"Do Asymmetric Garch models fit better exchange rate volatilities on emerging markets?"

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1. INTRODUCTION

As documented by Bollerslev, Engle and Nelson (1994), financial time series are generally characterized by the presence of fat-tails and volatility clustering. Therefore, the assumption of constant volatility is unsuitable and can drive to high levels of inaccuracy. However, another characteristic, asymmetry, is not a common attribute to all financial series. Even though, evidence of disparities in the volatility response to negative and positive returns has been described by several authors, it is believed only to exist on stock market returns. For example, Nelson (1990), based on an argument of Black (1976), documented the so-called "leverage effect" on stock returns using series from the US market. Additionally, Engle and Ng (1990) also reported asymmetry findings on a daily series of the Topix from 1980 to 1988.

As a result, no formal evidence of asymmetry behaviour has been found out of stock time series, especially in developed country exchange rates. In this context, the objective of this paper is to expand the analysis to emerging market time series. As the author believes, a thorough understanding of this data was not possible during and before the 1990's due to the side-effect of financial and banking crises. The latter events, triggered hyperinflation and instability which created uncontrolled devaluations and highly manipulated exchange rates.

Furthermore, this paper mainly aims at applying standard financial econometric tests to assess the performance of symmetric and asymmetric volatility models. The author will not stress on the original cause of asymmetry and the fundamental question, whether or not emerging markets should display different characteristics from developed ones. However, the author has based his analysis on an adaptation of the so-called *"volatility feedback hypothesis"* by Campbell and Hentschel (1992). A shock will raise the market volatility and the risk of holding a specific emerging market currency. This induces a portfolio shift out of it, leading to a depreciation of the exchange rate[1]. In other words, if the exchange rate is understood as the emerging market exchange nominal value needed to acquire one US dollar, a depreciation has to be treated as an increase in the nominal exchange rate and hence a positive return.

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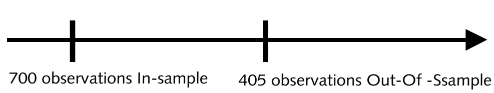
[1] A similar application of this hypothesis in a developing country can be found in Longmore R. and Robinson W. (2004).

2. METHODOLOGY AND DATA

Data

The analysis has been performed using daily exchange rate series from 2000 to 2004 of 7 countries in Asia and Latin America excluding the 10 world biggest economies. The selected countries were Brazil, Chile, Colombia, India, Mexico, South Korea, and Thailand. All information was obtained from Thomson DataStream and the selection criteria included among others, features such as exchange regime type and availability of information.

Every series has been divided in the following way. The first 700 observations constituted the In-Sample, the last 405 observations were left for the out-of sample set of data. The length of the first window was 400 and it started on day 501. The methodology included a one day volatility forecast on the out-of –sample series using an expanding window.



Modelling the conditional mean

It is well-known that failing to choose a good model for the conditional mean could generate autocorrelation in the squared residuals. Therefore, the author has chosen (when needed) among the family of the ARMA(p,q) models, a process to capture any dynamics on the conditional mean. The procedure consisted on plotting the autocorrelation functions and performing the corresponding Ljung Box test on each series of currency returns. A model for the in-sample conditional mean was chosen based on the Akaike and the Schwarz's Bayesian information criteria.

- Information Criteria

The MSE (mean squared error) always decreases when a new variable is added to certain regression even though this variable has no explanatory power. As a result, to overcome this problem, information criteria add a penalty term to the MSE. Being AIC (Akaike) and BIC (Schwarz's Bayesian) two information criteria, the best model can be selected minimizing the followings expressions,

$$AIC = \exp\left\{\frac{2k}{T}\right\}\frac{1}{T}\sum_{t=1}^{T} e_t^{2} \qquad BIC = T^{k/T}\,\frac{1}{T}\sum_{t=1}^{T} e_t^{2}$$

Where *k* is the number of parameters.

Modelling the conditional volatility.

After selected the best model for the conditional mean, the author proceed to plot the autocorrelation of the squared of the residuals to examine any dependence that could be captured using a GARCH model. At the same time, Ljung-Box test p-values are reported for each of the currencies. Three different Garch processes are fitted to the in-sample residuals; GARCH, EGARCH and GJR-GARCH processes. The evaluation method was developed as follows.

First, each model was cross-evaluated using values for AIC and BIC information criteria and the Maximum likelihood ratio test (wherever applicable). Additionally, in order to pass the first filter, currency return series had to have statistically significant coefficients for the GARCH-GJR and EGARCH models jointly.

Second, the author applied a more straight-forward filter on the currency returns to analyse if asymmetric Garch models outperform the symmetric Garch in-sample. For this purpose, a Mincer-Zarnowitz regression tested for any difference in explanatory power hence in optimality between the three models.

