EXCHANGE RATE VOLATILITY:
THE CASE OF TURKEY

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ABSTRACT

EXCHANGE RATE VOLATILITY:
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In this study, different from previous studies, the explanatory power of Student-t distribution is compared to normal distribution by employing both standard GARCH and EGARCH models to dollar/ lira (USD/TRY) exchange rate. Then the impact of Central Bank of Republic of the Turkey's (CBRT) decisions and actions on both the level of exchange rate and the volatility is investigated. Moreover the relationship between volatility and market liquidity is examined using spot foreign exchange (FX) market volume as a proxy. The results reveal that, in contrast to preceding findings, Student-t could not capture the leptokurtic property better than normal distribution does. Furthermore, an increase in Turkish government benchmark bond rates, CBRT FX purchase interventions and announcement of suspending/ decreasing-the-amount-of FX auctions lead Turkish lira to depreciate. Because of the significant positive leverage effect, the results of GARCH and EGARCH variance equations differ so much. Thereby the results should be evaluated cautiously. In addition it is observed that, only EGARCH model gives significant results when the spot market trading volume is included in the models

Key Words: Exchange Rate Volatility, GARCH/EGARCH models, Student-t Distribution, CBRT, Trading Volume

ÖZ

DÖVİZ KURU OYNAKLIĞI:
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Bu çalışmada, önceki çalışmalardan farklı olarak, dolar/lira kuruna GARCH ve EGARCH modelleri uygulanarak T dağılımının ve normal dağılımın açıklayıcılığının karşılaştırılması yapılmıştır. Daha sonra Türkiye Cumhuriyet Merkez Bankası'nın (TCMB) aldığı kararların ve hareketlerinin döviz kuru seviyesine ve oynaklığına olan etkisi araştırılmıştır. Ayrıca, döviz kuru oynaklığı ve döviz piyasası likiditesi arasındaki ilişki spot piyasa işlem hacminin modellere dahil edilmesi ile incelenmiştir. Sonuçlar önceki bulgulardan farklı olarak, T dağılımının leptokurtic özelliğinin açıklamada normal dağılımdan daha iyi olmadığını ortaya koymuştur. Bununla birlikte, gösterge Türk hazine bonosu oranlarındaki artış, döviz alım müdahaleleri ve döviz ihaleleri durdurma/ihale miktarını azaltma duyuruları Türk lirasında değer kaybına yol açmaktadır. Pozitif anlamlı kaldıraç etkisi nedeniyle ARCH ve GARCH modellerinin varyans eşitliklerine ait sonuçlar fazlasıyla farklılık göstermektedir. Bu nedenle sonuçlar dikkatli değerlendirmelidir. Spot piyasa hacmi modellere dahil edildiğinde yalnızca EGARCH modellinde anlamlı sonuçlar elde edilmiştir.

Anahtar Kelimeler: Döviz Kuru Oynaklığı, GARCH/EGARCH modelleri, T dağılımı, TCMB, İşlem Hacmi

To My Parents,

Cemile and Yakup Öztürk

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CHAPTER I

INTRODUCTION

Uncertainty is central to much of modern finance theory. When volatility is interpreted as uncertainty, it becomes a key input to many investment decisions and portfolio design. For instance, volatility is the most important variable in the pricing of derivative securities, whose trading volume has been growing enormously in recent years. Besides, financial risk management, which has taken a central role in finance industry since the first Basle Accord in 1996, effectively makes volatility forecasting a compulsory exercise for many financial institutions around the world. Moreover, world economy is largely affected by volatility in world financial markets. Policy makers often rely on market estimates of volatility as an indicator of the vulnerability of financial markets and the economy.

It is crucial to observe and interpret the underlying reasons for volatility as well as measuring it. Utilizing ARCH/GARCH models, this study tries to measure and explain the volatility in the USD/TRY exchange rate level.

Primary source for measuring the volatility of an exchange rate, distribution of exchange rate data, has important implications for several financial models and is characterized by mild and volatile periods. Two proposed processes, autoregressive conditional heteroscedasticity (ARCH) by Engle (1982) and general autoregressive conditional heteroscedasticity (GARCH) by Bollerslev (1986) have been shown to provide a good fit for many exchange rate series in the literature, allowing volatility shocks to persist over time by imposing autoregressive structure on the conditional variance. This persistence is consistent with periods of relative volatility and tranquility in returns and it is employed to explain the non-normalities in exchange rate series.

The objectives of this study are firstly to compare the explanatory power of Student-t distribution with normal distribution, then investigate the impact of Central Bank of Republic of the Turkey (CBRT) decisions and actions on both the level of exchange rate and the volatility and lastly explore the relationship between market volume and volatility. This study goes beyond previous work in several aspects. In contrast to former studies, this study is the first that uses and compares both normal and student-t distributions by employing both standard GARCH and EGARCH models to USD/TRY exchange rate. Although the volatility of the foreign exchange (FX) rate can be explained by a number of variables, the preliminary studies are concentrated in the effectiveness of CBRT's FX auctions and interventions. The contribution of this study is to extend the preceding analysis by investigating the impact FX interventions and short-term interest rate decisions of CBRT, analyzing the news effect of FX auctions and taking into account the changes in benchmark interest rates of Turkish government bonds and benchmark interest rate determined by US Federal Reserve Bank. The effect of these variables on the volatility of USD/TRY exchange rate is observed in the period of 2002-2006. In the analysis, both foreign exchange buying and selling interventions and are considered and the effect of rate hikes and cuts are evaluated separately. Moreover, this study is the primary study that uses USD/TRY trading volume as a proxy for market liquidity and analyzes the FX volatility and FX market liquidity relation. Different from previous works, in this study, the results of GARCH (1,1) and EGARCH (1,1) are compared in each model.

The study is organized as follows: Section 2 analyses salient features of financial time series data and provides an econometric framework for measuring exchange rate volatility. Section 3 briefly discusses the literature survey of the empirical application of GARCH models on exchange rate series. Section 4 provides the developments in Turkey between 2002 and 2006 and presents the applications of volatility models to Turkish case. Section 5 examines the USD/TRY exchange rate data, indicates the models and analyzes the results. Section 6 offers summary remarks and conclusions.

CHAPTER II

BASIC CHARACTERISTICS OF FINANCIAL MARKET VOLATILITY AND ARCH MODELS

Although volatility of the financial time series has a complex structure, there are several salient features of financial time series and the financial market volatility that are now well documented. These include the fat tail distributions of risky asset returns, volatility clustering, asymmetry, mean reversion and comovements of volatilities across assets and financial markets. Besides the basic characteristics of volatility, many approaches of measuring and forecasting the volatility have been proposed in the literature. That's because of the importance of volatility in asset-pricing and portfolio management decisions. Probably the most widely used models in volatility measurement are the family of ARCH models introduced by Engle (1982).

In this chapter of the study prominent features of financial time series are investigated and the ARCH processes that are used in the volatility measurement and forecasting are analyzed.

2.1 Salient Features of Financial Time Series

Financial time series are often available at a higher frequency than macroeconomic time series and many high-frequency financial time series have been shown to exhibit the property of "long memory" (the presence of statistically significant correlations between observations that are a large distance apart). Another distinguishing feature of many financial time series is time-varying volatility or "heteroscedasticity" of the data.

When discussing the volatility of time series, econometricians refer to the conditional variance of the data, and the time-varying volatility typical asset returns are otherwise known as conditional heteroscedasticity. The concept of conditional heteroscedasticity is introduced to economists by Engle (1982), who proposes a model in which the conditional variance of a time series is a function of past shocks; the autoregressive conditional heteroscedasticity (ARCH) model. In other words, instead of considering heteroscedasticity as a problem to be corrected, ARCH models treat it as a variance to be modeled and therefore, provide a rigorous way of empirically investigating issues involving the volatility of economic variables.

When the normality is considered; observed price changes deviate consistently from lognormality. That is, when a conditional normal distribution is assumed, it turns out that the unconditional distribution of the series will be non-normal. There are more very large changes and (consequently) more very small ones than a lognormal distribution calls for. The commonly used term for this is "fat tails:" The fat tail phenomenon is known as excess kurtosis. Time series that exhibit a fat tail distribution are often referred to as leptokurtic. There is more weight in the tails of the actual returns distribution than in a lognormal distribution with the same variance. In some markets, the lognormal diffusion model fails because the price can "jump" occasionally from one level to another without trading at the prices in between, as in the case of a formal devaluation of an exchange rate.

In addition, financial time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, of either sign, and small changes tend to follow small changes. This volatility clustering phenomenon is immediately apparent when asset returns are plotted through time. Furthermore, volatility clustering may account for some but not all of the fat tail effect (or excess kurtosis). A part of the fat tail effect can also result from the presence of non-Gaussian asset return distributions that just happen to have fat tails, such as Student's t.

Some studies (e.g. Baille and Bollerslev (1989a) and, Pagan and Schwert (1990)) find time series appear to have unit roots and warn against nonstationarity problem while estimating models.

As far as serial correlation is concerned, price movements in actual securities markets are not perfectly uncorrelated over time, especially not at very short intervals. Positive (negative) correlation between consecutive price changes lowers (raises) measured volatility relative to the true value.

One should keep in mind that the value of using all available data is severely limited by the fact that prices and returns for many securities appear to have some serial correlation. That is sampling at longer intervals is an easy way to limit the effect of serial dependence at high frequencies, but it also means using fewer data points, which increases sampling error. The empirical results exhibit clearly the tradeoff between increasing accuracy by using daily data with a larger number of observations and losing accuracy because of the relatively greater effect of transitory phenomena on daily prices.

2.2 ARCH Processes[1]

2.2.1 ARCH Model

Many financial time series exhibit periods of unusually large volatility followed by periods of relative tranquility. In such circumstances, the homoscedasticity is inappropriate; accordingly, economists have become interested in dynamic forms of heteroscedasticity. The first time-varying volatility model is the Autoregressive Conditional Heteroscedasticity (ARCH) model of Engle (1982). Consider a simple static regression model in which the x_t represents the exogenous explanatory variables and/or lagged values of the dependent variable y_t :

$$y_t = a_0 + ax_t + \varepsilon_t \tag{2.1.1}$$

where,

[1] The ARCH and GARCH class of models have become part of the standard toolbox discussed in econometrics and empirical oriented finance textbooks. Please refer to for more information Hamilton (1992), Campell, Lo and MacKinlay (1997), Franses and van Dijk (2000), Gourieroux and Jasiak (2001), Alexander (2001), Brooks (2002), McAleer and Oxley (2002), Wooldridge (2000), Harris and Sollis (2003), Enders (2004).

$$\varepsilon_t = z_t h_t^{1/2}, \tag{2.1.2}$$

z_t i.i.d., $\quad E(z_t)=0, \quad var(z_t)=1,$

with h_t a time-varying, positive, and measurable function of the time t-1 information set ad ε_t is assumed to be a unvaried process. In most applications ε_t will correspond to the innovation in the mean for stochastic process, $\{y_t\}$.By definition ε_t is serially uncorrelated with conditional and unconditional means which are zero, but the conditional variance of ε_t equals h_t^2, which may be changing through time. The conditional variance of ε_t refers to the variance of ε_t, conditional on information available at time t-1.For brevity; define Ψ_{t-1} to be the information set representing the information available at t-1.

When defining ARCH, Engle (1982) proposed the following model for the ε_t:

$$\varepsilon_t = z_t(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)^{1/2} \tag{2.1.3}$$

where α_0 and α_1 are constants such that $\alpha_0 > 0$ and $0 < \alpha_1 < 1$ to ensure the stability of autoregressive process and the conditional variance is never negative.

