on the past returns and of other available information in that instant (Morettin, 2004). As emphasized by Patterson (2000, p. 712), these models consider the characteristics of the financial series, such as the persistence, and the non-conditional distribution of the returns is leptokurtic when compared with the normal distribution. Additionally, Alexander (2002) suggests that the asymmetry should be included in the model, in way to capture any eventual leverage effect.

The time series of the volatility, measured by the conditional variance of the market returns, was calculated through the application of the EGARCH model of Nelson (1991) for allowing the asymmetry of the volatility. Among the several model specifications that didn't present serial autocorrelation in the residues, we select that with better information criteria according to AIC and BIC.

Table 4

Comparison among the specifications of the model EGARCH (p, d) AR(p)

	EGARCH(11)	EGARCH(11)	EGARCH(21)	EGARCH(21)	EGARCH(12)	EGARCH(12)
AR (p)	0	1	0	1	0	1
AIC	4.2702	**4.2350**	4.2652	4.2531	4.2595	4.2400
BIC	4.3122	**4.2855**	4.3240	4.3205	4.3099	4.2989
Q(1)	0.492		0.351		0.511	
Q(5)	0.979	0.497	0.956	0.995	0.989	0.701
Q(10)	0.985	0.554	0.954	0.982	0.975	0.788
Q(20)	0.551	0.099	0.590	0.667	0.683	0.202

AR(p) is the autoregressive term of order p for the auxiliary regression, p is the number of lags of the autoregressive terms, and d is the number of the variance lags. AIC is the Akaike's Information Criteria, BIC is the Bayesian Information Criteria of Schwartz and Q(p) is the significant value of the statistic Ljung-Box with p lags.

Table 4 presents the results from the specifications of the EGARCH model for the Ibovespa volatility. The last four rows display the P values for the Q statistic of Ljung-Box, which examines the serial autocorrelation in the residues. It is interesting to note the lack of serial autocorrelation in all of the specifications[6], suggesting that they are random and the volatility is appropriately modeled. Among the different specifications, that with better information criteria (*AIC* and *BIC*) is the EGARCH (1,1) with a autoregressive term in the auxiliary regression, indicating to be the most parsimonious model. The estimates are exhibited below, with the respective Z values inside brackets:

$$R_{m,t} = \underset{(-3,8766)}{-0,02149} - \underset{(-0,4496)}{0,0150} R_{m,t-1}$$

$$\log \sigma^2_{mt} = \underset{(35.685)}{0,1119} + \underset{(590,267)}{0,9719} \log \sigma^2_{mt-1} - \underset{(-250.726)}{0,0883} \left| \frac{\varepsilon_{m,t-1}}{\sigma_{m,t-1}} \right| - \underset{(-7,9019)}{0,0793} \frac{\varepsilon_{m,t-1}}{\sigma_{m,t-1}}$$

The term that captures the leverage effect (η = -0,0793) is negative and statistically different from zero, indicating the existence of such leverage effect in the excess returns of Ibovespa, allowing sustaining that the choice of a model able to detect the asymmetry of the market shocks reveals adequacy to model the series.

Based in the EGARCH (1,1) AR(1) model, we generate the series of conditional volatility of differences between the Ibovespa excess returns conditional volatility and its

[6] Up to 36 lag periods, we did not observe serial correlation both on the standardized residues or the square of the residues, in none of the EGARCH specifications.

mean $(s_{m,t} - \overline{s}_m)$, designated as *Dvol*, and the product of the difference of the volatility for Ibovespa excess returns $(s_{m,t} - \overline{s}_m)R_{m,t}$, designated as *DvolR*. As we can see in Figure 5, which exhibits the Ibovespa and *Dvol* for the period under analysis, it is possible to observe that volatility rises coincide with market falls.