Finally, if any currency had still been successful in the two previous steps, the author tested the volatility models forecasting power using a Diebold-Mariano test. This test has been left to the end because the author thinks it has the lowest rejecting power. The Diebold-Mariano Test was implemented in-sample and out-of-sample. Conclusions will be related to the findings in these three filters.

■ GARCH Family models

The three processes used in this paper to analyse the existence of asymmetry in developing exchange markets are: The GARCH, The GARH -GJR and the EGARCH.

The *GARCH* (p,q) model was first developed by Bollerslev (1986) as a response to several drawbacks of the ARCH(p) of Engle (1982). When applied to the volatility of a financial time series, a Garch(1,1) process can be written as:

$$\sigma^2_{t+1} = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2 \qquad E(\varepsilon_{t+1}|\Omega_t) = 0$$

Where σ_t is the conditional volatility and ε_t is a white noise representing the residual of the return process. In order to have a non-explosive process, $\alpha+\beta$ is restricted to be less than one. The innovation term could follow a normal, a t-student or any other distribution such as the GED distribution yet, the normal distribution makes the model easily estimated.

The *GJR-GARCH* (p,q,δ) was published by Glosten, Jagannathan and Runkle (1993). It is a similar version to the TARCH of Glosten and Zokodian (1990), yet, the conditional variance is modelling instead of the conditional standard deviation. The GJR-GARCH (1,1,1) can be written as,

$$\sigma^2_{t+1} = \omega + \alpha\varepsilon_t^2 + \delta\varepsilon_t^2 1\{\varepsilon_t < 0\} + \beta\sigma_t^2$$

Where, the new term δ, counts for any asymmetry on the volatility response to negative and positive returns. If δ is positive, negative and positive past returns will affect the variance in a magnitude of ($\alpha+\beta$) and α respectively.

The *E-GARCH* (p,q,γ) by Nelson (1991) is another flexible alternative to model asymmetric response of volatility to different return signs. As a main characteristic, the E-GARCH coefficients are not constraint by $\alpha+\beta<0$ because σ^2_t is replacing by its log. A general representation of an Egarch(1,1,1) model is,

$$\ln\sigma^2_{t+1} = \omega + \alpha\left|\frac{\varepsilon_t}{\sigma_t}\right| + \gamma\frac{\varepsilon_t}{\sigma_t} + \beta\ln\sigma_t^2$$

- Maximum likelihood ratio test

An alternative technique to assess the efficiency of volatility models is to establish if two models are different in terms of their Maximum likelihood function. Let LLF_1 and LLF_2 the maximum likelihood values of two volatility models. Let the first model be a constrained version of the second one. The statistic will be,

$$Q_{LR} = -2 * Ln\left(\frac{LLF_2}{LLF_1}\right) \sim X^2$$

Where X^2 is a Chi-squared random variable with 1 degree of freedom (In this special case the GARCH-GJR is just adding up one parameter to the constrained general Garch).

- Mincer-Zarnowitz regression.

The Mincer-Zarnowitz regression regresses the variance proxy, e_t^2(squared residuals) against the conditional variance generated by each of the three models $\hat{h}_t$. In order to consider a forecast optimal, the c and β coefficients have to be statistically equal to 0 and 1 respectively. A Mincer-Zarnowitz regression will be

$$e_{t+1}^2 = c + \beta\hat{h}_{t+1} + \eta_{t+1}$$

Where,

$$H_0: c = 0 \text{..and..} \beta = 1$$
$$H_1: c \neq 1 \text{..and..} \beta \neq 1$$

Using the fact that $E\left[e_{t+1}^2\right] = \sigma_{t+1}^2$

Optimality in this context means that the model is optimal with respect to the information that was utilized to create it. It is important to notice that the squared residuals are used because the volatility is an unobserved variable even when the set of information has been updated.

- Diebold-Mariano Test

The Diebold-Mariano test is a complementary method to compare forecasts of two different models in terms of the expected loss observed when using them. This expected loss is calculated following a loss function, which for this particular case will be the *Squared Errors*. The methodology of the D-M test can be summarised as:

First calculate each of the squared error series for every volatility model using the following formula,

$$\text{Squared...errors} = L(\hat{\sigma}_t^2, h_t) = (\hat{\sigma}_t^2 - h_t)^2$$

Then, create a variable that counts for the differences between the squared error series from two separate forecasts,

$$d_t = (e_t^A)^2 - (e_t^B)^2$$

Finally, test the null hypothesis that the expected value of d_t will be 0.

$$H_o = E[d_t] = 0$$

If the previous null hypothesis were rejected, it would mean that the series of squared errors are different and hence, there is a statistically significant disparity within the two forecasts tested.