The unconditional mean and variance of ε_t are:

$$\begin{aligned} &E(\varepsilon_t) = 0 \\ &\operatorname{var}(\varepsilon_t) = \frac{\alpha_0}{(1-\alpha_1)} \end{aligned} \tag{2.1.4}$$

The conditional mean and variance of ε_t for ARCH (1) are:

$$\begin{aligned} &E(\varepsilon_t \mid \psi_{t-1}) = 0 \\ &Var(\varepsilon_t \mid \psi_{t-1}) = E(\varepsilon_t^2 \mid \psi_{t-1}) = E(\varepsilon_t^2 \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) = E(\varepsilon_t^2 \mid \varepsilon_{t-1}) = h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \end{aligned} \tag{2.1.5}$$

The key point in the model is that although the errors are serially uncorrelated ($E(\varepsilon_t \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots.) = 0$), they are not independent since they are related through their second moment.

Also note that if y_t is generated by (2.1.1), with ε_t generated by (2.1.3), the conditional variance of y_t is given by:

$$Var(y_t \mid \psi_{t-1}) = h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \qquad (2.1.6)$$

The conditional heteroscedasticity in ε_t will result in y_t being an ARCH process. In terms of specification, ARCH directly affects the error terms ε_t: however, the dependent variable y_t, generated from a linear model with an ARCH error term, is itself an ARCH process. Thus, the ARCH model is able to capture periods of tranquility and volatility in the y_t series.

For the higher order ARCH process, ARCH (q), the model can be written:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (2.1.7)$$

$$= \alpha_0 + \alpha_1(L)\varepsilon_t^2 \qquad (2.1.8)$$

where L denotes the lag operator. One of the difficulties when using the ARCH model is the significance of high order ARCH process, in which often a large number of lagged squared error terms in the conditional variance are found to be significant. Consequently, in practice the estimation of ARCH models is not always straightforward. Then, an alternative and more flexible lag structure is often provided by the Generalized ARCH, or GARCH (p, q), model as in Bollerslev (1986).

2.2.2 GARCH Model

As a way to model persistent movements in volatility without estimating a very large number of coefficients in a high-order polynomial $\alpha(L)$, Bollerslev (1986) suggested a GARCH model. He introduces a conditional heteroscedasticity model that includes lags of the conditional variance $(h_{t-1}, h_{t-2}, \ldots.., h_{t-p})$ as regressors in the model for the conditional variance in addition to the lags of the squared error term $(\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots., \varepsilon_{t-q}^2)$. In a GARCH (p,q) model:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (2.2.1)$$

$$h_t = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)h_t \qquad (2.2.2)$$

where $p \geq 0, q > 0; \alpha_0 > 0, \alpha_i \geq 0$ $(i = 1,....,q)$ and β_j $(j = 1,...., p)$.

A GARCH model explains variance by two distributed lags, one (q) on past squared residuals to capture high frequency effects, and the second (p) on lagged values of the variance itself, to capture longer term influences.

The most commonly used model in the GARCH class is the simple GARCH(1,1) which can be written as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (2.2.3)$$

Also note that ε_t, is covariance stationary if and only if $(\alpha_1 + \beta_1) < 1$.

The GARCH (1,1) model embodies a very intuitive forecasting strategy: the variance expected at a given date is a combination of a long run variance and the variance expected for last period, adjusted to take into account the size of last period's observed shock.

If the equation (2.2.3) is rewritten as :

$$h_t = \alpha_0 + \alpha_1(\varepsilon_{t-1}^2 - h_{t-1}) + (\alpha_1 + \beta_1)h_{t-1} \qquad (2.2.4)$$

Conditional on time t-1 information (ψ_{t-1}), the term $(\varepsilon_{t-1}^2 - h_{t-1})$ has mean zero and can be thought of as the shock to volatility. Then, the coefficient α_1 measures the extent to which a volatility shock today feeds through into next period's volatility, while $(\alpha_1 + \beta_1)$ measures the rate at which this effect dies out over time. In other words, α_1 is the ARCH parameter that represents the degree of the instantaneous reaction of volatility to shocks. High α_1 indicates volatility reacting sharply to market movements. β_1 is the GARCH parameter that represents persistency of volatility and high β_1 implies persistency in volatility.

2.2.3 EGARCH Model

The basic GARCH model assumes that positive and negative shocks of the same absolute magnitude will have the identical influence on the future conditional variances. In contrast, the asymmetry effect is a feature of many financial time series. The asymmetry effect, also known as "leverage" effect, refers to the characteristic of time series on asset prices that an unexpected drop tends to increase volatility more than an unexpected increase of the same magnitude. The most popular method proposed to capture the asymmetric effects is Nelson's (1991) Exponential GARCH (EGARCH) model.

$$\log h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(\theta z_{t-i} + \gamma \left[|z_{t-i}| - E|z_{t-i}| \right] \right) + \sum_{l=1}^{p} \beta_i \log h_{t-i} \qquad (2.3.1)$$

If $\alpha_1 > 0$, Nelson's model implies that the deviation of $|z_{t-i}|$ from its expected value causes the variance of ε_t to be larger than otherwise, an effect similar to the idea behind the GARCH specification.

The z_{t-i} term multiplied by the parameter θ allows the sign of errors to affect the conditional variance, while the $|z_{t-i}|$ term multiplied by γ allows for a separate size effect. If the asymmetry effect is present, then $\theta < 0$, while there is no asymmetry effect, if $\theta = 0$. In particular, if $-1 < \theta < 0$, positive shock increases volatility less than negative shock. If $\theta < -1$, positive shock actually reduces volatility while negative shock increases.

One of the key advantages of Nelson's specification is that since (2.3.1) describes the log of h_t, the variance itself (h_t) will be positive regardless of whether the coefficients are positive. Thus, in contrast to GARCH model, no restrictions need to be imposed on estimation. On the other hand, because of the non-differentiability with respect to at zero, the EGARCH model is often somewhat more difficult to estimate and analyzed numerically.

2.2.4 ARCH-M Model

When modeling the returns from investing in a risky asset, one might expect that the variance of those returns would add significantly to the explanation of the behavior of the conditional mean, since risk-averse investors require higher returns to invest in riskier assets. The ARCH-in-Mean or ARCH-M model by Engle, Lilien, and Robins (1987) extends the basic ARCH framework to allow the mean of a sequence to depend on its own conditional variance.

Many theories in finance involve an explicit tradeoff between the risk and the expected return. The ARCH-M model is ideally suited to study asset markets. Engle, Lilien, and Robins (1987) express the idea by writing the excess return from holding a risky asset as

$$y_t = \mu_t + \varepsilon_t \tag{2.4.1}$$

where y_t is the excess return from holding the long-term bond, μ_t is the risk premium for investing long-term bond; ε_t is unforecastable shock to the excess return.

Engle, Lilien, and Robins (1987) assume that the risk premium is an increasing function of the conditional variance of ε_t; that is, the greater the conditional variance of returns, the greater the compensation necessary to induce the agent to hold the long-term asset. Mathematically,

$$\mu_t = \beta + \delta h_t, \tag{2.4.2}$$

where h_t is the conditional variance of ε_t:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2.4.3}$$

Estimation of the ARCH-M model poses no added difficulties. However, unlike the linear GARCH model, where consistent estimates of the parameters can be obtained even in the presence of misspecification, consistent estimation of the ARCH-M model requires the full model to be correctly specified. This parallels the results for asymmetric variance formulations such as the EGARCH model, where correct specification of the full model is generally required in order to guarantee consistency. Therefore, diagnostic tests for the variance specification become very important before interpretations are made about the parameter estimates.

2.2.5 IGARCH and FIGARCH Models

A common finding in much of the empirical literature using high-frequency financial data concerns the apparent persistence implied by the estimates for the conditional variance functions. In the linear GARCH (p, q) model, this is manifested by the presence of an approximate unit root in the autoregressive polynomial;

$$\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j = 1 \tag{2.5.1}$$

Engle and Bollerslev (1986) refer to this class of models as “Integrated in variance”, or IGARCH. If ε_t follows an IGARCH process, then the unconditional variance of ε_t is infinite, so neither ε_t nor ε_t^2 satisfies the definition of a covariance-stationary process. However, the IGARCH model is strictly stationary and ergodic, though not covariance stationary.

A shock in the volatility series seems to have very long memory and impact on future volatility over a long horizon. The Integrated GARCH (IGARCH) model of Engle and Bollerslev (1986) captures this effect but a shock in this model impacts upon future volatility over an infinite horizon, and the unconditional variances does not exist for this model. This gives rise to FIGARCH model of Baillie, Bollerslev and Mikkelsen (1996).

The GARCH and EGARCH models imply that shocks to the volatility decay at an exponential rate. The main feature of fractionally integrated process that distinguishes it from other time series processes is the very slow decay of its autocorrelations. For this reason, a fractionally integrated series is often referred to as having long memory.

But as Granger (2001) points out, this model has a time trend in volatility level which is not observed in practice. This is a major weakness of the fractionally integrated model for it to be adopted as a theoretically sound model for volatility.

2.2.6 Summary

Many financial series do not have constant mean and variance, and most exhibit phases of relative tranquility followed by periods of high volatility. In this part of the study, the stylized facts concerning the properties of financial time series are examined and the ARCH family models, which can capture periods of turbulence and tranquility, are investigated. The following chapter will present the review of empirical findings that are attained by employing ARCH models on exchange rate series.

CHAPTER III

APPLICATIONS OF ARCH TO FOREIGN EXCHANGE RATE DATA

The foreign exchange market is by far the largest financial market in terms of daily trading volume. As financial markets continue to integrate all over the world and the world trade continues to rise with cross-border investments continuing to mount, daily turnover is expected to bypass its current levels.

The modeling and forecasting of exchange rate volatility is an important area of research, which has implications for many issues in the arena of finance and economics. Such issues include the fundamental role foreign exchange volatility plays in currency related derivative pricing. Foreign exchange rate volatility may also impact on global trade patterns and thus affect a country's balance of payments position. To the extent the governments concerns on balance of payments; foreign exchange volatility can thus impact on national policy making decisions. Finally, exchange rate forecasting plays an important role in international capital budgeting and an understanding of volatility can assist in this most important activity.

This chapter is a survey of related work on exchange rate volatility. The chapter begins by looking at some fundamental issues raised by literature over exchange rate volatility, expanding on basic concepts of modeling and describing the results of the studies. After that, the well-known studies on the topic of volatility forecasting are reviewed. Finally, the realized volatility models, which enable capturing intraday movements, are investigated.

3.1 ARCH/GARCH Applications with Foreign Exchange Rates

Till Mussa (1979), and Friedman and Vandersteel (1982), the time series models did not take into account the stylized facts of exchange rate like having contiguous periods of volatility and stability, and leptokurtic unconditional distributions and foreign exchange rate series were assumed to be normally distributed. Using daily data on five different nominal U.S. dollar rates, Hsieh (1988) finds out that means and variances of exchange rate series change over time. In fact, the ARCH class of models is ideally suited to modeling such behaviors.

In this context, Hsieh (1989) employs ARCH, GARCH and EGARCH models for five foreign currencies, using 10 years of daily data. He finds that GARCH (1,1) and EGARCH(1,1) are extremely successful at removing conditional heteroscedasticity from daily exchange-rate movements. Moreover he claims that EGARCH is fitted to the data slightly better than standard GARCH using a variety of diagnostic checks.

As stated by Andersen et al. (1999),

> …exchange rate returns are well-known to be unconditionally symmetric but highly leptokurtic. Standardized daily or weekly returns from ARCH type models also appear symmetric but leptokurtic; that is, the distributions are not only unconditionally, but also conditionally leptokurtic, although less than unconditionally.

Accordingly, Milhoj (1987), Bollerslev (1987), Hsieh (1989) and Baillie and Bollerslev (1989b) assert that while the simple symmetric linear GARCH (l, 1) model might provide a good description for most exchange rate series under free float, the assumption of conditional normality does not capture all the excess kurtosis observed in daily or weekly data.