Figure 5

Excess returns conditional volatility of Ibovespa modeled by EGARCH (1,1) AR(1)

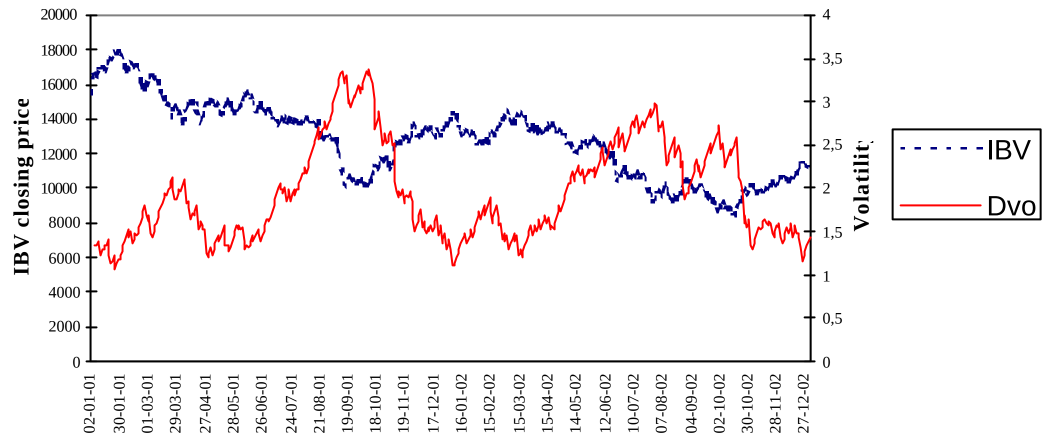


Figure 6

Ibovespa and the product of the difference of the conditional volatility for its excess returns

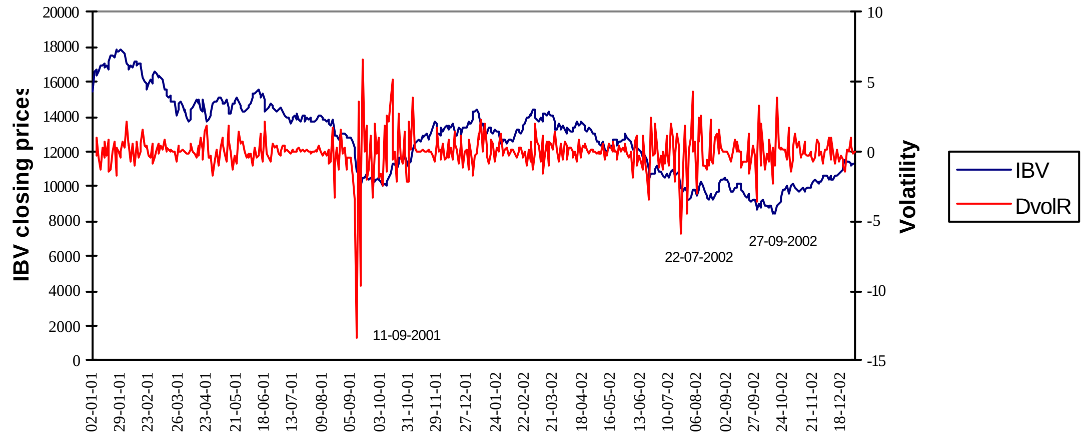


Figure 6 shows the series of *DvolR* and Ibovespa. The series of variable DvolR is the main explanatory variable in the Busses's model, once it intends to describe the asymmetric sequence of the conditional volatility, whose larger intensity arises in moments of the market fall. We can observe clearly moments of shock, persistence and asymmetry of the modeled series, whose behavior justifies the evaluation model proposed by Busse, given that, as the risk perception influences directly the assets value (Pattersson, 2000) and as it is possible to foresee the volatility, the manager should react dynamically to avoid potential losses. When the manager of a active managed portfolio is able to identify the moments that precede the crisis periods and try to minimize potential losses, he should act in way to decrease its risk exposition.

The summary of the estimates of timing coefficients, g_c, for the 60 funds, is shown in Table 5 below (full results are available in the appendix 2).

