Institut für Höhere Studien
Institute for Advanced Studies
Vienna

TU WIEN
Continuing Education Center

MSc Economics

Modeling Exchange Rate Volatilities in Emerging and Developed Markets

A Master's Thesis submitted for the degree of
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Robert Kunst

Xuefei Dang

0926893

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Affidavit

I, Xuefei Dang

hereby declare

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Modeling Exchange Rate Volatilities in Emerging and Developed Markets

32 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and that I have not prior to this date submitted this Master's Thesis as an examination paper in any form in Austria or abroad.

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Abstract

This thesis aims at modeling the exchange rate volatilities in developed and emerging markets. Particularly, the efforts have been made in testing the hypothesis that due to risk prevailing and higher uncertainty in emerging markets, asymmetric GARCH models fit better for their exchange rate volatility than the one of developed markets. The considered sample range from 2000 to 2007 for both types of markets, the exchange rates returns are fitted through symmetric and asymmetric GARCH models and the forecasting power and significance of the models are compared. The outcomes show evidence against the hypothesis that exchange rate returns in emerging markets should be better described by asymmetric GARCH models. The main finding is that the so-called “gain/loss asymmetry” stylized fact is not significant enough for the asymmetric GARCH model to outperform the symmetric GARCH model in both developed and emerging markets.

1. Introduction

The study of exchange rate volatility is important for two main reasons. The first one is that national governments have increasingly felt the impact of the volatility of exchange rates on their own monetary policies, especially for those countries where export growth provides a large stimulus to their domestic economy's growth. Since neither the role of central banks nor the governments is passive in the foreign markets, they continue to intervene to maintain an "orderly market", through trading in the exchange market. Secondly, the investors today are increasingly participating in international portfolios, and hence exchange rate volatility would largely influence the well-being of individual investors.

The objective of this research is to find empirical evidence which helps to characterize the behavior of exchange rate volatility in developed and emerging markets. Findings in empirical results show little serial correlation in returns, however, the squared returns and absolute returns are often found correlated. The research work could be found in Taylor (1986). Though the volatility is unobservable, there are several characteristics that are often seen in asset return. As documented by Bollerslev, Engle and Nelson (1994), the presence of volatility clustering and fat-tails are characteristics observed in high frequency financial time series. The volatility clustering is the feature that big shocks tend to be followed by big shocks in positive or negative direction and small shocks tend to follow small shocks. Fat tailed behaviors are the cases that the extreme values occur more frequently compared to normal distribution. As a result, the assumptions of normal distribution of error terms and constant volatility are not suitable and could contribute to inaccuracy. The stylized facts are considered to be captured by Autoregressive Conditional Heteroskedasticity (ARCH) introduced by Engle (1982) and the extension of which, namely the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model developed by Bollerslev (1986). The latter one has more parsimonious structure while ARCH models often require many parameters to adequately describe the volatility process.

Another stylized fact is the asymmetric magnitudes in asset return volatility. In reality, individuals tend to be more sensitive to decreases in their levels of well-being than to rises since they are risk averse (Benartzi et. al., 1995). As a result, it is quite possible that an unexpected drop in price impacts stronger on future volatility than an unexpected increase in price of similar magnitude (Verbeek, 2004). This one of the stylized facts of assets returns was discovered by Black (1976) as leverage effect and it has been referred as the "gain/loss asymmetry" by Cont (2001). Some refinements of GARCH models are proposed by researchers to better capture the characteristics that are seen in asset return. In order to capture the potential asymmetry, two approaches are relied on in this research, the exponential GARCH (EGARCH) model proposed by Nelson (1990) and the GJR-GARCH model developed by Glosten, Jagannathan and Runkle (1993).

As it is known, emerging markets are relatively more volatile than developed markets since emerging markets face a larger amount of uncertainties which might come from, for instance, political instability, lack of liquidity and concerns over corporate governance. As a consequence, with more doubts and cautions, investors holding currencies of emerging markets might be more sensitive to currency depreciations. Hence, the main hypothesis of the thesis is that an asymmetry effect exists in exchange rate time series of a currency from a developed economy to a currency from an emerging economy, whereas no asymmetry exists in exchange rate series of two developed markets' currencies.

To illustrate the point, the following case has been investigated. If the developed market exchange rate to the U.S. dollar increases, currency depreciates and thus it is bad news to the holders in developed market. On the other hand, if the exchange rate decreases, the U.S. dollar depreciates and then it is bad news to dollar holders. Nevertheless, since both currency and the U.S. dollar are developed markets' currencies, one does not expect an asymmetric effect exists here. And as a result, if investors holding currencies of emerging economies are more cautious and sensitive to bad news, it is reasonable to expect an asymmetric GARCH model fits this case better than a symmetric GARCH specification.

The relevant related studies in this field have been published by Nelson (1990) and Engle and Ng (1990). Nelson (1990) studied how new information is incorporated into volatility estimates on stock returns using series from the US market. Engle and Ng (1990) report asymmetry findings on a daily return series of the Japanese TOPIX index from 1980 to 1988. As documented by Sandoval (2006), the presence of asymmetry is not a common attribute to all financial series; it is believed only to exist on stock market returns. Nonetheless, the analysis of asymmetric GARCH models is extended to foreign exchange rate time series, and both developed and emerging economies are considered and compared.

The remainder of this study is organized as follows. The background of currency exchange rate data is presented in the next section. The third section includes the model and methodology used in this study. All the results will be discussed in the fourth section and the conclusion will be stated in the last section.

2. Data

The analysis is performed on daily nominal exchange rates series against the U.S. dollar from 2000 to 2007 for a total of 10 countries. The selected currencies are the Australian Dollar (AUD), British Pound (GBP), Japanese Yen (JPY), Swiss Franc (CHF), Swedish Krona (SEK), Indian Rupee (INR), South Korean Won (KRW), Mexican Peso (MXN), Brazilian Real (BRL) and South African Rand (ZAR). The data is obtained from Bloomberg. The first five currencies are considered as developed markets following the World Bank classification, while the last five are considered as the emerging markets. The country selection criterioa includes features such as exchange regime type and availability of the information among other criterion. The series that are studied here are the differenced logarithms.

The observations before 1990 and after 2007 are not included, because modeling exchange rate before the 1990's is complicated due to the side-effect of financial and banking crisis. Considering exchange rates series after 2007 would also introduce complications due to the present financial crisis. This crisis triggered by a liquidity crisis in the United States banking system resulted in the collapse of large financial institutions, the bailout of banks by national governments, downturns in stock markets and active policies to stabilize the foreign exchange markets. However, the period of the global financial crisis is of interest to researchers since it shows how volatility responds under more extreme conditions.

The forecasting for each time series is carried out in order to verify the validity of the fitted forecasting models. Each time series is divided into two samples. The first 1,305 observations from 2000 to 2004 are considered as the in-sample data set that will be used for the in-sample estimations while the last 781 observations from 2005 to 2007 are left for the out-of-sample forecasting. The approach of using an expanding window to forecast exchange rates one day ahead on the out-of-sample series is used.

3. Methodology and Estimation Method

To begin with the analysis, stylized facts are examined and some diagnostic tests are performed on the return series in order to justify the use of a correct forecasting model: the use of symmetric or asymmetric GARCH models will be highly supported if patterns of volatility clustering are found. Secondly, the models are fitted to the data, the behavior of the time series are predicted and tests are applied in order to evaluate whether an asymmetric model possesses more forecasting power than asymmetric one.

