# Volume 34, Issue 3

Models for forecasting exchange rate volatility: a comparison between developed and emerging countries

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# Abstract

The main objective of this paper is to test the hypothesis that emerging markets are more sensitive to negative shocks than positive ones, and also that developed ones do not exhibit this same pattern. Using the family of ARCH models, the conditional variances of exchange rates in Brazil, Mexico and Singapore, representing the emerging countries, and the Euro Zone, UK and Japan, representing the developed ones, are estimated and forecasted. The results indicate that there is no relationship between the country being either developed or emerging, and its best fit is given by a model symmetrical or asymmetrical.

Citation: Marcelo Griebeler, (2014) "Models for forecasting exchange rate volatility: a comparison between developed and emerging countries", *Economics Bulletin*, Vol. 34 No. 3 pp. 1618-1630. Contact: Marcelo Griebeler - griebeler.marcelo@gmail.com. Submitted: March 15, 2014. Published: July 26, 2014.

## 1 Introduction

An useful measure of uncertainty about the economic environment of a country is its exchange rate volatility. In this sense, high variability in the exchange rate is directly linked to frequent changes in demand for domestic currency, caused mainly by the entry and exit of foreign capital. There is consensus in economics that investment decisions become more difficult under this type of environment. In doubt whether the return will realize or not, economic agents tend to postpone their decision to invest. Thus, low economic growth and even recession can result from lack of market information, because investment is an important part of GDP.

The exchange rate predictability is not only of interest to investors. Exporters and importers - retailers and consumers, ultimately - decide their actions based on the value of domestic currency and also on their volatility. Additionally, policymakers need accurate forecasts about future values of exchange rates. One of their main concerns is the socalled pass-through, a major mechanism to which the exchange interferes in economic aggregates. It consists mostly of going over the devaluation to domestic prices in the form of inflation.

Despite the great need, the task of forecasting exchange rates has been very arduous. Cheung et al. (2002), for instance, present a survey of the literature on forecasting exchange (conditional mean) based on macro fundamentals. The authors did not find papers with good predictive power and able to overcome the random walk hypothesis. In fact, following the seminal study of Meese and Rogoff (1983), many tests have been done in trying to find macroeconomic fundamentals that have good power for forecasting movements in the exchange rate. Univariate models of the ARIMA family have also been getting little success, largely due to high volatility in the data presented in some countries, especially the emerging ones (e.g. Pippenger and Goering, 1998; Tambakis and van Royen, 2002).

The vulnerability of emerging economies is clearly evidenced by the behavior of their exchange rates, which were very volatile. With the exception of those countries that adopt fixed exchange rate (very few, currently), emerging countries generally suffer from large capital flight to any domestic bad signal (some information or news that harms the economy) or systematic risk. In this sense, the current global financial crisis has greatly affected these economies. Meanwhile, developed countries tend to be more stable in relation to their currencies, even if they are not immune to financial crisis<sup>1</sup>.

This paper has as main objective to test the hypothesis implicit in the discussion above, namely, that emerging countries are more sensitive to negative shocks than positive ones, and also that developed ones do not exhibit this same pattern, at least not with the same intensity. The exchange rate volatility is used here as a proxy for macroeconomic uncertainty. Through the family of ARCH models, the conditional variances of exchange rates in Brazil, Mexico and Singapore, representing the emerging countries and the Euro Zone, Britain and Japan, representing the developed ones, will be estimated and forecasted for the period from January 2nd, 1999 to October 7th, 2008. Econometric tests on the adequacy of the models and their predictive power give support the conclusions.

The paper is structured as follows. Section 2 presents a brief review of the literature on modeling and forecasting exchange rates, both of mean and of conditional variance. The structure of the data and its details are presented in section 3. The following one

<sup>&</sup>lt;sup>1</sup>For a didactic explanation about the behavior of financial crises see Mishkin (1992).

deals with the estimation process and its findings. Section 5 concludes, followed by references and an appendix with additional information.

