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REEXAMINING OF GARCH MODELS FOR EXCHANGE RATES VOLATILITY

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Abstract:

This paper compares the GARCH in Mean, the GARCH and the EGARCH models in measuring exchange rate volatility to determine which model is more efficient in terms of forecasting of volatility. Analysis of forecasts of exchange rate volatility using Mean Squared Error (MSE) shows that the EGARCH (1,1) model does better in describing the data for half of the sample countries' exchange rates than the GARCH (1,1) and the GARCH-M (1,1) models. When the Mean Absolute Percentage Error (MAPE) is used for performance measure, the results are mixed. These results imply that the GARCH (1,1) model might not be an excellent model for measuring and forecasting volatility when it varies over time.

Özet:

Garch Modellerinin Döviz Kurlarındaki Dalgalanma İçin Yeniden İncelenmesi

Bu çalışma, döviz kurlarındaki dalgalanmaların ölçülmesinde dalgalanmanın öngörülmesi açısından hangi modelin daha etkin oldugunu belirlemek için GARCH in Mean, GARCH ve EGARCH modellerini karşılaştırır. Hata karelerinin ortalaması (Mean Squared Error-MSE) kullanılarak döviz kuru dalgalanmalarının öngörülmesinin analizi, EGARCH (1,1) modelinin örnekte yer alan ülke döviz kurlarının yarısında veriyi tanımlamada GARCH (1,1) ve GARCH-M (1,1) modellerinden daha iyi olduğunu göstermiştir. Performans ölçümü için

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ortalama mutlak hata yuzdesi (Mean Absolute Percentage Error - MAPE) kullanıldığında sonuçlar modeller arasinda kesin bir ayırım yapamamıştır. Bu sonuçlar GARCH (1,1) modelinin zaman içerisinde oluşan dalgalanmanın öngörüsü ve ölçülmesinde mükemmel bir model olamıyacağını işaret eder.

I. Introduction:

In the finance literature, there has been extensive research dealing with the prediction of exchange rate volatility, and it has been shown that exchange rate volatility is predictable. As Engle (1993) pointed out, a prediction of high volatility for exchange rates is in reality a prediction of high variance, showing that potential size of an exchange rate move is very large.

It has been observed that volatility clustering, which is one of the oldest noted characteristics of financial data, is also present in the behavior of exchange rates. This characteristic of exchange rates implies that the variance of exchange rate changes is not constant. It indicates something about the predictability of volatility. If large changes in exchange rates tend to be followed by more large changes, in either direction, then volatility must be predictably high after large changes.

The original tool for analyzing volatility forecasts is the Autoregressive Conditional Heteroskedasticity or ARCH model, introduced by Engle (1982). This is generalized to GARCH (Generalized ARCH) by Bollerslev (1986), which has been further extended by Nelson's (1991) EGARCH (Exponential GARCH) and by Schwert (1990). These models allow the variance of the regression to change over time, and all are models of the conditional variance that the variance in one period can depend upon variances and disturbances from previous periods. Moreover, Diebold and Nerlove (1989) observe that ARCH and GARCH models are consistent with the unconditional leptokurtosis, which is one of the general findings concerning the behavior of exchange rate changes. It implies that the distribution of exchange rates has fatter tails than the normal distribution.

The ARCH and GARCH models have been used to measure volatility of exchange rates. Hsieh (1988, 1989a, 1989b), Baillie and Bollerslev (1989), McCurdy and Morgan (1987), Milhoj (1987), Diebold (1988), Diebold and Nerlove (1989), and Najand and Seifert (1992) have all applied ARCH and GARCH models to exchange rate data.

Most investigators have also found that the GARCH (1,1) is generally an excellent model for a wide range of financial data.[1] This suggests that only when special needs arise should an investigator feel compelled to go through the entire menu of other implications of ARCH models. On the other hand, it may be argued that the nonnegativity constraints in the linear GARCH model are too restrictive. The EGARCH model proposed by Nelson (1991) allows positive and negative values of the error term from the original model to have different impacts on volatility. In addition, as we will show in the methodology section of this paper, the use of logarithms means that the parameters can be negative without variance becoming negative.

