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Research Article

ASYMMETRIC GARCH-TYPE AND HALF-LIFE VOLATILITY MODELLING OF USD/KZT EXCHANGE RATE RETURNS

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ABSTRACT

Empirical studies have shown that a large number of financial assets returns exhibit fat tails (leptokurtosis) and are often characterized by volatility clustering and asymmetry. This paper considers the ability of the asymmetric GARCH-type models to capture the stylized features of volatility in USD/KZT exchange rate returns. Therefore, the half-life parameter of the USD/KZT returns series were calculated for three sub-periods. The results revealed that the half-life was 6 days, 16 days and 12 days for 1st sub-period, 2nd sub-period and 3rd sub-period respectively. According to the results, in the presence of asymmetric responses to innovations in the Kazakhstan foreign exchange market, the EGARCH (1.1)-GED model which accommodates the kurtosis of financial time series is preferred. Also, these results show that the USD/KZT exchange rate returns have strong mean reversion and short half-life.

Keywords: EGARCH, GJRGARCH, APGARCH, USD/KZT exchange rate, Half-life volatility.

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INTRODUCTION

Devaluation is one of the intentionally downward adjustment tools of the value of a national currency relative to another national currency or group of national currencies. Devaluation is a monetary reform tool used by central banks to manage the national currency value (Zholamanova et al., 2018: 832). An example from the newest history of Kazakhstan - on August 20 of 2015, the National Bank announced devaluation and introduced a free exchange rate of tenge. From August to December 2015, the Kazakhstan tenge (KZT) depreciated from 188.38 to 349.12 KZT against the US dollar (USD).

Because of the weakening of the Chinese yuan and the decrease in the price of Brent crude oil from early 2015, the pressure on the economy of Kazakhstan was exacerbated. This economic condition forced the National Bank of Kazakhstan to switch to a floating rate in August 20, 2015 and the KZT devaluated by 24.6%. From August 19, 2015 to August 20, 2015, the KZT depreciated from 197.28 to 252.40 KZT against the USD. However, this creates certain risks for the economy that will face some adaptation troubles. The devaluation appears to produce more negative effects to the economy of Kazakhstan.

Because of the empirical studies have shown that a large number of exchange rate returns exhibit fat tails (leptokurtosis) and asymmetry in volatility, the main purpose of this paper is to examine the adequacy of the asymmetric GARCH-type models to capture the stylized features of volatility in USD/KZT exchange rate returns. Moreover, the average number of time periods for the volatility to revert to its long run level is measured by the half-life of the volatility shock.

The remainder of this paper proceeds as follows. Section 2 attempts to review the relevant literature. Section 3 details the general models. Section 4 describes the USD/KZT exchange rate returns data to be used in this study and presents the empirical results. Section 5 contains some concluding remarks.

LITERATURE REVIEW

Volatility modeling of exchange rates have many practical applications in finance with wide discussion in academic literature. Kamal et al. (2012) examine the performance of GARCH family models in forecasting the volatility behavior of Pakistani FOREX market. They founded asymmetric behavior of volatility, where TARCH model showed insignificance. Olowe (2009) used GARCH type models to investigate the volatility of Naira/US Dollar exchange rate. According to the results, all the coefficients of the variance equations were significant, and TS-GARCH and APARCH models were the best models. Hafner (1998) has analyzed high-frequency foreign exchange rate (HFFX) series with ARCH class models. The results showed important asymmetries in volatility. Additionally, according to EGARCH model, the news impact curves have different shapes for different lags. Ahmed et al. (2018) examine and compare the mean reversion estimation in developed and emerging stock markets. The results show that the South Korean market has the slowest mean reversion, and the Pakistan stock exchange exhibited the fastest mean reverting process. Abdalla (2012) considers the GARCH approach in modelling exchange rate volatility with a panel of nineteen of the Arab countries using daily observations. The paper concludes

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that the exchange rates volatility can be adequately modelled by GARCH type models. Gbenro and Moussa (2019) analyzed the mean reversion property on the West African stock market. The results showed that the estimated half-life time declines slightly for composite index. Many recent empirical studies also investigate the characteristics of exchange rate volatility in the context of time series analysis of financial returns. For example, Longmore and Robinson (2004), Wang (2006), Yoon and Lee (2008), Hamadu and Adeleke (2009), and Fiser and Roman (2010).

As far as we have determined, no previous study has been found on the volatility modeling and half-life volatility estimation of USD/KZT exchange rate. Therefore, the distinctive contribution of this study to the literature is the asymmetric volatility modeling of the USD/KZT exchange rate and the half-life volatility estimation.

METHODOLOGY

In the theoretical and empirical studies, it is strongly highlighted the invalidity of using unconditional homoscedastic variance instead of conditional heteroskedastic variance and models. Particularly, studying with high frequency models like financial time series analysis requires working with heteroskedastic models (Baltagi, 2000: 375). The basic statistical features of financial time series may be classified as leptokurtic distribution, volatility clustering, leverage effect-asymmetric information and co-movement process. Exchange rate returns are approximately uncorrelated but not independent through time as large (small) price changes tend to follow large (small) price changes which is commonly referred to as volatility clustering. The features mentioned above discloses the requirement for different type of conditional heteroskedastic models. In today's financial engineering techniques, there are more than six hundred derivative models of conditional heteroskedastic models. However, the most basic types of it are those introduced by Engle (1982) as ARCH (AutoRegressive Conditional Heteroskedasticity) and Bollerslev (1986) as GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) models. The importance of these models arises from their usage on portfolio risk and volatility analysis (Brooks, 2002: 439). Here are the basic definitions and theoretic properties of the models.