Table 5

Summary of Timing estimates according to the model of Busse

Mean g	-0,0106	
t stat	(-0,3989)**	
	Positive	Negative
g_c significant 5%	0	6
g_c non significant 5%	20	34

** Significant at 1%.

It is expected that a mutual fund manager exhibiting ability of volatility timing to present the g_{mc} coefficient with negative sign, once it would reflect the manager's managing to decrease the exposure to the systematic risk in moments of high volatility. The results suggest that mutual funds are able to anticipate volatility changes. In fact, the mean sample coefficient displays the expected negative signal, besides being highly significant. It is observed that most of the gamma estimates present negative signs, more specifically, 67% of the mutual funds in the sample present volatility timing (g_{mc}<0), of which six statistically significant at 5%, namely, OU04 (-0,0655), OU13 (-0,0700), BA03 (-0.0094), BA06 (-0.0437), BA07 (-0.0192) and BA15 (-0,0647). While some of the funds present positive timing coefficients, none is significant.

Analyzing the mutual fund categories separately, and in spite of funds BT do not display statically significant coefficients as those evidenced in the categories OR and BT, the ANOVA, shown in Table 6, confirmed by Krukal-Wallis (Figure 7 and Appendix 3), does not reveal significant differences among the three categories. Examining simply the distribution of negative coefficients among the categories, it is observed, once more, some equilibrium, so it may allow us to conclude that the fact of avoiding strong exposure to the systematic risk in moments of higher volatility is a common practice among the categories.

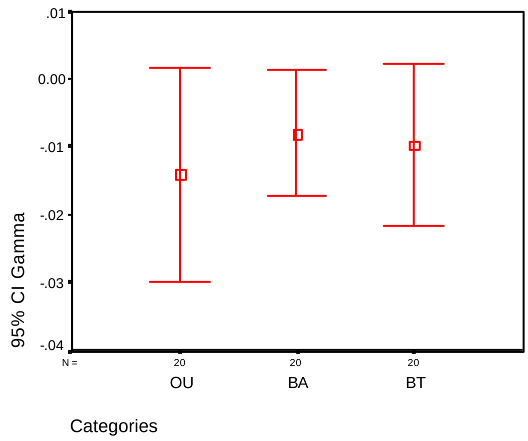
Table 6

ANOVA for the volatility timing on the categories of mutual funds

	SS	DF	MS	F	Sig
Between	0.0004	2	0.0002	0.2703	0.7641
Within	0.0414	57	0.0007		
Total	0.0418	59			

Figure 7

Gammas for category of mutual funds



As far as we know, this is the first time in Brazil, that the mutual fund manager's skills in identifying market turbulence and act properly in order to limit (or reduce) potential losses, are documented. In spite of such behavior to be expected in a context of professional managers, the most used evaluation models for measuring the capacity of timing in this market do not focus on the conditional volatility. Therefore, and once again, the results of the empiric tests of volatility timing implemented in the sample of Brazilian mutual funds, through the model of Busse (1999), clearly reject the null hypothesis, for that it may be conclude that the managers reveal timing abilities.

6. Concluding Remarks

The first evidence that stands out from this study is that mutual fund managers are able to implement strategies that allow them to answer properly to the eminent rise of the market volatility, and that are capable to stay persistently above its competitors. The tests to forecast the capacity of anticipate periods of high market volatility, were implemented according to the model of Busse, with very expressive and promising results (highly statistical significant). It was observed that 67% of the managers decrease the systematic risk exposition face to moments of higher volatility, and a more detailed exam revealed that such capacity is similar among the three different studied categories, denoting the timing abilities of the managers.

Undoubtedly that to predict the market oscillations it is an important factor for risk managers, specially in unstable economies such as the Brazilian economy. Thus, it should be emphasized that it was observed that a conditional model that rely on the assumption that the manager acts based on publicly available information and adopts dynamic strategies, revealing capacities not observed in the traditional performance methodologies that, in turn, assume that the investors' expectations are formed without using the information concerning the economy fundamental variables. Another way towards the accuracy of the evaluation process should be the use of the information provided by the portfolio holdings. However, the major handicap of this alternative relies on the lack of available information to the public (or the evaluator) in databases with regular time frequency, for most of the financial markets.

