# 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.

## Introduction

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

Since the seminal papers of Sharpe (1966) and Jensen (1968), which seek to incorporate 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. Specifically, the ability to anticipate the macro movements of the market - market timing - can contribute to add value to actively managed portfolios.

Traditionally the timing 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 approach behind modern financial theory, which has been taken as time constant, termed unconditional. In such a context, the historical volatility, computed as the standard deviation of one given period, is assumed to remain 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 professional 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 of large oscillations in specific periods of time is an extremely important factor for risk management.

## Literature Review

One of the first to analyze empirically the market timing ability of funds managers was Treynor and Mazuy (1966). According to the authors, funds managers try to anticipate the conditions for market falls and rises. In consequence of this activity, the characteristic line, which represents the relationship between the portfolio excess return and the market excess return, is curve and changes constantly, indicating that the manager answer continuously to the conditions of the market. By examining 57 mutual funds, from 1953 to 1962, the authors find no evidence of timing activities.

Later, Fama (1972) was 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), Pfleiderer and Bhattacharya (1983), Admati and Ross (1985) and 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 a put option on market portfolio with strike price set to risk-free rate. Based on this study, Henriksson and Merton (1981) developed statistical procedures that allow detecting timing abilities. Their measure presumes that managers select different levels of systematic risk according to their expectations, increasing the portfolio risk level when predicting the market excess return is positive and decreasing it otherwise.

Most studies find little evidence that fund managers reveal 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 evidenced 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 able of anticipating the market macro movements. Also Casarin, Pelizzon and Piva (2002) do not find evidence of timing in the Italian market. In Brazil, Varga (2001) does not verify statistically significant timing coefficients either.

Another performance evaluation approach involves information asymmetry and the portfolio holdings, and where proposed by Cornell (1979), based on the Event Study Measure, Grinblatt and Titman (1989; 1993) with the Portfolio Change Measure, and the asymmetric information of Elton e Gruber (1991) which developed a set of measures supposed to identify the performance, either global or decomposed into timing and selectivity. However, because the portfolio holdings are rarely available, at least at regular time frequency for most of the financial markets, there are very few empirical applications of these techniques; Hwang (1988) observes significant and positive timing estimates and Machado-Santos (1997), in the Portuguese market, found evidence of some market timers.

### Volatility Timing

Generally, the studies about portfolio managers' timing ability focus exclusively on the market returns, in the attempt to verify whether the portfolio risk exposition increases before the market raise or it decreases before the market falls. In other words, determine the ability of predict the macro movements 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 fund's risk exposition is properly adjusted as the market volatility changes.

The Busse's 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 related 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. (1999), who used publicly available economic variables 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:

$$R_{pt} = \alpha_p + \beta_{mp} R_{mt} + \varepsilon_{pt} \qquad (1)$$

where, $R_{pt}$ is the portfolio excess return in the day $t$; $R_{mt}$ is the benchmark excess return in $t$; $\beta_{mt}$ is the beta parameter; $\alpha_p$ is the portfolio abnormal return; and $\varepsilon_{pt}$ 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 market excess return term $R_{m,t-1}$ to the model, as follows:

(2)

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

(3)

Therefore, once the portfolio manager is able of predicting the market volatility, he must adjust his systematic risk exposition correctly, decreasing it when expecting volatility rises in order to avoiding possible losses. In such a manner, the $\gamma_{mp}$ sign is supposed to be negative, reflecting the fact that, in periods exhibiting volatility higher than usual, the portfolio systematic risk exposition level should be lower, as stated in equation 3 above. Thus the proposed empirical model is:

(4)

where can be interpreted as the timing market volatility estimator, computed as the product between volatility difference in period $t$, $R_{mt}$.

### Data and Methodology

The sample data consists on daily log returns of 60 open-end mutual funds, in the period of 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-Brasil). Three classes are analyzed: Active Bovespa funds, Balanced funds and Other Stocks funds. Active Ibovespa are stock funds that try explicitly to beat the Bovespa Index[1]; Balanced are funds that invest in different classes of assets (e.g.: stocks, bonds and exchange markets); and Other Stocks are stock funds that do not fit on the special ANBID classes. The Ibovespa is used as the benchmark. Excess returns are defined as:

(5)

where, denotes the excess return on portfolio in day $t$; is the log return and is the Brazilian government bonds rate (Selic interest rate obtained in Central Brazilian Bank), used as a proxy for the risk-free, daily discounted as follows:

