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Mexican Stock Market Index Volatility

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Abstract

In order to determine which model explains with greater precision the historical performance of the Mexican Stock Market Index (IPC) the ARCH family models were applied. We analyze market volatility using daily returns of the index during the period 2000-2008, trying to avoid the incidence of the financial crises over stock markets on successive years. To analyze market volatility, GARCH EGARCH and TARCH models were compared according to traditional evaluation criteria. Finally we conclude that the EGARCH model (1.1) has the best predictive power.

Keywords: Garch, Egarch, Tarch Models, Prediction, Mexican stock market

1. - Introduction

For many years, in the academia and finance sector the following question has been subject of discussion and controversy: how to extent, the historical data of stock prices to predict their behavior? The answers to this question have been addressed firstly by the chartist theory and the theory of random walks. The focus of chartists' theories (primarily Dow Theory and Technical analysis) based on the same assumptions; assume that the historical data of asset price have much information that can be used to predict their behavior. The pattern of past prices tends to recur in the future, that is, history repeats itself.

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Thus, an analysis based on this approach to identify patterns can be used to predict future behavior of prices and thus increase expected profits (Murphy, 2000).

In contrast, theory of random walks says that stock prices are determined in a random walk, its mean, cannot predict future prices from past prices (Fama, 1965). In statistical terms, theory says that the price changes are random variables, independent and identically distributed (Johnston & Dinardo, 1997). That is, past prices do not provide such information that can be used to predict future prices. Fame (1970) proposed three levels of market efficiency with respect to the information reflected in prices. The weak form holds that the history of stock prices does not contain information that can be used to obtain yields above which gives a random portfolio.

Therefore, in an efficient market in its weak form, prices follow a random walk. In semi-strong market efficiency prices even reflect public available information. With strong market efficiency prices add private information.

Fame (1970) proposes three levels of markets efficiency in relation to the information of prices. The weak form sustains that the track record of stock prices does not contain information that could be used to obtain higher yields than those obtained by a portfolio of stocks, even taken at random. Hence it is written that in an efficient market in its weak form, prices follow a random walk. A market have semi-strong efficiency, whether in addition the above, the prices reflect the publicly available information. An efficient market is strong, whether in addition the above, the prices reflect private information.

In order to verify these assertions (despite the difficulty to test the semi-strong and strong efficiency) some statistical tests were developed to determine whether stock prices follow a random walk, example of this is: serial correlation analysis, unit root test and the variance ratio. The majority of the researches for developed countries and Latin American markets (Worthington and Higgs, 2006; López, 1998, 2004; Ramírez, 2002) have found the presence of autocorrelation of stock returns, so random walk hypothesis it is rejected. In the last twenty years, several time series models have been proposed to represent the information of generation process on the basis of characteristics of the series of interest, the empirical evidence about behavioral and financial time series modeling show a more outstanding characteristic (Fama, 1965; Lamoureux & Lastrapes, 1990; Hassan, Islam & Abul, 2000; Geng, 2006; Balaban, Bayar & Faff, 2003; Ebeid & Bedeir, 2004), following it describes.

i) Variance of series is not constant along the time, which violates the assumption of homoscedasticity from traditional models.
ii) Substantial changes and conditioned volatility clusters in which the volatility is followed by high volatility and low volatility is followed by low volatility. This behavior suggests that the volatility of financial series is determined by an autoregressive process (serial correlation) and non-constant variance (heteroscedasticity).
iii) The distribution of gains although centered in zero show lightweights bias and the kurtosis value is greater relative to standard normal (excess kurtosis), implying biased results when assuming normality.
iv) Volatility effect on stock prices. Bad news and good news affect the volatility in different ways: the first ones have greater effect than the seconds' ones, therefore, if the volatility incremented, prices fall and vice versa, which allows observing a negative correlation.

The above results show the importance of modeling the financial series incorporating volatility (risk). From Engle (1982) famous work: *Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation*, a family of models of autoregressive conditional heteroscedasticity (ARCH) have been developed, mostly used to explain the volatility of financial yields.

With regard to empirical evidence, there are a large number of studies that used ARCH models to analyze the behavior of volatility. In particular, we identify models that are more predictive for ex-post forecasts.