Therefore, this paper compares the GARCH in Mean (1,1), the GARCH (1,1) and the EGARCH (1,1) models in measuring exchange rate volatility to see which model performs better in forecasting volatility. It should be noted that even perfect predictability of variances does not mean perfect predictability of the size of the exchange rate moves or of their direction. In this sense, this paper does not look for a perfect model to measure and forecast exchange rate volatility over time.

It is found that the EGARCH model does better in describing the data for half of the sample countries' exchange rates than the GARCH (1,1) and the GARCH-M (1,1) models when Mean Squared Error (MSE) is used as a performance measure of forecast of exchange rate volatility. For the other half of the sample countries the GARCH (1,1) model has the smallest MSE. When the Mean of Absolute Percentage Error (MAPE) is used for performance measure, the results are mixed. With this measure, the GARCH-M (1,1) model appears to perform better even when the coefficient of the conditional standard deviation is insignificant for every exchange rate. It is clear that the added regressor decreases the residuals of the regressions and makes MAPE smaller. These results imply that the GARCH (1,1) model might not be an excellent model for measuring and forecasting volatility when it varies over time.

The remainder of the paper is organized as follows. The next section describes the data and methodology employed in the analysis. Section three presents empirical results. The section four provides concluding remarks.

II. Data and Methodology:

Data:

1948 daily exchange rates from January 2, 1990 through September 30, 1997 for the U.S. dollar versus the currencies of Belgium, France, Germany, Italy, Netherlands, Spain, Sweden, Switzerland, Luxembourg, and United Kingdom are analyzed in this paper. For the following countries' currencies, only 941 daily exchange rates from January 30, 1994 through September 30, 1997 are available: Austria, Denmark, Finland, Greece, Norway, and Portugal. Thus, exchange rate volatility is measured and forecast for 16 European countries. The source of the data is "Exchange Rates, Balance of Payments and Trade Data" provided by The Federal Reserve Bank of St. Louis.

Methodology:

Volatility clustering is present in the behavior of exchange rates. This characteristic of exchange rates implies that the variance of exchange rate changes is not constant. That is, error variance of regression is heterocedastic. There are several approaches to heteroscedasticity. If the error variance at different times is known, weighted regression is a good method. If, as is usually the case, the error variance is unknown and must be estimated from the data, we can model the changing error variance.

The GARCH model is one approach to modeling time series with heteroscedastic errors. The GARCH model is developed from the autoregressive conditional heteroscedasticity (ARCH) model. The ARCH model allows the conditional variance to change over time as a function of past errors. The strength of the ARCH technique is that the conditional means and variances can be estimated jointly, using traditional specified model for economic variables.

To measure exchange rate volatility three models are used: GARCH in Mean, GARCH and EGARCH.

1) GARCH Model: The GARCH model assumes conditional heteroscedasticity, with homoscedastic unconditional error variance. That is, the GARCH model assumes that changes in variance are a function of the realizations of preceding errors and that these changes represent temporary and random departures from a constant unconditional variance.

The GARCH (p,q) regression model can be written as follows:

$$Y_t = \beta X_t + \varepsilon_t \quad \varepsilon_t = Y_t - \beta X_t$$

where $\varepsilon_t \sim N(0,h_t)$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{q} \gamma_j h_{t-1} \quad \text{where}$$

$p \geq 0 \quad q > 0$
$\omega > 0 \quad \alpha_i \geq 0 \quad i = 1,\ldots\ldots,q,$
$\gamma_j \geq 0 \quad j = 1,\ldots\ldots,p.$

2) GARCH in MEAN Model: the GARCH-M (p,q) model has the added regressor that is the conditional standard deviation:

$$Y_t = \beta X_t + \delta \sqrt{h_t} + \varepsilon_t$$

where $\varepsilon_t \sim N(0,h_t)$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{q} \gamma_j h_{t-1} \quad \text{where}$$