In order to deal with this problem, Bollerslev (1987) successfully presents the leptokurtic property of daily data for foreign exchange rates and finds that the GARCH (1,1) model with Student-t distribution fits quite well though not fully removes leptokurtic property. In the same way, Baillie and Bollerslev (1989b) compare two leptokurtic distributions, Student-t and power exponential distributions, in order to produce a more adequate representation of data. They claim that the Student-t distribution compares favorably to the power exponential and captures the excess kurtosis for most of the rates. The Student-t distribution is also estimated by Hsieh (1989), together with the generalized error distribution, a normal-Poisson, and a normal-lognormal mixture distribution.

As well as non-normality issue, very similar results are reported in Bollerslev (1987), Hsieh (1988), Baillie and Bollerslev (1989) and Hsieh (1989) concerning the persistence of the conditional variance. Generally, $\alpha_1 + \beta_1$ in equation (2.2.3) appears to be very close to 1, indicating an integrated-variance. Besides, Sengupta and Sfeir (1996) argue that the market volatility measured by conditional variances follow a persistent nonlinear behavior.

On the other hand, Lastrapes (1989) finds that the ARCH process is nonstationary in the sense that the unconditional variance changes significantly across policy regimes. That is, including dummy variables in the conditional variance to capture for the changes in the policy of the FED reduces the degree of leptokurtosis in the standardized residuals.

When modeling volatility of returns, the choice of the observation frequency and issues related to the effect of temporal aggregation arise naturally. Generally, the model is said to be closed under temporal aggregation if the model keeps the same structure, with possibly different parameter values, for any data frequency. In an insightful paper Drost and Nijman (1993) prove, theoretically and for a special case (for GARCH (1,1)) that volatility structure should be preserved through temporal aggregation. This means that the structure of the volatility does not depend on frequency of the data used. In other words, hourly, daily, or monthly intervals in the data would end up in the same volatility structure. However, it is well known that this is not the case in practice; volatility persistence, which is highly significant in daily data, weakens as the frequency of data decreases. In fact, Diebold (1988) shows that conditional heteroscedasticity disappears if the sampling time interval increases to infinity.

While ARCH effects are highly significant with daily and weekly data, both Diebold (1988) and Baillie and Bollerslev (1989b) note that ARCH effects tend to weaken with less frequently sampled data. For example, Baillie and Bollerslev (1989b) find that there are neither significant ARCH effects nor any substantial departures from normality in monthly data.

Concerning the properties of exchange rate series, Hsieh (1988) draw attention to how the unconditional distributions of exchange rate changes differ across different days of the week. In the related context, Baillie and Bollerslev (1989b) show the existence of day-of-the-week and vacation effects in the mean and the conditional variances.

In order to explain the presence of ARCH effects, some economists suggest the mixture of distributions hypothesis, in which the rate of information arrival is the stochastic mixing variable. In this context, Lamoureux and Lastrapes (1990) use the daily stock trading volume as a proxy for the information arrival time and show that volume has an explanatory power regarding the variance of daily returns. Moreover, they claim that ARCH effects tend to disappear when volume is included in the variance equation.

In contrast to Lamoureux and Lastrapes (1990), Bollerslev and Domowitz (1993) employ the bid-ask spreads as a proxy for the information arrival and find out a positive relation between exchange rate and spreads in which persistence in GARCH parameter remains strong.

Galati (2000) examines the relationship between foreign exchange rates and trading volumes and finds that in most cases unexpected trading volumes and volatility are positively correlated. Similarly, Bauwens, Rime and Sucarrat (2005) search the impact of information arrival on exchange rate volatility and find positive and statistically significant results.

While the hypothesis that contemporaneous trading volume is positively correlated with financial market volatility is supported in the data, the result that a single latent variable jointly determines both, is formally rejected by Lamoureux and Lastrapes (1994).

Another topic, which takes attention of economists, is the effects of foreign exchange intervention by central banks on the behavior of exchange rates. The role of central banks is not passive one in the foreign exchange markets. They continue to intervene to maintain an "orderly market", through trading in exchange market. In the well-known study, Dominguez (1998) examines the effects of US, German and Japanese monetary and intervention policies on dollar-mark and dollar-yen exchange rate volatility over the 1977-1994 period. In addition to the intervention variables, day-of-the-week and holiday dummy variables, dummy variables capturing exchange rate policy news and spread between country interest rates are included. According to the results, the sign and significance of the intervention variables measured in magnitudes or dummy variable form are often quite similar and confirm that just the presence of a central bank in the foreign exchange market influences volatility.

On the other hand, Beine, Bénassy-Quéré and Lecourt (1999) claim that traditional GARCH estimations tend to underestimate the effects of central bank interventions and employ FIGARCH model. Compared to Dominguez (1998), their study covers shorter period of time, 1985-1995. Their result suggests that official purchases of dollars increase the exchange rate volatility.

3.2 Forecasting Models

Forecasting is a very different operation from in-sample estimation. Given that the structure does not remain constant, there is a great premium on the models and the estimation procedures that are robust against small changes. As stated by Figlewski (2004), the more detailed and elaborated a model is, the better the fit one is generally able to obtain in-sample, but the faster the model tends to go off track when it is taken out-of-sample. For any procedure to be useful in forecasting, it must be sufficiently stable over time that one can fit coefficient estimates on historical data and be reasonably confident that the model will continue to hold as time goes forward. Thus, an oversimplified but robust forecasting approach that captures the major features of the system may give significantly more accurate prediction, particularly for longer horizons, than a more ambitious model, which tries to capture its fine structure that may change relatively faster over time.

Comparing forecasting performance of competing models is one of the most important aspects of a forecasting exercise. Ideally, an evaluation exercise should measure the usefulness of a volatility forecast to investors and to do that one needs to know the decision process that will include these forecasts and the costs or benefits that result from using these forecasts. In practice, however, these costs and benefits are not known and it is usual to simply use measures suggested by statisticians.

Popular evolution measures used in the literature include Mean Error (ME), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE).

In this respect Balaban (2004) investigates the out-of-sample forecasting accuracy of the symmetric and asymmetric conditional variance models for the US dollar-Deutsche mark exchange rate volatility. In the study, daily exchange rate returns between 2 January 1974 and 30 December 1997 period are used for 72-month rolling estimation procedure. The forecasts' performances are evaluated with respect to ME, MAE, MSE and MAPE measures. The results suggest that although all the models are systematically over-predict volatility, the standard symmetric GARCH model appears as relatively good forecasts of monthly exchange rate volatility.

A well-known study in the exchange rate forecast evaluation belongs to West and Cho (1995). They compare the out-of-sample forecasting performance of univariate homoscedastic, GARCH, autoregressive and nonparametric models for conditional variances, using five weekly exchange rates between 1973 and 1989. The forecasts are performed for one, twelve and twenty-four-weeks horizons and mean squared prediction error (MSPE) is used as a measure of performance. The results of the study indicate that for a one-week horizon GARCH models slightly edge over other models, but for longer horizons none of the models stand out with its performance.

In the same way, Figlewski (2004) points out that ARCH models are not designed for forecasting many steps ahead and their performance tends to degrade rapidly as the forecast horizon is extended.

Complication in choice of forecast horizon is partly due to volatility mean reversion. In general, volatility forecast accuracy improves as data sampling frequency increases relative to forecast horizon (Andersen et.al (1999)). However, for volatility forecasts over a long horizon Figlewski (2004) finds forecast error doubled in size when daily data, instead of monthly data, is used to forecast volatility over 24 months. In some cases, e.g. when the forecast horizon exceeds ten years, a volatility estimate calculated using weakly or monthly data is better because volatility mean reversion is difficult to adjust using high frequency data. In general, model based forecasts lose supremacy when the forecast horizon increases with respect to the data frequency, Figlewski (2004).

Andersen et al. (2004) suggest the GARCH volatility models as a convenient and parsimonious framework for modeling key dynamic features of returns, including volatility mean reversion, long-memory, and asymmetric response. Accordingly in many empirical studies GARCH (1,1) appear as a benchmark model for forecast performance evaluation.

Neeley and Weller (2001) suggest that although genetic programming forecasts outperform the GARCH model on MAE, GARCH model's forecasting performance is superior when R^2 and MSE are considered. When compared to implied volatility forecasts, Jorion (1995) finds that despite being biased forecasts, implied standard deviations outperform statistical time series models including GARCH (1,1). Besides, Tabak, Chang and Andrade (2002) argue that implied volatilities give superior forecasts of realized volatility if compared to GARCH (p,q). Sucarrat (2006) found that out-of-sample forecast accuracy of general-to-specific (GETS) derived models of weekly NOK/EUR volatility is better than GARCH (1,1) and EGARCH (1,1) models while explaining big movements in the exchange rate. On the contrary, Figlewski (2004) states that forecast results show that implied volatility frequently dominates historical volatility in an encompassing regression and he emphasizes that these results do not mean that implied volatility is necessarily a more accurate forecast of future volatility or that it is a better volatility parameter to use as an input to a pricing model, but the results only mean that implied volatility contains useful information.

3.3 Realized Volatility

Exchange rate may fluctuate a lot during the day, and yet end up close to its value the same time the previous day. The squared daily return will be small, even though volatility was high. It has been demonstrated that one can significantly improve the forecasting power of the GARCH model by measuring volatility as the sum of intraday squared returns (Andersen and Bollerslev (1998)). Rather than seeking to perfect the forecast evaluation procedures, building on continuous-time stochastic volatility framework, they demonstrate how high-frequency data allow for the construction of improved ex-post volatility measurements via cumulative squared intraday returns.

Taking into consideration the fact that the volatility is not constant over the day, it is obvious that the realized volatility is not equal to the forecast from the discrete-time GARCH model, which utilizes the daily return observations. Instead, there is a random component to the volatility process as it evolves stochastically over the trading day. As a result, the daily return observations do not convey all relevant information and the GARCH model simply cannot produce fully efficient forecasts compared to what is theoretically possible given higher frequency intraday data.

Realized volatility helps modeling volatility directly through standard time series techniques with discretely sampled observations, while effectively exploiting the information in intraday high-frequency data.

Concerning distributions of realized volatility measures constructed from high-frequency data, Andersen et al. (1999) found that exchange rate returns are nearly Gaussian. However this study is limited in scope as it examined only two exchange rates.

3.3.4 Summary

In this chapter the celebrated empirical studies on exchange rate volatility are surveyed. The various papers discussed here, which share a common econometric motivation, attempt to estimate and forecast the exchange rate volatility using ARCH processes. While initial studies focus on the estimation performance of ARCH models, excess kurtosis and persistency problems, the following studies present the outcomes of mixture of distribution hypothesis and effectiveness of FX interventions. Moreover, there are several studies which explore forecasting performance of ARCH models and investigate the results of realized volatility models. Next chapter will present the empirical studies that analyze the Turkish case.

CHAPTER IV

APPLICATION OF VOLATILITY MODELS TO TURKEY

Recovered from many financial and economic crises, Turkey has been an excellent case study for economists. As exchange rate and volatility in the markets are closely related with overall health of the economy, there are quite many studies which examine Turkish case, especially the effectiveness of interventions. The purpose of this chapter is firstly to provide brief information regarding the evolution of the Turkish economy after the crisis in 2001 and then present the empirical studies concerning Turkish experience.

4.1 Brief Historical Background for the Turkish Economy

The Turkish economy has been characterized by high levels of inflation and many stabilization programs for nearly 30 years. Although some of those programs have succeeded, they have been temporary and caused every new stabilization program lose its credibility. Similarly, after the crisis in February 2001, the challenge for the CBRT was to re-establish confidence and contain volatility in financial markets while pursuing new program.