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Appendix 1: The model of Busse (1999)

Theoretically, Busse assumes a generating process of k-factors and sensibility to the factors that change over time, and defines the return of the fund on period $t+1$ through the following equation:

$$R_{c,t+1} = \alpha_{ct} + \sum_{j+1}^{k} \beta_{jct} R_{j,t+1} + \varepsilon_{c,t+1} \qquad \text{(A1)}$$

where, $R_{c,t+1}$ is the excess return of portfolio c on period $t+1$; $R_{j,t+1}$ is the excess return of the factor j on period $t+1$; β_{jct} is the sensibility of the portfolio c to the factor j chosen by the manager on period t; α_{ct} is the portfolio abnormal return on period t; $\varepsilon_{c,t+1}$ is the residual term of portfolio c on period $t+1$. The returns are considered as being distributed normal and conditionally, $E_t(\varepsilon_{c,t+1}) = 0$ and $E_t(R_{j,t+1}\ \varepsilon_{c,t+1}) = 0$, in which E(.) is the expectation conditioned to the available information in t. This way the expected return is:

$$E_t(R_{c,t+1}) = \alpha_{ct} + \sum_{j+1}^{k} \beta_{jct} E_t(R_{j,t+1}) \qquad \text{(A2)}$$

Supposing although that the factors are orthogonal, the conditional variance in t is defined as:

$$\sigma_t^2(R_{c,t+1}) = \sum_{j+1}^{k} \beta_{jct}^2 \sigma_{j,t+1}^2 + \sigma_t^2(\varepsilon_{c,t+1}) \qquad \text{(A3)}$$

In a temporal perspective, the maximization problem is the following:

$$\max_{\beta_{1ct},\ldots,\beta_{kct}} \mathrm{E}_t\left[\mathrm{U}_{t+1}(\mathrm{R}_{c,t+1})\right] \qquad \text{(A4)}$$

Differentiating $E_t\left[U_{t+1}(R_{c,t+1})\right]$ in relation to β_{jct} for $j = 1 \ldots k$ and equaling the result to zero, Busse obtains:

$$\begin{aligned}
\frac{\partial}{\partial \beta_{jct}} E_t\left[U_{t+1}(R_{c,t+1})\right] &= E_t\left[U'_{t+1}(R_{c,t+1})\right] E_t\left[R_{j,t+1}\right] + \operatorname{cov}\left[U'_{t+1}(R_{c,t+1}), R_{j,t+1}\right] \\
&= E_t\left[U'_{t+1}(R_{c,t+1})\right] E_t\left[R_{j,t+1}\right] + E_t\left[U''_{t+1}(R_{c,t+1})\right] \operatorname{cov}(R_{c,t+1}, R_{j,t+1}) \qquad \text{(A5)} \\
&= E_t\left[U'_{t+1}(R_{c,t+1})\right] E_t\left[R_{j,t+1}\right] + \beta_{jct} E_t\left[U''_{t+1}(R_{c,t+1})\right] \operatorname{var}(R_{j,t+1}) \\
&= 0 \qquad j = 1,\ldots,k
\end{aligned}$$

where the second line follows the lemma of Stein (1973). Solving the equation in order to β_{jct}, it becomes:

$$\beta_{jct} = \frac{1}{a} \frac{E_t(R_{j,t+1})}{\sigma_{j,t+1}^2} \qquad j = 1,\ldots,k, \qquad \text{(A6)}$$

where a is the measure of risk aversion of Rubinstein (1973), $-E_t\left[U''_{t+1}(R_{c,t+1})\right] / E_t\left[U'_{t+1}(R_{c,t+1})\right]$, which is supposed to be an assumed parameter. Calculating the partial derivate of the optimal beta factor with respect to the standard deviation, obtains:

$$\frac{\partial \beta_{jct}}{\partial \sigma_{j,t+1}} = \frac{1}{a \sigma_{j,t+1}^2} \left[\frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} - \frac{2 E_t(R_{j,t+1})}{\sigma_{j,t+1}} \right] \qquad j = 1,\ldots,k \qquad \text{(A7)}$$

if

$$\frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} \leq 0 \qquad \text{(A8)}$$

Then, the portfolio sensibility to the factor j should be reducing when the volatility of that factor increases. It is expected, therefore, a negative relationship between β_{mc} and σ_m.