#### 2 A Brief Literature Review

#### 2.1 Models for the Conditional Mean

A seminal attempt to forecast the behavior of exchange rates was that of Meese and Rogoff (1983). Using a multivariate approach, the authors defined macroeconomic variables - such as trade balance, money supply and nominal income - as possible determinants of exchange rate changes and assessed their forecasting power. The result was known in the literature as *exchange rate disconnect puzzle*, because the macroeconomic fundamentals were not good predictors and a random walk model presented higher predictive power. Conjectures of Meese and Rogoff (1983) to justify their results indicate a possible variability of parameters over time. They note that monetary and fiscal policies, for example, has changed in many countries since the early seventies (the beginning of the sampling period), when the schemes of fixed exchange rates derived from Bretton Woods collapsed. Many subsequent studies have tried to resolve the *disconnect puzzle*, but the random walk hypothesis seems to persist.

A good review of the theories that have emerged to explain the exchange rate variability may be found in Cheung et al. (2002). Besides presenting different approaches, these authors test four of them for exchange rates in Canada, Great Britain, Germany, Switzerland and Japan, all based on U.S. dollars. The models used are: stick-price monetary model, in line with Dornbush-Frankel; Balassa-Samuelson, which considers productivity differentials among countries; Behavioral Equilibrium Exchange Rate (BEER), which incorporates features of a wide range of models; and Unconvered Interest Rate Parity. For the period from the second quarter of 1973 to fourth of 2004, Cheung et al. (2002) found that none of the tested models outperforms the random walk on forecasting, using the criterion of mean squared error. However, over longer horizons, structural models presented on average a higher forecasting power than the random walk hypothesis.

With respect to univariate models, the difficulty to forecast exchange rate is also large. In fact, models of ARIMA and GARCH family are often overcome by the random walk. In the intention to investigate this question, Tambakis and van Royen (2002) analyze the differences in predictability exchange between short and long horizons. To model the daily returns of exchange rates Pound/US Dollar and German Mark/US dollar, GARCH models were used and also the Uncovered Interest Rate Parity. The researchers' conclusions were that exchange rates were less predictable using the GARCH modeling than with random walk, but more predictable using the Interest Rate Parity. Additionally, GARCH had better predictability in the short term than in the long term.

Pippenger and Goering (1998) make use of an alternative model for the exchange rate. The nonlinear model Self-Exciting Threshold Autoregressive (SETAR) is used and generates, in general, better forecasts than the modeling standards and the random walk. The idea behind the method is to include regime changes (representing economic policy) in exchange behavior. Furthermore, in SETAR, the nonlinearity is different from a standard ARCH structure because it can not be detected by a traditional LM test.

In short, the random walk hypothesis as the best predictor for exchange rates seems to dominate the literature of modeling the conditional mean, even with advances such as those of Pippenger and Goering (1998). In the other hand, with respect to the conditional variance, the traditional models, as it will see the next subsection, have greater predictive power.

#### 2.2 Models for the Variance

The similarity between the behavior of exchange rates and conventional assets have already been highlighted in the introduction. As will be seen later (figure 2), the volatility of currency returns shows clusters, suggesting the use of GARCH models. Recently, part of the literature has suggested the possibility of asymmetric volatility models to fit better than symmetrical ones, particularly in the cases of emerging countries.

Sandoval (2006), for example, with a daily sample that begins in 2000 and up to 2004 for seven countries of Asia and Latin America<sup>2</sup> tests the hypothesis that their exchange rates are asymmetric for positive and negative shocks. The GARCH models used were traditional GARCH, GJR-GARCH (a similar version of TARCH) and EGARCH. Using the Akaike and Schwartz criteria, besides the likelihood ratio test, the author found that four of the seven currencies were asymmetric<sup>3</sup>. In relation to forecasting, the symmetric models outperformed the asymmetric ones. Therefore, the finding of this study was that emerging countries did not show widespread evidence of asymmetry.

Longmore and Robinson (2004) make the same kind of test for the Jamaican currency. Their main hypothesis is that the Jamaican market is susceptible to speculative volatility, since it is still developing, and thus negative shocks would generate more volatility than positive ones. The sample comprised a period from January 2nd, 1998 to February 12th, 2003, totaling 1280 observations. The authors find evidence of asymmetry, justifying the choice of non-linear GARCH models (in particular, the GJR-GARCH, and TS-GARCH). These models were also better than symmetrical ones with respect to the predictive power of exchange rate volatility<sup>4</sup>.