Geng (2006) applies ARCH family models to analyze the characteristics of the volatility of the Chinese stock market. Compares several models by using standard criteria and concludes that the model EGARCH (1,1) and EGARCH-M model (1.1) have the same efficiency to forecast series. Ebeid & Bedeir (2004) evaluates the capacity of ARCH models to forecast stock market yields from Egypt and concludes that the GARCH (1,1) model is more appropriate for modeling the volatility of the market price index. Ludlow and Mota (2006) analyzes the financial markets volatility based on three indexes (IPC, Nasdaq, S & P500) using a multivariate model GARCH (1,1) and conclude that shocks derived from bad news have an impact with more force on market deeper.

The work of Lopez (2004) evaluates the contribution of three models of the family ARCH (GARCH (1,1), TARCH (1,1), EGARCH (1,1)), for modeling the behavior of the Mexican stock market based in the IPC.The criterion used for the evaluation was; verify if the forecasted values of the IPC, once modeled the volatility, is capable of reproducing the first four moments of the distribution of the IPC. Concludes that the EGARCH (1,1) has better qualities to predict.

The purpose of this work is to analyze the features of the volatility of the stock market in Mexico and identify the model with the best predictive ability. To this end, we apply the ARCH family models using daily returns of the Mexican stock market index. To identify the model with the highest predictive ability, it follows closely the work of Lopez (2004).

The preparation of this exercise was justified by the great attention given the volatility term, not only by academics but also by investors in the stock market in Mexico which requires a measure of risk when making transactions. The investment portfolio design, the fixing of prices, calculation of value at risk, and financial strategies, justify the importance of modeling and forecasting the conditional volatility of returns. The main conclusion of this paper presents empirical evidence for EGARCH models for forecasting effects of ex-post.

The work is organized as follows: second section presents the theoretical conceptualization of ARCH and GARCH models of Engle (1982), Bollerslev (1986), Zakoian (1990) and Nelson (1991). Third section presents the results of the estimation, statistical tests and forecasts. Fourth section presents the main conclusions.

2. Models

To capture volatility characteristics, Robert Engle (1982) propose to model the conditional volatility through a conditional heteroscedasticity autoregressive process (ARCH) in which the process mean is zero and variance dependent on conditional the random errors passed.

However, empirical evidence shows that it requires a large amount of remnants to capture the dynamics of the conditional variance.

Bollerslev (1986) developed a special technique using an ARMA process to the conditional variance of errors called GARCH (p, q) which has an autoregressive component and moving average on heteroscedastic variance.

The advantage of GARCH about the ARCH model is that the GARCH model could to have more parsimony and representation that it is easier identify and estimate. The GARCH model is denoted as follows:

$$y_t = x_t' \gamma + \varepsilon_t \qquad (1)$$

$$\varepsilon_t = v_t \sqrt{\sigma_t^2} \qquad (2)$$

Where:

$$\sigma_v^2 = 1, \qquad (3)$$

And to model GARCH (1,1)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (4)$$

Like in the ARCH model v_t , is white noise process which is independent from the past achievements of ε_{t-i}. The conditions over the parameters that guarantee the stability of the model are: $\alpha_0 > 0, \alpha_1 + \beta_1 < 1$.

The conditional variance depends upon three terms: the mean α_0, information on the volatility of the previous period measured by the lag of the squared residuals (ARCH term) obtained from equation 1); and the last period forecast variance (GARCH term).

GARCH model (p, q) is:

$$\varepsilon_t = v_t \sqrt{\sigma_t^2} \quad (5)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 \quad (6)$$

The conditions on parameters are:

$$\alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_j \geq 0 ,\quad \alpha_1 + \alpha_2 + \cdots + \alpha_q + \beta_1 + \beta_2 + \cdots + \beta_p < 1 \quad (7)$$

Despite the fact that GARCH model is used to forecast volatility and determine the behavior of prices, there are situations that GARCH model cannot explain. The biggest problem is that standard GARCH models assume that the error terms positive and negative have the same symmetrical effects on volatility. That is, good news and bad news have the same effect on volatility in this model. The exponential GARCH (EGARCH) and Threshold ARCH model (TARCH) describe asymmetric market response under positive and negative impacts.