3.1 Modeling the conditional mean

In order to choose an appropriate model to fit the conditional mean, the family of the ARMA(p,q) models are taken into consideration for capturing the serial correlations in data. The models for the conditional mean could be selected according to the results of information criteria such as Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

3.2 Modeling the conditional volatility

The study then proceeds to examine the conditional volatility. Unlike the constant unconditional variance, the conditional variances depending on the past information vary over time. According to Engle (2001), when there is conditional heteroskedasticity, the regression coefficients for an ordinary least squares regression (OLS) are still not biased, but the standard errors and confidence intervals will be too narrow to give precise result. Hence, applying the autoregressive conditional heteroskedasticity (ARCH) model proposed by Engle (1982) or the generalized ARCH (GARCH) suggested by Bollerslev (1986) would be more appropriate. The focus is on these following models.

3.2.1 GARCH

Bollerslev (1986) extended the ARCH(q) model which was introduced by Engle (1982) to form the so called GARCH model. In its general form the GARCH(p,q) model can be written as:

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

$$\varepsilon_t = \sigma_t e_t, \quad e_t \sim i.i.d.\, N(0,1) \qquad (2)$$

$$\omega > 0, \qquad \alpha_i \geq 0, \qquad \beta_j \geq 0, \tag{3}$$

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1 \tag{4}$$

where ${\sigma_t}^2$ is the conditional variance and ϵ_t is a white noise representing the residual of the return process. ${\sigma_t}^2$ depends upon the squared error terms from previous periods plus the past conditional variance. The non-negativity of σ_t^2 is ensured by (3). In order to have a non-explosive process the following condition (4) must hold. When p equals to zero, this reduces into ARCH(q) model.

Unlike the symmetric GARCH model introduced above, asymmetric GARCH models allow for the possibility that "bad news" have a different impact on future volatility than "good news" of similar magnitude. The class of asymmetric GARCH model presented here are the Exponential GARCH model and the GJR-GARCH model.

3.2.2 EGARCH

The EGARCH(p,q,γ) was introduced by Nelson (1990) and its simplest representation EGARCH(1,1,1) has the following form:

$$\log \sigma_t^2 = \omega + \alpha\left(\frac{|\epsilon_{t-1}|}{\sigma_{t-1}} - E\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right)\right) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta \log \sigma_{t-1}^2 \tag{5}$$

where α, β and γ are constant parameters. Because the term $\frac{\epsilon_{t-1}}{\sigma_{t-1}}$ is included in the equation, the asymmetric effect is captured by coefficient γ as long as $\gamma \neq 0$. When $\gamma < 0$, positive shocks generate less volatility than negative shocks. The logarithmic transformation guarantees that variances will never become negative. Therefore neither α nor β is constrained to be non-negative anymore. Typically, one would expect that $\gamma + \alpha > 0$ while $\gamma < 0$.

3.2.3 GJR-GARCH

The GJR-GARCH model is another flexible alternative to model asymmetric response of volatility to different shocks. The GJR-GARCH (p,q,δ) model was proposed by Glosten, Jagannathan and Runkle (1993), it allows the conditional variance to react differently to the positive and negative shocks. The simplest representation GJR-GARCH(1,1,1) can be written as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \delta\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1}^2 \tag{6}$$

where $I(.)$ denotes the indicator function, δ accounts for any asymmetry of the volatility response to negative and positive shocks which is typically found to be positive. In particular, negative and positive past returns will affect the variance in a magnitude of $\alpha + \delta$ and α respectively.

3.3 Estimation

To estimate the family of ARCH, GARCH model, the maximum likelihood method is commonly used. The log likelihood function has the form as following:

$$\mathrm{L} = \sum_{t=1}^{T} -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\sigma_t^2) - \frac{(r_t-\mu_t)^2}{2\sigma_t^2} \tag{7}$$

The parameter estimates are produced by maximizing the log-likelihood function with non-linear optimization routines. The assumption for the distribution of error term needs to be made before the estimation. Several leptokurtic distribution, such as Student-t distribution and Generalized error distribution (GED) are used by researchers. In this study, the distribution of error term is assumed to be normal with zero mean and unit variance.

4. Results

4.1 Estimation

Figure 1 in Appendix 2 shows the patterns of the exchange rates series (in logarithms) of the 10 countries under analysis from 2000 to 2004 in sample. Each of the ten series exhibits the sign of random walk rather than mean-reverting process which suggests that they might not be stationary. The data to be examined later is the first difference of log of exchange rates, and it could be interpreted as return. Some summary statistics in Table 1 illustrate the non-normality of exchange rates return. The mean and variance are quite small, and it shows that the sample has excess kurtosis which exhibits the evidence of the fat tails stylized fact in financial time series. The skewness shows that the distributions of all the return series are skewed whereas JPY, INR and BRL are skewed to the left.

TABLE 1. Summary Statistics for exchange rate series return

	Mean	Med	Min	Max	Std.Dev	Skewness	Kurtosis
AUD/USD	-0.0001	-0.0005	-0.0446	0.0341	0.0076	0.3063	5.2613
GBP/USD	-0.0001	-0.0003	-0.0209	0.0193	0.0053	0.1632	3.7240
JPY/USD	0.0000	0.0000	-0.0291	0.0248	0.0061	-0.1588	4.4104
SEK/USD	-0.0002	-0.0001	-0.0276	0.0241	0.0070	0.1025	3.6340
CHF/USD	-0.0002	-0.0002	-0.0207	0.0301	0.0069	0.2250	3.5874
INR/USD	0.0000	0.0000	-0.0117	0.0116	0.0017	-0.2263	15.1100
MXN/USD	-0.0001	-0.0003	-0.0171	0.0315	0.0046	0.5659	6.1180
KRW/USD	0.0001	0.0001	-0.0233	0.0213	0.0048	0.1583	4.2803
BRL/USD	0.0003	0.0000	-0.0600	0.0544	0.0100	-0.1246	8.3508
ZAR/USD	-0.0001	0.0000	-0.0965	0.0759	0.0113	0.2090	11.0371

In order to model the conditional mean of the exchange rate series, the first-difference of the logarithmic exchange rates is used from the in-sample set of observations (that is the first 1,305 observations from 2000 to 2004). Figure 2 (Appendix 2) shows the in-sample exchange rate returns tend to look like stationary conforming graphically mean-reverting processes.

In the first step, by the use of Ljung-Box test, it can be confirmed whether some exchange rates returns need to be modeled through a model from the ARMA(p,q) family. In other words, the test of current value of the first-differenced log exchange rate, r_t, depends on its past value, r_{t-1}. This can be done by looking at the p-values attached to the Q-statistics obtained through the Ljung-Box test. As can be seen from

Table 5 in Appendix 1, in five out of the ten return series, this is the case: some lags in the Australian Dollar, Indian Rupee, Swiss Franc, Brazilian Real and South African Rand exchange rates returns have p-values lower than 0.05. This test also suggests that the GBP, SEK, KRW and MXN return series can be modeled using ARMA(0,0), which is simply white noise.

In order to choose the appropriate lags, p and q, to fit the ARMA(p,q) models for the AUD, INR, CHF, BRL and ZAR exchange rates returns, alternative models have been finally evaluated by taking into considerations of the information criteria, AIC and BIC, and individual significance of the parameters. The estimation results of the ARMA(p,q) models for each currency return together with the corresponding values of the two information criterion are reported in Appendix 1, Table 6. Following this strategy, the models that best fit the conditional mean of the AUD, INR, CHF, BRL and ZAR exchange rates are ARMA(0,0), ARMA(0,0), ARMA(1,0), ARMA(1,2) and ARMA(0,0), respectively.