(6)

where $i_{ao}$ is the Selic interest rate per year[2] 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[3]. 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 (4) proposed by Busse (1999). The market conditional volatility ($\sigma_{mt}$) 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-symmetrically to shocks, accounting to a important stylized fact for financial series, the leverage effect. The leverage effect was first observed by Mandelbrold (1963) 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:

$$
\begin{aligned}
R_{mt} &= c_m + \sum_{j=0}^{p} c_p R_{m,t-p} + \varepsilon_{mt} \\
\varepsilon_{mt} \mid \varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \cdots &\sim N(0, \sigma_{mt}^2) \\
\log \sigma_{mt}^2 &= \omega + \sum_{j=1}^{p} \beta \log \sigma_{m,t-1}^2 + \sum_{i=1}^{q} \alpha \left| \frac{\varepsilon_{m,t-i}}{\sigma_{m,t-i}} \right| + \sum_{i=1}^{q} \eta \frac{\varepsilon_{m,t-i}}{\sigma_{m,t-i}}
\end{aligned}
\tag{7}
$$

where the first line is a auxiliary regression, $p$ is the number of autoregressive lags and $d$ is the number of values of standard residuals; $c_m$, $c_p$, $\omega$, $\beta$ e $\eta$ are parameters that can take any value, $\eta$ captures the asymmetry in the returns response to positive and negative chocks, and conditional variance, $\sigma^2_{mt}$, 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 (4) to each sample mutual fund;
- To infer the statistical significance of volatility timing coefficient, .

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:

$$Y = X\hat{\theta} + \hat{e} \tag{8}$$

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

$$\text{where} \quad \hat{Y} = X\hat{\theta} \tag{9}$$

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

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

$$Y_b^* = \hat{Y} + \hat{e}_b^* \tag{10}$$

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

$$Y_b^* = X\hat{\theta}_b^* + \hat{e} \tag{11}$$

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

$$t = \frac{\hat{\theta}_{p,original}}{\sigma(\hat{\theta}_{p,bootstrap})} \tag{12}$$

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 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.

## The Results

The study was preceded firstly by 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.

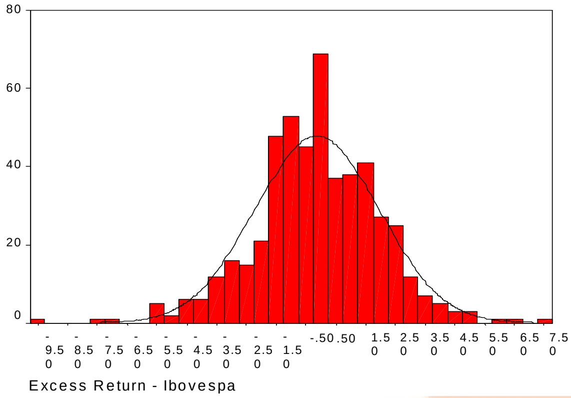


**Figure 1 :**
**Empirical Distribution of Ibovespa Excess Returns**

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.

**(a)** Normal Q-Q Plot of Ibovespa in excess **(b)** Detrended Normal Q-Q Plot of Ibv in excess

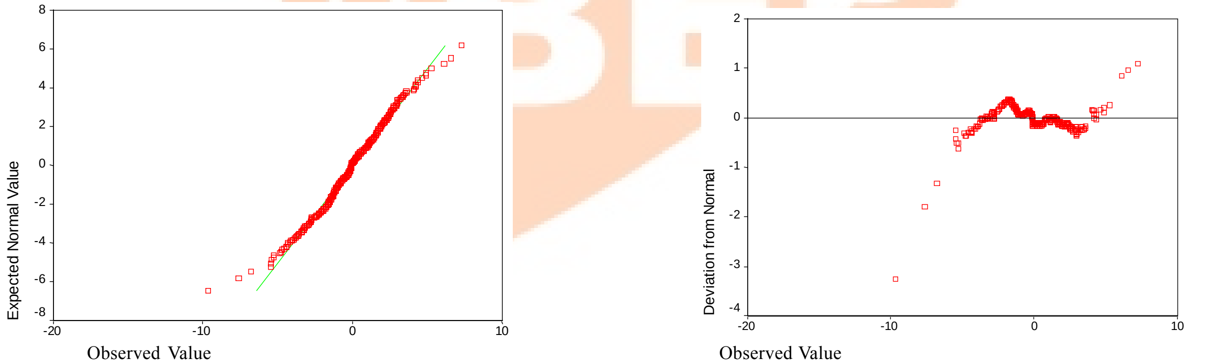


**Figure 2 :**
**Q-Q Plot and Detrended Q-Q Plot of the Empiric Ibovespa Excess Returns Distribution**

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 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[1], 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 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.