A more recent study is Yoon and Lee (2008). The currency used is the Korean Won (Won/Dollar) for the period from March 2nd, 1998 to June 30th, 2006. As in previous studies, the exchange rate return was the variable chosen, due to non-stationarity of its value in level. The hypothesis of asymmetry and leverage effect was tested by GARCH, TARCH and EGARCH models. The conclusion that TARCH and EGARCH fit better the Korean currency has as likely explanation, according to the authors, the uncertainties about the economic policy of Korea during the period in question.

As it may be seen in this brief review, although the theory suggests that developing countries suffer more from adverse shocks, the empirical literature still shows weak evidences that corroborate it. What will be done in the next sections is to try to contribute to this debate by testing both developed and emerging countries.

# 3 Data

Our sample of 2460 daily observations covers the period from January 2nd, 1999 to October 7th, 2008. The choice of this period is mainly due to a change in monetary regime implemented in Brazil in early 1999. The practically fixed exchange rate performed before

<sup>&</sup>lt;sup>2</sup>Brazil, Colombia, Chile, India, Mexico, South Korea and Thailand.

<sup>&</sup>lt;sup>3</sup>Brazil, India, Mexico and Korea.

<sup>&</sup>lt;sup>4</sup>An interesting feature of the study is to model the conditional mean as a process of long dependency. Using the GHP estimator (Geweke-Porter-Hudak), it was found a value for the order of differentiation of d = 0.83.

such regime change made data present low variability, hindering the econometric exercise. All series were obtained at the website of the Federal Reserve Bank of St. Louis and will be indexed such that  $y_t$  denote the exchange rate y on time t.

As may be seen in figure 1, the exchange rates<sup>5</sup> of Singapore, Great Britain, the Euro Zone and Brazil have similar behavior, while Japan and Mexico clash. Another detail that jumps out is that the levels of exchange rates do not appear to be stationary. In fact, the ADF test presented in the appendix A does not reject the hypothesis of unit root for any of the series. Therefore, we will work with the return of the exchange rate, defined as  $r_t = \ln(y_t/y_{t-1})$ . To justify its use, note that there is an economic intuition behind the return, namely that the currency may be seen as any other asset, since it has the characteristic of reserve of value.

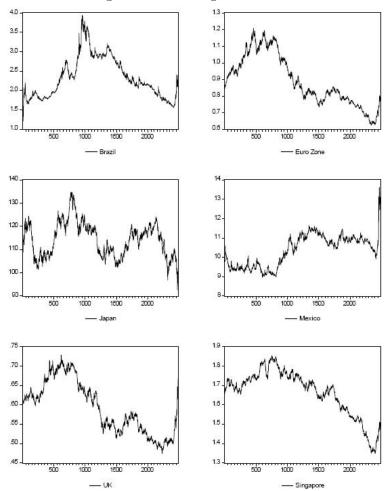


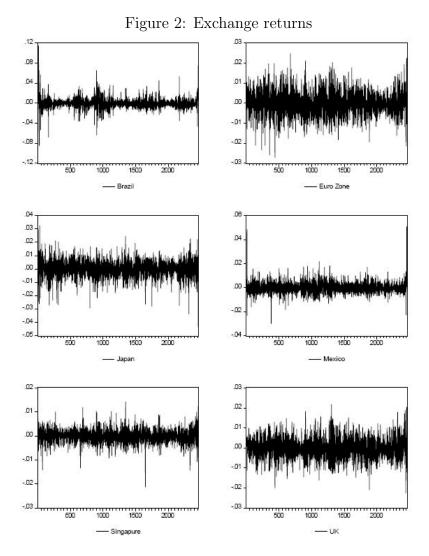
Figure 1: Exchange rate in level

Notice in figure 2 that, unlike the level, the returns are stationary (outcome confirmed by the test ADF). Additionally, one can observe that the assumption of constant variance is not valid for all series. The so-called clusters of volatility are noticed. In particular, the returns of the exchange rate of Brazil show that by the index 1000, equivalent to mid-2002, its variability has increased considerably. Returning to figure 1, we see that the level of the exchange rate also jumped during the period analized. These two graphs

<sup>&</sup>lt;sup>5</sup>In all the paper it will refer simply to as "exchange rate of country A" as the necessary amount of money from country A to buy one U.S. dollar.

support the argument about the uncertainty of the election period that year.