However, a new era opened in the Turkish Economy following the Financial Crisis in 2001. After then, economic policies aimed to stabilize the economy by reducing chronic and high inflation, achieving fiscal austerity, a viable debt position and sustained growth. Tight monetary and fiscal policies put into effect in combination with an ambiguous structural reform process including financial sector. Within this context, floating exchange rate regime placed to one of the corners of stabilizing process. Monetary policy effectiveness improved with no specific target on exchange rate. More importantly, vulnerability to exogenous shocks has decreased in the economy. In this sense, floating exchange rate regime has been implemented successfully in Turkey. Starting from late 2001, the results of the program were very positive: inflation expectations followed a downward trend, inflation rates have almost continuously declined, the public debt-to-GDP ratio was significantly reduced, while the Turkish economy started first to recover and then to show high growth rates. However, it should be noted that the success of the policy underlie in its changing dynamics. Following these positive results, also dollarization effect through the Turkish economy started to decline. This new conditions in the Turkish economy affected directly the monetary policy decisions including exchange rate policy. Furthermore, decrease in dollarization also lead to a reduction in exchange rate pass through effect in the general level of prices. So as a result, exchange rate policy was adjusted to the variations in the domestic and international markets.

Starting from year 2002, the implicit inflation targeting became a strong anchor beside base money. Under floating exchange rate regime, short-term interest rates have been used actively as a monetary policy tool for the price stability goal. With the satisfaction of necessary condition, the CBRT has been implementing explicit inflation targeting since the beginning of year 2006.

Discretionary interventions and FX-auctions construct the general framework of the exchange rate policy, during this period. According to the first tool, the level of exchange rate is determined by the supply and demand conditions in the market, simultaneously. Therefore, the CBRT is not an active player in the market unless there are excess volatility in the foreign exchange rate, which cannot be explained by the fundamentals. Under the floating exchange rate regime, achieving exchange rate stability with the minimum Central Bank intervention is very important for the inflation targeting regime. This fact clarifies rare and exceptional discretionary interventions of the CBRT in the period 2001 and 2006. As can be seen from the Table 4.1, the CBRT conducted relatively higher purchase interventions than selling. This development can be attributed the high capital inflows due to favorable liquidity conditions.

Table 4.1 Dates of Interventions (2002-2006)

Purchase Intervention	Sale Intervention
02.12.2002	11.07.2002
12.05.2003	24.12.2002
21.05.2003	11.05.2004
09.06.2003	13.06.2006
18.07.2003	23.06.2006
10.09.2003	26.06.2006
25.09.2003	
16.02.2004	
27.01.2005	
09.03.2005	
03.06.2005	
22.07.2005	
04.10.2005	
18.11.2005	
15.02.2006	

Source: Central Bank of the Republic of Turkey

According to the second tool, the CBRT conducts daily FX buying/selling auctions depending on the conditions in the domestic and international markets. FX auctions are pre-announced and their results are published with no delay. This feature of FX auctions adds to the monetary policy transparency. FX selling auctions were conducted only twice, once in 2001 and once in 2006[2]. In contrast, the CBRT continued to conduct FX buying auctions except the suspension periods in 2003, 2004 and 2006. The adjustment to changing dynamics lies under that part. Liquidity conditions in the FX market determined the suspension periods.

The level of international reserves still matters and are seen as a buffer for bad times, under the floating exchange rate regime if the country is a highly indebted one. Especially, for a country like Turkey, whose government and private sector have

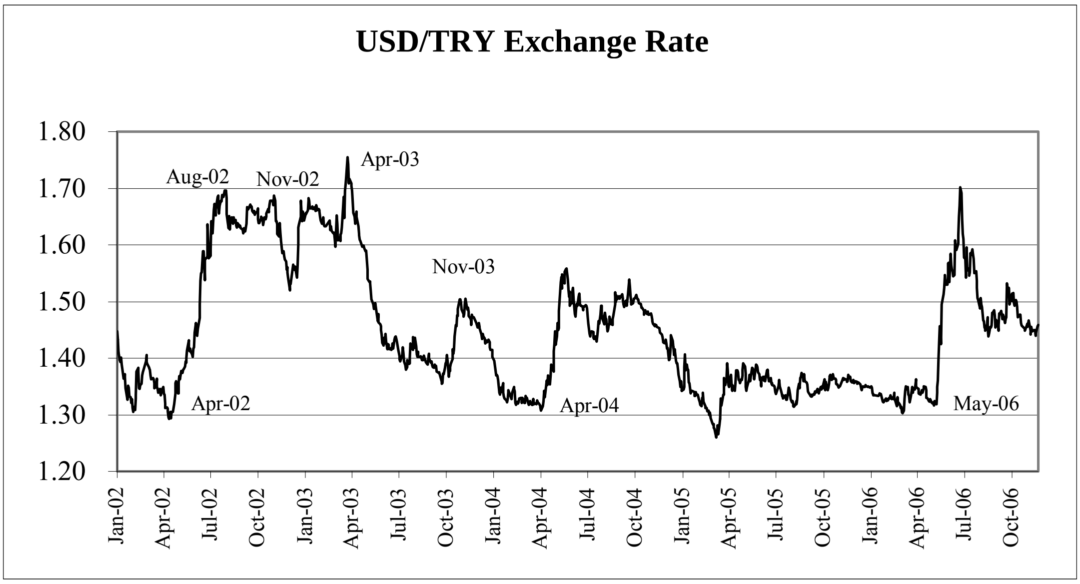
[2] The selling auctions held in 2006 differ from basic CBRT auctions both in methodology and the amount (USD 500 million). Therefore, in this study the selling auctions held on 26th and 27th of July are assumed to be selling interventions.

huge amount of FX denominated debts, accumulating strong international reserves is a must. Within that context, FX buying auctions help to decrease the vulnerability of the country by contributing to restoration of international reserves.

Foreign exchange buying auctions have been held when foreign exchange supply increased more than foreign exchange demand. The purpose of buying auctions is not to affect the supply and demand conditions structurally, but to increase the foreign currency reserve moderately. The intention of the CBRT in this subject has been emphasized in several public announcements. In fact, in order to minimize the impact of auctions on the foreign exchange market, starting from end of December 2004, the CBRT has been announced yearly program for auctions. By this way, misperceptions on the exchange rate policy of the CBRT caused by adjustment of auction amounts have been prevented. Besides, it is made explicit that the CBRT is not going to change the program unless extraordinary changes are observed in terms of foreign exchange liquidity conditions.

The movements in USD/TRY parity are displayed in the below graph for the period January 2002 to November 2006. The sharp increase between April 2002 and August 2002 was a result of conflict in European Union (EU) harmonization laws and the worsening of state of health of prime minister. Because of the perception of political uncertainty and the climate of election, high level was kept till November 3rd elections. Next depreciation in Turkish lira was observed during the Iraqi crisis which ended at the begging of April 2003. However, till November 2003, Turkish lira appreciated to the levels of 2002, the significant property of this term was 6 purchase interventions of the CBRT.

During November 2003, USD/TRY parity increased because of shrinkage in supply side and balance sheet arrangements. Till April 2004 USD/TRY parity was mostly affected by the domestic developments, however after the beginning of US rate hikes, TL market has become more vulnerable to developments in US and in EU side.



Source: Central Bank of the Republic of Turkey

Figure 4.1 USD/TRY Exchange Rate

As can be seen from the graph, the one year period between April 2005 and 2006 was relatively stable. During this term, the CBRT conducted 6 purchase interventions kept conducting daily purchasing auctions.

At the beginning of 2006 there started a new regime for the Turkish economy, and it met with the inflation targeting. The implementation of inflation targeting first made positive impact on the FX markets and as a result of this USD/Turkish Lira parity decreased to its lowest level since 2001. But with the change of global liquidity conditions and increased concerns about the inflation rate and current account deficit, the Turkish Lira started to depreciate in the FX market and its volatility increased.

The May-June 2006 period was the most volatile period between 2002 and 2006. Although this sharp depreciation was apparent in other emergency country currencies, the movement was sharpest in Turkey. In order to stabilize the markets, the CBRT increased short term interest rates 3 times from 13.25 to 17.50 and intervened to the market three times in two weeks time. Moreover the CBRT conducted two high amounted selling auctions to normalize the liquidity conditions.

4.2 Empirical Evidence from Turkey

The economical developments in Turkey have been good illustrations of the macroeconomic theories and therefore, there are quite many studies concerning Turkish experience. As far as the exchange rate volatility concerned, generally the ARCH family models have been preferred. This section will provide the short review of those studies.

Aysoy et al. (1996) assess the daily exchange rates in the Turkish foreign exchange market within the framework of volatility and day-of-the week effect for the period January 1988 to December 1995. They find that the volatility of the Turkish foreign exchange market is low except instability and crisis period and all week days are significant in US dollar and German mark return series according to the GARCH (1,1) model with a crisis dummy in variance function.

The other study performed by Akcay et al.(1997) search for the currency substitution's effect on exchange rate instability in Turkey using EGARCH-M model for the period January 1987 to March 1996. Their results assert that the higher the dolarization, the higher is the volatility of the exchange rate. Moreover, the ARCH-M coefficient is positively significant implying that an increase in the conditional variance of depreciation will increase the mean of depreciation series itself.

Guleryuz (1998) examines the period between January 1989 and April 1998 under different models and offered the ARMA(2,2)-ARCH(2) with dummy on Thursday in variance model as the best explaining model according to significance of parameters, R^2, AIC and SBC. On the other hand Tuna (2002) investigates the relationship between CBRT monetary policies and exchange rate volatility using ARCH (1) model. Tuna (2002) divides the period from April 1988 to October 2000 into five groups with respect to CBRT's monetary policies and uses dummies in the conditional variance equation accordingly. The result of the study suggestes that the exchange rate volatility affected by the CBRT's policies mostly in the January 1990-March 1994 period.

Aysoy and Balaban (1996) compare the realized volatility and implied volatility under random walk hypothesis by employing daily observations of the U.S. dollar and German mark against Turkish lira for the period July 1981 to December 1995. They find that the term structure of volatility in the Turkish foreign exchange does not seem consistent with the implications of random walk hypothesis. Although, both the U.S dollar and German mark returns are less volatile than random walk model asserts in the short-term, in the long-term they are more volatile than random walk.

The effect of exchange rate risk on interest rates is examined by Berument and Gunay (2003) within the uncovered interest rate parity condition for Turkey using the data from December 1986 to January 2001. In the study conditional variance of the exchange rate is used as the exchange rate risk. Their results offer a positive relation between the exchange rate risk and the interest rates. On the other hand, Demiroz (2001) investigates the possible cross relationships between the volatilities of foreign exchange and interest rates using the daily market FOREX rates for US dollar in terms of Turkish liras and repo interest rates between 4th January, 1999 and 26th December, 2000 with the multivariate GARCH(1,1) process augmented with various dummies for stabilization programs. The results suggest that the covariances are high in absolute value but because of negative sign a decline in the volatility of either assets cause a rise in the volatility of the other. Besides it is observed that the effects of random shocks on interest rate volatility are more persistent than those of exchange rates.

Additionally, Berument and Dincer (2004) investigate the effects of real exchange rate risk on the economic performance of Turkey. The ratio of total foreign exchange liabilities to: (1) total reserves; (2) the CBRT's reserves; and (3) total TL liabilities are taken as a proxy of exchange rate risk and VAR models are specified to observe the risks. According to the models' results, the exchange rate risk decreases output, increases inflation and causes depreciation for Turkey during the period February 1987 to September 2002.

Being affected by the recent wave of studies concerning the effectiveness of interventions, Turkish case is examined by Domac and Mendoza (2002), Agcaer (2003), Guimarães and Karacadag (2004) and Akinci et al. (2005a) and (2005b). All the studies analyze the empirics of foreign exchange intervention in Turkey in the aftermath of float in February 2001.

The first study in this area belongs to Domac and Mendoza (2002) who investigate the impact of CBRT's auctions on exchange rate volatility for the period February 22nd 2001 to May 30th 2002. They employ EGARH model in order to investigate the distinguishing effects of sale auctions on the conditional variance. To signal exchange policy intentions, a dummy is included which takes a value of unity on the day of public report. Moreover, overnight interest rate is added to the model in order to discover the effects of auctions in the money market. Their results suggest that overall central bank auctions have reduced the conditional variance. However, when the impact of auctions is studied separately, the reduction of volatility is a result of sales and purchase operations do not seem to have statistically significant effect on volatility of exchange rate. Furthermore, the results imply that an increase in the overnight interest rate has a negative effect on exchange rate volatility.