$p \geq 0 \quad q > 0$
$\omega > 0 \quad \alpha_i \geq 0 \quad i = 1,\ldots\ldots,q,$
$\gamma_j \geq 0 \quad j = 1,\ldots\ldots,p.$

3) EGARCH Model: The EGARCH model was proposed by Nelson (1991). Nelson argues that the nonnegativity constraints in the linear GARCH model are too restrictive. The GARCH model imposes the nonnegative constraints on the parameters ω, α_i and γ_j, while there are no restrictions on these parameters in the EGARCH model. In the EGARCH (p,q) model, the conditional variance, h_t, is an asymmetric function of lagged disturbances ε_{t-1}:

$$Y_t = \beta X_t + \delta \operatorname{Ln}(h_t) + \varepsilon_t$$

where $\varepsilon_t \sim N(0,h_t)$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1} / \sqrt{h_{t-1}} + \sum_{j=1}^{q} \gamma_j \operatorname{Ln}(h_{t-1}) \quad \text{where}$$

$p \geq 0 \quad q > 0$

EGARCH (p,q) regression model above allows positive and negative values of ε to have different impacts on volatility. In addition, the use of logarithms means that the parameters may be negative without variance becoming negative.

Hsieh (1989a) uses a GARCH (1,1) model and finds that a simple GARCH (1,1) model does better in describing the data than the ARCH (1,2) model. A similar conclusion is reached by Baillie and Bollerslev (1989) with the daily data over the 1980 through 1985 period for six different exchange rates. McCurdy and Morgan (1987) also find the GARCH (1,1) model to fit better than an ARCH (5) model for daily returns on Deutsche Mark futures for 1981-1985. Bollerslev (1987) has also shown that the GARCH (1,1) adequately fits many economic time series. Bollerslev, Chou and Kroner (1992) show that most investigators have also found that the GARCH (1,1) is a generally excellent model for a wide range of financial data. This paper tests the performance of the GARCH (1,1) model in measuring exchange rate volatility for a sample of exchange rates by comparing with the EGARCH (1,1) and the GARCH-M (1,1) models.

III. Empirical Results:

Measuring of Exchange Rate Volatility:

Table I reports various descriptive statistics in order to assess the distributional properties of the daily exchange rate changes series, including mean, variance, standard deviation, skewness, kurtosis and a normality test.

The null hypothesis of normality is rejected at one-percent level. The sample skewness and kurtosis measures give further evidence on the nature of the deviation from normality. While skewness is very close to zero, kurtosis measures for most of the sample exchange rates are large. This shows that much of the non-normality comes from leptokurtosis.

Lagrange Multiplier (LM) and Portmateau Q statistics are also computed from the OLS residuals (the results are not shown here) assuming that disturbances are white noise. These two tests, along with normality test and the sample skewness and kurtosis measures, can help determine the order of the ARCH model appropriate for the data. The LM tests for each exchange rate changes are significant ($p < .0001$) through order 12. Q statistics show the nonlinear effects (for example, GARCH effects) present in the residuals.

Table I
Distributional Statistics on Exchange Rate Changes Series

Country	N	Mean	Variance	Std.Dev.	Skewness	Kurtosis	Normal
Austria	941	1.4E-5	3.6E-5	.00601	-.10925	1.9089	.9759*
Belgium	1948	5.2E-6	4.7E-5	.00688	.01024	1.9096	.9730*
Denmark	941	-1.0E-5	3.4E-5	.00582	-.04661	3.3802	.9811*
Finland	941	-1.1E-4	3.5E-5	.00588	-.0385	1.7982	.9844*
France	1948	7.4E-6	4.2E-5	.00648	-.0208	1.7393	.9749*
Germany	1948	1.6E-5	4.7E-5	.00686	.0401	1.7518	.9769*
Greece	941	1.14E-4	3.2E-5	.00566	-.2832	2.2281	.9853*
Italy	1948	1.52E-4	4.7E-5	.00682	1.111	9.7101	.9446*
Netherla.	1948	1.5E-5	4.8E-5	.00693	.0237	1.7707	.9669*
Norway	941	-7.0E-5	3.2E-5	.00569	.0420	1.7146	.9766*
Spain	1948	1.54E-4	4.7E-5	.00685	.2464	4.7061	.9715*
Portugal	941	1.7E-5	3.2E-5	.00562	-.0961	1.5405	.9847*
Sweden	1948	9.7E-5	5.0E-5	.00703	.5662	7.1391	.9639*
Switzer.	1948	-4.0E-5	5.8E-5	.00758	-.1221	1.5027	.9838*
Luxemb.	1948	1.7E-5	2.8E-5	.06829	.0682	1.8747	.9735*
UK	1948	2.98E-6	4.0E-5	.00635	-.3624	2.5768	.9629*