Appendix 2

Performance parameters for the model of Busse

I	α	t(α)	P(α)	β_c	t(β)	P(β)	γ_c	t(γ)	P(γ)	β_{t-1}	t(β_{t-1})	P(β_{t-1})	R^2
OU01	0,0727	2,4081	0,0164*	0,2573	16,1108	0,0000	0,0332	1,3623	0,1737	0,1402	9,6856	0,0000	0,47
OU02	-0,0007	-0,0180	0,9856	0,6205	28,8022	0,0000	-0,0437	-1,3798	0,1683	0,3459	17,4711	0,0000	0,72
OU03	0,0333	0,9739	0,3306	0,3216	17,8087	0,0000	-0,0354	-1,3059	0,1922	0,1731	10,5788	0,0000	0,49
OU04	0,0501	1,2900	0,1976	0,4714	22,2070	0,0000	-0,0655	-2,0821	0,0378*	0,2806	15,0302	0,0000	0,61
OU05	0,0055	0,1344	0,8932	0,6514	31,0040	0,0000	0,0092	0,2957	0,7676	0,3563	18,6019	0,0000	0,74
OU06	0,0061	0,1354	0,8923	0,6874	28,5662	0,0000	-0,0428	-1,1738	0,2410	0,3839	17,7469	0,0000	0,71
OU07	0,0881	2,2767	0,0232*	0,3694	18,8060	0,0000	0,0292	0,9480	0,3436	0,1841	10,0242	0,0000	0,51
OU08	0,1042	2,9563	0,0033**	0,3535	18,9433	0,0000	0,0241	0,9161	0,3601	0,2195	13,2163	0,0000	0,56
OU09	0,0123	0,3219	0,7477	0,5287	26,5527	0,0000	-0,0186	-0,6172	0,5374	0,3067	16,8946	0,0000	0,68
OU10	0,0821	2,9291	0,0036**	0,2616	18,0635	0,0000	-0,0339	-1,5220	0,1286	0,1579	11,1823	0,0000	0,47
OU11	0,0709	1,9345	0,0536	0,3749	19,7918	0,0000	0,0493	1,7391	0,0826	0,2125	12,4873	0,0000	0,57
OU12	0,0593	1,8638	0,0629	0,3395	20,9532	0,0000	-0,0157	-0,6514	0,5151	0,1398	9,1475	0,0000	0,54
OU13	-0,1077	-2,8673	0,0043**	0,1935	9,9750	0,0000	-0,0700	-2,3779	0,0178*	0,1426	8,1825	0,0000	0,25
OU14	0,0138	0,3426	0,7320	0,6160	29,0856	0,0000	-0,0228	-0,7436	0,4575	0,3363	17,6024	0,0000	0,72
OU15	0,0366	1,0783	0,2814	0,3164	18,9377	0,0000	-0,0313	-1,1958	0,2324	0,1708	10,9785	0,0000	0,50
OU16	0,0228	0,3954	0,6927	0,6453	21,3617	0,0000	0,0111	0,2307	0,8176	0,3531	12,6030	0,0000	0,58
OU17	-0,0278	-0,8383	0,4023	0,4671	27,1526	0,0000	-0,0371	-1,4681	0,1427	0,2736	17,2164	0,0000	0,69
OU18	0,0155	0,4464	0,6555	0,5561	31,1057	0,0000	-0,0115	-0,4187	0,6756	0,2713	17,0138	0,0000	0,73
OU19	0,0855	2,3627	0,0185*	0,1826	9,8043	0,0000	-0,0304	-1,0725	0,2840	0,1151	6,5715	0,0000	0,23
OU20	0,1255	3,8237	0,0001**	0,3476	20,6457	0,0000	0,0202	0,7826	0,4342	0,2214	14,7745	0,0000	0,59
BA01	0,0013	0,0424	0,9662	0,3941	25,7777	0,0000	-0,0395	-1,7258	0,0850	0,2731	20,0646	0,0000	0,70
BA02	-0,0060	-1,5180	0,1296	0,0138	6,6873	0,0000	-0,0002	-0,0771	0,9386	0,0135	7,2921	0,0000	0,18
BA03	-0,0027	-0,6599	0,5096	0,0504	23,9740	0,0000	-0,0094	-2,8861	0,0041**	0,0287	14,4062	0,0000	0,62
BA04	0,0029	0,1678	0,8668	0,0776	8,8052	0,0000	0,0218	1,6026	0,1097	0,0588	7,4817	0,0000	0,23
BA05	0,0106	0,3650	0,7152	0,4063	28,0497	0,0000	0,0036	0,1636	0,8701	0,2289	16,7769	0,0000	0,70
BA06	0,0024	0,1346	0,8930	0,1663	18,1111	0,0000	-0,0437	-3,0826	0,0022**	0,0955	11,4022	0,0000	0,48
BA07	-0,0024	-0,3194	0,7496	0,0683	16,9598	0,0000	-0,0192	-3,1904	0,0015**	0,0413	11,2326	0,0000	0,46
BA08	-0,0046	-0,9751	0,3300	0,0022	0,8963	0,3705	0,0006	0,1667	0,8677	0,1116	51,0170	0,0000	0,83
BA09	-0,0086	-2,2113	0,0275*	0,0011	0,5824	0,5606	-0,0002	-0,0694	0,9447	0,0010	0,5359	0,5923	0,00