EGARCH model of Nelson (1991) is denoted as

$$\ln(\sigma_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i g(v_{t-i}) + \sum_{i=1}^{p} \beta_j \ln(\sigma_{t-j}) \quad (8)$$

$$g(v_t) = \varphi_i v_t + \left| \frac{\varepsilon_t}{\sqrt{\sigma_t}} \right| - E \left| \frac{\varepsilon_t}{\sqrt{\sigma_t}} \right| \quad (9)$$

When $\varphi \neq 0$, the effects of information are asymmetric. When $\varphi < 0$ there is presence of effect “leverage”. There are not restrictions on parameters, which is an advantage of EGARCH model compared with the GARCH model.

TARCH Model proposed by Zakoian (1990) have the follow expression:

$$\sigma_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \varphi \varepsilon_{t-1}^2 d_{t-1} + \sum_{i=1}^{p} \beta_j \sigma_{t-j} \qquad (10)$$

Where d is a latent variable

$$d = \begin{cases} 1 & \varepsilon_t < 0 \\ 0 & \varepsilon_t \geq 0 \end{cases} \qquad (11)$$

In this model, good news ($\varepsilon_t < 0$) and bad news $\varepsilon_t \geq 0$ have different effects on conditional variance. Good news has an impact of α while bad news has an impact $\alpha + \varphi$. If $\varphi > 0$ there is leverage effect. If $\varphi \neq 0$ the impact of news is asymmetric.

3. Estimation and Testing

3.1 Data

To carry out the estimation of the ARCH model, index of the Mexican Stock Market (BMV) are used. The daily yields are calculated as:

$$R_t = \ln(IPC_t / IPC_{t-1}).$$

Time series of IPC as representing the "price" of the stock market is used due to IPC is the main indicator of yields offered by investment in shares traded on the BMV and it consists of a sample of stocks with higher trading volume weighted on the basis of the proportion they have on market capitalization.

Data used were daily closing of the IPQ, including all days of operations of the BMV for the period January 3th, 2000 to July 11th, 2008. We didn´t considere successive values in order to avoid stock return volatilities due to the impact of the recent global financial crises called the first largest crisis after the recession of 1930s (Ali and Afzal, 2012).

In total 2136 observations, published in http://mx.finance.yahoo.com/. For data processing excel spreadsheet was used and to estimate the E-views 3 package was used.

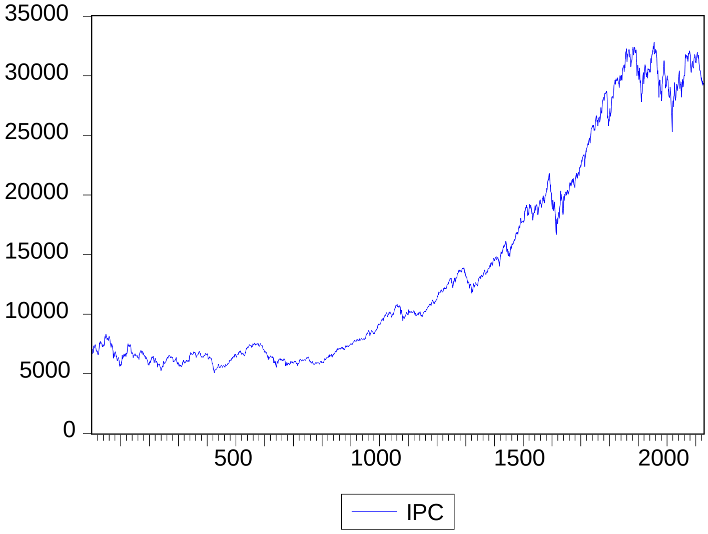
To identify the model which allows us to explain with more accuracy the historical performance of the IPC, and to obtain forecasts, the following methodology is used:

a) 2127 sample observations are used to adjust the models.
b) Volatility is modeled and the best model based on standard evaluation criteria (Akaike criterion, Schwarz criterion and value of the maximum likelihood function) is selected.
c) With the resulting models, nine periods forward (July 1st to July 11th, 2008) are forecast and the results with real data from the same period, are compared.
d) Accuracy measures are calculated (mean square error, mean absolute error, theil inequality coefficient and decomposition of the mean square error). This, because they allow evaluating the forecasts, and the model in which the difference between the forecasted values and real values is minimal, is chosen.