Significance level: * = 1 percent

As a result, these distributional statistics imply that a GARCH application is more appropriate than standard statistical models.

Table II and Table III report maximum likelihood estimates of the GARCH-M (1,1) and the GARCH (1,1) models, respectively. In these tables, w represents the estimate for $ARCH_0$, α represents $ARCH_1$, and γ represents $GARCH_1$. $ARCH_0$, $ARCH_1$ and $GARCH_1$ are the GARCH parameters. The coefficients of these three parameters are always significant at one-percent level for both models, with one exception. In addition to this, if we look at

$\alpha+\gamma$, we see that $\alpha+\gamma$ is close but slightly less than unity as it has been documented by many researchers. According to Engle and Bollerslev (1986), if $\alpha+\gamma=1$ in the GARCH (1,1) process, then the model is known as Integrated GARCH (IGARCH), which implies persistence of the conditional variance over all future horizons.

On the other hand, the coefficient of the added regressor, which is the conditional standard deviation in the GARCH-M (1,1) model, is insignificant for each sample of exchange rates (the estimate coefficients for the conditional standard deviation are not shown in the Table II). Thus, the results show that use the GARCH in MEAN model is unnecessary, and that the GARCH (1,1) model is sufficient to describe the data.[2]

Table II

Maximum Likelihood Estimates of GARCH-M (1,1) Model

Country	ω	α	γ	R-square
Austria	5.1E-7 (3.07)*	0.041 (4.85)*	0.945 (81.6)*	0.0004
Belgium	6.8E-7 (4.21)*	0.058 (7.83)*	0.929 (100.7)*	0.0011
Denmark	1.5E-6 (3.04)*	0.078 (4.24)*	0.878 (29.35)*	0.0004
Finland	5.8E-7 (2.26)**	0.040 (4.2)*	0.944 (68.61)*	0.0005
France	4.9E-7 (4.22)*	0.051 (6.63)*	0.938 (100.7)*	0.003
Germany	6.3E-7 (4.25)*	0.053 (6.65)*	0.934 (95.13)*	0.0016
Greece	3.0E-7 (2.65)*	0.046 (5.28)*	0.946 (97.32)*	0.004
Italy	5.5E-7 (4.55)*	0.084 (10.43)*	0.910 (103.4)*	0.004
Netherlands	6.9E-7 (4.1)*	0.058 (6.59)*	0.928 (85.17)*	0.0004
Norway	2.8E-7 (2.98)*	0.046 (5.28)*	0.946 (95.45)*	0.0002
Spain	8.9E-7 (4.63)*	0.073 (9.21)*	0.908 (87.01)*	0.0014
Portugal	4.9E-7 (2.97)*	0.043 (4.04)*	0.942 (66.97)*	0.0014
Sweden	3.9E-7 (3.13)*	0.053 (9.22)*	0.941 (149.1)*	0.0042
Switzerland	1.3E-6 (4.00)*	0.045 (5.69)*	0.932 (76.45)*	0.0026
Luxembourg	2.1E-7 (3.93)*	0.045 (7.04)*	0.948 (133.7)*	0.0012
UK	4.1E-7 (4.62)*	0.054 (8.42)*	0.936 (129.5)*	0.0066

Significance level: * = 1 percent, ** = 5 percent

$Y_t = \beta Y_{t-1} + \delta \sqrt{h_t} + \varepsilon_t$ where $\varepsilon_t \sim N(0,h_t)$ $h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{q} \gamma_j h_{t-1}$