BA10	-0,0278	-1,5788	0,1150	0,0031	0,3177	0,7508	-0,0049	-0,3370	0,7362	0,2015	21,9436	0,0000	0,51
BA11	-0,0031	-0,3881	0,6981	0,0036	0,9079	0,3644	0,0021	0,3527	0,7244	0,2111	54,8853	0,0000	0,86
BA12	0,0104	0,6078	0,5436	0,0075	0,8037	0,4220	0,0072	0,5393	0,5899	0,4980	59,4197	0,0000	0,88
BA13	-0,0040	-1,0653	0,2873	0,0138	6,9374	0,0000	-0,0003	-0,1112	0,9115	0,0135	7,6398	0,0000	0,18
BA14	-0,0151	-7,1854	0,0000**	0,0005	0,4082	0,6833	-0,0003	-0,2043	0,8382	0,0007	0,7016	0,4832	0,00
BA15	0,0055	0,1992	0,8422	0,2630	17,3558	0,0000	-0,0647	-2,8701	0,0043**	0,1572	11,5471	0,0000	0,48
BA16	0,0128	1,4258	0,1546	-0,0042	-0,8574	0,3916	-0,0026	-0,3440	0,7310	0,1038	23,9128	0,0000	0,52
BA17	-0,0009	-0,0288	0,9770	0,4542	29,0691	0,0000	-0,0107	-0,4515	0,6518	0,2670	18,3210	0,0000	0,72
BA18	-0,0064	-0,6379	0,5238	0,0004	0,0758	0,9396	-0,0014	-0,1773	0,8593	0,0501	9,9128	0,0000	0,16
BA19	-0,0237	-1,8847	0,0601	0,0018	0,2775	0,7815	-0,0034	-0,3515	0,7253	0,1272	21,9744	0,0000	0,48
BA20	-0,0013	-0,1125	0,9105	0,0051	0,8633	0,3884	0,0036	0,4241	0,6717	0,3108	57,9654	0,0000	0,87
BT01	0,0249	0,6190	0,5362	0,6786	32,1271	0,0000	0,0263	0,8515	0,3949	0,3630	18,0305	0,0000	0,75
BT02	0,0038	0,0877	0,9301	0,6497	29,0669	0,0000	-0,0034	-0,1015	0,9192	0,3740	18,3978	0,0000	0,73
BT03	0,0209	0,5945	0,5525	0,4551	25,2542	0,0000	0,0369	1,3853	0,1666	0,2621	16,1738	0,0000	0,67
BT04	0,0182	0,4461	0,6557	0,6054	27,4128	0,0000	-0,0262	-0,8149	0,4155	0,3525	17,8893	0,0000	0,71
BT05	0,0296	0,6913	0,4897	0,6346	27,5274	0,0000	0,0082	0,2483	0,8040	0,3675	18,0028	0,0000	0,72
BT06	0,0179	0,4044	0,6861	0,6670	29,0725	0,0000	-0,0276	-0,8132	0,4165	0,3480	16,9014	0,0000	0,71
BT07	0,0353	0,7922	0,4286	0,6611	27,7245	0,0000	0,0121	0,3281	0,7430	0,3426	15,5682	0,0000	0,69
BT08	0,0053	0,1203	0,9043	0,6346	28,0662	0,0000	0,0081	0,2354	0,8140	0,3676	18,3156	0,0000	0,72
BT09	0,0181	0,4341	0,6644	0,6718	30,1422	0,0000	-0,0103	-0,3032	0,7619	0,3549	17,2945	0,0000	0,74
BT10	0,0132	0,3104	0,7564	0,6346	27,7121	0,0000	0,0083	0,2518	0,8013	0,3674	18,6708	0,0000	0,72
BT11	0,0246	0,5803	0,5620	0,6526	29,7153	0,0000	-0,0081	-0,2456	0,8061	0,3695	17,8788	0,0000	0,73
BT12	0,0134	0,2976	0,7662	0,6883	29,9176	0,0000	-0,0430	-1,2735	0,2034	0,3219	15,4305	0,0000	0,72
BT13	0,0161	0,3762	0,7069	0,6493	28,6808	0,0000	-0,0449	-1,3551	0,1760	0,3703	17,5891	0,0000	0,72
BT14	0,0315	0,7591	0,4482	0,6645	29,8974	0,0000	0,0320	0,9922	0,3216	0,3411	16,8714	0,0000	0,74
BT15	0,0367	0,8618	0,3892	0,6811	31,9835	0,0000	-0,0478	-1,4331	0,1524	0,3614	17,8968	0,0000	0,74
BT16	0,0033	0,0817	0,9349	0,5961	29,4370	0,0000	-0,0111	-0,3576	0,7208	0,3471	18,2505	0,0000	0,72
BT17	0,0220	0,5087	0,6112	0,6299	27,9960	0,0000	-0,0242	-0,6900	0,4905	0,3464	17,5678	0,0000	0,71
BT18	0,0345	0,8476	0,3971	0,6389	29,7056	0,0000	-0,0261	-0,8162	0,4148	0,3548	18,3857	0,0000	0,73
BT19	-0,0118	-0,2771	0,7818	0,6616	29,8535	0,0000	-0,0132	-0,3931	0,6944	0,3549	17,3190	0,0000	0,72
BT20	-0,0009	-0,0239	0,9810	0,5558	28,1992	0,0000	-0,0391	-1,2825	0,2003	0,3145	18,2172	0,0000	0,71