After estimating the best model for the conditional mean, the residuals are obtained and the Jarque-Bera normality test is performed. The p-values presented below in Table 2 suggest that in all of the series, the null hypothesis of normality of the residuals is rejected.

TABLE 2. Normality test on the residuals after modeling the conditional means (p-values)

	AUD	GBP	JPY	SEK	CHF	INR	MXN	KRW	BRL	ZAR
p-value	0	3.66E-08	0	3.51E-07	0	0	0	0	0	2.68E-07

In Appendix 1 Table 7, the results of the Ljung-Box test are presented for the square of the residuals obtained after modeling the conditional mean of the exchange rates returns in order to examine any dependence that could be captured by GARCH models. The null hypothesis is that there exists absence of ARCH effects, consequently, conditional heteroskedasticities are observed in all the series. For the cases of the SEK, CHF and GBP exchange rates, these effects are not so obvious at the first lags but indication is found by increasing the number of lags. Furthermore, the conclusion drawn from conducting the Lagrange Multiplier test have been exactly the same. Please refer to the results which are presented in the table.

A practical issue is the determination of the appropriate number of lags of GARCH model. The individual significance of the lagged residuals and variances as well as the AIC and BIC criteria have been considered in the selection of a GARCH model with appropriate number of lags. Particularly, for each exchange rate time series, GARCH(1,1), GARCH(1,2), GARCH(2,1) and GARCH(2,2) are estimated. Then, the most appropriate specification may be determined by the AIC and BIC information criteria. If values of the information criteria for two models are quite similar, the more parsimonious model is selected.

Once the return data is fitted by appropriate symmetric ARMA-GARCH models, the work proceed to directly test the hypothesis that due to typically higher uncertainty and risk prevailing in emerging markets relative to developed markets, it is expected that asymmetric stochastic volatility models should fit the emerging markets' exchange rates better than symmetric ones and vice versa. In order to check the validity of this hypothesis, steps described in section 3 are followed. The in-sample EGARCH and GJR-GARCH models are estimated first and the currency return series are verified whether statistically significant coefficients for the EGARCH and GJR-GARCH models are found. The estimates of parameters in variance equation for GARCH, EGARCH, GJR-GARCH models are presented in Appendix 1 Table 8. The standard deviations are presented below the estimates.

The models that are chosen for the exchange rates return series are all GARCH(1,1). The GARCH(1,1) models are often chosen and are hard to be outperformed (Zivot, 2008). Table 3 includes the AIC valued in the first row for each currency return and BIC in the second. It shows that BIC proposed that EGARCH is the best model for AUD, GJR-GARCH for INR, EGARCH for MXN, EGARCH for KRW, and GJR-GARCH for BRL. In Appendix 2 Figure 3, the conditional deviation estimated by GJR-GARCH model for return of Brazilian Real is presented along with the plots of return series and the innovations. Hence, asymmetric effect has been detected for four of the exchange rate return series in emerging markets while one in developed market.

4.2 Diagnostics checking

Appendix 1 Table 9 reports the p-values at 5% from the test of portmanteau Ljung-Box on standardized residuals. One can see that the p-values are larger than 0.05 except for Australian Dollar, Swiss Franc and Indian Rupee. Table 10 in Appendix 1 shows the p-values of the Ljung-Box test on squared standardized residuals. All returns have p-values larger than 0.05 except for Swiss Franc and Australian Dollar at lower lags. As a consequence, the other alternative model specifications are estimated and the diagnostic checking is performed again. But since the significance of the additional parameter is not large, in the following, GARCH(1,1) will be considered.

TABLE 3. Model Selection Criteria for Estimated GARCH(p,q) Models

(For each return, the first row shows AIC of corresponding models, the second shows BIC.)

	GARCH(1,1)	EGARCH(1,1)	GJR(1,1)	chosen
AUD/USD	-9080.7	-9095.9	-9087.7	EGARCH
	-9060.1	-9070	-9061.8	
GBP/USD	-9996.7	-9990.6	-9995.9	GARCH
	-9976	-9964.7	-9970.1	
JPY/USD	-9595.3	-9595.2	-9593.3	GARCH
	-9574.6	-9569.3	-9567.4	
SEK/USD	-9272.4	-9277.1	-9273.2	GARCH
	-9251.7	-9251.3	-9247.3	
CHF/USD	-9241.4	-9246.4	-9241.1	GARCH
	-9215.5	-9215.3	-9210	
INR/USD	-1380.4	-13793	-13810	GJR
	-13783	-13767	-13784	

MXN/USD	-10294	-10296	-10294	EGARCH
	-10270	-10270	-10268	
KRW/USD	-10513	-10519	-10511	EGARCH
	-10492	-10493	-10486	
BRL/USD	-8926.9	-8932	-8941	GJR
	-8890.7	-8890.7	-8899.6	
ZAR/USD	-8373.1	-8375.4	-8373	GARCH
	-8352.4	-8349.5	-8347.1	

4.3 Forecasts

Next, the one-step-ahead forecasts are carried out for the symmetric and asymmetric GARCH models in order to check the out-of-sample forecasting power. The one-step-ahead forecast uses the model parameters which are estimated in sample and the information that is available at time period t. Then, the estimates for the model parameters are updated after forecasting.

To evaluate the performance of the GARCH models, 780 one-step-ahead forecasts are generated and the traditional forecast evaluation statistics like mean square error (MSE) is calculated to evaluate the forecasting ability. The estimates of parameters in GARCH models are obtained through in-sample estimation and the one-step-ahead forecast is conducted. Then the new estimates of parameters are produced in the sample with one more observation, and new forecast is generated. The forecasts proceed until the full sample of return series is used.

In applications, the interest lies mainly in forecasting future conditional variance. However, the value of conditional variance is not known which makes it difficult to evaluate the performance of forecasting and hence a proxy is needed for replacing it. The squared return is a standard choice for proxy.

TABLE 4 presents the MSE of the one-step-ahead forecasts with squared return as proxy. The model is chosen by the smallest MSE is reported in the last column. It can be seen that, for AUD, GBP, JPY, INR, MXN, KRW and BRL returns, the asymmetric GARCH model EGARCH outperforms GARCH(1,1) by 0.0045 $\times 10^{-8}$, 0.0001 $\times 10^{-8}$, 0.0251 $\times 10^{-8}$, 0.042 $\times 10^{-8}$, 0.0241$\times 10^{-8}$, 0.0186$\times 10^{-8}$ and 0.3525$\times 10^{-8}$ respectively. Model GARCH(1,1) is considered to be the best for SEK, CHF, ZAR according to MSE. In conclusion, for most of returns, asymmetric model does an either equally good or even better job than symmetric specifications in the perspective of out-of-sample forecasting power.

Figure 4 (Appendix 2) shows the forecasts of the conditional standard deviation for return Australian Dollar from asymmetric models and GARCH(1,1). As EGARCH model for Australian Dollar has the smallest MSE, it could be considered as a better model in forecasting.

The MSE of forecasts in out-of-sample shows different result compared to the one from in-sample estimation. Asymmetric effect is not found for emerging markets in forecasting one-step-ahead.