3.2) Description of the Information

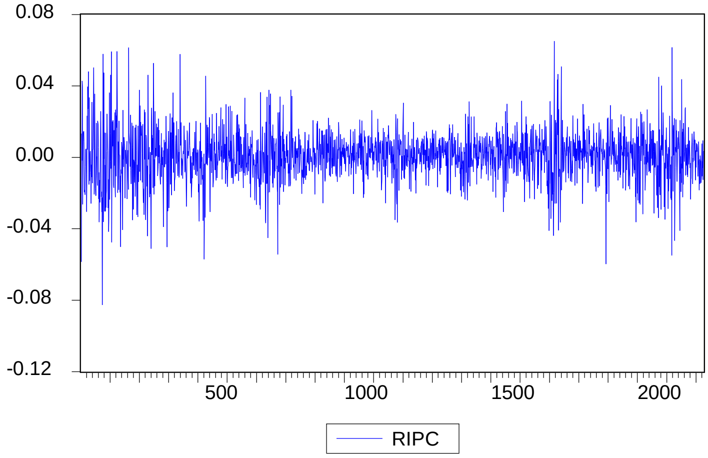
This work begins obtaining a graph of the IPC in order to consider appropriate initial transformations. In graph 1 it can be observed an increasing tendency of the IPC over time, starting from an intercept. The graph is very similar as a random walk with trend.

Graph 1: Historical IPC



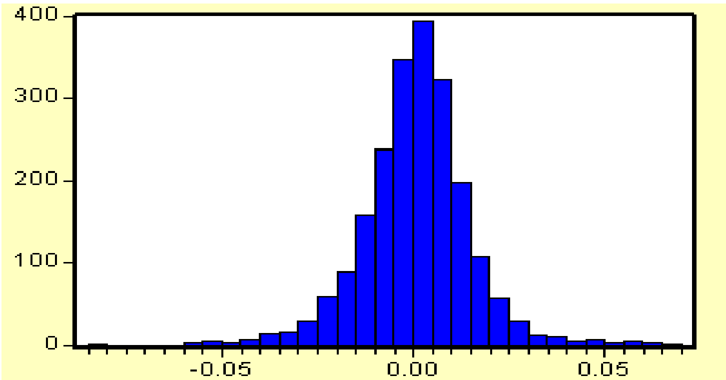
Daily yield of the IPC over the sample period are presented in Graph 2 and it is possible to observe that series consistently fluctuates around zero, it´s variance is not constant through time and shows an autocorrelation behavior.

Graph 2: Yields of IPC



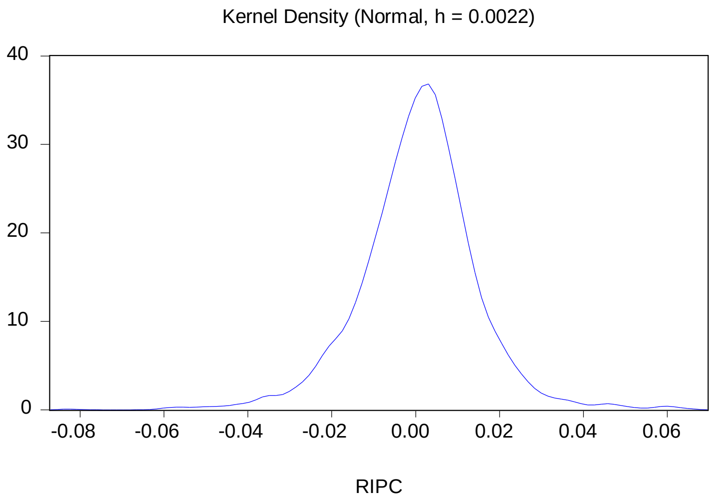
Properties of the returns distribution of the IPC (histogram) are shown in Graph 3. The histogram of the series remains centered at the zero with a slight negative bias (-0.1059) and a kurtosis value of (5.7674), which shows excess kurtosis with regard to the standard normal.

