

Forecasting Overnight Interest Rates Volatility with Asymmetric GARCH Models

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Abstract

This study investigates models for overnight interest rate volatility in Turkey and USA using the Asymmetric GARCH models and determines the best forecasting volatility models. These models are then completed with the use of out of sample forecasting. The best forecasting volatility models were chosen as the best forecasting is done with taking importance of the choosing criteria. First of all, for purposes of assessing volatility, the monthly data were used to investigate the leverage effect and features of fat tail for the period between 2000.01 and 2011.06. Student-t, GED and normal distributions are mentioned with GARCH models, which reflect the symmetric movements; and the EGARCH, GJR-GARCH, Asymmetric PARMA-CGARCH are used for the asymmetric movements. The models are estimated for the period between 2000.01 and 2011.06, and models are evaluated for out of sample forecasting for the period between 2011.08 and 2012.01. The best forecasting models are determined in these estimated models, following which the best forecasting models are estimated for five months until 2012.01. These forecastings are compared with the volatility for same real period, and the models forecastings were evaluated. The asymmetric and leverage effects are seen in the estimation results.

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1 Introduction

Interest volatility is an issue of great importance for business and policy-makers alike. For many years, volatility in the financial market has been the focus for researchers due to its importance in policy making, as well as its importance in investment analysis, derivative securities, pricing and risk management. There are many studies that focus on the application of interest rate volatility. In these studies, the most important point is the performance of models, and this situation is changing with the volatility forecasting. For example: Aydemir (1998), Balaban, Bayar Baff (2006), Balaban (2004), Feinstein (1987), Franses ve Ghijsels (1999), Knight ve Satchell (1998), Kupiec (1991), Loudon, Watt ve Yadav (2000), Tse (1998), Mc.Kenzie, Mitchel (2000), Anderson, Bollerslev (2000), Lee (1991), Vilasuso (2002).

In recent years, these models have been used for interest rates volatility. In the studies of Galati and Ho (2003), bad news had a greater effect on volatility than good news in dollar/euro volatility. Engle and Ng (1993) suggested different ARCH models for the asymmetric effect on Exchange rates and determined that the Switching ARCH (swarch) models were the best to this end. The studies of Sanches ve Fung (2003) determined that nonlinear GARCH models provide better results than linear GARCH for out of sample forecasting .

Interest rates volatility studies are performed with overnight, monthly and weekly frequencies. These types of interest rates include deposit rates, borrow loan, lend loan and fund rates. For example, the USA interest rates volatility is evaluated in the study of Fabio Fornari (2005). On the other hand, Bliss and Ronn (1995) evaluated the *asymmetric effects* on USA interest rates. Austin ve Dutt (2007) studied short term USA interest rates volatility, and Friedman (1983) evaluated the USA interest rates.

The aim of this study is to evaluate the volatility forecast performance of various models for Interest rate returns in Turkey and the USA. We use asymmetric volatility models to this end. We also introduce different densities such as the Gaussian normal, the student-t and the Generalized Error Distribution (GED). The remaining parts of the paper are organized as follows: The following section comprises the introduction; Section 2 introduces estimation methods, distributions, models, performance criteria, data set used and estimation results, respectively; the final section includes the conclusions.

2 Methodology

2.1 Distribution

Financial time series are generally fat tailed. For this reason, it is not possible to use normal distributions. In case the time series do not reflect a normal distribution, the student-t, skewed student-t and GED distributions are recommended. Such distributions are listed in Table 1.

Table 1: Distributions

Normal	$L_{normal} = -\frac{1}{2} \sum_{t=1}^T [\ln(2\pi) + \ln(\sigma_t^2) + z_t]$
Student-t	$L_{student-t} = \ln \left[\Gamma \left(\frac{\nu+1}{2} \right) \right] - \ln \left[\Gamma \left(\frac{\nu}{2} \right) \right] - \frac{1}{2} \ln[\pi(\nu - 2)] - \frac{1}{2} \sum_{t=1}^T \left[\ln \sigma_t^2 + (1 + \nu) \ln \left(1 + \frac{z_t^2}{\nu-2} \right) \right]^{(b)}$
GED	$L_{GED} = \sum_{t=1}^T \left[\ln \left(\frac{\nu}{\lambda_\nu} \right) \right] - 0.5 \left \frac{z_t}{\lambda_\nu} \right ^\nu - (1 + \nu^{-1}) \ln(2) - \ln \Gamma \left(\frac{1}{\nu} \right) - 0.5 \ln(\sigma_t^2) \quad (c)$