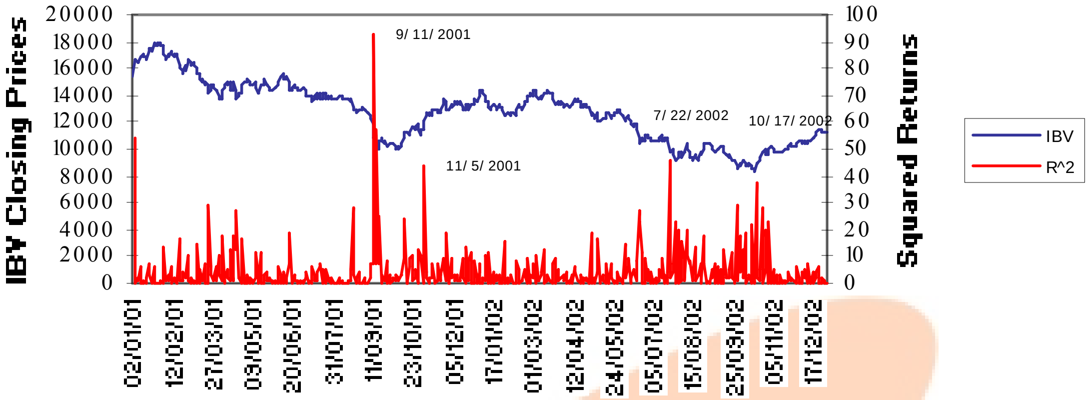


**Figure 3:**
**Ibovespa Index and Ibovespa Instantaneous Volatility**

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

**Table 2 :**
**Autocorrelation Tests for the Ibovespa Excess Returns and Instantaneous Volatility**

| | R | | | $R^2$ | |
|---|---|---|---|---|---|
| *P* | 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 the excess returns (Table 2). Serial autocorrelation was not detected in the Ibovespa returns alone, though, tests for the instantaneous volatility 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) states 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 excess returns (Table 3), which allows verifying strong evidence of heteroscedasticity, or ARCH effect, in the series.

**Table 3:**
**Tests for Heteroscedasticity for the Excess Returns of Ibovespa**

| Order | LM ARCH | Statistic | p-value |
|---|---|---|---|
| 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 heteroscedastic 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[1], 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 an 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 ($\eta$ = -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 mean $(\sigma_{m,t} - \overline{\sigma}_m)$, designated as *Dvol*, and the product of the difference of the volatility for Ibovespa excess returns $(\sigma_{m,t} - \overline{\sigma}_m)R_{m,t}$, designated as *DvolR*. As we can see in Figure 4, which exhibits the Ibovespa and *Dvol* for the period under analysis, it is possible to observe that volatility rises coincide with market falls.