The effects of the recent financial crisis - although this represents relatively a short period in the entire sample - also appear to have strong influence on the exchange rate variability in those countries. All diagrams of figure 2 show an increase in the amplitude of its variability in the last 50 observations. In particular, it may be noted the large increase in the final period sampled, coinciding with the collapse of U.S. investment bank Lehman Brothers on September 15th. While the crisis was already being felt in world financial markets since the beginning of 2008, the FED's aids to Fannie Mae and Freddie Mac softened its negative impacts. Note also that the magnitude of these effects was similar in both developed countries and emerging markets.



Focusing our attention on more technical issues, appendix A provides table 7 with descriptive statistics of the variables. There we may see another typical feature of financial time series and exchange rates: the heavy tails of their distributions. This peculiarity make them away of the normal distribution and it also make them have excess of kurtosis. In fact, the Jarque-Bera statistic (JB) rejects the hypothesis of normality in all cases. In the same table it is noticed that the exchange rate of Brazil clash with others because it has a higher standard deviation, 0.011044, whereas the second highest value, the Japanese rate, is 0.006435, almost half of the Brazil's value. Once again, this reinforces the uncertainty in the Brazilian economic environment in the period, compared to some

developed and emerging markets.

#### 4 Modelling, Forecast and Results

# 4.1 Modelling

The first step in modeling the conditional volatility of a series consists of modeling its conditional mean, such that we may withdraw all its serial autocorrelation. In order to do that, we use models of the ARIMA family. The selection of the best fit was based primarily on correlograms, the power of "cleansing" of the autocorrelation of the series and then in the information criteria (Akaike and Schwartz) and parsimony. Below, in table 1, are the best models found for the conditional means of exchange rates and their selection criteria.

Table 1: Models for the conditional mean						
	Brazil	Euro Zone	UK	Mexico	Singapore	Japan
AR(1)	0.092	0.061	-	0.080	-	-0.042
	$(0.020)^{\dagger}$	$(0.020)^{\dagger}$		$(0.020)^{\dagger}$		$(0.020)^{\dagger}$
AR(3)	0.074	-	-	-	-	-
	$(0.020)^{\dagger}$					
AR(4)	-	-	0.054	-	0.056	-
			$(0.020)^{\dagger}$		$(0.020)^{\dagger}$	
AR $(5)$	-	-	-	-	0.045	-
					$(0.020)^{igodom}$	
AIC	-6.185	-7.400	-7.701	-7.800	-8.924	-7.256
BIC	-6.180	-7.398	-7.699	-7.798	-8.919	-7.253
Q~(2~lags)	-	0.499	0.463	0.807	-	0.941
Q (4 lags)	0.366	0.893	0.512	0.537	0.230	0.866

Note: Standard errors in parentheses.<sup> $\dagger$ </sup>,  $\blacklozenge$  and  $\clubsuit$  means 1%, 5% and 10% of significance, respectively.

In the table 1, Q (n lags) represents the Ljung-Box test for the lag n (p-value). Note that the models of the six exchange rates accept the null hypothesis of no autocorrelation at high levels of significance. The model that best adjusted the exchange rate in Brazil was an AR (1,3), while the AR (1) was the best one - considering the criteria mentioned above - to the Euro Zone, Mexico and Japan. Moreover, Great Britain was modeled as an AR (4) and Singapore as an AR (4,5). The next stage of modeling is to test for the presence of ARCH structure in the residual of the equations of means.

Table 2: LM ARCH test							
	Brazil	Euro Zone	UK	Mexico	Singapore	Japan	
LM $(lag 2)$	0.000	0.143	0.007	0.000	0.026	0.000	
LM $(lag 4)$	0.000	0.002	0.001	0.000	0.062	0.000	
LM $(lag 8)$	0.000	0.000	0.000	0.000	0.000	0.000	

As expected, the LM test for the presence of heteroskedasticity in the ARCH form does not accept the null hypothesis of homoskedasticity in almost any case, as presented in table 2. Note that even in the more distant lags the p-value is still very low, suggesting a strong autoregressive effect on conditional volatility. The exceptions are the second lag of the Euro Zone (homoskedasticity is accepted with 14%) and fourth in Singapore (6%).