Graphic 3: Histogram yields IPC



The estimated distribution of the yields (Kernel Epanechnikov, with Silverman bandwidth value h = 0.0022) is shown in Graph 4, in which is again observed the excess kurtosis. The Jarque Bera test rejects the normal distribution in yields of the IPQ (Jarque Bera = 682.4052).

Graph 4: Estimated Distributions of the IPQ Yields



Statistically, the risk or volatility is the dispersion of the yields. Daily performance (average profitability) for the period under review is 0.000670 and the risk (standard deviation) per day is 0.014114, which reflects the high volatility of the Mexican Stock Index. Table 1 summarizes the descriptive statistics in yields of the IPC.

Table 1: Descriptive Statistics in Yields of the IPC

Statistics	**Value**
Mean	0.000670
Median	0.001179
Standard Deviation	0.014114
Bias	-0.105974
Kurtosis	5.767421

Source: own

3.3 Unitary Root Test

In order to detect if the IPC yields series covariance is stationary, unit root test is carried out with the statistical Dickey-Fuller. Results are shown in Table 2.

Table 2. Unitary Root Test

Augmented Dickey – Fuller Unit Root Test on RIPC			
ADF Test Statistic	-21.56508	1% Critical Value*	-3.4364
		5% Critical Value	-2.8634
		10% Critical Value	-2.5678
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Source: own

It was confirmed that the series RIPQ has not unit root, therefore, we can apply the conventional methodology of analysis for time series stationary in covariance.

3.4 Models

For adjusting the model series RIPQ, the AR and MA terms defining the process are identified, using 2127 observations.

Different estimates were carried out by ordinary least squares and based on the Akaike, Schwarz and Log Likelihood criteria, the following ARMA (5,1) was chosen. The results are summarized in table 3.

$$RIPQ_t = \varphi_0 + \varphi_1 RIPQ_{t-1} + \varphi_5 RIPQ_{t-5} + \theta_1 \xi_{t-1} + \xi_t \qquad (12)$$

Rescuing the residual of the model, is verified through the ARCH-LM test (Lagrange multipliers) In order to get the residual of model, we may identify trough test ARCH-LM (Lagrange multiplications), if the squared errors (conditional variance are correlated with its past.

Test result shows that errors are correlated with their immediate past, which indicates that we have ARCH effects (1) in the ARMA model. The RIPQ series is volatile.

These results suggest modeling the effect of the autoregressive conditional volatility, therefore, a GARCH (1,1) model is proposed, thus we obtain the following equation:

$$RIPQ_t = \varphi_0 + \varphi_1 RIPQ_{t-1} + \varphi_5 RIPQ_{t-5} + \theta_1 \xi_{t-1} + \xi_t \qquad (13)$$

$$\sigma^2 = \alpha_0 + \alpha_1 \xi_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (14)$$

When estimating jointly the equations 1) and 2) by the method of maximum likelihood, it is observed that the parameters of the terms AR (1), AR (5), MA (1), ARCH (1) and GARCH (1) is significant according to statistical z.

As shown, the value of the sum of the coefficients of ARCH and GARCH term (0.081392 + 0.89368 = 0.975072) is very close to 1, which shows the existence of high volatility. This suggests that given the possibility of a shock expected market the fluctuations do not stop in the near term. This is a signal of high risk. Similarly, considering that the sum of both parameters is less than unity, the proposed GARCH (1,1) model is a stationary process.

In order to verify this, the WALD test was performed. The test ARCH-LM shows that are not taken problems of heteroscedasticity in the model.

For describing the asymmetric market response under positive and negative shock, we proceed to estimate the EGARCH (1,1) model and TARCH (1,1) model.

The first results show that skewness coefficient is statistically different from zero (z = -6.104619) and negative (-0.117746) which gives evidence of leverage effect on the Mexican Stock market for the sample period. This is, volatility caused by negative shocks is greater than those caused by positive shock.

Results of the second model show that the asymmetry coefficient is statistically different from zero (z = 5.776392) and positive (0.163874), which also shows evidence of leverage effect. This is consistent with the bulk of the research.