TABLE 4. MSE of one-step-ahead forecasts (out-of-sample)

	GARCH	GJR	EGARCH	chosen
AUD/USD	1.1434E-08	1.1511E-08	1.1389E-08	EGARCH
GBP/USD	1.3597E-09	1.3601E-09	1.3596E-09	EGARCH
JPY/USD	8.3765E-09	8.3812E-09	8.3454E-09	EGARCH
SEK/USD	2.7523E-09	2.7588E-09	2.7960E-09	GARCH
CHF/USD	2.0978E-09	2.0996E-09	2.1735E-09	GARCH
INR/USD	5.4648E-10	5.5332E-10	5.4228E-10	EGARCH
MXN/USD	9.7917E-10	9.7903E-10	9.7676E-10	EGARCH
KRW/USD	1.1405E-09	1.1420E-09	1.1219E-09	EGARCH
BRL/USD	5.9616E-08	5.9050E-08	5.6091E-08	EGARCH
ZAR/USD	2.1236E-08	2.1270E-08	2.1456E-08	GARCH

5. Conclusion

The objective of this research is to characterize the behavior of exchange rate volatilities in emerging and advanced markets. The study focus on the assessment of what type of models fit the exchange rate volatility better in a sample of emerging and advanced market. For this, stochastic volatility models such as symmetric and asymmetric GARCH are relied on.

The findings are that asymmetric GARCH models are more suitable in explaining the data than symmetric ones in Mexican Peso, Indian Rupee, South Korean Won, Brazilian Real, four out of five emerging markets for in-sample estimation. Meanwhile, only SEK, CHF, ZAR exhibit higher performance in one-step-ahead forecasts of the general GARCH models. These results represent evidence against the initial hypothesis that exchange rate returns in emerging markets should be better described by asymmetric GARCH models due to the "gain/loss asymmetry" effect. Since squared return is the proxy for forecasting, which could introduce noise, MSE would be biased.

The “gain/loss asymmetry” effect has been claimed to be more commonly present in stock returns. That is, the distinction between good and bad news is more sensible for stock markets than for exchange rates, where agents typically are on both sides of the market. This means that good news for one agent may be bad news for another (Verbeek, 2004), and because of this, the ultimately asymmetric effect is reduced.

Another possible explanation of the absence of asymmetric effects in the returns might be the intervention of the countries in the foreign exchange markets in order to stabilize when facing unfavorable economic conditions. Such governmental policies influence investors’ expectations which consequently might lead to a less significant asymmetric effect in the exchange rates returns.

Taking squared return as proxy for conditional variance would add large noise to forecast error of MSE, giving rise to imprecision to the result of forecasting. One might extend this current study to estimation in a nested GARCH model. In addition, fat tails stylized fact could be better captured by other distributions such as student-t or GED distribution. These are out of the scope of this study and are left for further research.

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Appendix 1

Please note that in all tables below, the number below each estimated parameter is the standard deviation.

Table 5. Ljung-Box P-values at 5% for return series

	AUD/USD	GBP/USD	JPY/USD	SEK/USD	CHF/USD	INR/USD	MXN/USD	KRW/USD	BRL/USD	ZAR/USD
1	0.1858	0.5545	0.0815	0.6452	0.0035	0.7357	0.1326	0.1326	0.0015	0.1199
2	0.1198	0.726	0.2187	0.7768	0.0082	0.0032	0.1792	0.1792	0.0006	0.1769
3	0.0457	0.3851	0.3555	0.4913	0.0008	0.0024	0.184	0.184	0.0011	0.1881
4	0.0349	0.2403	0.4538	0.4761	0.0003	0.0009	0.1612	0.1612	0.0005	0.2416
5	0.0594	0.3541	0.4604	0.5502	0.0007	0	0.2182	0.2182	0.0013	0.2852
6	0.0756	0.4633	0.5716	0.6089	0.0015	0	0.3143	0.3143	0.0027	0.1005
7	0.1178	0.4727	0.6402	0.6917	0.0026	0	0.4126	0.4126	0.0038	0.1549
8	0.1693	0.5814	0.6427	0.717	0.0047	0	0.4162	0.4162	0.0046	0.1906
9	0.2287	0.6587	0.6414	0.6816	0.0013	0	0.4441	0.4441	0.0067	0.0333
10	0.1485	0.7086	0.7166	0.7648	0.002	0	0.4111	0.4111	0.0074	0.0427

Table 6. Modeling Conditional Mean of Exchange Rates Return

				BRL/USD			
	AIC	BIC	C	AR(1)	AR(2)	MA(1)	MA(2)
ARMA(0,0)	-8288	-8277	0.00027796				
			0.00027855				
ARMA(1,0)	-8296	-8280	0.0002535	0.088087			
			0.00027827	0.013271			
ARMA(0,1)	-8297	-8282	0.00027763			0.099644	
			0.00030512			0.013307	
ARMA(1,1)	-8297	-8276	0.00033605	-0.21338	0.31156		
			0.00038054	0.15284	0.15019		
ARMA(2,0)	-8300	-8279	0.00027094	0.094048	-0.06765		
			0.00028615	0.013637	0.014405		
ARMA(0,2)	-8299	-8278	0.0002781			0.090281	-0.047575
			0.00029715			0.01371	0.014895
ARMA(1,2)	-12927	-12901	-1.7206E-06	0.1224	-0.13438	0.10694	
			0.000047102	0.13232	0.13302	0.011625	
ARMA(2,1)	-8298	-8272	0.00024229	0.2091	-0.078451	-0.11554	
			0.00025756	0.22742	0.020541	0.22969	
ARMA(2,2)	-8301	-8270	0.00071516	-1.0528	-0.59743	1.1547	0.67068
			0.00078682	0.12303	0.08897	0.12277	0.087644

			ZAR/USD				
	AIC	BIC	C	AR(1)	AR(2)	MA(1)	MA(2)
ARMA(0,0)	-7988.5	-7978.1	-0.000054981				
			0.00031281				
ARMA(1,0)	-7988.9	-7973.4	-0.00005738	-0.043036			
			0.00033702	0.014322			
ARMA(0,1)	-7989.1	-7973.5	-0.000054912		-0.045918		
			0.00032299		0.014127		
ARMA(1,1)	-7988.4	-7967.7	-0.000031036	0.42871	-0.47847		
			0.00018174	0.30839	0.29855		
ARMA(2,0)	-7988.1	-7967.4	-0.000058951	-0.044335	-0.03019		
			0.00034307	0.014693	0.022468		
ARMA(0,2)	-7988.3	-7967.6	-0.000054761			-0.046335	-0.029798
			0.00031832			0.014691	0.022616
ARMA(1,2)	-7986.7	-7960.8	-0.000038426	0.29376		-0.33923	-0.018884
			0.00022435	0.58114		0.57782	0.041871
ARMA(2,1)	-7986.7	-7960.9	-0.000038309	0.3154	-0.019413	-0.36044	
			0.00022325	0.50014	0.037665	0.49647	
ARMA(2,2)	-7993.9	-7962.8	-0.000012844	1.648	-0.86127	-1.6997	0.90674
			0.00007063	0.046818	0.047405	0.041922	0.040708