(a) T number of data

(b) ν degree of freedom, $2 < \nu \leq \infty$ ve $\Gamma(\cdot)$ gamma function

(c) $\lambda_\nu = \sqrt{\frac{\Gamma(1/\nu 2^{-2/\nu})}{\Gamma(3/\nu)}}$, ν positif parameter

2.2 Autoregressive Conditional Heteroscedasticity Models

The GARCH model was introduced by Bollerslev (1986) as a generalized version of Engle's (1982) AutoRegressive Conditional Heteroscedasticity (ARCH). The GARCH(p,q) model suggests that conditional variance of returns is a linear function of lagged conditional variance terms and past squared error terms. The standard GARCH(p,q) model specification is as follows:

$$y_t = x_t' \theta + \varepsilon_t \quad \varepsilon_t \sim N(0; \sigma_t^2) \tag{1}$$

$$\sigma_t^2 = \varpi + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \tag{2}$$

The mean equation provided in (1) is written as a function of exogenous variables with an error term. In this equation, ϖ is a constant term, ε_{t-i}^2 is an ARCH term and σ_{t-j}^2 is the GARCH term. This model is widely used, especially in financial time series analysis. While the vast majority of the earlier studies relied on the ARCH framework, there is now a large and diverse time series literature on volatility modelling (for instance, Asymmetric GARCH modelling, such as EGARCH, GJR-GARCH, APARCH, ACGARCH).

The Exponential GARCH (EGARCH) model proposed by Nelson(1991) is the earliest extension of the GARCH model that incorporates asymmetric effects in returns from speculative prices. The GJR-GARCH(p,q) model is another volatility model that allows asymmetric effects. This model was proposed by Glosten, Jaganattan and Runkle (1993). In a recent article, Ding, Granger and Engle (1993) introduced a class of autoregressive conditional heteroscedastic models called Asymmetric Power Autoregressive Conditional Heteroscedastic (APARCH) models. Engle and Lee (1993) proposed the component GARCH model in order to investigate the long-run and the short-run movement of volatility. The component GARCH or CGARCH model allows mean reversion to a time varying level. These models are shown below in Table 2.

Table 2: Conditional Heteroscedasticity Models

Equation	$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2$	$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$	$\ln(\sigma_t^2) = \omega + \gamma \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + \alpha \left[\left(\frac{ \varepsilon_{t-1} }{\sigma_{t-1}} - \left(\frac{2}{\pi} \right)^{0.5} \right) \right] + \beta \ln(\sigma_{t-1}^2)$ ^(a)	$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma D_{t-1}^- \varepsilon_{t-1}^2$ ^(b)	$\sigma_t^\delta = \omega + \alpha_1 (\varepsilon_{t-1} - \gamma_1 \varepsilon_{t-1})^\delta + \beta_1 \sigma_{t-1}^\delta$ ^(c)
Model	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH (1,1)	APARCH (1,1)

(a) α external shocks , γ leverage effect and β continuity

(b) When Dummy variable D_{t-1}^- , $\varepsilon_{t-1} < 0$ it is the dummy variable that replaces 0 This term allows for the asymmetry effect

(c) γ represents the leverage or asymmetry parameter, and δ represents the force parameter

2.3 Forecasting Criteria

Symmetric and asymmetric forecasting criteria are used to evaluate the performance of forecasting for conditional heteroscedasticity models. In our study, the commonly used MAR, MAPE and TIC criteria are employed. These criteria are listed in Table 3.

Table 3: Forecasting Criteria

MAE	$\frac{1}{h+1} \sum_{t=s}^{s+h} \hat{\sigma}_t^2 - \sigma_t^2 $
MAPE	$\frac{1}{h+1} \sum_{t=s}^{s+h} (\hat{\sigma}_t^2 - \sigma_t^2) / \sigma_t^2 $
TIC	$\frac{\sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} (\hat{\sigma}_t^2 - \sigma_t^2)^2}}{\sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} \sigma_t^2} \sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} \hat{\sigma}_t^2}}$
h represents the forecasting term number , s number of data $\hat{\sigma}^2$ forecasting variance and σ^2 real variance	

3 Data

This paper examines the overnight interest rates of two countries in the time period from January 2000 to June 2011. All data used in this study are provided Xignite.com

Economic Research Federal Reserve Bank of St Louis and International Financial Statistics website (www.xignite.com and <http://research.stlouisfed.org>, respectively).