The t-statistics of the test will be,

$$DM = \frac{\bar{d}}{\sqrt{\hat{V}[d]}} \sim N(0,1)..as..T \to \infty$$

Even though this is a quite straight forward procedure, it is not taking into account the possibility of autocorrelation on d. For this reason, a stronger variance estimator, the Newey-West, is used. Thus, the complete variance formula will be,

$$\hat{V}[d] = \frac{1}{T}\hat{V}[d_t] + \frac{2}{T}\sum_{j=1}^{M}\left(1 - \frac{j}{M+1}\right)\widehat{Cov}[d_t, d_{t+j}]$$

where, the first part relates to the normal t-statistic and the second consider the effect of autocorrelation in the series d. Generally, the sum on the covariances is truncated at a value *M* which could be calculated using the following formula,

$$M = 4\left(\frac{T}{100}\right)^{\frac{2}{9}}$$

3. RESULTS

As shown in A*ppendix 1*, three of the seven exchange rate return series evidence autocorrelation on the returns. These currencies are the brazilean real, the Chilean Peso and the Indian Rupee. To model this condition, the author selected and ARMA(2,2), a AR(2) and an ARMA(2,1) process respectively. As mentioned before, the selection has been based on results provided by the AIC and BIC information criteria and only aims to eliminate any autocorrelation that could pass from the residuals to the squared residuals (*Appendix 2.*).

Having extracted the conditional mean from the return series, the author moved to plot the autocorrelation of the squared of the residuals. (*Appendix 3.*). asymmetric and symmetric models to all the series were applied finding that the GARCH model successfully captured some dynamics in all the variance processes.

Evaluating the BIC and AIC information criterion, as well as the likelihood ratio test results, the author observed that only in four of the seven currencies, the asymmetric Garch models showed a significant difference with the standard garch. Therefore, our sample of currencies reduced to four series; Brazil, India, Mexico and South Korea.

Before moving on to analysis more thoroughly the results on the corresponding series, the author would like to emphasise that even though the tests did not show high levels of statistical significance, the majority of the coefficients of the asymmetric GARCH models showed a negative γ in the GJR. Even strange at first sight, it has to be remained that nominal exchange rates were calculated using local currencies per one US Dollar. Inverting the scale will cause the following effect. The coefficient γ will change sign and redistribute its value with α. However, no changes in the Likelihood optimum values were reported hence the conclusions found by the likelihood ratio test and the information criteria are still valid.

After discarded three of the seven currencies, a Mincer-Zarnowitz regression on the South Korean Won, the brazilian real, the Indian rupie and the Mexican peso return series was fitted. As examined on *Appendix 5*, All the regressions against the in-sample forecast of the Garch-variance, showed a clear lack of explanatory power and sub-optimality in the models. The coefficients β was always below 1 therefore, the null hypotheses ($C=0$ and β=1) was always rejected. In regards to the GARCH-GJR and the E-GARCH, the null hypotheses were rejected in two of the four cases. It seems that only in the Korean Won and India Rupie series the asymmetric models forecast could not outperform the garch volatility estimates.

Finally, *Appendix 5* also shows the application of the Diebold-Mariano test. As mentioned before, the main objective of the test is to distinguish between two forecasts in terms of the minimization of certain loss function. In-sample, tests do not confirm the results obtained before. Even in the best case (Brazilian real), the argument of an EGARCH outperforming the GARCH forecast can only be accepted at the 90% confidence level. In the author's opinion this confidence level is not sufficient. Additionally, for the GJR forecast, the D-M test has not found any significant difference with the General GARCH's.

Out-of-Sample Evaluation.

the D-M test showed in some cases higher t-statistics compared to those obtained in-sample. However, the null hypotheses are not rejected either. This result wiped out completely the in-sample weak evidence of asymmetry. Neither the brazilian real not the Mexican peso shows evidence of volatility asymmetry response in the out of sample series.

4. CONCLUSIONS

The set of emerging market exchange rates did not show generalised asymmetric evidence. Out of a sample of 7 countries, only two series, the brazilian real and the Mexican peso managed to pass the first two steps of our analysis. However, the asymmetric effects on the latter were not sufficiently strong to overpass our strongest test, the Diebold-Mariano. Two main conclusions can be extracted from these results.

- An analyst interested in modelling volatility of an emerging exchange rate series for pricing has to be aware of the possible effect of asymmetry. However, on average, a practitioner involved in forecasting will not obtain a statistically significant better forecast when shifting from a symmetric to an asymmetric GARCH model.

- It is also essential to highlight the different results obtained In-sample and Out-of-sample. It could be stated that practitioners who were to analyse data in-sample would obtain in average more optimistic results that the one obtained by practitioners using an out-of-sample approach. Therefore, the conclusion in this paper, absence of statistically significance between asymmetric and symmetric models in developing exchange rate series, is conditional to the fact of applying in-sample and out-of-sample tests jointly.