Table 3: Parameter Estimates and Diagnostics of the Models

	Models			
Terms ARMA	AR(1), AR(5), MA(1)	AR(1), AR(5), MA(1)	AR(1), AR(5), MA(1)	AR(1), AR(5), MA(1)
Parameters	ARMA(5,1)	GARCH(1,1)	EGARCH(1,1)	TARCH(1,1)
ϕ_0	0.000660 (0.000312) 2.114489	0.00128 (0.000253) 5.071421	0.000786 (0.000260) 3.019394	0.000877 (0.000260) 3.376556
ϕ_1	-0.378290 (0.131065) -2.886274	-0.315002 (0.120769) -2.608306	-0.300079 (0.121641) -2.466918	-0.343568 (0.123114) -2.790641
ϕ_5	-0.055764 (0.020027) -2.784496	-0.059082 (0.021191) -2.788073	-0.048604 (0.020582) -2.361544	-0.050880 (0.021108) -2.410490
θ_1	0.481759 (0.124842) 3.858934	0.404675 (0.116990) 3.459058	0.392119 (0.118283) 3.315092	0.436423 (0.119088) 3.664721
ARCH(1)		0.081392 (0.013212) 6.160275	0.128319 (0.020068) 6.394098	0.006874 (0.012468) 0.551294
GARCH(1)		0.899368 (0.016351) 55.00287	0.965980 (0.008411) 114.8426	0.877360 (0.016949) 51.76405
φ_1			-0.117746 (0.019288) -6.104619	0.163874 (0.028370) 5.776392
Standard error of regression	0.013906	0.013932	0.013923	0.013922
log likelihood	6060.702	6242.034	6286.126	6279.839
Akaike criterion	-5.711176	-5.879334	-5.919968	-5.914039
Schwarz criterion	-5.700502	-5.860656	-5.898621	-5.892692
F-statistic	12.03360	5.137749	4.951903	4.995343
ARCH-LM test	F= 38.89053	F= 0.403016	F=0.20484	F=0.360630
Observations	2127	2127	2127	2127

Note: the values in each box are the coefficients of each term, their standard errors and the value of z-statistic, respectively.

Source: own

It is observed in table 4, when comparing the values of the mean square error and the mean absolute error associated with the prediction of each of the models, that EGARCH model (1.1) has the minimum value, which suggests that the best model to forecast the IPC. Similarly, the coefficient value of inequality of Theil associated to EGARCH (1,1) is minimum, indicating that is the best fit model. However, the decomposition of the mean square error given by the bias ratio variance and covariance shows that GARCH (1,1) overcomes the other models. According to the value of the errors of each of the models, the forecast errors (proportion of bias and proportion of variance) are very large, up from 0.1 for the case of bias, which means the presence of a systematic bias (Pindyck, 2001).

Table 4: Assessment of Predictive Ability of the Models

Indicator	GARCH(1,1)	EGARCH(1,1)	TARCH(1,1)
Root mean square error	1345.00	1260.474	1274.684
Mean Absolute Error	1234.881	1158.502	1171.084
Theil inequality coefficient	0.023207	0.021778	0.022018
Proportion of bias	0.842957	0.844744	0.844056
Proportion of variance	0.064700	0.091298	0.085941
Proportion of covariance	0.092344	0.063958	0.070004

Source: own

4. Conclusions

To determine which is the model that explain more precisely the behavior of the Mexican Stock Market Index for the period January 3th, 2000 to July 11th, 2008 has been used an ARMA model (5.1) in which the ARCH effects are identified, so the process is modeled through the models from the ARCH / GARCH family.

The findings of this research provide evidence on the existence of highly persistent volatility of returns of the IPC. The significance of the asymmetry parameters about TARCH and EGARCH models suggest the existence of the leverage effect. The volatility of returns of the IPC caused by the bad news is greater than those caused by the good news. The above evidence is consistent with the bulk of research on the volatility of returns of stock prices and stock indices.

GARCH (1,1), EGARCH (1,1) and TARCH (1,1) models, allow us suitably adjust the IPC series.

However, the EGARCH (1,1) model shows to be the best model for estimating according to the standard evaluation criteria. The forecasting results by using the three models, give evidence that the EGARCH (1,1) model has the best predictive capability.

Finally we can say that the forecasts obtained from these results, show the rapidity with they tend to their unconditional mean, which indicates, that the forecast horizon of these models is very short, provides immediate predictions (2 -3 days) before stabilizing .

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