$R_{c,t} = \alpha_{4c} + \beta_{0mc} R_{mt} + \gamma_{mc} (\sigma_{mt} - \bar{\sigma}_m) R_{mt} + \beta_{1mc} R_{m,t-1} + \varepsilon_c$, in which $R_{c,t}$ and $R_{m,t}$ are respectively the daily excess returns of the fund and the market in relation to the risk-free rate (*Selic)* on period *t*, α_c is the intercept, β_0 is the coefficient of the portfolio systematic risk, γ_c is the estimator of the market volatility timing R_m of the fund, measured by the product of the difference between the conditional volatility on period *t* and its mean and the market excess return (σ_{mt} – `σ_m)R_{mt}; and ε_c is the regression residual term. The parameter estimators are obtained by the OLS method and the statistical significance is achieved with the parametric t-test, in which the errors are adjusted by the bootstrap method.

Appendix 3

Tests for distributions and mean equality of the gammas of the categories OU, BA and BT computed with the model of Busse.

Distribution statistics and normality test

	OU	BA	BT
Mean	-0.0141	-0.0081	-0.0097
Maximum	0.0493	0.0218	0.0369
Minimum	-0.0700	-0.0647	-0.0478
Std Deviation	0.0336	0.0199	0.0256
Skewness	0.2392	-1.5175	0.2177
Kurtosis	2.0813	4.8756	2.0505
Jarque-Bera	0.89	10.61	0.91
P(JB)	0.64	0.00	0.63

The statistic JB tests the null hypothesis of normality for the sample distribution.

Test of homogeneity of variances

Levene Estatistic	df1	df2	Sig.
4,0688	2	57	0,0223

The statistics of Levene tests the null hypothesis of homogeneity of variances for the sample distributions.

Kruskal-Wallis test

Statistic H test:	
Qui-square	0,7400
Df	2
Sig.	0,6907

The non-parametric statistic *H* of *KW* tests the null hypothesis that the sample means are equal.