In the same context, Agcaer (2003) employs the EGARCH to a larger sampler, from February 2001 to November 2003, with direct intervention data. In the study, the effects of foreign exchange auctions and direct interventions on the exchange rates have been analyzed both as a whole and individually. The results of the study suggest that the presence of central bank matters and foreign exchange auctions and direct interventions have a favorable impact on both the level and volatility of exchange rates. However in contrast to Domac and Mendoza (2002) the purchases have a positive effect on the level of exchange rates, while sales have no such significant effect.

On the other hand, Guimarães and Karacadag (2004) examine nearly same period like Agcaer (2003) but employ Asymmetric Component Treshold GARCH (ACT-GARCH) specification. Their model departs from the standard GARCH representation by assuming that the long-term volatility is constant. That is, a third equation for long-term volatility which depends on its own lagged values and past shocks is introduced. The results of the study reveal that neither foreign exchange sales nor purchases appear to be significant in affecting exchange rate level. When variance equations are examined, only the foreign exchange sales find to be reducing volatility in the short-term, but increasing it in the long-term.

Akinci et al. (2005a) and (2005b) examine the causes and effectiveness of interventions in Turkey between 16 May 2003 and 31 December 2003 employing different methodologies. Akinci et al. (2005a) use probit analysis and Granger causality tests to analyze the main motivation of CBRT interventions. Probit analysis suggests that an increase in volatility induces intervention, which is inline with CBRT's official statements. They find that, although there is two-way causality between sale interventions and volatility, there is only one way causality between purchase interventions and volatility, explicitly purchase interventions Granger causes exchange rate volatility. Moreover the effectiveness of the interventions is analyzed with GARCH framework using different dummies and found that large and isolated purchase interventions decreased the exchange rate volatility. Similarly, Akinci et al. (2005b) employ event-study analysis and proposed new methodology, a time-varying parameter model, in order to analyze the effectiveness of interventions. Their results are based on both methodologies reveal that the purchase interventions that took place at the second half of 2003 appear to be more effective.

Concerning the impact of exchange rate volatility on the exports, Doğanlar (2002) examine the data in Turkey, South Korea, Malaysia, Indonesia and Pakistan using an Engle-Granger residual-based cointegration technique and found out that increases in the volatility of the real exchange rate exert a significant negative effect upon exports. Similarly, Ozturk and Acaravci (2002-2003) examine the effects of exchange rate volatility on the export of Turkey in the context of cointegration model over the monthly period of January 1989 to August 2002 and suggest the same results. Vergil (2002) investigates the period from January 1990 to December 200 and suggestes that long-run relationship between Turkey's real exports and its exchange rate volatility is negative and statistically significant for Germany, France and the United States. In contrast to these findings, Kasman and Kasman (2005) examine the data for the period 1982 to 2001 for the Turkey's nine most important trading partners and claim a positive effect of exchange rate volatility on export volume in the long run. In all four studies moving sample standard deviation is used as a volatility measure.

Latest research concerning the foreign exchange volatility belongs to Ayhan (2006). In this study the impact of exchange rate regimes on exchange rate volatility is examined using GARCH (1,1) and EGARCH(1,1) for the 1980-2005 period in "de jure" and "de facto" classification. According to the research results, instantaneous reaction of volatility is dominant ($\alpha_1 > \beta_1$) in the foreign exchange rate series. Moreover, in both de jure and de facto classification the impact of free float, managed float and crawling peg regimes on volatility is similar.

4.4.3 Summary

In this part of the study, monetary and exchange rate policies in Turkey in the post-crisis period are investigated then the applications of ARCH processes to model exchange rate volatility in Turkey are presented. Most of the empirical studies concerning Turkish experience are focused on the effectiveness of the CBRT's interventions and auctions. Different from them, this study takes into account the impact of the CBRT's short term interest rate decisions, news effect of auctions and effect of market liquidity. The following chapter will introduce the data employed in this study and provide the models and their results.

CHAPTER V

DATA AND THE EMPIRICAL MODELS

This chapter presents the data used in the study, constructs the empirical models and displays the results. The first section describes the foreign exchange rate data in brief, whereas next section introduces notation and describes the models and their results respectively.

5.1 Overview of the Data

A broad consensus has emerged that nominal exchange rates over the free float period are best described as non-stationary, or specifically I (1), type processes: see e.g. Baille and Bollerslev (1989b). Therefore in this empirical study, exchange rate series is calculated as the daily difference in the logarithm form:

$$Dlfx = \ln fx_t - \ln fx_{t-1} \tag{5.1.1}$$

The foreign exchange rate data (*fx*) are the daily CBRT's indicative foreign exchange selling rate for 1 USD. Until 1 April 2002, indicative exchange rates were computed by averaging the averages of the buying and selling rates as quoted for 1 USD by banks in the interbank foreign exchange market at 15:30 local time. However, as stated in the press release number 2002-25 published by CBRT on 28 March 2002 effective from 1 April, 2002, the indicative exchange rates have been determined by averaging the 6 observations which are obtained at 10.30, 11.30, 12.30, 13.30, 14.30 and 15.0 by taking the average value of the averages of the buying and selling rates as quoted by banks in the interbank foreign exchange market for 1 USD. Therefore, instead of using the closing rates, use of indicative rates enables capturing the daily movements.

Data consist of daily prices from 28 January 2002 and 21 November 2006, for a total of 1,213 observations excluding weekends and holidays. The period right after crisis is excluded as the year 2001 was highly unstable. Furthermore, the analyzed data enclose the period in which the inflation targeting regime implemented, though implicitly targeted between 2002 and 2005. In fact, the sampled period offers clear picture as it includes both appreciation and depreciation periods, and both rate hikes and rate cuts.

Graphical illustration of the data in Figure 5.1 displays volatility clustering which means that there are periods of high and low variance.

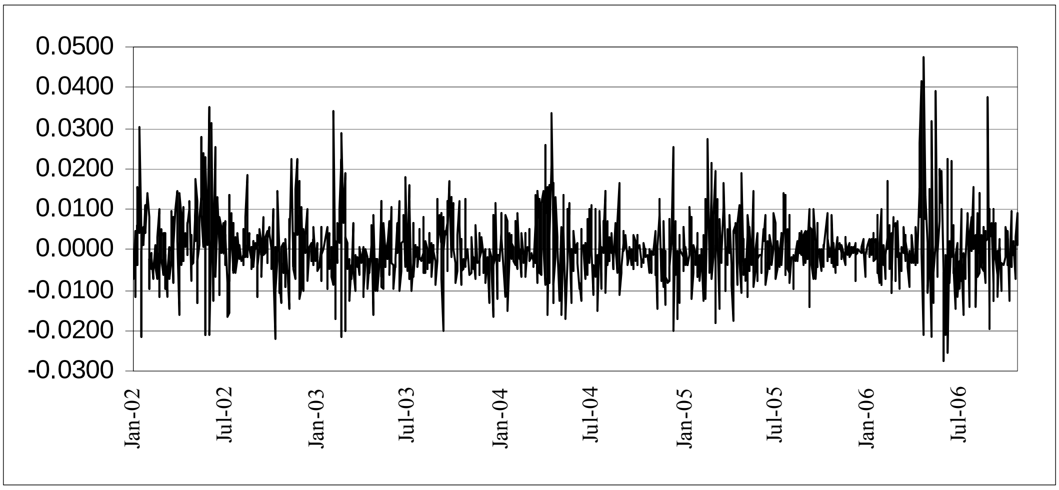


Figure 5.1 Volatility in USD/TRY series (daily difference in the logarithm form (Dlfx))

When the descriptive properties are investigated, Figure 5.2 indicates that foreign exchange rate series is both right skewed and fat tailed relative to the normal distribution. The statistics reported in the Table 5.1 confirm that impression: the sample skewness is near 0.9, the sample kurtosis is well above the normal value of 3.0 and Jarque-Bera statistics strongly rejects the null hypothesis of normal distribution.

Table 5.1 Descriptive Statistics

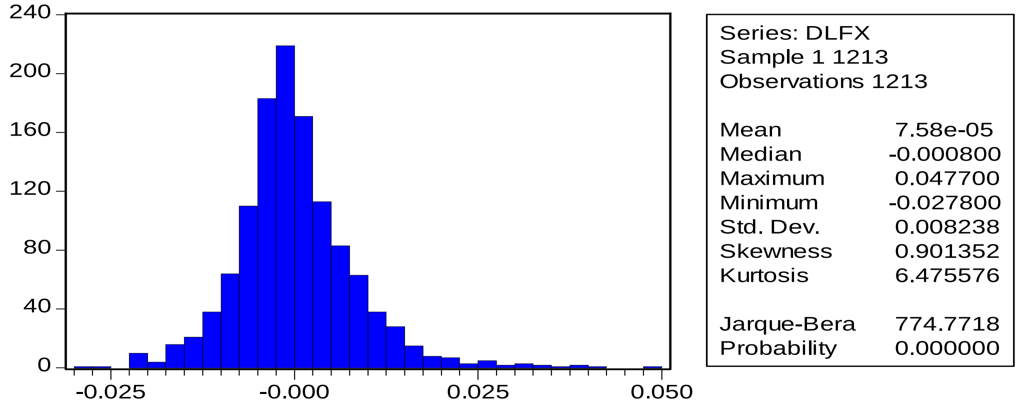


Figure 5.2 Histogram of Exchange Rate Series

One another important issue before modeling is stationarity of the data. In order to test the stationarity of the series three different unit root tests: (1) the Augmented Dickey-Fuller (ADF) test with optimal lag length determined by both the Schwarz Info Criterion and Akaike Info Criterion, (2) the Phillips-Perron (PP) test, and (3) the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are employed. While the ADF and PP test statistics test the null hypothesis that exchange rate return series contains a unit root, KPSS statistics test the null hypothesis that series is stationary. The tests are repeated with constant term and with constant and trend terms. Table 5.2 displays the results of the tests and all tests indicate the stationarity of the first difference of the foreign exchange rate series denoted with $Dlfx_t \sim I(0)$.

Table 5.2 Unit Root Tests

	ADF test Statistic		**PP test statistic**	**KPSS test statistic**
Lag Length Selection	**Schwarz C.**	**Akaike C.**	**-**	**-**
With Constant	-33.33*	-10.41*	-33.48*	0.09*
With Constant and Trend	-33.32*	-10.41*	-33.47*	0.08*

(*) : significant at 1% level

Additionally, Table 5.3 reports the Ljung-Box–Pierce Q statistics of autocorrelation of the deviations and the squared deviations of exchange rate series from its sample mean. Ljung-Box–Pierce Q statistics[3] carries out the Breusch-Godfrey Lagrange multiplier test for high-order serial correlation. While the Q-statistic of the deviations employed to detect autocorrelation, Q-statistic of the squared deviations (Q^2)[4] employed to test the volatility clustering or ARCH effects. For the exchange rate series, the statistics are calculated for lags up to 50 days and only those for lags 1, 5, 10, 20 and 50 are presented in the Table 3. According to the results, there is not serial correlation and Q^2 statistic displays strong evidence of ARCH effect.

Table 5.3 Q Statistics of Deviations and Squared Deviations

Lags	**Q Statistics of deviations**	**Q Statistics of squared deviations**
1	2.20 (0.14)	34.68 (0.00)
5	10.19 (0.07)	186.95 (0.00)
10	25.04 (0.01)	266.48 (0.00)
20	40.40 (0.01)	365.32 (0.00)
50	70.81 (0.03)	390.60 (0.00)

Note: P- values are given in parenthesis

5.2 The Models

The absence of serial dependence in the conditional first moments along with the dependence in the conditional second moments is one of the implications of GARCH (p,q) process. Moreover, in the literature, GARCH (1,1) generally found to be sufficient to eliminate ARCH effects from the error terms. Therefore, as a first step a simple GARCH (1,1) will be estimated and its performance with Student-t distribution and EGRACH (1,1) will be investigated.