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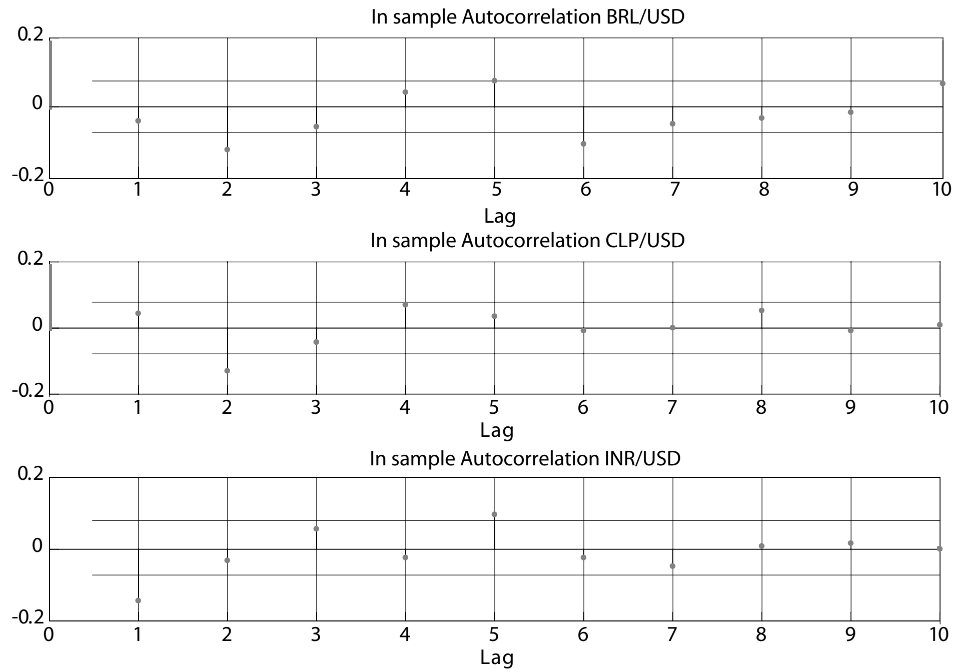
APPENDIX 1. IN-SAMPLE AUTOCORRELATION OF RETURNS

In-Sample Autocorrelation graphs



Ljung-Box Test P-values at 5%.

	COP/USD	BRL/USD	CLP/USD	MXN/USD	KRW/USD	THB/USD	INR/USD
QLB(1)	0,242535	0,271773	0,227573	0,651802	0,315835	0,958304	0,000103
QLB(2)	0,244362	0,003604	0,00082	0,509912	0,188429	0,847174	0,000324
QLB(3)	0,420402	0,003744	0,001509	0,375721	0,295907	0,238648	0,000385
QLB(4)	0,549441	0,005276	0,00083	0,503753	0,292317	0,346512	0,000915
QLB(5)	0,691894	0,002083	0,00131	0,332657	0,047253	0,244182	0,000137
QLB(6)	0,705494	0,000195	0,002843	0,357723	0,081658	0,260631	0,000263
QLB(7)	0,725323	0,000233	0,005707	0,397898	0,110353	0,359343	0,000319
QLB(8)	0,794705	0,00037	0,004883	0,428671	0,163132	0,450019	0,000672
QLB(9)	0,72894	0,000721	0,008623	0,276843	0,011363	0,518614	0,001255
QLB(10)	0,242535	0,271773	0,227573	0,651802	0,315835	0,958304	0,000103

APPENDIX 2. IN-SAMPLE MODELLING OF CONDITIONAL MEANS

* Coefficients not significant at 5%.