The first attempts to set a model of conditional variance were made by symmetrical models, the popular ARCH and GARCH. The choice of the orders of the ARCH and GARCH parts was given by the correlogram of squared residuals, as it is standard. Again, the selection criteria were: a total absence of serial autocorrelation, the criteria of Akaike, Schwartz, parsimony and now also the total absence of ARCH structure in the residual. In addition, we have that in this modeling there are some restrictions on the parameter values. For example, they must be nonnegative and their sum must be less than one. These restrictions were also taken into consideration in the decision. Table 3 shows the best settings for the conditional variance using symmetric models<sup>6</sup>.

Table 5. Symmetric Orritori models						
	Brazil	Euro Zone	UK	Mexico	Singapore	Japan
Constant	4.0E-5	7.0E-8	4.1E-7	1.1E-6	1.9E-7	8.5E-7
	$(4.1E-7)^{\dagger}$	(5.1E-8)	$(1.6\text{E-7})^{\dagger}$	$(1.7\text{E-7})^{\dagger}$	$(5.3\text{E-8})^{\dagger}$	$(1.9\text{E-7})^{\dagger}$
ARCH $(1)$	0.243	0.023	0.040	0.123	0.048	0.033
	$(0.022)^{\dagger}$	$(0.004)^{\dagger}$	$(0.007)^{\dagger}$	$(0.013)^{\dagger}$	$(0.007)^{\dagger}$	$(0.005)^\dagger$
ARCH $(2)$	0.220	-	-	-	-	-
	$(0.018)^{\dagger}$					
ARCH $(3)$	0.180	-	-	-	-	-
	$(0.021)^{\dagger}$					
GARCH $(1)$	-	0.975	0.946	0.832	0.929	0.946
		$(0.004)^{\dagger}$	$(0.011)^{\dagger}$	$(0.016)^{\dagger}$	$(0.012)^{\dagger}$	$(0.008)^{\dagger}$
AIC	-6.595	-7.457	-7.744	-7.967	-8.964	-7.306
BIC	-6.583	-7.447	-7.734	-7.957	-8.952	-7.299
Q~(2~lags)	0.116	0.314	0.221	0.376	-	0.541
Q (4 lags)	0.191	0.762	0.398	0.488	0.381	0.944
LM $(2 \ lags)$	0.495	0.073	0.577	0.768	0.970	0.241
LM $(4 \ lags)$	0.837	0.111	0.246	0.792	0.745	0.311

Table 3: Symmetric GARCH models

Note: Standard errors in parentheses.<sup>†</sup>,  $\blacklozenge$  and  $\clubsuit$  means 1%, 5% and 10% of significance, respectively.

We have Brazil differing from the other countries again. In the specific case above, the country was modeled as an ARCH (3), while the others were best fitted to a GARCH (1,1). A more parsimonious model was tested for Brazil, but their coefficients did not meet the restrictions. It is important to note that all the models above are symmetric, that is, we are not taking into account the possibility of presenting positive and negative shocks of different magnitudes on the exchange rate volatility. This will be the next step of work, but before that we have to check if ARCH-M models may be useful in modeling exchange rate.

It is perfectly possible that the conditional variance or the standard deviation of a series affects its conditional mean. In other words, the volatility of a variable may be incorporated as a regressor in a GARCH model and presents influence on the estimated level of the mean. That is what makes the models of the ARCH-M family (ARCH in mean). Often used in financial data, where the risk and return are inextricably linked,

 $<sup>^{6}</sup>$ The AR (3) part of Brazil is no longer significant. From here we will always use the average exchange rate of Brazil as a pure AR (1).

this model may well fit the series from other segments. The procedure adopted here was to include variance or standard deviation of conditional series as regressors in GARCH models above (table 3) and see whether its coefficient was significant and whether there also was improvement in the information criteria.

Among all the exchange rates, the only one that his mean was affected by the conditional volatility was that of Brazil. In fact, in this case, both the variance and the standard deviation were significant and improved the information criteria. The standard deviation adjusted the data even better, leading to better values of AIC (-6602) and BIC (-6588). The other exchange rates had not significant coefficient or, which was quite common, the optimization algorithm of the software<sup>7</sup> did not converged to the optimum after 500 iterations. Below it follows a representation of the ARCH-M for Brazil (standard error in parentheses), with all coefficients significant at 1%.

$$y_t = \underset{(0.021130)}{0.021130} y_{t-1} - \underset{(0.022686)}{0.022686} \sqrt{h_t} + \varepsilon_t$$
$$h_t = 3.86E - 5 + \underset{(0.021935)}{0.239618} \varepsilon_{t-1}^2 + \underset{(0.019222)}{0.21922} \varepsilon_{t-2}^2 + \underset{(0.022067)}{0.189} \varepsilon_{t-3}^2$$