[3] The null hypothesis of the test is that there is no serial correlation in the residuals up to the specified order.

[4] Rejection of the null hypothesis implies volatility clustering in the series.

5.2.1 Benchmark Models

In Model 1, mean equation is estimated with only a constant, as ACF and PACF of exchange rate series do not indicate significant serial correlation. As expected, the pre-estimation tests yield same results with estimation on constant mean term.

Tabel 5.4 Pre-estimation Test Results

Lags	**Q Statistics of deviations**	**Q Statistics of squared deviations**	**ARCH LM test**
1	2.20 (0.14)	34.68 (0.00)	35.52 (0.00)
5	10.19 (0.07)	186.95 (0.00)	29.13 (0.00)
10	25.04 (0.01)	266.48 (0.00)	16.48 (0.00)
20	40.40 (0.01)	365.32 (0.00)	9.80 (0.00)
50	70.81 (0.03)	390.60 (0.00)	4.27 (0.00)

Note: P- values are given in parenthesis

However, in this part, to verify the existence of ARCH effect, ARCH LM test also employed. The LM test is based on estimated error terms of the mean equation for a specified number of lags. For each specified order, the squared residual series is regressed on constant and its own lags (k) where k= 1, 5, 10, 20, 50 : $\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, ..., \varepsilon_{t-k}^2$. After estimating the equation, F test with null hypothesis that all the parameters equal to zero. If the test fails to reject the null hypothesis, then it can be concluded that there is a constant variance, that is there are no ARCH effects. The LM and Q^2 tests that are reported in Table 5.4 show powerful evidence that the error terms of Model 1 display an ARCH effect. These results confirm efforts to estimate a conditional heteroscedasticity model for foreign exchange rate.

Table 5.5[5] Benchmark GARCH (1,1) and EGARCH (1,1) Models with normal and student-t distributions

	GARCH (1,1)	GARCH(1,1)-t	EGARCH(1,1)	EGARCH(1,1)-t
Mean Equation				
C	-0.0004	-0.0006	-0.0003	-0.0005
	0.0223	0.0001	0.1017	0.0015
Variance Equation				
C	3.01E-06	2.33E-06	-0.986117	-0.904899
	0.0000	0.0000	0.0000	0.0000
α_1	0.2236	0.2233	0.3710	0.3630
	0.0000	0.0000	0.0000	0.0000
β_1	0.7529	0.7685	0.9284	0.9361
	0.0000	0.0000	0.0000	0.0000
γ_1			0.0535	0.0687
			0.0042	0.0222
S	0.71	0.71	0.66	0.65
K	5.66	5.71	5.33	5.44
Jarque-Bera	460.23	471.18	363.48	387.17
Akaike criterion	-6.9986	-7.0570	-7.0065	-7.0598
Schwarz criterion	-6.9818	-7.0360	-6.9854	-7.0346

Both α_1 and β_1 appear to be highly significant in each model. Similar to the findings in the literature, GARCH (1,1) models exhibit high degree of persistence as $\alpha_1 + \beta_1$

[5] Although α_1 and β_1 are coeffecients of different variables in GARCH and EGARCH, as they are interpreted in the same manner, they are tabulated together for GARCH and EGARCH models.

is very close to 1. When $\alpha_1 + \beta_1 = 1$, the GARCH process is said to be integrated-in-variance, which is analogous to a unit root in conditional mean, and is characterized by a degree of persistence.

Contrary to Ayhan (2006), in both GARCH and EGARCH estimations imply higher volatility persistency than instantaneous reaction of volatility to shocks ($\beta_1 > \alpha_1$).

Moreover, Bollerslev et al. (1994) emphasized that 'standard model selection criteria such as Akaike and Schwartz criterion have been widely used in the ARCH literature, though their statistical properties in ARCH context are unknown'. Therefore, although those criteria are reported in the tables, they will not be taken into consideration while analyzing the results.

According to the distributional assumptions of models, the adjusted error $\varepsilon_t / h_t^{1/2}$ should be normally distributed, if the GARCH model totally accounts for the leptokurtic unconditional distribution. The sample kurtosis for the adjusted error in Table 5.5 indicates that models account for some, but not all, of the leptokurtosis. That is kurtosis for the adjusted errors is generally lower than that for the unadjusted errors, but they remain significantly different from the normal value, three.

When normal and Student-t distribution compared in both GARCH models, the Student-t models not only display higher persistence but also have higher kurtosis effect. Therefore, in contrast to previous literature, Student-t distribution is not able to capture the excess kurtosis.

Although GARCH and EGARCH models are not directly comparable in classical testing procedure, they can be compared in terms of diagnostics. Then, in terms kurtosis property, EGARCH model seems to be slightly better though not fully removes leptokurtic property.

Table 5.6 ARCH LM Test, Q and Q^2 Statistics of GARCH Models

Lags	GARCH (1,1)			GARCH (1,1)-t		
	Q Statistics	Q2 Statistics	ARCH LM test	Q Statistics	Q2 Statistics	ARCH LM test
1	3.37 (0.07)	0.02 (0.90)	0.02 (0.90)	2.89 (0.09)	0.01 (0.91)	0.01 (0.91)
5	5.64 (0.34)	2.58 (0.77)	0.51 (0.77)	4.99 (0.42)	2.66 (0.75)	0.53 (0.76)
10	14.99 (0.13)	4.08 (0.94)	0.45 (0.92)	13.67 (0.20)	4.49 (0.92)	0.50 (0.89)
20	23.70 (0.26)	5.45 (1.00)	0.28 (1.00)	22.03 (0.34)	6.11 (1.00)	0.31 (1.00)
50	55.07 (0.29)	25.07 (1.00)	0.54 (1.00)	53.29 (0.35)	27.00 (1.00)	0.57 (0.99)

Note: P- values are given in parenthesis

Table 5.7 ARCH LM Test, Q and Q^2 Statistics of EGARCH Models

Lags	EGARCH (1,1)			EGARCH (1,1)-t		
	Q Statistics	Q2 Statistics	ARCH LM test	Q Statistics	Q2 Statistics	ARCH LM test
1	3.23 (0.07)	0.07 (0.80)	0.07 (0.79)	2.78 (0.10)	0.08 (0.77)	0.09 (0.77)
5	5.53 (0.36)	2.18 (0.82)	0.43 (0.83)	4.75 (0.45)	1.97 (0.85)	0.39 (0.86)
10	16.50 (0.09)	4.18 (0.94)	0.44 (0.93)	15.03 (0.13)	3.81 (0.96)	0.41 (0.94)
20	26.19 (0.16)	6.45 (1.00)	0.31 (1.00)	24.5 (0.22)	5.86 (1.00)	0.28 (1.00)
50	55.98 (0.26)	31.08 (0.98)	0.64 (0.98)	54.34 (0.31)	32.29 (0.98)	0.65 (0.97)

Note: P- values are given in parenthesis

In order to test the existence of ARCH effect after GARCH estimations ARCH LM and Q^2 tests repeated. The results are displayed in Table 5.6 and 5.7 and show powerful evidence that the residuals from GARCH and EGARCH models display no ARCH effect. In addition, the Ljung-Box Q-statistic shows no sign of autocorrelation. Thus, all GARCH models seem sufficient to capture volatility clustering.

5.2.2 Impact of CBRT

Generally, the literature investigating Turkish experiences focused on the effectiveness of the CBRT interventions and auctions. Differently, in this study the impact of the CBRT's short term interest rate decisions and news effect of auctions will be examined. In fact, the preliminary studies, consistent with the CBRT official statements, suggest that auctions do not have significant impact on exchange rate volatility. However when foreign exchange rate series analyzed, there are big movements on the days that the CBRT made official announcements concerning auctions.

Moreover, as Student-t distributions do not appear to fit very well in the previous section, normal distribution assumption kept. The models run both for GARCH and EGARCH (1,1) processes.

In order to examine the impact of the CBRT's decisions on both the level and the volatility of exchange rates, all explanatory variables included in both mean and variance equations. Also, instead of overall effect of decisions, this study focuses on the individual effects of decisions. Therefore, the following model is proposed to model the exchange rate returns and conditional volatility:

$$
\begin{aligned}
Dlfx &= \delta_0 + \delta_{aucneg} Aucneg + \delta_{aucpos} Aucpos + \delta_{\mathrm{int}vs} Intvs + \delta_{\mathrm{int}vp} Intvp + \delta_{ratehike} Ratehike \\
&+ \delta_{ratecut} Ratecut + \delta_{dbenchtr} Dbenchtr + \delta_{drateus} Drateus + \varepsilon_t
\end{aligned}
\tag{5.3.1}
$$

where,

$\varepsilon_t \sim (o, h_t)$, $\varepsilon_t = z_t h_t^{1/2}$, $z_t \sim iid(0,1)$

For GARCH (1,1),

$$
\begin{aligned}
h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \alpha_{aucneg} Aucneg + \alpha_{aucpos} Aucpos + \alpha_{\mathrm{int}vs} Intvs \\
&+ \alpha_{\mathrm{int}vp} Intvp + \alpha_{ratehike} Ratehike + \alpha_{ratecut} Ratecut + \alpha_{dbenchtr} Dbenchtr + \alpha_{drateus} Drateus
\end{aligned}
\tag{5.3.2}
$$

For EGARCH (1,1)

$$\ln h_t = \alpha_0 + \alpha_1(|z_{t-1}| + \gamma z_{t-1}) + \beta_1 \ln h_{t-1} + \alpha_{aucneg} Aucneg + \alpha_{aucpos} Aucpos + \alpha_{\text{int}\,vs} Intvs$$
$$+\alpha_{\text{int}\,vp} Intvp + \alpha_{ratehike} Ratehike + \alpha_{ratecut} Ratecut + \alpha_{dbenchtr} Dbenchtr + \alpha_{drateus} Drateus \tag{5.3.3}$$

"Intvs" and "Intvp" are dummies with a value of unity on the day of sale and purchase interventions respectively. "Aucpos" dummy variable takes one if the CBRT announces to start auctions or increase the auction amount whereas "Aucneg" takes one, if the CBRT announces to decrease the auction amounts or stop auctions. In the same manner "Ratehike (Ratecut)" is a dummy which takes the value of one when the CBRT hikes (cuts) short-term interest rates.

In addition to dummy variables, difference of Turkish benchmark government bond rate (Dbenchtr) and difference of US federal funs overnight interest rates (Drateus) are included in the equations.