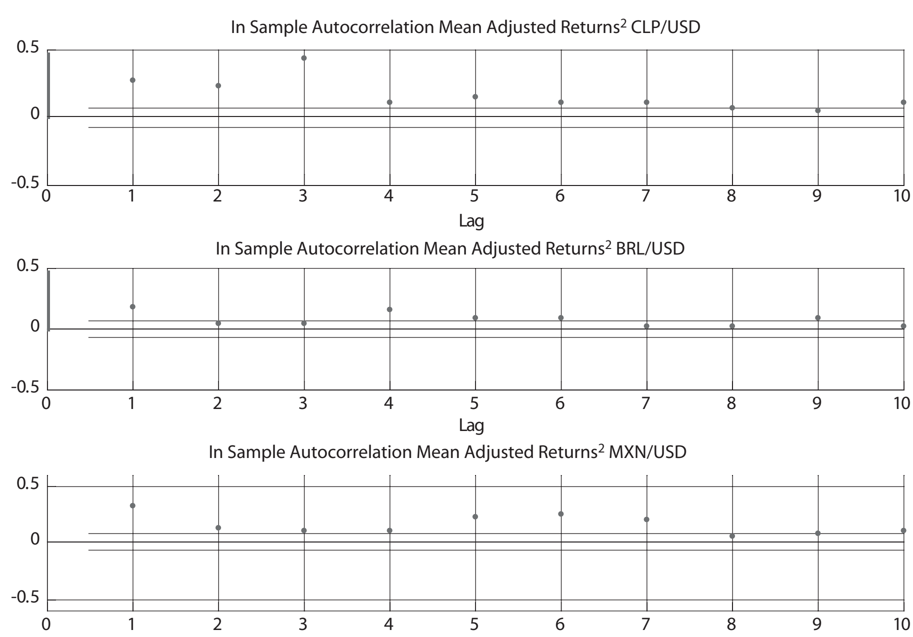
BRL/USD							
	AIC	BIC	C	AR 1	AR 2	MA 1	MA 2
CONST	-43,031	-43,077	0.0008 * 0.1896				
MA(1)	-42,982	-43,073	0.0008 * 0.1635			-0.0553 0.0108	
AR(1)	-42,978	-43,069	0.0008 * 0.1731	-0.0414 * 0.0825			
ARMA(1,1)	-42,991	-43,127	0.0003 * 0.1132	0.6397 0.0000		-0.7275 0.0000	
AR(2)	-43,067	-43,158	0.0009 * 0.1399		-0.1196 0.0000		
MA(2)	-43,062	-43,153	0.0008 * 0.1366				-0.1157 0.0000
ARMA(2,2)	-43,023	-43,251	0.0009 * 0.1512	0.8232 0.0000	-0.9158 0.0000	-0.8889 0.0000	0.9063 0.0000
ARMA(2,1)	-42,971	-43,153	0.0007 * 0.1160	0.2646 * 0.1098	-0.1130 0.0000	-0.3168 0.0397	
ARMA(1,2)	-42,964	-43,147	0.0006 * 0.1117	0.2542 * 0.1638		-0.3087 0.0671	-0.1049 0.0000
CHL/USD							
	AIC	**BIC**	**C**	**AR 1**	**AR 2**	**MA 1**	**MA 2**
CONST	-52,726	-52,772	0.0004 * 0.1527				
MA(1)	-52,680	-52,771	0.0004 * 0.1848			0.0618 * 0.0777	
AR(1)	-52,675	-52,766	0.0004 * 0.1818	0.0455 0.2240			
ARMA(1,1)	-52,649	-52,785	0.0006 * 0.2335	-0.4323 0.3304		0.5115 * 0.2255	
AR(2)	-52,789	-52,880	0.0005 * 0.0947		-0.1347 0.0009		
MA(2)	-52,774	-52,865	0.0004 * 0.0945				-0.1197 0.0055
ARMA(2,2)	-52,640	-52,868	0.0006 * 0.1344	0.1152 * 0.6364	-0.5175 0.0090	-0.0653 * 0.7386	0.3867 0.0937
ARMA(2,1)	-52,680	-52,862	0.0004 * 0.1351	0.1581 * 0.6293	-0.1425 0.0003	-0.1084 * 0.7061	
ARMA(1,2)	-52,661	-52,843	0.0004 * 0.1672	0.1412 * 0.6803		-0.0938 * 0.7405	-0.1246 0.0037

Note: Coefficients and p-values are reported.

IND/USD							
	AIC	BIC	C	AR 1	AR 2	MA 1	MA 2
CONST	-71,198	-71,244	0.0002 * 0.0423				
MA(1)	-71,298	-71,389	0.0002 * 0.0109			-0.1579 0.0000	
AR(1)	-71,284	-71,376	0.0002 * 0.0148	-0.1464 0.0000			
ARMA(1,1)	-71,234	-71,371	0.0001 * 0.0105	0.0739 * 0.6938		-0.2289 * 0.2919	
AR(2)	-71,142	-71,234	0.0002 * 0.0490		-0.0370 * 0.3533		
MA(2)	-71,143	-71,234	0.0002 * 0.0447				-0.0392 * 0.3308
ARMA(2,2)	-71,144	-71,371	0.0003 * 0.0161	-0.8819 0.0000	-0.2038 * 0.4010	0.7325 0.0000	0.0390 * 0.7794
ARMA(2,1)	-71,209	-71,391	0.0003 * 0.0144	-0.8582 0.0000	-0.1662 0.0000	0.7077 0.0001	
ARMA(1,2)	-71,202	-71,384	0.0003 * 0.0109	-0.7864 0.0001		0.6408 0.0014	-0.1629 0.0000

Note: Coefficients and p-values are repported

APPENDIX 3. IN-SAMPLE AUTOCORRELATION OF THE SQUARE OF THE RESIDUALS[2]



[2] The residuals have been calculated subtracting the conditional mean from the returns.

Ljung-Box Test P-values at 5%.