			AUD/USD				
	AIC	BIC	C	AR(1)	AR(2)	MA(1)	MA(2)
ARMA(0,0)	-9019.3	-9009	-0.00013671				
			0.0002125				
ARMA(1,0)	-9019	-9003.5	-0.00014156				
			0.00021829	-0.036632			
ARMA(0,1)	-9019.2	-9003.7	-0.00013642	0.022515		-0.040473	
			0.00021048			0.022389	
ARMA(1,1)	-9019.7	-8999	-0.000070033	0.48222		-0.53333	
			0.00011319	0.35544		0.34507	
ARMA(2,0)	-9019.7	-8999	-0.00014731	-0.038311	-0.045174		
			0.00021961	0.022703	0.027913		
ARMA(0,2)	-9020	-8999.3	-0.00013608			-0.043002	-0.044204
			0.00020128			0.022761	0.028288
ARMA(1,2)	-9018.9	-8993	-0.000097912	0.27725		-0.31827	-0.036098
			0.00015472	0.49456		0.4938	0.039791
ARMA(2,1)	-9019.1	-8993.3	-0.00010003	0.30116	-0.040157	-0.34079	
			0.00015531	0.42522	0.036332	0.42456	
ARMA(2,2)	-9022.3	-8991.3	-0.00018	1.0803	-0.98316	-1.0962	0.98614
			0.00018742	0.01135	0.01061	0.011129	0.01014

			CHF/USD				
	AIC	BIC	C	AR(1)	AR(2)	MA(1)	MA(2)
ARMA(0,0)	-9.2373	-9.2269	-0.00023894				
			0.00019368				
ARMA(1,0)	-9.2438	-9.2283	-0.00025876	-0.080951			
			0.00019317	0.029927			
ARMA(0,1)	-9.2435	-9.228	-0.00023926			-0.078132	
			0.00017836			0.030085	
ARMA(1,1)	-9.2467	-9.226	-0.00042174	-0.7296		0.66003	
			0.00032228	0.13691		0.15289	
ARMA(2,0)	-9.2425	-9.2218	-0.00025289	-0.079102	0.022297		
			0.00019309	0.030053	0.029363		
ARMA(0,2)	-9.2419	-9.2212	-0.00023907			-0.077457	0.016422
			0.00018169			0.029977	0.02921
ARMA(1,2)	-9.2448	-9.219	-0.00043243	-0.76968		0.69404	-0.014186
			0.00032594	0.18287		0.18678	0.038814
ARMA(2,1)	-9.2448	-9.2189	-0.00043938	-0.78314	-0.013466	0.70844	
			0.00033287	0.2257	0.042696	0.22485	
ARMA(2,2)	-9.2434	-9.2124	-0.00023387	-0.32275	0.35207	0.24107	-0.34595
			0.00042446	0.96275	0.65019	0.9597	0.5758

			INR/USD				
	AIC	BIC	C	AR(1)	AR(2)	MA(1)	MA(2)
ARMA(0,0)	-12919	-1.2909	-1.6319E-06				
			0.00004713				
ARMA(1,0)	-12918	-1.2902	-1.5665E-06	-0.0093439			
			0.000048442	0.013059			
ARMA(0,1)	-12917	-1.2902	-1.6006E-06			-0.0079201	
			0.000047854			0.012974	
ARMA(1,1)	-12917	-1.2896	-2.4638E-06	-0.38878		0.36135	
			0.000065544	0.42895		0.43215	
ARMA(2,0)	-12927	-1.2906	-1.1215E-06	-0.0084226	0.093627		
			0.000048198	0.012886	0.011149		
ARMA(0,2)	-12929	-1.2908	-1.9945E-06			-0.014483	0.1083
			0.000052341			0.013228	0.011197
ARMA(1,2)	-12927	-1.2901	-1.7206E-06	0.1224		-0.13438	0.10694
			0.000047102	0.13232		0.13302	0.011625
ARMA(2,1)	-12927	-1.2901	-5.5223E-07	0.78502	0.069664	-0.80255	
			9.6851E-06	0.050974	0.014193	0.046475	
ARMA(2,2)	-12926	-1.2895	-5.8129E-07	0.61314	0.29082	-0.63494	-0.22097
			0.000007109	0.25012	0.25504	0.25235	0.25404

Table 7. Ljung-Box and Lagrange Multiplier test on the Square of the Residuals after Modeling the Conditional Mean (p-values at 5%)

			Ljung-Box P-value							
	AUD/USD	GBP/USD	JPY/USD	SEK/USD	CHF/USD	INR/USD	MXN/USD	KRW/USD	BRL/USD	ZAR/USD
1	0.000000057	0.5361	0.0253	0.3605	0.0716	0	9.668E-08	0.00000202	0	0
5	0.000004133	0.0355	0.199	0.0256	0.0299	0	0	0	0	0
10	0.000001599	0	0.3897	0.0188	0.0344	0	0	0	0	0
			LM test P-value							
1	0	0.8061	0.0055	0.6258	0.3023	9.119E-11	0.044	0.5598	0	0
5	9E-15	0.4383	0.1291	0.7276	0.0616	0	0.2211	0.9936	0	0
10	4.804E-12	0	0.4737	0.726	0.1824	0	0.6929	0.9999	0	0

Table 8. Estimations of the GARCH models of the Exchange Rates Return

				AUD/USD						
	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-9080.7	-9060.1	-0.00032675	7.4489E-07	0.94933		0.038305			4544.4
			0.00019355	2.6117E-07	0.0084353		0.0060281			
GARCH(1,2)	-9078.7	-9052.9	-0.00032021	7.3274E-07	0.94984		0.038125	0		4544.4
			0.0002014	2.6544E-07	0.010548		0.0092597	0.013188		
GARCH(2,1)	-9081.4	-9055.5	-0.00031087	1.1146E-06	0.43458	0.49162	0.055113			4545.7
			0.00019713	4.4645E-07	0.31805	0.30791	0.010569			
GARCH(2,2)	-9079.4	-9048.4	-0.00030994	1.2006E-06	0.43129	0.49257	0.055925	0		4545.7
			0.00020043	8.2227E-07	0.76517	0.7218	0.012374	0.038726		
GJR-GARCH	-9087.7	-9061.8	-0.00044196	7.9964E-07	0.95742		0.045475		-0.037422	4.55E+03
			0.00018574	3.6276E-07	0.013085		0.012619		0.016949	
EGARCH	-9095.9	-9070	-0.0004085	-0.22801	0.97691		0.081366		0.050534	4.55E+03
			0.00018537	0.096198	0.009739		0.027036		0.012045	

GBP/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-9996.7	-9976	-0.0001742	5.80E-07	0.93537		0.044429			5002.4
			0.0001397	2.38E-07	0.015637		0.0097602			
GARCH(1,2)	-9997.1	-9971.2	-0.00015688	6.97E-07	0.92667		0.0044697	0.044807		5003.5
			0.0001394	2.74E-07	0.017495		0.02579	0.027591		
GARCH(2,1)	-9994.5	-9968.7	-0.00015688	6.97E-07	0.92667		0.0044697	0.044807		5002.3
			0.0001394	2.74E-07	0.017495		0.02579	0.027591		
GARCH(2,2)	-9995	-9963.9	-0.00017069	5.10E-07	0.94032	0	0.042707			5003.5
			0.00014118	4.16E-07	0.78658	0.74366	0.032976			
GJR-GARCH	-9995.9	-9970.1	-0.00015959	6.41E-07	0.93095	0	0.007147	0.039614	-0.019976	5.00E+03
			0.00013929	4.28E-07	0.69825	0.65904	0.026124	0.037844	0.012831	
EGARCH	-9990.6	-9964.7	-0.00014623	-0.29088	0.97202		0.097383		0.0102	5.00E+03
			0.00014255	0.10711	0.01019		0.02059		0.011804	