Table 5.8 Mean Equation and Pre-estimation Test Results

Dlfx=0.00021+0.00951Aucneg-0.00252Aucpos+0.00529Intvs+0.00254Intvp

(0.32) (0.00) (0.15) (0.05) (0.16)

-0.00504Ratehike-0.00071Ratecut+0.00455Dbenchtr+0.00262Drateus

(0.22) (0.61) (0.00) (0.43)

Lags	Q Statistics of deviations	Q Statistics of squared deviations	ARCH LM test
1	0.65 (0.42)	40.86 (0.00)	42.09 (0.00)
5	6.38 (0.27)	185.20 (0.00)	28.26 (0.00)
10	17.02 (0.07)	242.67 (0.00)	15.29 (0.00)
20	39.69 (0.01)	319.36 (0.00)	9.82 (0.00)
50	72.06 (0.02)	396.90 (0.00)	5.04 (0.00)

Note: P- values are given in parenthesis

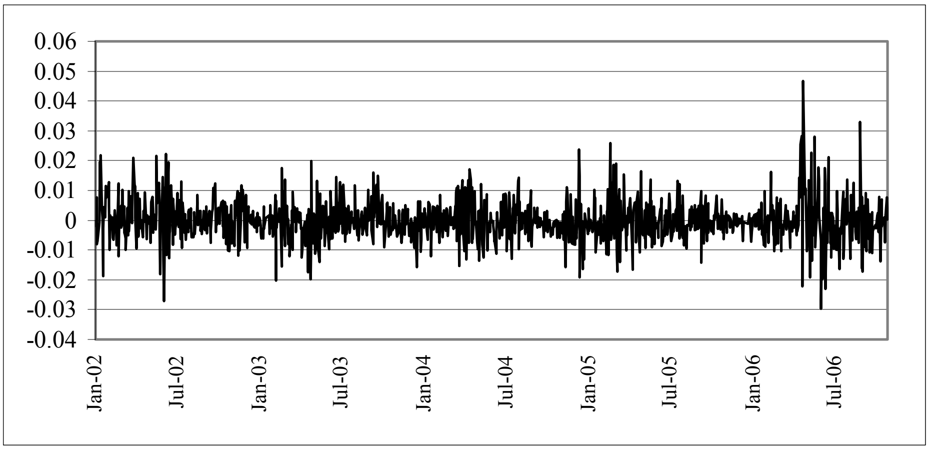


Figure 5.3 Error Terms from the OLS estimation of mean equation

The results of standard OLS estimation of equation (5.3.1) are reported in Table 5.8, with the test statistics applied to estimated error terms. As can be seen from the graphical representation of estimated errors (Figure 5.3), although addition of explanatory variables to the model relatively loosens the clustering, the ARCH effect in series is obvious. Moreover, Ljung-Box serial correlation tests show no sign of autocorrelation and the test p-values of Q^2 shown in the Table 5.8 are all zero, resoundingly rejecting the "no ARCH" hypothesis. As for the ARCH LM test for absence of conditional heteroscedasticity, it is highly significant at any level.

Table 5.9 Results of Model 2

	GARCH (1,1)			EGARCH(1,1)	
Mean Equation					
	Coefficient	Probability		Coefficient	Probability
δ_0	0.00018	0.68	δ_0	-0.00017	0.31
δ_{Aucneg}	0.00915	0.01	δ_{Aucneg}	0.00954	0.04
δ_{Aucpos}	-0.00207	0.37	δ_{Aucpos}	-0.00122	0.36
δ_{Intvs}	0.00551	0.12	δ_{Intvs}	0.01014	0.07
δ_{Intvp}	0.00263	0.09	δ_{Intvp}	0.00517	0.00
$\delta_{Ratehike}$	-0.00418	0.78	$\delta_{Ratehike}$	-0.00296	0.90
$\delta_{Ratecut}$	-0.00027	0.90	$\delta_{Ratecut}$	0.00024	0.84
$\delta_{Dbenchtr}$	0.00450	0.00	$\delta_{Dbenchtr}$	0.00402	0.00
$\delta_{Drateus}$	0.00188	0.77	$\delta_{Drateus}$	0.00007	0.98
Variance Equation					
α_0	0.000036	0.01	α_0	-1.13258	0.00
α_1	0.142070	0.02	α_1	0.30899	0.00
$\beta 1$	0.574737	0.00	$\beta 1$	0.91275	0.00
			γ	0.05258	0.02
α_{Aucneg}	0.000004	0.94	α_{Aucneg}	0.50538	0.18
α_{Aucpos}	-0.000034	0.03	α_{Aucpos}	0.00895	0.97
α_{Intvs}	0.000005	0.91	α_{Intvs}	0.30451	0.50
α_{Intvp}	-0.000046	0.00	α_{Intvp}	0.46940	0.04
$\alpha_{Ratehike}$	0.000006	0.97	$\alpha_{Ratehike}$	0.57966	0.56
$\alpha_{Ratecut}$	-0.000041	0.00	$\alpha_{Ratecut}$	0.05413	0.80
$\alpha_{Dbenchtr}$	0.000005	0.23	$\alpha_{Dbenchtr}$	0.07212	0.00
$\alpha_{Drateus}$	-0.000061	0.46	$\alpha_{Drateus}$	-0.37623	0.52
AIC	-6.8851			-7.3024	
SIC	-6.8009			-7.2141	

Results of the Model2, estimated with GARCH (1,1) and EGARCH(1,1), are displayed in Table 5.9. When the impact on level of exchange rate investigated, as expected, in both models Turkish benchmark government bond rates are estimated to be positive and statistically significant, which can be interpreted as, an increase in interest rates causes Turkish lira to depreciate. Although this result contradicts with the accepted negative interest rate-exchange rate relation, this may be caused by a higher risk perception in the economy.

As can be seen from the table, only the purchase interventions have significant impact on exchange rate level. That is, purchase interventions cause USD/TRY parity to increase.

The results also suggest that the announcement of stopping an auction or decreasing the amount of auctions is significant in both models and implies the depreciation of Turkish lira. Furthermore, rate hike/cut decisions do not have significant impact on exchange rate level.

When the GARCH and EGARCH mean equation estimations compared, they show consistent results but differ in significance level.

However same proposition cannot be made for variance equation estimates. Although purchase interventions appear to be significant in both models, GARCH model suggests that purchase interventions decrease exchange rate volatility whereas EGARCH model implies the opposite.

Moreover, GARCH model results propose that the rate cuts and starting/increasing amount news concerning auctions have decreasing impact on volatility, though they are not significant in EGARCH estimation. Similarly, Turkish benchmark government bond rates appeared to be significant only in EGARCH estimation results.

The difference in results can be attributed to the significant positive leverage effect ($\gamma > 0$). This suggests that when there is an unanticipated increase in exchange rate, volatility increases more than when there is unanticipated decrease in exchange rate. Therefore, parameters, which decrease volatility in GARCH model, are insignificant in EGARCH model. This effect can be easily observed from the graphics of conditional standard deviations of GARCH and EGARCH estimations.

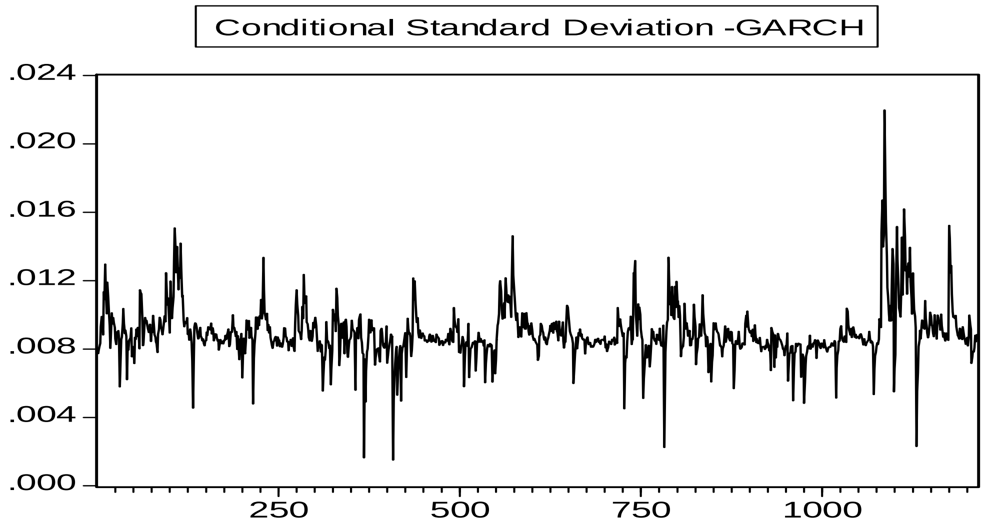


Figure 5.4 Conditional Standard Deviation of GARCH Model

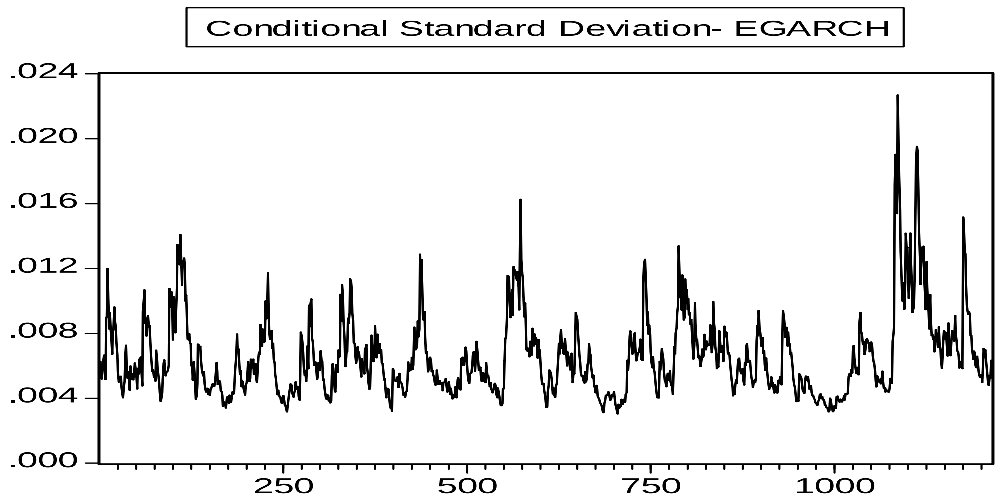


Figure 5.5 Conditional Standard Deviation of EGARCH Model

Although the EGARCH model has better Akeike and Schartz values, as stated before since their evaluation performance have not been proven, they are not employed as model selection criteria.

When the results compared with the benchmark models estimated in the previous section, decrease in persistence, especially in GARCH model, is considerable.

Table 5.10 ARCH LM Test, Q and Q^2 Statistics of GARCH and EGARCH Models 1

	GARCH (1,1)			EGARCH (1,1)		
Lags	**Q Statistics**	**Q2 Statistics**	**ARCH LM test**	**Q Statistics**	**Q2 Statistics**	**ARCH LM test**
1	0.55 (0.45)	0.01 (0.90)	0.01 (0.90)	0.001 (0.97)	0.14 (0.70)	0.14 (0.70)
5	4.16 (0.52)	0.44 (0.99)	0.08 (0.99)	2.83 (0.72)	3.99 (0.55)	0.77 (0.56)
10	15.02 (0.13)	1.68 (0.99)	0.15 (0.99)	11.70 (0.30)	4.77 (0.90)	0.54 (0.86)
20	27.82 (0.11)	4.35 (1.00)	0.20 (0.99)	21.52 (0.36)	6.19 (0.99)	0.36 (0.99)
50	54.60 (0.30)	12.03 (1.00)	0.21 (1.00)	52.05 (0.39)	30.48 (0.98)	0.64 (0.97)

Note: P- values are given in parenthesis

The Ljung-Box test statistic for the standardized error terms, $\varepsilon_t / h_t^{1/2}$, and the standardized squared error terms ε_t^2 / h_t from the estimated GARCH (1,1) model are displayed in the Table 5.10 and thus do not indicate any further first or second order serial dependence. Moreover, ARCH LM test statistics approve the removal of ARCH effects from the series.

5.2.3 Models with Trading Volume

Although, market liquidity is an important determinant of volatility there are not any data that allow foreign exchange market liquidity to be measured directly. Instead, trading volumes or bid-ask spreads are used as indirect measures.

In fact, finance theory suggests a close relationship between the volume and the volatility. In particular according to the mixtures of distribution hypothesis, the evolution of returns and trading volumes are both determined by the same latent mixing variable that reflects the amount of new information that arrives at the market. The relationship between returns and trading volumes is examined by Lamoureux and Lastrapes (1990), Galati (2000) and Bauwens, Rime and Sucarrat (2005) and found positive and statistically significant results.

In this context, in order to investigate the effect of trading volume on volatility, logarithm of spot market trading volume (Lvol) included in the variance models. Moreover, since preliminary analysis did not find any statistically significant impact of trading volume on the mean return process, this study limits its scope and focuses on conditional variance.