	COP/USD	**BRL/USD**	**CLP/USD**	**INR/USD**	**IDR/USD**	**MXN/USD**	**KRW/USD**	**SGD/USD**	**THB/USD**
QLB(1)	0,00	0,00	0,00	0,12	0,00	0,00	0,00	0,00	0,00
QLB(2)	0,00	0,00	0,00	0,10	0,00	0,00	0,00	0,00	0,00
QLB(3)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(4)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(5)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(6)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(7)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(8)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(9)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
QLB(10)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

APPENDIX 4. IN-SAMPLE MODELLING OF VOLATILITY

Significant at 5% - Insignificant at 1%
+ Non-significance *Pvals of the Likelihood ratio test

IN-SAMPLE ANALISYS								
	Constant	**AR**	**MA**	**EGARCH-Param**	**GJR-Param**	**LLF**	**AIC**	**BIC**
COLOMBIAN PESO								
Garch	0.0000	0.6590	0.3049	0	0	2933,05	-5862,11	-5853,01
Egarch	-0.8854	0.9191	0.3448	+ 0.0599	0	2934,65	-5863,30	-5849,65
GJR	0.0000	0.6903	0.3524	0	-0.1692 *	2935,20	-5864,41	-5850,75
BRAZILIAN REAL								
Garch	0.0000	0.8805	0.1195	0	0	2372,40	-4740,81	-4731,70
Egarch	-0.0509	0.9939	0.1916	0.0902	0	2383,00	-4759,99	-4746,34
GJR	0.0000	0.8947	0.1549	0	-0.0992	2381,88 (0.00)*	-4757,75	-4744,10
CHILEAN PESO								
Garch	0.0000	0.8824	0.1108	0	0	2698,83	-5393,66	-5384,56
Egarch	-0.3931	0.9620	0.2180	0.0526 *	0	2699,21	-5392,43	-5378,77
GJR	0.0000	0.8861	0.1244	0	-0.0407 +	2699,77	-5393,54	-5379,88
MEXICAN PESO								
Garch	0.0000	0.7730	0.1381	0	0	2746,59	-5489,19	-5480,09
Egarch	-0.5265	0.9505	0.1651	0.0837	0	2751,59	-5497,18	-5483,53
GJR	0.0000	0.8800	0.1396	0	-0.1197	2752,11(0.00)*	-5498,21	-5484,56
SOUTH KOREAN WON								
Garch	0.0000	0.7249	0.2751	0	0	2949,77	-5895,54	-5886,44
Egarch	-0.7467	0.9320	0.4580	0.0978	0	2955,72	-5905,44	-5891,79
GJR	0.0000	0.7301	0.3492	0	-0.1587	2954,28(0.00)*	-5902,56	-5888,90
THAILANDIA								
Garch	0.0000	0.8624	0.1161	0	0	3013,92	-6023,85	-6014,74
Egarch	-0.4188	0.9626	0.2342	0.0121 *	0	3011,73	-6017,47	-6003,81
GJR	0.0000	0.8543	0.1302	0	-0.0252 *	3014,34	-6022,68	-6009,03
INDIAN RUPEE								
Garch	0.0000	0.4928	0.2722	0	0	3665,61	-7327,23	-7318,13
Egarch	-40.182	0.6916	0.4433	0.1583	0	3665,95	-7325,90	-7312,25
GJR	0.0000	0.4969	0.4021	0	-0.2917	3671,73(0.00)*	-7337,45	-7323,80

APPENDIX 5. TESTING OPTIMALITY OF IN-SAMPLE VOLATILITY MODELS

BRL/COP
Mincer-Zarnowitz regression.

		Dependent Variable: RET2BRL		
		Method: Least Squares		
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	3,014E-05	-1,207E-05	7,2356E-05	SI
HTGARCH	0,73135561	0,57428234	0,88842888	NO
		R2=0.10692709		
		Dependent Variable: RET2BRL		
		Method: Least Squares		
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	-3,733E-06	-4,719E-05	3,9729E-05	SI
HTEGARCH	0,99154532	0,80739478	1,17569587	SI
		R2=0.1380152		
		Dependent Variable: RET2BRL		
		Method: Least Squares		
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	8,0035E-06	-3,393E-05	4,9937E-05	SI
HTGJR	0,88872149	0,72825466	1,04918833	SI
		R2=0.14485935		

Diebold-Mariano test In-sample with robust errors

		BRL		
		debold-Mariano Test		
		Dependent Variable: d(garch-egarch)		
		Method: Least Squares		
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	1,3155E-08	8,0123E-09	1,6419	0,101
		Dependent Variable: d(garch-GJRgarch)		
		Method: Least Squares		
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	1,4447E-08	1,1914E-08	1,2126	0,225
		Dependent Variable: d(GJRgarch-Egarch)		
		Method: Least Squares		
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	1,2912E-09	5,9949E-09	0,2154	0,829

MXN/USD
Mincer-Zarnowitz regression.