Since the model is GARCH-M (1,1), p and q equal 1.
h_t is the conditional variance.
ω is the constant in the conditional variance equation ($ARCH_0$)
α is the coefficient of one period lagged squared residuals ($ARCH_1$)
γ is the coefficient of one period lagged conditional variance ($GARCH_1$)
The estimated parameters for the lag values of squared residuals and conditional variance in the conditional variance are positive, statistically significant and the total of two is less than one. Therefore, the non negativity and non-explosiveness conditions for the conditional variance equations that Bollerslev (1986) suggested are satisfied.

Table III

Maximum Likelihood Estimates of GARCH (1,1) Model

Country	ω	α	γ	R-square
Austria	5.1E-7 (3.07)*	0.041 (4.98)*	0.945 (82.79)*	0.00036
Belgium	6.9E-7 (4.23)*	0.058 (7.87)*	0.929 (101.1)*	0.0009
Denmark	1.4E-6 (3.03)*	0.076 (4.43)*	0.882 (30.47)*	0.0005
Finland	5.9E-7 (2.26)**	0.040 (4.2)*	0.944 (68.98)*	0.00005
France	5.0E-7 (4.31)*	0.051 (6.74)*	0.938 (102.4)*	0.0022
Germany	6.3E-7 (4.27)*	0.053 (6.71)*	0.934 (95.36)*	0.0013
Greece	3.0E-7 (2.64)*	0.045 (5.46)*	0.947 (100.4)*	0.0043
Italy	5.6E-7 (4.73)*	0.083 (10.51)*	0.911 (103.8)*	0.0002
Netherlands	6.9E-7 (4.12)*	0.058 (6.71)*	0.928 (85.49)*	0.0003
Norway	2.9E-7 (3.02)*	0.046 (5.31)*	0.946 (95.49)*	0.0002
Spain	9.0E-7 (4.68)*	0.074 (9.30)*	0.908 (87.05)*	0.0004
Portugal	4.9E-7 (2.98)*	0.043 (4.14)*	0.942 (67.60)*	0.0015
Sweden	4.0E-7 (3.18)*	0.054 (9.33)*	0.940 (147.5)*	0.0001
Switzerland	1.3E-6 (4.06)*	0.046 (5.77)*	0.933 (77.76)*	0.0012
Luxembourg	2.1E-7 (4.00)*	0.045 (7.10)*	0.948 (134.6)*	0.00001
UK	4.2E-7 (4.51)*	0.055 (8.48)*	0.935 (127.9)*	0.0022

Significance level: * = 1 percent, ** = 5 percent

$Y_t = \beta Y_{t-1} + \varepsilon_t$ where $\varepsilon_t \sim N(0,h_t)$ $h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{q} \gamma_j h_{t-1}$

Since the model is GARCH (1,1), p and q equal 1.

h_t is the conditional variance.

ω is the constant in the conditional variance equation ($ARCH_0$)

α is the coefficient of one period lagged squared residuals ($ARCH_1$)

γ is the coefficient of one period lagged conditional variance ($GARCH_1$)

The estimated parameters for the lag values of squared residuals and conditional variance in the conditional variance are positive, statistically significant and the total of two is less than one.