JPY/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-9595.3	-9574.6	-2.16E-05	6.98E-07	0.96065		0.0205			4801.7
			0.00016818	3.84E-07	0.015642		0.0069976			
GARCH(1,2)	-9593.3	-9567.4	-2.20E-05	6.86E-07	0.96032		0.021167	0		4801.6
			0.00016812	4.35E-07	0.018389		0.015821	0.018471		
GARCH(2,1)	-9594.9	-9569	-3.01E-05	1.44E-06	0.1928	0.7323	0.036008			4802.4
			0.00016858	7.37E-07	0.24428	0.24329	0.011782			
GARCH(2,2)	-9593.5	-9562.4	-3.38E-05	1.30E-06	0	0.92914	0.028952	0.0066191		4802.7
			0.00016751	8.10E-07	0.042964	0.035107	0.0092677	0.010825		
GJR-GARCH	-9593.3	-9567.4	-2.34E-05	6.92E-07	0.96232		0.020758		-0.00344	4.80E+03
			0.00016922	4.02E-07	0.015997		0.0088506		0.0094908	
EGARCH	-9595.2	-9569.3	-2.25E-05	-0.33167	0.96729		0.060288		-0.010425	4.80E+03
			0.0001697	0.16735	0.016438		0.020276		0.011422	

SEK/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-9272.4	-9251.7	-0.00022374	2.4194E-06	0.91881		0.030621			4640.2
			0.0001924	1.4918E-06	0.039985		0.012654			
GARCH(1,2)	-9270.4	-9244.6	-0.0002235	2.4463E-06	0.91764		0.029309	0.0018904		4640.2
			0.00019281	1.5987E-06	0.043204		0.024645	0.025788		
GARCH(2,1)	-9275.5	-9249.7	-0.0002563	3.4509E-06	0.0066456	0.87128	0.049946			4642.8
			0.00019048	2.1411E-06	0.046482	0.063875	0.016711			
GARCH(2,2)	-9273.4	-9242.4	-0.00025893	2.9313E-06	0.011	0.87959	0.048149	0		4642.7
			0.00019046	2.0841E-06	0.066811	0.063324	0.016383	0.016559		
GJR-GARCH	-9273.2	-9247.3	-0.0001949	3.0263E-06	0.90383		0.048626		-0.032867	4641.6
			0.0001918	1.5365E-06	0.040603		0.018802		0.020513	
EGARCH	-9277.1	-9251.3	-0.0001528	-0.66158	0.93341		0.076254		0.038707	4643.6
			0.00018951	0.305	0.030636		0.027863		0.01768	

CHF/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-9241.4	-9215.5	-0.00027117	8.3272E-07	0.97315		0.0096053			4625.7
			0.00019158	9.2634E-07	0.023387		0.0066686			
GARCH(1,2)	-9237.8	-9206.8	-0.00025869	0.000032141	0.33542		0	0		4624.9
			0.0001939	1.6511E-06	1.5001E-08		0.027632	0.022539		
GARCH(2,1)	-9240.7	-9209.6	-0.00027941	1.9355E-06	0.039005	0.90551	0.015338			4626.3
			0.00019207	2.3768E-06	0.10372	0.11454	0.011947			
GARCH(2,2)	-9238.2	-9201.9	-0.00027605	1.1758E-06	0.10296	0.85941	0.013137	0		4626.1
			0.00019137	1.6351E-06	0.41055	0.39588	0.017193	0.018968		
GJR-GARCH	-9241.1	-9210	-0.00026902	9.3989E-07	0.9739		0.012244		-0.011847	4626.5
			0.00019262	9.7742E-07	0.022903		0.0081057		0.011792	
EGARCH	-9246.4	-9215.3	-0.0003112	-5	0.49743		-0.095716		0.078483	4629.2
			0.00018819	2.1043	0.21135		0.050893		0.034229	

INR/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-1380.4	-13783	-1.4045	0.0000002	0.55563		0.4348			6905.9
			0.000025903	1.1677E-08	0.017059		0.034641			
GARCH(1,2)	-1380.3	-13777	-1.4038	0.0000002	0.53579		0.39485	0.064421		6906.4
			0.000025575	1.4283E-08	0.026366		0.045549	0.053375		
GARCH(2,1)	-1380.2	-13776	-1.4038	0.0000002	0.52485	0.025092	0.44158			6906
			0.000026275	1.8589E-08	0.10225	0.06821	0.049628			
GARCH(2,2)	-1380.2	-13771	-0.000064174	2.1521E-07	0.27112	0.17945	0.38306	0.16638		6907.1
			0.000024312	1.257E-08	0.0083407	0.017219	0.042012	0.037028		
GJR-GARCH	-13810	-13784	-0.000044704	0.0000002	0.54688		0.55206		-0.20929	6909.9
			0.000028046	1.2531E-08	0.016762		0.054155		0.054334	
EGARCH	-13793	-13767	-0.000020835	-1.4386	0.88775		0.58601		0.06705	6901.3
			0.000026458	0.085396	0.0062371		0.0268		0.016721	

MXN/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-10294	-10270	0.00011138	9.4868E-07	0.87706		0.083344			5149.5
			0.00012442	2.9348E-07	0.021241		0.013619			
GARCH(1,2)	-10289	-10263	0.00011209	0.000001075	0.86911		0.085755			5149.6
			0.00012499	3.7761E-07	0.028853		0.025244	0		
GARCH(2,1)	-10296	-10270	0.00008103	1.4813E-06	0.22595	0.57674	0.13608	0.031224		5152.8
			0.00012438	4.4198E-07	0.11461	0.10675	0.022513			
GARCH(2,2)	-10294	-10263	0.000081589	0.000001434	0.23058	0.57483	0.13567	0		5152.8
			0.00012532	5.7834E-07	0.26614	0.21871	0.029764	0.054449		
GJR-GARCH	-10294	-10268	0.000089715	1.0011E-06	0.86359		0.12852		-0.067247	5152.1
			0.00011932	3.6729E-07	0.029467		0.029003		0.03294	
EGARCH	-10296	-10270	0.00015572	-0.44674	0.95802		0.149		0.058992	5153.2
			0.00012492	0.12261	0.011445		0.022151		0.015492	

KRW/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-10513	-10492	-0.000067726	5.0248E-07	0.88338		0.09651			5260.5
			0.00010781	1.0045E-07	0.01183		0.009895			
GARCH(1,2)	-10511	-10485	-0.000064623	4.667E-07	0.88681		0.095494	0		5260.5
			0.00010801	1.0002E-07	0.014045		0.01823	0.024058		
GARCH(2,1)	-10514	-10488	-0.000069091	6.8476E-07	0.43011	0.41143	0.13097			5262.1
			0.00010885	1.4986E-07	0.15917	0.14771	0.015134			
GARCH(2,2)	-10512	-10481	-0.000071054	6.5714E-07	0.42757	0.41534	0.13157	0		5262.1
			0.00010864	2.9753E-07	0.49609	0.43629	0.023189	0.067429		
GJR-GARCH	-10511	-10486	-0.000081818	4.7963E-07	0.88473		0.092212		0.010542	5260.7
			0.00011387	9.7345E-08	0.011652		0.012676		0.015573	
EGARCH	-10519	-10493	-0.00011786	-0.53775	0.94922		0.23201		-0.0013947	5264.4
			0.00010729	0.095411	0.008723		0.021034		0.012586	