Dependent Variable: RET2MXN Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	1,1015E-05	2,643E-06	1,9388E-05	NO
HTGARCH	0,53979685	0,25428475	0,82530896	NO
R2=0.01935843				

Dependent Variable: RET2MXN Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	8,8885E-07	-9,3931E-06	1,1171E-05	SI
HTEGARCH	0,96806645	0,58608104	1,35005186	SI
R2=0.03425527				

Dependent Variable: RET2MXN Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	5,2248E-06	-3,7333E-06	1,4183E-05	SI
HTGJR	0,78009272	0,46280232	1,09738311	SI
R2=0.03230468				

Diebold-Mariano test In-sample with robust errors

MXN debold-Mariano Test Dependent Variable: d(garch-egarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	9,7495E-11	6,4132E-11	1,5202	0,128
Dependent Variable: d(egarch-GRJgarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	8,3412E-11	6,5821E-11	1,2673	0,205
Dependent Variable: d(egarch-GRJgarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	-1,4083E-11	1,9769E-11	-0,7124	0,476

KWN/USD
Mincer-Zarnowitz regression.

Dependent Variable: RET2KWN Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	6,6762E-06	2,5127E-06	1,084E-05	NO
HTGARCH	0,58908117	0,46429681	0,71386554	NO
R2=0.10958938				

Dependent Variable: RET2KWN Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	3,1747E-06	-1,1874E-06	7,5369E-06	SI
HTEGARCH	0,79706869	0,64743452	0,94670287	NO
R2=0.1354406				

Dependent Variable: RET2KWN Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	5,8687E-06	1,7689E-06	9,9684E-06	NO
HTGJR	0,61633644	0,49684053	0,73583234	NO
R2=0.12809881				

Diebold-Mariano test In-sample with robust errors

KRW debold-Mariano Test Dependent Variable: d(garch-egarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	1,595E-10	1,0436E-10	1,5283	0,126
Dependent Variable: d(garch-egarch) **Method: Least Squares**				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	4,7501E-11	7,1631E-11	0,6631	0,507
Dependent Variable: d(egarch-GRJgarch) **Method: Least Squares**				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	-1,12E-10	7,0993E-11	-1,5776	0,115

INR/USD
Mincer-Zarnowitz regression.

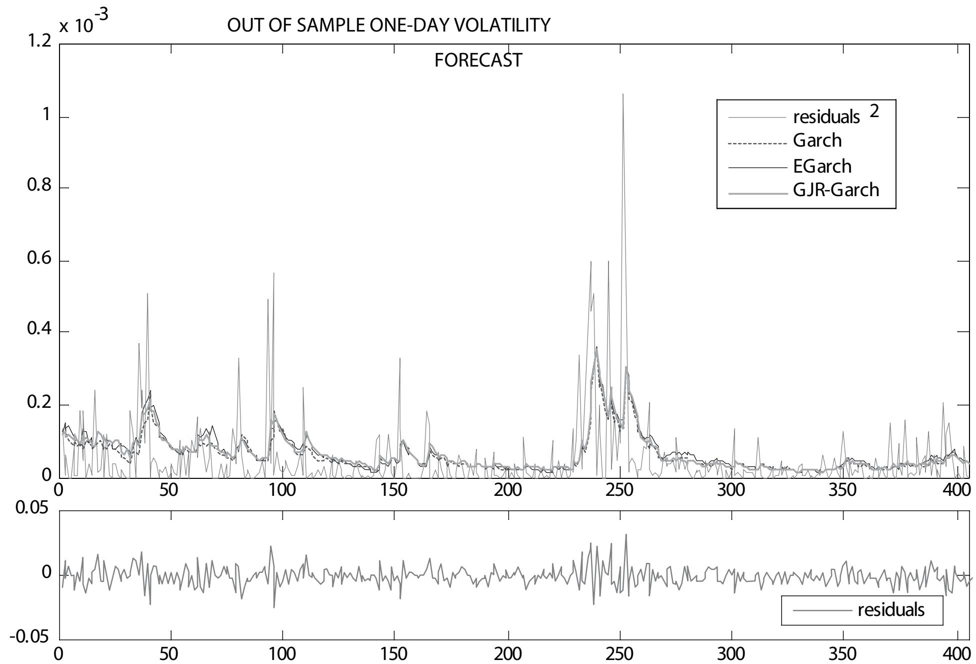
Dependent Variable: RET2IND				
Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	4,219E-07	-3,3163E-07	1,1754E-06	SI
HTGARCH	0,78679438	0,59364074	0,97994802	NO
R2=0.08394351				
Dependent Variable: RET2IND				
Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	5,2064E-07	-2,626E-07	1,3039E-06	SI
HTEGARCH	0,76575564	0,54753022	0,98398105	NO
R2=0.06375748				
Dependent Variable: RET2IND				
Method: Least Squares				
Variable	**Coefficient**	**95% Confidence interv.**		**C=0 y B=1**
C	9,1515E-07	1,6524E-07	1,6651E-06	NO
HTGJR	0,54882189	0,37173657	0,72590722	NO
R2=0.05037313				