The interest rate returns are determined as:

$$r_{.t} = s_t - s_{t-1}$$

Where s_t denotes the log and Interest rate, and $r_{.t}$ denotes the returns for countries examined. We analyze the volatility of Interest rate between the USA federal fund and the overnight interest rates in Turkey. Following the estimates, we expanded the models' the range of data and used the period from August 2011 to January 2012 for the five months of volatility forecasting.

4 Results

In this study, we estimated the exponential GARCH (EGARCH) model, the GJR-GARCH model, the asymmetric power ARCH (APARCH) and the asymmetric component GARCH (ACGARCH) model aside from the symmetric GARCH model in order to determine the best performing forecasting model for Interest rate volatility in the countries examined.

In this paper, we calculate the descriptive statistics for the interest rate returns of each country and summarize them in Table 4. In Table, skewness, kurtosis, Jarque-Bera (1980; JB, here after) normality test, Q and Q^2 Ljung-Box test statistics and ARCH-LM test results are presented for two series.

Tablo 4. Descriptive Statistics of Returns Series

Returns	ortalama	eğiklik	basıklık	J.B.	Q(12)	$Q^2(12)$	ARCH(2)
Turkey GT	-1.0450	1.3866	33.3242	5640.780 (0.0000)	111.03 (0.0012)	57.1635 (0.6323)	71.4045 (0.0000)
USA GUS	-2.6107	- 0.09626	6.090012	57.5114 (0.0000)	56.707 (0.0035)	12.734 (0.2534)	7.6467 (0.0009)

- i. r indicates the return series for each country.
- ii. Figures in parenthesis represent the p values.
- iii. Q, Q^2 denotes the Ljung-Box Test statistics for residual serial correlation
- iv. LM, TR^2 denotes the test statistics for ARCH (c)

Results in Table 4 demonstrate that the returns for the USA are positively skewed and that the returns are negatively skewed for Turkey. Kurtosis coefficients are larger than 3, implying a fat tailed empirical distribution of the returns over all the periods.

A JB test based skewness and kurtosis coefficient rejects at any reasonable level the null hypothesis distributed normally in all countries. If we look at the sample, given the fact that the return series exhibited some excess kurtosis, it can be predicted that a fatter tailed

distribution such as the student-t or maybe a Generalized Error distribution (GED) would generate better results than just a normal distribution. The robustness of the estimation, different distributional assumptions for the innovations, Gaussian Distribution, student-t distribution and GED were applied in this study. Both the student-t and GED have fat tails. We have determined that the AIC, SBC and Log-likelihood criteria especially favour student-t distribution and GED for the Interest rate returns.

Engle (1982) LM test indicates the presence of ARCH processes in the conditional variance. Two series show signs of heteroscedasticity in the sample, indicating the legitimacy of using ARCH/GARCH model. In this study, we have used the Box-Jenkins method to determine the mean models and found that the most suitable model is the ARMA(1,0).

Table 5 indicates that the GARCH models show, $\alpha + \beta$ restriction near 1 or less than 1. This restriction is taken with Wald test, and all models are determined as being stable. In APARCH models, the asymmetry parameter γ was statistically significant and determined as positive for the Turkey. This indicates that the negative shocks have a greater effect on volatility than positive shocks. For the APARCH models, the Wald test was performed to compare the restriction $\delta = 1$ and $\delta = 2$ and the hypothesis. The most suitable APARCH models are the null hypothesis, which $\delta = 1$ was not rejected. For Turkey, the asymmetry parameter is found statistically significant and positive. This situation shows that the effect of bad news on the volatility is stronger than that of good news. However, the restriction $\alpha + \beta$ for GARCH models for Turkey was performed with the Wald test, and all models were found to be stable.