Table IV
Maximum Likelihood Estimates of EGARCH (1,1) Model

Country	ω	α	γ	R-square
Austria	-0.173 (-2.23)**	0.096 (4.51)*	0.983 (130.9)*	0.0004
Belgium	-0.217 (-2.76)*	0.145 (5.85)*	0.978 (124.7)*	0.0009
Denmark	-0.304 (-1.08)	0.135 (2.41)**	0.970 (35.66)*	0.0010
Finland	-10.29 (-40.2)*	0.304 (4.6)*	-0.0005 (-0.021)	0.0002
France	-0.177 (-3.1)*	0.119 (6.02)*	0.982 (174.2)*	0.0022
Germany	-0.168 (-2.57)*	0.119 (5.83)*	0.983 (150.4)*	0.0013
Greece	-0.150 (-1.74)**	0.111 (3.87)*	0.985 (118.5)*	0.0042
Italy	-0.227 (-3.51)*	0.193 (7.62)*	0.977 (154.5)*	0.0002
Netherlands	-0.159 (-2.69)*	0.119 (5.93)*	0.984 (166.5)*	0.00001
Norway	-0.167 (-2.15)*	0.119 (4.62)*	0.983 (131.5)*	0.0001
Spain	-0.278 (-3.1)*	0.162 (6.62)*	0.972 (108.9)*	0.0000
Portugal	-0.167 (-1.78)	0.093 (3.83)*	0.983 (109.0)*	0.0014
Sweden	-0.154 (-2.23)**	0.143 (6.34)*	0.984 (142.1)*	0.0042
Switzerland	-0.179 (-2.4)**	0.084 (4.12)*	0.982 (131.0)*	0.0011
Luxembourg	-0.115 (-3.27)*	0.103 (7.03)*	0.989 (294.6)*	0.0001
UK	-0.177 (-2.9)*	0.136 (7.05)*	0.982 (165.5)*	0.0021

Significance level: * = 1 percent, ** = 5 percent

$Y_t = \beta Y_{t-1} + \varepsilon \, Ln(h_t) + \varepsilon_t$ where $\varepsilon_t \sim N(0,h_t)$ $\qquad h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-1}/\sqrt{h_{t-1}} + \sum_{j=1}^{q} \gamma_j Ln(h_{t-1})$

Since the model is EGARCH (1,1), p and q equal 1.
h_t is the conditional variance.
ω is the constant in the conditional variance equation ($ARCH_0$)
α is the coefficient of one period lagged ratio of residuals to squared root of the conditional variance ($ARCH_1$)
γ is the coefficient of one period lagged natural logarithm of conditional variance ($GARCH_1$)
The estimated parameter for the constant in the conditional variance equation is significantly negative, which is appropriate for the modification of EGARCH (1,1) model. Again, the estimated parameters for the lag values of squared residuals and conditional variance in the conditional variance are positive, statistically significant and the total of two is less than one.

In this paper, we seek to determine the effectiveness of the EGARCH model in describing the sample data. For this reason, maximum likelihood estimates of the EGARCH (1,1) model are given at table IV. Since there are no restrictions on the GARCH parameters in the EGARCH model, the estimates of ω which represents the estimate for $ARCH_0$ became negative. On the other hand, the estimates of γ which represents $GARCH_1$ became higher and closer to unity than the estimates of the GARCH (1,1) model. There is one exception, which is Finland. The estimate of γ for this country is very low and it is insignificant, but the estimate of ω is very small negative number and it is significant at one-percent level. However, with this result of the exchange rate for Finland, Mean Squared Error of forecasting has the smallest value for this country (See table V). This evidence may show the viability of the argument that the nonnegativity constraints in the linear GARCH model are too restrictive.

Comparison of the GARCH Models:

Table V reports the MSE and MAPE for each forecast of exchange rate volatility using the last 45 days in the sample. According to the results based on MSE performance measure, The GARCH-M (1,1) model never has the smallest MSE. When we compare the GARCH (1,1) and the EGARCH (1,1) models, we see that the EGARCH (1,1) model proves to be the best forecasting model by having the smallest MSE for the 8 out of 16 countries' exchange rates, which is the number of half of the sample countries. For the other half of the sample, the GARCH (1,1) model appears to be a better model.

In terms of using MAPE, the results are mixed to identify which model is more efficient. The EGARCH (1,1) model has four and the GARCH (1,1) model has only two the smallest value. The number of countries with the smallest MAPE numbers is ten for the GARCH-M (1,1) model. The reason for this is that the added regressor, which is the conditional standard deviation, decreases residual values from the forecast of exchange rate volatility even though the estimate coefficients for this variable are never significant. Since MAPE is measured as the mean of the ratio of residuals to actual values during the last 45 days of the sample period, smaller residuals causes MAPE to become smaller.