Now that we obtained the best symmetric models for conditional volatility of exchange rates, it is important to test the asymmetry in their impact. This may be done by testing for the presence of so-called leverage effect. A simple test to capture this effect is suggested by Enders (2003). Let  $s_t$  be the residual of the standardized GARCH models, such that  $s_t = \hat{\varepsilon}_t / \sqrt{\hat{h}_t}$ , where  $\hat{\varepsilon}_t$  is the estimated error of the model and  $\hat{h}_t$  is the variance, one estimate the following regression

$$s_t^2 = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 s_{t-2} + \dots$$

If there is no leverage effect, the errors squared must not be correlated with the error term level. Thus, one may conclude by their presence if the value of the F test under the null hypothesis  $\alpha_0 = \alpha_1 = \alpha_2 = \dots = 0$  exceeds the critical value of the table. In other words, if the test point out the coefficients are significantly different from zero, then there is leverage effect.

The test's results indicated the presence of leverage effect in the currencies of Brazil, Mexico and Japan, while the Euro Zone, Singapore and UK do not seem to suffer from this type of asymmetry. The p-values of F tests were 0.000 for the first three and 0.149, 0.274 and 0.119 for the last three, respectively. Thus, it is expected that countries that are affected by this effect are best fitted by asymmetric models. However, since this test takes into account only one type of asymmetry, asymmetrical models were estimated for all six countries.

Table 4 shows the best fits of the asymmetric models for the six series. Additionally, it presents their information criteria. In order to facilitate comparison with the symmetrical ones, the values of AIC and BIC of the latter are repeated. The models tested were asymmetric EGARCH and TARCH, both with the possibility of the effect of volatility on average (TARCH-M and EGARCH-M). Note by the values of information criteria for all countries that the asymmetrical model fit the data better, except UK.

The inference that may be made from the table 4 is that there is more asymmetry on the exchange rate shocks in emerging countries compared to developed ones, at least

<sup>&</sup>lt;sup>7</sup>Eviews.

	Brazil	Euro Zone	UK	Mexico	Singapore	Japan
Asym.	TARCH-M	EGARCH	EGARCH	EGARCH	EGARCH	EGARCH
	$(3,\!0)$	(2,1)	(1,1)	(1,1)	(1,1)	(1,1)
AIC	-6.605	-7.459	-7.742	-7.984	-8.966	-7.314
BIC	-6.588	-7.443	-7.730	-7.972	-8.952	-7.302
Sym.	GARCH-M	GARCH	GARCH	GARCH	GARCH	GARCH
	$(3,\!0)$	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)
AIC	-6.602	-7.457	-7.744	-7.967	-8.964	-7.306
BIC	-6.588	-7.447	-7.734	-7.957	-8.952	-7.299

Table 4: Asymmetrical and symmetrical models

during the period studied and the countries sampled. Negative shocks - such as negative news in the financial market or advertisement of heterodox economic policies by governments - seem to increase volatility in the exchange rate more than good news (disclosure of some good result of a large local company, for example). Moreover, this is a trend for all countries, regardless of its external weakness, as evidenced by the best fitting asymmetric models to Japan and the Euro Zone.

Even with the results of table 4 it is still important to investigate and compare the predictive power of symmetric and asymmetric models. Given that not always the best fit provides the best forecasting, in the next subsection we evaluate the predictability of the conditional variance of the two models.

#### 4.2 Volatility Forecast

We chose only the models of table 4, the best symmetric and the best asymmetric of each country to compare its predictability of exchange rate volatility within the sample. The forecasting outside the sample was not performed because of the peculiarities of the period (financial crisis), as highlighted in section 3. The criterion used was the mean square error  $(MSE)^8$ . The results may be seen in table 5 below.