Therefore variance equations re-estimated with Lvol data (Model3):

For GARCH (1,1):

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \alpha_{aucneg} Aucneg + \alpha_{aucpos} Aucpos + \alpha_{\text{int} vs} Intvs + \alpha_{\text{int} vp} Intvp$$
$$+ \alpha_{ratehike} Ratehike + \alpha_{ratecut} Ratecut + \alpha_{dbenchtr} Dbenchtr + \alpha_{drateus} Drateus + \alpha_{lvol} Lvol \tag{5.4.1}$$

For EGARCH (1,1):

$$\ln h_t = \alpha_0 + \alpha_1 (|z_{t-1}| + \gamma z_{t-1}) + \beta_1 \ln h_{t-1} + \alpha_{aucneg} Aucneg + \alpha_{aucpos} Aucpos + \alpha_{\text{int} vs} Intvs$$
$$+ \alpha_{\text{int} vp} Intvp + \alpha_{ratehike} Ratehike + \alpha_{ratecut} Ratecut + \alpha_{dbenchtr} Dbenchtr + \alpha_{drateus} Drateus$$
$$+ \alpha_{Lvol} Lvol \tag{5.4.2}$$

Table 5.11 Results of Model3

	GARCH (1,1)			EGARCH(1,1)	
Mean Equation					
	Coefficient	Probability		Coefficient	Probability
δ_0	0.00020	0.59	δ_0	-0.00016	0.33
δ_{Aucneg}	0.00935	0.03	δ_{Aucneg}	0.00949	0.04
δ_{Aucpos}	-0.00224	0.15	δ_{Aucpos}	-0.00120	0.35
δ_{Intvs}	0.00541	0.17	δ_{Intvs}	0.01051	0.05
δ_{Intvp}	0.00260	0.03	δ_{Intvp}	0.00520	0.00
$\delta_{Ratehike}$	-0.00496	0.16	$\delta_{Ratehike}$	-0.00315	0.88
$\delta_{Ratecut}$	-0.00044	0.79	$\delta_{Ratecut}$	0.00026	0.83
$\delta_{Dbenchtr}$	0.00446	0.00	$\delta_{Dbenchtr}$	0.00400	0.00
$\delta_{Drateus}$	0.00249	0.65	$\delta_{Drateus}$	0.00001	1.00
Variance Equation					
α_0	0.00004	0.13	α_0	-1.39011	0.00
α_1	0.14969	0.00	α_1	0.31303	0.00
$\beta 1$	0.59879	0.00	$\beta 1$	0.90741	0.00
			γ	0.05492	0.01
α_{Aucneg}	0.00004	0.58	α_{Aucneg}	0.50944	0.20
α_{Aucpos}	-0.00003	0.02	α_{Aucpos}	0.02344	0.91
α_{Intvs}	0.00007	0.10	α_{Intvs}	0.37622	0.42
α_{Intvp}	-0.00004	0.00	α_{Intvp}	0.43774	0.06
$\alpha_{Ratehike}$	-0.00010	0.26	$\alpha_{Ratehike}$	0.33905	0.75
$\alpha_{Ratecut}$	-0.00003	0.00	$\alpha_{Ratecut}$	0.08672	0.68
$\alpha_{Dbenchtr}$	0.00000	0.19	$\alpha_{Dbenchtr}$	0.06992	0.00
$\alpha_{Drateus}$	-0.00005	0.38	$\alpha_{Drateus}$	-0.60520	0.35
α_{Lvol}	0.00000	0.64	α_{Lvol}	0.02626	0.03
AIC	-6.985623			-7.302706	
SIC	-6.897314			-7.210193	

Though it is not significant in GARCH estimation, in EGARCH estimation- trading volume appears to affect volatility positively. This result is consistent with the previous studies however, there is not much decrease observed in persistence of volatility as claimed by the Bauwens, Rime and Sucarrat (2005). After the inclusion volume data into the models, there are not much change in the impacts and significance of the explanatory variable.

Table 5.12 ARCH LM Test, Q and Q^2 Statistics of GARCH and EGARCH Models 2

	GARCH (1,1)			**EGARCH (1,1)**		
Lags	**Q Statistics**	**Q2 Statistics**	**ARCH LM test**	**Q Statistics**	**Q2 Statistics**	**ARCH LM test**
1	0.64 (0.42)	0.03 (0.86)	0.03 (0.86)	0.01 (0.90)	0.24 (0.62)	0.24 (0.62)
5	4.45 (0.48)	1.09 (0.95)	0.21 (0.95)	2.86 (0.72)	3.74 (0.58)	0.72 (0.60)
10	14.71 (0.14)	3.60 (0.96)	0.33 (0.97)	11.95 (0.28)	4,77 (0.90)	0.54 (0.85)
20	26.76 (0.14)	8.74 (0.98)	0.39 (0.99)	22.27 (0.32)	6.35 (0.99)	0.38 (0.99)
50	54.98 (0.29)	21.26 (1.00)	0.37 (0.99)	53.01 (0.35)	34.49 (0.95)	0.70 (0.93)

Note: P- values are given in parenthesis

Residual diagnostics displayed in Table 5.12 for ARCH effect and serial correlation. The results of the LM and Q^2 tests indicate powerful evidence that the residuals from GARCH and EGARCH models display no ARCH effect. In addition, the Ljung-Box Q-statistic shows no sign of autocorrelation. Thus, all GARCH models seem sufficient to capture volatility clustering.

CHAPTER VI

CONCLUSION

In everyday language, volatility refers to the fluctuations observed in some phenomenon over time. Within economics, it is used slightly more formally to describe, the variability of the random component of a time series, the standard deviation.

Even cursory look at financial data suggests that some periods are riskier than others, indicating heteroscedasticity. In fact, ARCH and GARCH models have become widespread tools for dealing with time series heteroscedastic models. The goal of such models is to provide a volatility measure –like a standard deviation- that can be used in financial decisions (Engle (2001)).

In this context, characterizing exchange rate volatility is important for developing asset and pricing models, constructing optimal portfolios, and understanding how the exchange rate markets function.

It is obvious that exchange rate series does not have a fixed structure with constant but unknown parameters, but rather it is a system that evolves over time. Because its evolution is partly stochastic, no amount of past data will be sufficient to know the exact structure of the system. Moreover, assuming that all relevant information is observed and the model is correctly specified in GARCH processes apparently strong, but has powerful and very convenient implications.

Therefore, this study focused on fitting a conditional variance model to exchange rate series with different distributional assumptions and different explanatory variables, and investigating their in-sample properties. The analysis covers the 2002-2006 period.

As a first step, standard GARCH (1,1) and EGARCH(1,1) models estimated assuming both Student-t distribution and normal distribution. Even though the unconditional error distribution corresponding to the GARCH models with conditionally normal errors are leptokurtic, the results of this study show that employed models do not fully account for the leptokurtosis in the exchange rate series. Moreover, in contrast to previous studies, Student-t could not capture the leptokurtic property better than normal distribution. Consequently, GARCH (1,1) and EGARCH (1,1) models with normal distributions are taken as benchmark models.

Although GARCH and EGARCH models can not be compared directly, both are employed in order to further investigate the properties of exchange rate series of Turkey.

Exchange rate volatility depends on many factors such as market conditions, economic fundamentals and country specific factors. In this study, the CBRT's decisions and actions related with interventions, auctions and short-term interest rates, changes in benchmark interest rates of Turkish government bonds and Federal Reserve Bank and trading volume are considered and their impacts are investigated by bringing such factors together in a general framework and trying to disentangle their distinct effects on exchange rate volatility.

In the model without trading volume, the mean equation results of the both model are consistent with each other. According to the results of the models an increase (decrease) in Turkish benchmark government bond rates causes Turkish lira to depreciate (appreciate). This result contradicts with the well- known economic theory, which suggests that an increase in interest rates causes appreciation of the domestic currency. This may be resulted from the higher risk perception in the economy. Furthermore, purchase interventions and announcement of suspending/ decreasing-the-amount-of auctions lead USD/TRY parity to increase. This result however contradicts with official statement of CBRT.

Although a reduction of persistence in volatility is observed with the inclusion of new explanatory variables in the models, the results of variance equation differ highly. Even though purchase interventions are significant in both models, GARCH model suggests that purchase interventions decrease exchange rate volatility whereas EGARCH model implies the opposite.

Moreover, GARCH model results propose that the rate cuts and starting/increasing amount news concerning auctions have decreasing impact on volatility, though they are not significant in EGARCH estimation.

Besides, Turkish benchmark government bond rates appeared to be significant only in EGARCH estimation results. Since exchange rates are closely tied to the health of the economy, it is natural to expect that changes in benchmark bono interest rate help explain changes in foreign exchange rate volatility.

When spot market trading volume is included in the models, it is significant only in EGARCH model. Consistent with the previous studies trading volume affects volatility of the exchange rate positively. However, contrary to their findings, decrease in persistence cannot be observed.

According to this study's results, the difference in estimations emerged from the significant positive leverage effect. Put it differently, this can be interpreted as, in the EGARCH model; bad news tends to increase volatility more than good news.

The important outcome stood out from this study is the importance of model selection. Although Ljung-Box t and ARCH LM test statistics approve the removal of ARCH effects from the series when estimated with either GARCH or EAGRCH, in the presence of leverage effect, the results of GARCH model can be misleading. Consequently model selection and evaluation should be made cautiously when modeling financial time series.

The results suggest at least two directions for future research. First, given the complex relationship between exchange rate and interest rate, next step will be investigation of cross relation between USD/TRY parity and short-term interest rates. Second, taking into account the crucial role of leverage effect, it will be beneficial to analyze the volatility of USD/TRY's parity with other ARCH family models.

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APPENDIX A

CBRT Interest Rates

Date	Borrowing	Lending
20.02.2002	57,00	62,00
14.03.2002	54,00	61,00
08.04.2002	51,00	58,00
30.04.2002	48,00	55,00
05.08.2002	46,00	53,00
11.11.2002	44,00	51,00
25.04.2003	41,00	48,00
04.06.2003	38,00	45,00
16.07.2003	35,00	41,00
06.08.2003	32,00	38,00
18.09.2003	29,00	35,00
15.10.2003	26,00	31,00
05.02.2004	24,00	29,00
17.03.2004	22,00	27,00
08.09.2004	20,00	24,00
20.12.2004	18,00	22,00
11.01.2005	17,00	21,00
09.02.2005	16,50	20,50
09.03.2005	15,50	19,50
11.04.2005	15,00	19,00
10.05.2005	14,50	18,50
09.06.2005	14,25	18,25
11.10.2005	14,00	18,00
09.11.2005	13,75	17,75
09.12.2005	13,50	17,50
02.01.2006	13,50	16,50
28.04.2006	13,25	16,25
08.06.2006	15,00	18,00
26.06.2006	17,25	20,25
28.06.2006	17,25	22,25
21.07.2006	17,50	22,50

APPENDIX B

CBRT Press Releases Concerning Auctions

Press Release Date	CBRT Announcements
28.03.02	Start Buying Auctions
28.06.06	Suspension of Buying Auctions
05.05.03	Resume Buying Auctions
29.05.03	Increase Auction Amount
13.06.03	Abolish Maximum Price Application
30.06.03	Increase Auction Amount
16.07.03	Increase Auction Amount
29.08.03	Increase Auction Amount
10.09.03	Increase Auction Amount
06.10.03	Increase Auction Amount
20.10.03	Decrease Auction Amount
22.10.03	Suspend Buying Auctions
22.01.04	Resume Buying Auctions
27.02.04	Increase Auction Amount
31.03.03	Increase Auction Amount
06.04.04	Increase Auction Amount
14.04.04	Decrease Auction Amount
27.04.04	Suspend Buying Auctions
30.04.04	Suspend Buying Auctions
20.12.04	Resume Buying Auctions
05.12.05	Continued Buying Auctions
15.05.06	Suspend Buying Auctions
10.11.06	Resume Buying Auctions