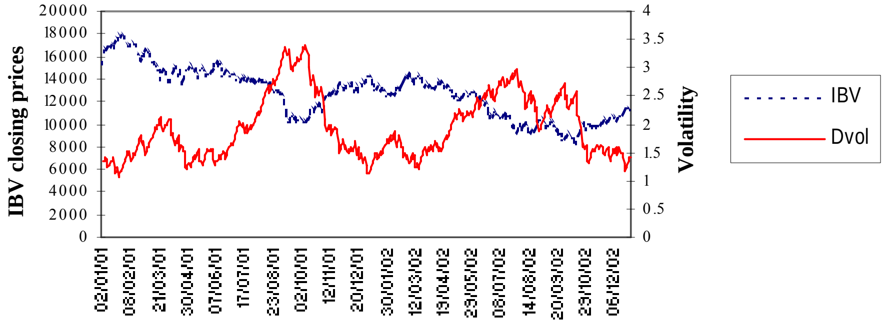


**Figure 4:**
**Conditional Volatility of Ibovespa Excess Returns Modeled by EGARCH (1,1) AR(1)**

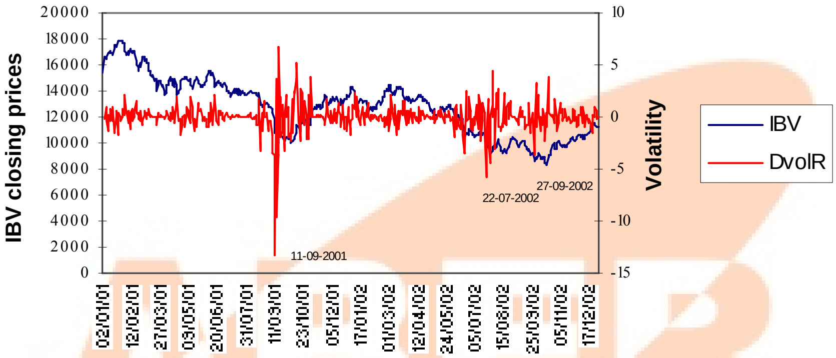


**Figure 5:**
**Ibovespa and the Product of the Difference of the Conditional Volatility for its Excess Returns**

Figure 5 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, $\gamma_c$, for the 60 funds, is shown in Table 5 below (full results are available in the appendix 3).

**Table 5:**
**Summary of Timing Estimates according to the Model of Busse**

| | | |
|---|---|---|
| Mean $\gamma$ | -0,0106 | |
| t stat | (-0,3989)** | |
| | Positive | Negative |
| $\gamma_c$ significant 5% | 0 | 6 |
| $\gamma_c$ non significant 5% | 20 | 34 |

** Significant at 1%.

It is expected that a mutual fund manager exhibiting ability of volatility timing to present the $\gamma_{mc}$ coefficient with negative sign, once it would reflect the manager's care 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 ($\gamma_{mc}$ <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 6 and Appendix 2), 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 | | | |

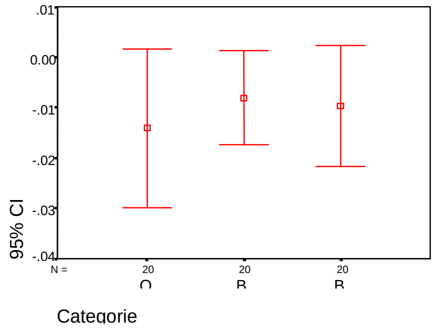


**Figure 6:**
**Gammas for Category of Mutual Funds**

As far as we know, this is the first time in Brazil that the mutual fund manager’s skills in identifying market instability 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.

## 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 able 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 falls and rises it is an important factor for risk managers, specially in unstable economies such as the Brazilian. 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.

## APPENDIX I : 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 $t+1$; $\beta_{jct}$ is the sensibility of the portfolio *c* to the factor j chosen by the manager on period *t*; $\alpha_{ct}$ 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:

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

---

[1] *The Bovespa Index (Ibovespa) refers to the São Paulo Stock index.*
[2] *The Selic interest rate is the rate on the overnight inter-bank loans collateralized by government bonds and it is publicized compounded per 252 working days a year.*
[3] *Andrezzo and Lima (1999) and Fortuna (2002) describe in detail the rule changes in Brazilian Fund Industry.*
[4] *For a more detailed discussion see Campbel, Lo and MacKinlay (1997, ch.12).*
[5] *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.*

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

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

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

$$\max_{\beta_{1ct},\cdots,\beta_{kct}} E_t\left[U_{t+1}(R_{c,t+1})\right] \tag{A4}$$

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

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

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

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

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:

$$\frac{\partial \beta_{jct}}{\partial \sigma_{j,t+1}} = \frac{1}{a\sigma_{j,t+1}^2}\left[\frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} - \frac{2E_t(R_{j,t+1})}{\sigma_{j,t+1}}\right] \qquad j = 1,\ldots,k \quad \textit{if} \quad \frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} \le 0 \tag{A8}$$

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 $\beta_{mc}$ and $\sigma_m$.

**APPENDIX II :**

Tests for distributions and mean equality of the gammas for 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.

## APPENDIX III :
## Performance Parameters for the Model of Busse

| I | α | t(α) | P(α) | | βc | t(β) | P(β) | γc | t(γ) | P(γ) | | $\beta_{t-1}$ | $t(\beta_{t-1})$ | $P(\beta_{t-1})$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***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*, $\alpha_c$ is the intercept, $\beta_0$ is the coefficient of the portfolio systematic risk, $\gamma_c$ 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 $(\sigma_{mt} - \sigma_m)R_{mt}$; and $\varepsilon_c$ 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.

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