.Table 5: Estimation of Conditional Heteroscedasticity Models

	rTUR			rUSA			
	ARMA(1,0) APARCH	ARMA(1,0) GJR- GARCH	ARMA(1,0) GARCH	ARMA(1,0) ACGARCH	ARMA(1,0) EGARCH	ARMA(1,0) EGARCH	ARMA(1,0) EGARCH
Distribution	GED	GED	Student-t	GED	Normal	Student-t	GED
Constant (M)	-1.5720 [0.4262] (0.0002)	-1.8157 [0.4813] (0.0002)	-	0.5634 [0.0068] (0.0000)	-37.632 [0.6856] (0.0000)	-21.098 [5.8540] (0.0000)	0.5209 [0.0061] (0.0000)
AR(1)	-0.2002 [0.0581] (0.0006)	-0.2669 [0.1117] (0.0169)	-0.6777 [0.0630] (0.0000)	-0.2358 [0.02210] (0.0000)	0.0803 [0.0160] (0.0000)	0.0421 [0.0125] (0.0008)	-0.0069 [0.0012] (0.0005)
MA(1)	-	-	-	-	-	-	-
Constant(V)	-	-	7.0880 [2.7043] (0.0088)	-	0.9431 [0.6856] (0.0000)	9.1755 [0.4501] (0.0000)	10.9213 [1.5793] (0.0000)
ARCH(α)	-	2.9501 [1.1620] (0.0111)	0.01873 [0.0055] (0.0004)	-	-	-	-
GARCH(β)	-	0.1289 [0.0460] (0.0051)	0.1951 [0.07527] 0.0095	-	-	-	-

EGARCH(α)	-	-	-	-	-0.9613 [0.1180] (0.0000)	-0.7379 [0.1204] (0.0000)	-0.7664 [0.1199] (0.0006)
EGARCH(β)	-	-	-	-	0.0659 [0.0204] (0.0002)	0.0514 [0.0159] (0.0004)	0.0184 [0.0057] (0.0000)
EGARCH(γ)	-	-	-	-	-1.6408 [0.2992] (0.0000)	-1.4648 [0.2014] (0.0000)	-1.5243 [0.2445] (0.0000)
GJRGARCH(γ)	-	2.2487 [0.7138] (0.0001)	-	-	-	-	-
A-CGARCH (γ)	-	-	-	0.3297 [0.1023] (0.0001)	-	-	-
APARCH(α)	0.6994 [0.2458] (0.0044)	-	-	-	-	-	-
APARCH(β)	0.3734 [0.1144] (0.0011)	-	-	-	-	-	-
APARCH(γ)	0.4226 [0.1261] (0.0008)	-	-	-	-	-	-
APARCH(δ)	0.6171 [0.1916] (0.0007)	-	-	-	-	-	-
t-distribution	-	-	19.702 [6.1186] (0.0000)	-	-	2.0056 [0.1706] (0.0000)	-
GED param.	0.3711 [0.0630] (0.0000)	-	-	0.4189 [0.0489] (0.0000)	-	-	0.2889 [0.0346] (0.0000)
AIC	7.0365	7.0745	7.0828	11.4225	12.8501	12.8818	13.6829
SC	7.1864	7.2030	7.2199	11.6152	12.9786	12.8903	13.8429
LL	477.4848	475.0705	471.8755	864.4813	863.8075	849.5671	720.1436
Q(12)	13.030 (0.3679)	3.7479 (0.9883)	18.621 (0.0984)	34.768 (0.0321)	26.910 (0.0080)	26.745 (0.0080)	27.669 (0.0060)
Q ² (12)	5.3369 (0.9467)	0.9302 (0.9967)	104.85 (0.1252)	9.8962 (0.6259)	9.7197 (0.6410)	17.220 (0.1427)	17.442 (0.1347)
LM(2)	2.7713 (0.2543)	0.1234 (0.8840)	17.100 (0.8865)	0.1045 (0.9008)	0.0350 (0.9655)	2.0367 (0.3611)	2.3061 (0.3156)
Wald	$\delta=1$	0.6171 (0.0008)	-	-	-	-	-
	$\delta=2$	1.3828 (0.4239)	-	-	-	-	-