BRL/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-8926.9	-8890.7	-0.000022948	0.000001131	0.83918		0.15902			4470.4
			0.00017014	2.9785E-07	0.014972		0.016858			
GARCH(1,2)	-8924.8	-8883.4	-0.000037367	1.1049E-06	0.8415		0.15672	0		4470.4
			0.00022869	3.0636E-07	0.017391		0.032517	0.037521		
GARCH(2,1)	-8925.3	-8883.9	-0.000036054	1.1516E-06	0.7165	0.11274	0.16916			4470.6
			0.0001901	3.4896E-07	0.22249	0.19486	0.03235			
GARCH(2,2)	-8923.3	-8876.8	-0.000025285	1.1627E-06	0.71266	0.11578	0.16978	0		4470.7
			0.00018377	1.5573E-06	1.445	1.2192	0.034063	0.23333		
GJR-GARCH	-8941	-8899.6	0.00026845	9.9901E-07	0.85393		0.19562		-0.10425	4478.5
			0.00028574	2.645E-07	0.014741		0.023019		0.022443	
EGARCH	-8932	-8890.7	0.00033009	-0.20431	0.97904		0.26745		0.065373	4474
			0.00033855	0.067735	0.0069787		0.035478		0.011795	

ZAR/USD

	AIC	BIC	C	K	GARCH(1)	GARCH(2)	ARCH(1)	ARCH(2)	leverage	Likelihood
GARCH(1,1)	-8373.1	-8352.4	0.00015783	1.0172E-06	0.89261		0.10643			4190.5
			0.00023311	3.8943E-07	0.010291		0.011065			
GARCH(1,2)	-8371.1	-8345.2	0.00015935	1.0246E-06	0.89265		0.1063	0		4190.5
			0.0002343	3.954E-07	0.011509		0.022676	0.025538		
GARCH(2,1)	-8373	-8347.2	0.00016917	1.3098E-06	0.51424	0.34552	0.13882			4191.5
			0.00023318	5.4214E-07	0.17904	0.16283	0.021124			
GARCH(2,2)	-8371	-8340	0.00016868	1.2909E-06	0.51448	0.34588	0.13839	0		4191.5
			0.00023394	7.8315E-07	0.50179	0.44514	0.025925	0.06911		
GJR-GARCH	-8373	-8347.1	0.00023538	9.3178E-07	0.89615		0.11718		-0.02706	4191.5
			0.0002467	3.8941E-07	0.010272		0.012977		0.014931	
EGARCH	-8375.4	-8349.5	0.00031919	-0.13317	0.98448		0.22247		0.032758	4192.7
			0.00024578	0.051132	0.0055593		0.021159		0.0097776	

Table 9. Diagonostic Checking: Ljung-Box test on standardized residuals of each selected ARMA-GARCH model (p-values at 5%)

	AUD/USD	GBP/USD	JPY/USD	SEK/USD	CHF/USD	INR/USD	MXN/USD	KRW/USD	BRL/USD	ZAR/USD
1	0.2751	0.6188	0.1428	0.7669	0.9848	0.8768	0.0162	0.2934	0.1637	0.2425
2	0.3314	0.8835	0.3163	0.9508	0.7843	0.7772	0.0424	0.3044	0.1088	0.2771
3	0.1058	0.6186	0.5024	0.5931	0.0995	0.1071	0.052	0.4656	0.2012	0.4274
4	0.0486	0.2545	0.5287	0.5677	0.038	0.0416	0.0572	0.3027	0.289	0.5413
5	0.0802	0.374	0.5763	0.6523	0.0531	0.0582	0.0975	0.191	0.3872	0.6205
6	0.1266	0.484	0.6874	0.6594	0.0848	0.0915	0.152	0.0079	0.1585	0.1383
7	0.1866	0.505	0.7121	0.7439	0.1125	0.1194	0.2169	0.0057	0.2253	0.1683
8	0.2625	0.6032	0.7208	0.7412	0.1612	0.1694	0.1951	0.0102	0.3038	0.0933
9	0.3253	0.6972	0.7443	0.7192	0.0415	0.0452	0.2262	0.0175	0.3646	0.0586
10	0.1908	0.6683	0.7917	0.7975	0.0483	0.053	0.2272	0.0286	0.1185	0.086

Table 10. Diagonostic Checking: Ljung-Box test on squared standardized residuals of each selected ARMA-GARCH model (p-values at 5%)

	AUD/USD	GBP/USD	JPY/USD	SEK/USD	CHF/USD	INR/USD	MXN/USD	KRW/USD	BRL/USD	ZAR/USD
1	0.0337	0.2325	0.3594	0.9089	0.0497	0.7787	0.159	0.6318	0.63	0.4593
2	0.0396	0.4796	0.4972	0.3472	0.0328	0.9577	0.316	0.8902	0.3515	0.3916
3	0.0241	0.6885	0.6765	0.1763	0.0276	0.9627	0.1978	0.9557	0.1766	0.5731
4	0.0512	0.5404	0.8006	0.2883	0.0466	0.9862	0.3144	0.9086	0.2069	0.5777
5	0.0891	0.647	0.7388	0.4167	0.031	0.9966	0.3432	0.9187	0.1091	0.6915
6	0.1259	0.5631	0.8257	0.5155	0.032	0.9646	0.4079	0.9369	0.1733	0.7799
7	0.1748	0.6773	0.8719	0.3588	0.0462	0.9847	0.2292	0.9274	0.097	0.8187
8	0.194	0.2821	0.88	0.3882	0.0435	0.98	0.2586	0.9315	0.1124	0.8858
9	0.2646	0.3487	0.9227	0.4663	0.0323	0.9888	0.2971	0.8785	0.1318	0.9308
10	0.2904	0.437	0.8277	0.4993	0.0406	0.9925	0.2595	0.765	0.155	0.952

Appendix 2

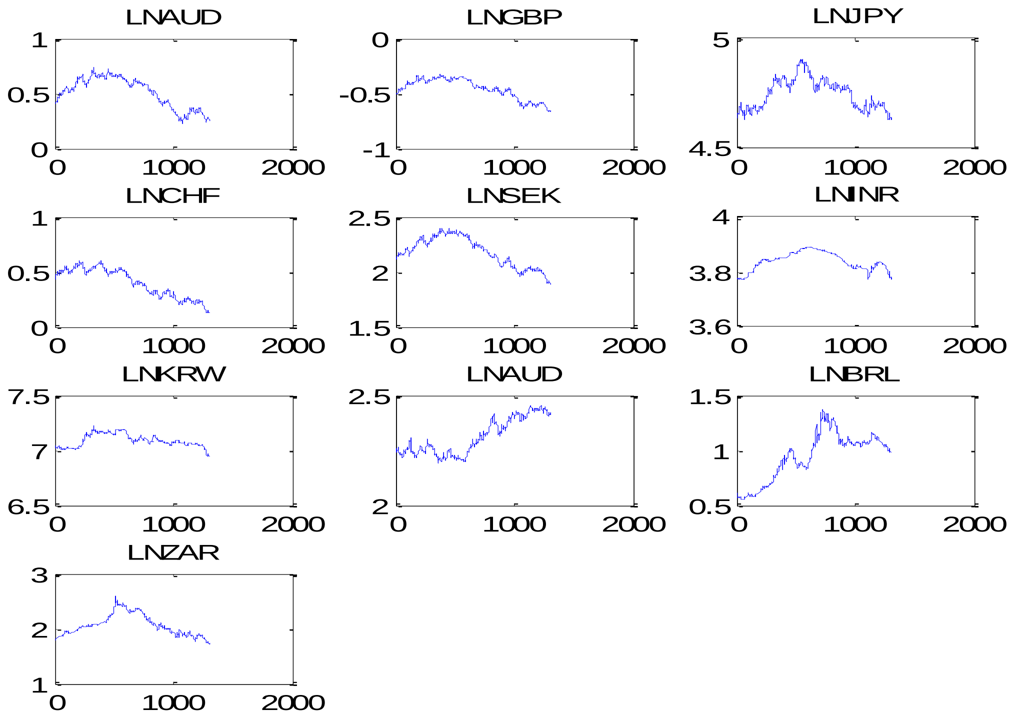

Figure 1. Daily nominal exchange against the US Dollar from 2000 to 2004 (in logarithms)