Table 5: MSE (value multiplied by $10^8$ )						
	Symmetric	Asymmetric				
UK	0.18733	0.18760				
Singapore	0.02881	0.02863				
Mexico	0.63040	0.61709				
Brazil	18.4937	18.9323				
Euro Zone	0.35828	0.35762				
Japan	0.77528	0.76903				

Note that in four currencies the asymmetric models predict conditional variance of the exchange rate better than the symmetric models. They are Singapore, Mexico, Euro Zone and Japan. In the case of Brazil and UK, symmetric models were superior. The important result is that there is no relationship between the better predictability of a model symmetric or asymmetric with the fact that the country is developed or emerging,

<sup>&</sup>lt;sup>8</sup>For a review of criteria for assessing the predictability of exchange models see, for example, Tambakis and van Royen (2002).

reinforcing the conclusion of the previous subsection when it was found that exchange rates are better adjusted by asymmetric GARCH models regardless the type of country.

Thus what may be concluded in this section, both about the fit of the model and about its forecasting, is that negative shocks do not make the exchange more volatile only in developing countries, where financial markets are still in development, but also in developed countries, where macroeconomic fundamentals are solid and financial systems more robust. Additionally, predictive power of volatility shows no relationship between the model to be symmetric and the country to be developed and vice versa, contradicting the initial hypothesis of the paper.

# 5 Concluding Remarks

This study aimed to test the hypothesis that the asymmetric models for conditional variance adjust better to the exchange rates of emerging countries than in developed ones. The intuition behind this conjecture is that by having more fragile external positions, macroeconomic fundamentals and financial systems, negative shocks in emerging countries tend to increase the exchange rate volatility more than positive ones. In contrast, developed countries, because the fact of having strong economies, would suffer in the same way from positive and negative exchange rate shocks.

The methodology was to model the exchange rate return of three emerging countries, Brazil, Mexico and Singapore, and three developed, Great Britain, Japan and the Euro Zone by both ymmetrical and asymmetrical GARCH models. The results indicated that there is no relationship between the country being developed or emerging, and its best fit to be given by a standard symmetrical or asymmetrical model. In fact, all six countries sampled were best fitted by nonlinear GARCH (TARCH, and especially EGARCH). A country that had a differentiated modeling was Brazil, probably because of its macroeconomic peculiarities. The model that best fit their exchange was a TARCH-M, that is, a model that incorporates conditional volatility as a regressor in the conditional mean.

The predictability of the conditional variance of symmetric and asymmetric GARCH models is also not connected with the fact that the country belongs to one of the two classes studied in the paper. There was no uniformity among the models that best predicted and its nature, if symmetrical or not. Countries like Brazil and UK have their exchange volatility best predicted by GARCH linear, whereas the others have their best future values adjusted for EGARCH. The difficulty of forecasting may be related to the peculiarities of the period, which includes in its final observations a financial crisis of major proportions.

Finally, as may be seen above, the question of whether asymmetric conditional volatility models fit better the exchange rate seems to have been strengthened. What may not be said, however, is that there is a separation between emerging and developed countries, at least not with the sampled in this study. In other words, the initial hypothesis of the study was not verified. Moreover, the difficulty of the exchange rate predictability, as in classical literature, was also present, because both asymmetric and symmetric models do not have demonstrated superiority in forecasting future values of exchange rate volatility during the period in question.

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# A Appendix

	Table 6: ADF test					
	Constant and Trend	Constant	None			
UK	-2.13	-1.09	-0.35			
Singapore	-2.32	-0.22	-0.86			
Mexico	-2.48	-1.10	0.77			
Brazil	-2.23	-2.16	0.22			
Euro Zone	-3.07	-0.62	-0.51			
Japan	-2.37	-2.22	-0.41			

Note: All the values accept the null hipothesis of unit root at 10%.

Table 7: Descriptive statistics of returns

	UK	Singapore	Mexico	Brazil	Euro Zone	Japan
Mean	-0.00002	-0.00005	0.00008	0.00025	-0.00005	-0.00003
Median	-0.00007	-0.00005	-0.00018	0.00000	0.00000	0.00000
Maximum	0.02170	0.01423	0.05069	0.11441	0.02472	0.03236
Minimum	-0.02254	-0.02124	-0.02995	-0.08470	-0.02708	-0.04348
SD	0.00515	0.00280	0.00491	0.01104	0.00599	0.00645
Asymmetry	0.10146	-0.15265	1.06059	0.92041	0.03247	-0.37058
Kurtosis	3.82154	5.82761	13.36405	17.49199	3.93136	5.67611
J-B	73.3714	828.747	11466.43	21865.25	89.3080	790.042
P-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Obs	2459	2459	2459	2459	2459	2459