Table V

Analysis of Forecasts of Exchange Rate Volatility Using MSE and MAPE

	MEAN SQUARED ERRORS			MEAN ABSOLUTE PERC. ERRORS		
Country	Garch(1,1)	Garch-M	Egarch 1,1	Garch(1,1)	Garch-M	Egarch 1,1
Austria	6.2726E-5	6.2734E-5	**6.2708E-5**	103.5408	**103.4156**	105.6508
Belgium	6.1115E-5	6.1316E-5	**6.1081E-5**	**98.6984**	98.9558	98.8204
Denmark	6.1401E-5	6.1737E-5	**6.1293E-5**	99.5472	**97.1345**	100.1634
Finland	6.4441E-5	6.4140E-5	**6.4004E-5**	99.4668	**97.2749**	99.1170
France	**6.0323E-5**	6.0741E-5	6.0473E-5	99.7279	97.4229	**99.2748**
Germany	**6.1412E-5**	6.1631E-5	6.1491E-5	90.0428	91.5199	**88.2836**
Greece	4.9711E-5	4.9895E-5	**4.9653E-5**	56.4397	**53.3143**	55.0437
Italy	5.0100E-5	5.0638E-5	**5.0093E-5**	107.4429	**89.3865**	103.5458
Nether.	**6.7100E-5**	6.7190E-5	6.7266E-5	98.6997	98.7588	**97.5296**
Norway	6.1393E-5	6.2088E-5	**6.1075E-5**	101.5212	**97.6870**	103.5339
Spain	**5.2488E-5**	5.2733E-5	5.2543E-5	99.7617	98.7887	**98.5953**
Portugal	5.7685E-5	5.7740E-5	**5.7620E-5**	100.0911	**100.0681**	100.1622
Sweden	**4.2530E-5**	4.2697E-5	4.2738E-5	**98.9757**	102.8025	104.4759
Switzer.	**4.9763E-5**	4.9846E-5	4.9854E-5	98.9342	**97.4523**	98.5077
Luxemb.	**3.2371E-5**	3.2521E-5	3.2372E-5	100.0539	**99.4203**	100.2081
UK	**4.6670E-5**	4.6680E-5	4.6675E-5	107.5272	**103.0312**	107.3065

Note: The smallest values in the two groups, MSE and MAPE, are shown as bold characters.

$MSE = 1/45 \sum E_i^2$ $MAPE = 1/45 \sum (E_i / Y_{it})*100$

where E_i = residuals from forecast and Y_{it} = actual value

It is clear that the MAPE performance measure gives more credit to a model having more independent variables to find the conditional error values from the forecast. Therefore, based on MAPE, the GARCH-M (1,1) and

EGARCH (1,1) models are found to be more efficient than the GARCH (1,1) model.

These results based on a sample of exchange rates imply, as opposed to findings of several researchers, that the GARCH (1,1) model might not be the excellent model for measuring and forecasting volatility when it varies over time. The EGARCH model appears to be a model that can also be used in measuring exchange rate volatility.

IV. Conclusions:

It is a fact that the GARCH models have been used quite often to model exchange rates. Most of the past studies have also showed that the GARCH (1,1) is a generally excellent model for a wide range of financial data. On the other hand, it is argued that the nonnegativity constraints in the linear GARCH model are too restrictive. The EGARCH model proposed by Nelson (1991) allows positive and negative values of error term from the original model to have different impacts on volatility. In this paper, I compare the GARCH-M (1,1), the GARCH (1,1) and the EGARCH (1,1) models to see which model forecasts exchange rate volatility better. The evidence shows that the EGARCH (1,1) model is more efficient in describing the data for half of the sample countries′ exchange rates than the GARCH (1,1) and the GARCH-M (1,1) models. This evidence indicates that the GARCH (1,1) model may not be an excellent model to measure and forecast exchange rate volatility.

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Notes:

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[1]See the survey by T. Bollerslev, R. Chou and K. Kroner (1992).

[2] Even with this result, we want to keep the GARCH-M(1,1) in comparison of the models.