- i. Figures in parenthesis represent the p values, while the figures in brackets represent standard deviation
- i. LM, TR² denotes the test statistics for ARCH (c)
- ii. *indicates statistical significance at the 5% level.
- iii. Q, Q² denotes the Ljung-Box Test statistics for residual serial correlation
- iv. LM, TR² denotes the test statistics for ARCH (c)
- v. ARMA(p,q) for the mean models and determined ARMA(1,0)
- vi. M is the equation for the mean, while V is the equation for variance

Table 5 provides the EGARCH models for USA. The leverage effect is significant and determined to be negative. This situation demonstrates that bad news' (negative shocks') effect on the volatility is more significant than the effect of good news. The best model for USA is the ACGARH model. In this model, γ leverage effect is statistically significant

and determined as negative, indicating that there is an asymmetric effect in USA and condition. >0 there is a temporary leverage effect depends on the γ_i coefficient significance and this restriction so model shows that there is a not continued leverage effect for USA. All models indicate that the most suitable distributions are the GED and the Student-t. This situation demonstrates that the asymmetric conditional heteroscedasticity models are better than the symmetric conditional heteroscedasticity models. In our study, in order to compare all the models in table 5 and determine the best forecasting models, we have used performance criteria such as MAE, MAPE ve TIC. These criteria are listed in Table 6. Using these performance criteria, we choose the best forecasting models and determined in the sample the 5 months forecasting and estimates for the models. When we analyzed the models, we realized that the best volatility models were changing when we determined the best forecast.

Table 6. Results for Forecasting Criteria

Returns	Models	MAE	MAPE	TIC
Turkey rTUR	GJR-GARCH (GED)*	10.8382	91.3043	0.9999
	GARCH(student-t)	10.8387	91.3017	0.9999
	APARCH(GED)	10.9163	93.1189	0.9896
USA rUS	EGARCH (GED)*	95.0180	103.0054	0.9896
	EGARCH(student-t)	95.041	11.0793	0.9922
	ACGARCH(GED)	95.2757	405.3754	0.9986
	EGARCH(normal)	113.9692	1483.813	0.9996

* best volatility forecasting model

We can see from the table that the criteria values are very close to one another, and that the minimum value is the best model. In our study, we found that the asymmetric conditional heteroscedasticity models demonstrate a better performance than symmetric conditional heteroscedasticity models. In our study, we choose the sample range over the period from August 2011 to January 2012 for in sample forecasting. We found that the best volatility forecasting model is the GJR-GARCH (GED) for Turkey. We observed that the best volatility model and the best forecasting volatility models changed. Therefore, this situation indicates that the volatility forecasting model is changing, and that we must discuss the result with the best model. We can see the forecasting volatility in the statistical graphs. We evaluate the forecasting volatility with the forecast of variance and the forecast of return series for the two countries. We used the statistical forecasting figures below:

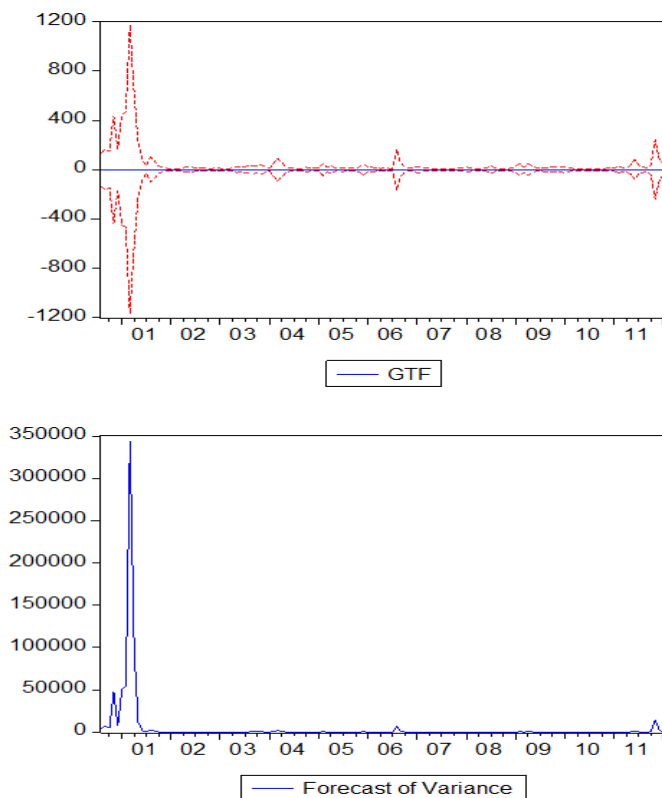


Figure 1. Interest rate forecasting volatility for Turkey

Figure 1 shows the forecasting return series for Turkey and the volatility forecasting. We can see volatility clustering from this graph and the forecasting data. Figure 1 demonstrates the forecasting data of Turkey’s interest rates, which appears to increase slightly for a brief period of time. When we looked at the volatility graph, we could see, based on the volatility that peaked in 2001 and for 5 months in the last year, that the interest rates will increase; however, this increase will be slight. So we can say that the increasing returns series reflects the increasing volatility in these terms. The USA interest rate forecasting and volatility forecasting are displayed in Figure 2:

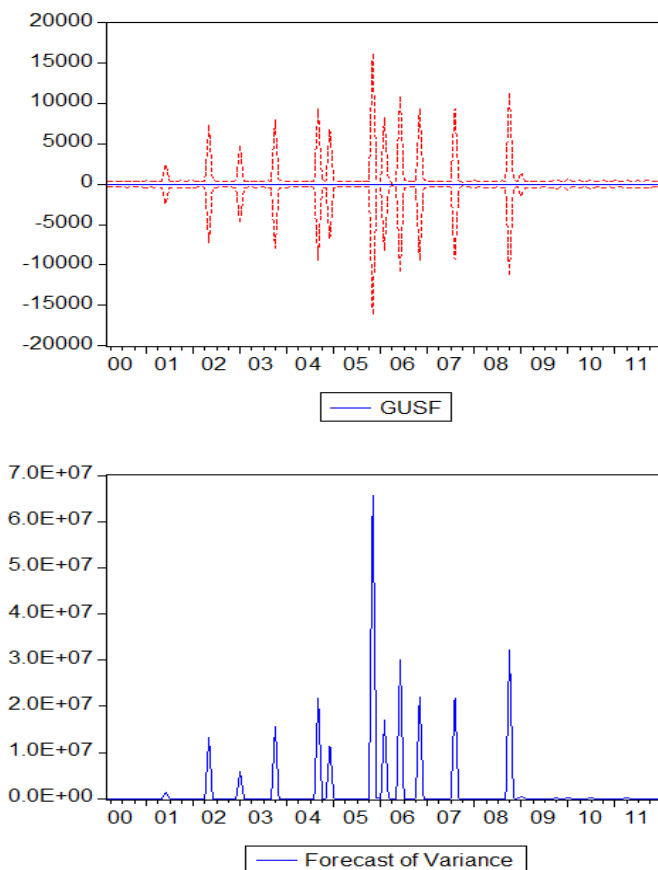


Figure 2. Interest rate forecasting volatility for the USA

Figure 2 demonstrates that the interest rates are stable in this 5 months term; however, when we reviewed the forecasting volatility even will be stable for 5 months yet we might observe a slight increase. We can see especially observe the peak year as the volatility clustering. When the interest rates decreased to zero in USA, volatility had peaked in 2008 because of the global crisis. In this graph, the return series appear to be stable, and the volatility will continue to be stable for USA. This situation could be used for USA FED interest rates policy decisions.

5 Conclusion

Interest rate volatility has received considerable attention from both academics and practitioners in the recent years. Recent value at risk, option pricing etc., highlight the importance of modelling and forecasting the conditional volatility returns.

In our study, the comparison focused on two different aspects: the difference between the best asymmetric GARCH models and the asymmetric distributions, as well as the best performance volatility forecasting models and the forecasting criteria for interest rates in the USA and Turkey. We have then determined that the best forecasting volatility with different conditional heteroscedasticity models, which we later used as forecasting

criteria. The estimation results show that the forecasting performance of asymmetric GARCH models is better than symmetric GARCH models for two countries examined, especially when time series that reflect fat-tailed asymmetric densities are taken into account for the conditional volatility. Distributions are generally GED and student-t, skewed student-t in this for 5 months in sample forecasting. We observed that the increasing overnight interest rates' effect on volatility forecasting was different for the USA and Turkey.

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