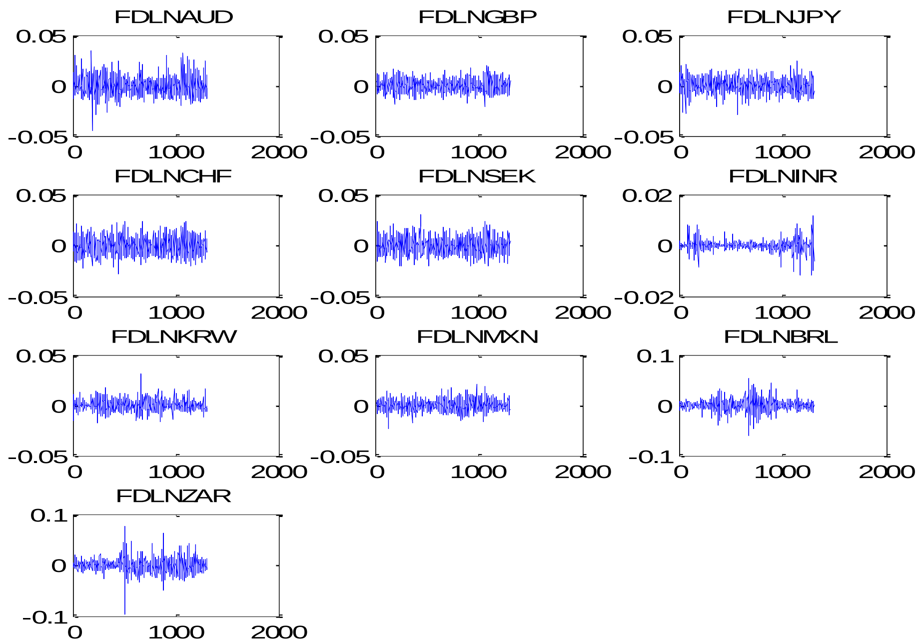

Figure 2. First-difference daily nominal exchange against the US Dollar

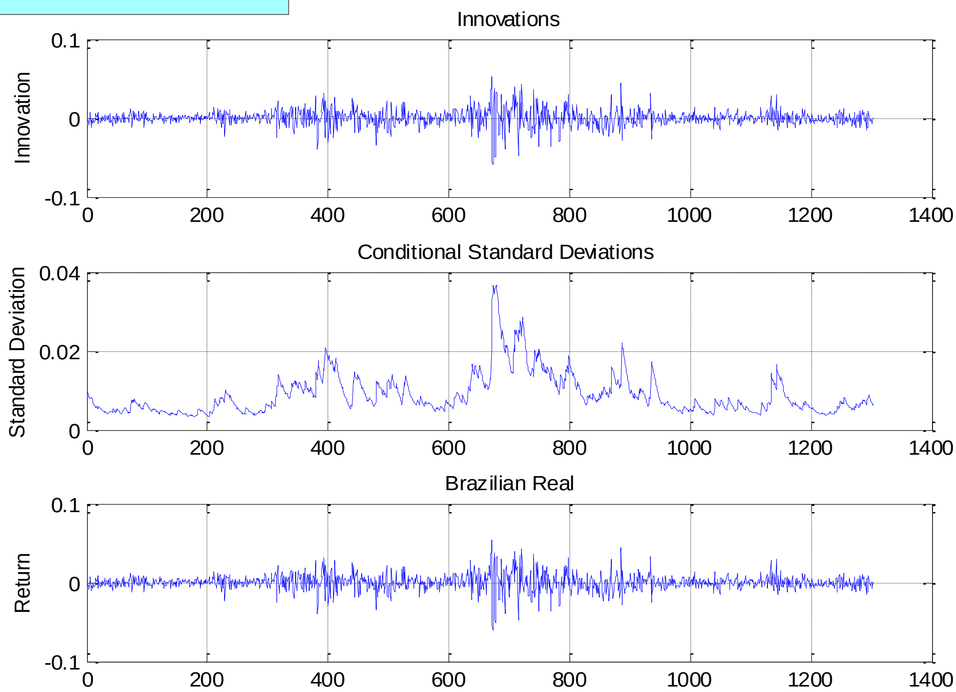

Figure 3. Comparison of Innovations, Conditional Standard Deviations and Observed Returns of Brazilian Real

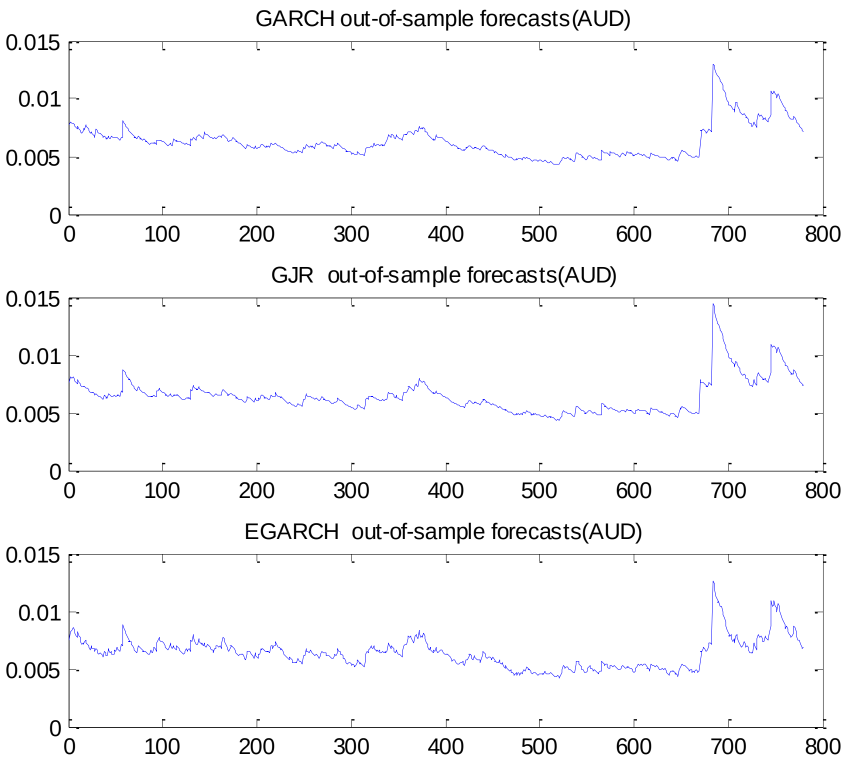

Figure 4. Out-of-sample forecasts for Australian Dollar return