Diebold-Mariano test In-sample with robust errors

IND rupee				
debold-Mariano Test				
Dependent Variable: d(garch-egarch)				
Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	-8,6226E-11	8,5499E-11	-1,0085	0,313
Dependent Variable: d(garch-GJRgarch)				
Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	-4,6934E-12	3,3862E-12	-1,3860	0,166
Dependent Variable: d(egarch-GJRgarch)				
Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	8,1533E-11	8,4439E-11	0,9656	0,334

APPENDIX 5. OUT OF SAMPLE ONE DAY VOLATILITY FORECAST

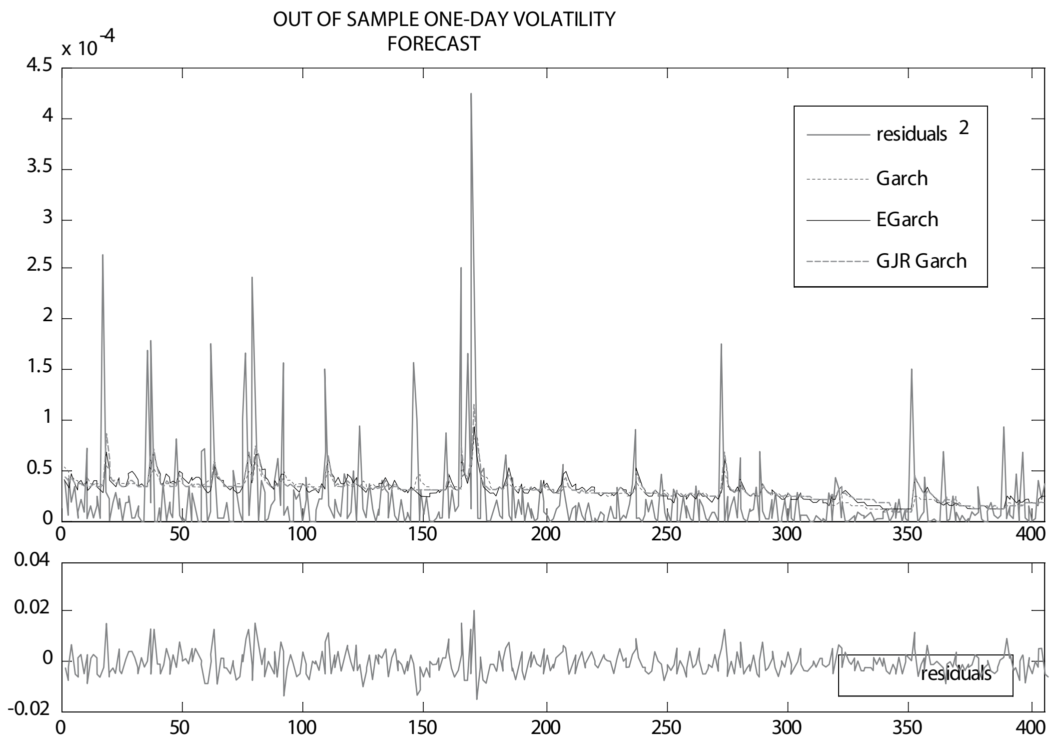
BRL/USD (Brazilian real)



Diebold-Mariano Test on the out-of-sample results with robust errors

debold-Mariano Test Dependent Variable: d(garch-egarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	7,6728E-17	5,13069E-17	1,4955	0,135
Dependent Variable: d(garch-GJRgarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	4,844E-15	3,20609E-15	1,5109	0,131
Dependent Variable: d(egarch-GJRgarch) Method: Least Squares				
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	4,7673E-15	3,16973E-15	1,5040	0,133

MXN/USD (Mexican peso).



Diebold-Mariano Test on the out-of-sample results with robust errors

	debold-Mariano Test			
	Dependent Variable: d(garch-egarch)			
	Method: Least Squares			
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	2,7329E-19	5,9391E-19	0,4602	0,645
	Dependent Variable: d(garch-GJRgarch)			
	Method: Least Squares			
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	1,3689E-16	8,7375E-17	1,5667	0,117
	Dependent Variable: d(egarch-GJRgarch)			
	Method: Least Squares			
Variable	**Coefficient**	**St. Error**	**t-statistic**	**pval**
C	1,3661E-16	8,6997E-17	1,5703	0,116