ARCH (q) and GARCH (p,q) Models

The basic idea of the ARCH models is that the mean corrected asset return model is serially uncorrelated, but dependent and the dependence of this model can be described by a simple quadratic function of its lagged values (Chatfield, 2003: 83). Specifically, a basic ARCH (*q*) model can be described as generalizing *q* process for the model below:

$$\sigma_t^2 = w_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 + \cdots + \alpha_n \varepsilon_{t-1}^2 \qquad (1)$$

Hence the basic ARCH model is:

$$\sigma_t^2 = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (2)$$

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Further extension introduced by Bollerslev (1986) known as the Generalized ARCH (GARCH) model which suggests that the time-varying volatility process is a function of both past disturbances and past volatility. The GARCH (p,q) model may be formalized with the equation below:

$$\sigma_t^2 = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (3)$$

where w_0 is a constant parameter, ε_t is the innovation process, σ_t is the conditional standard deviation, z_t is an independently and identically distributed (i.i.d.) process. $f(.)$ represents the distribution function with zero mean and unit variance. Here α_i and β_j are the standard ARCH and GARCH parameters. Given that $w_0 > 0$, $\alpha_i \geq 0$ and $\beta_j \geq 0$ the GARCH model requires $\alpha_i + \beta_i < 1$ to be stationary. Consequently, the GARCH model enables to include the lagged values of ε_t^2 and σ_t^2 to the model process.

Empirical studies have shown that a large number of exchange rate returns exhibit fat tails and are often characterized by volatility clustering and asymmetry. Both the ARCH and GARCH models allow taking the first two characteristics into account, but their distributions are symmetric and therefore fail to model the third stylized fact, namely the "leverage effect". Exchange rate returns data commonly exhibits an asymmetry in that positive and negative shocks to the market do not bring forth equal responses. In order to solve this problem, many nonlinear extensions of the GARCH model have been proposed. Among the most widely spread are the EGARCH, GJRGARCH and APGARCH models.

EGARCH (p,q) Model

Nelson (1991) brought out exponential GARCH (EGARCH) models with a conditional variance formulation that successfully captured asymmetric response in the conditional variance. EGARCH model has a number of advantages over the basic GARCH model, as the non-negativity constraint does not need to be imposed and the asymmetries are also allowed to be used in this model:

$$\ln\left(\sigma_t^2\right) = w_0 + \sum_{i=1}^{p} \alpha_i \frac{\left|\varepsilon_{t-i}\right| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (4)$$

where w_0 is a constant parameter, ε_t is the innovation process, σ_t is the conditional standard deviation. Here α_i and β_j are the standard ARCH and GARCH parameters, γ_i is the leverage parameter.

In the equation γ_i represent leverage effects which accounts for the asymmetry of the model. While the basic GARCH model requires the constraints to be set, the EGARCH model allows unrestricted estimation of the variance (Thomas and Mitchell, 2005: 16). If $\gamma_i \neq 0$ impact is asymmetric. If $\gamma_i > 0$ it indicates leverage effect exist and if statistically significant, a positive shock (good news) in the past increases volatility more than a negative shock (bad news). If $\gamma_i < 0$ it indicates again leverage effect exist and if statistically significant, a negative shock (bad news) in the past increases volatility more than a positive shock (good news). However, the general expectation is that negative shocks in financial markets further increase volatility (Ural, 2010: 93).

GJRGARCH (p,q) Model

The models nested so far have assumed a symmetrical response of volatility to

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innovations in the market. However, empirical evidence suggests that positive and negative returns to the market of equal magnitude will not generate the same response in volatility. Glosten et al. (1993) provided one of the first attempts to model asymmetric or leverage effects with a model which utilizes a GARCH type conditional variance specification. The GJRGARCH model is proposed by Glosten et al. (1993). The generalized specification for the conditional variance is given by:

$$\sigma_t^2 = w_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-i}^2 I_{t-k}^- + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (5)$$

where $I_{t-k}^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In this model, good news $(\varepsilon_{t-i} > 0)$ and bad news $(\varepsilon_{t-i} < 0)$, have differential effects on the conditional variance, good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_k$. If $\gamma_k \neq 0$, the news impact is asymmetric. A positive (resp. negative) value of the γ_k means that past negative (resp. positive) shocks have a deeper impact on current conditional volatility than past positive (resp. negative) shocks.

APGARCH (p,q) Model

The ARCH literature has developed rather rapidly. One recent development in the ARCH literature has focused on the power term by which the data are to be transformed. Ding et al. (1993) introduced a new class of ARCH model called The Generalized Asymmetric Power ARCH (APGARCH) model, which estimates the optimal power term. They also found that the absolute returns and their power transformations have a highly significant long-term memory property as the returns are highly correlated. The APGARCH model is presented in the following framework (Harris and Sollis, 2003: 237-238):

$$\sigma_t^\delta = w_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \quad (6)$$

Where again w_0 is a constant parameter, ε_t is the innovation process, σ_t is the conditional standard deviation. Here α_i and β_j are the standard ARCH and GARCH parameters, γ_i is the leverage parameter and δ is the parameter for the power term. A positive (resp. negative) value of the γ_i means that past negative (resp. positive) shocks have a deeper impact on current conditional volatility than past positive (resp. negative) shocks. Also, $w_0 > 0,\ \alpha_i \geq 0,\ \beta_j \geq 0,\ \delta \geq 0$ and $|\gamma_i| \leq 1$. The model imposes a Box and Cox (1964) transformation in the conditional standard deviation process and the asymmetric absolute innovations. In the APGARCH model, good news ($\varepsilon_{t-i} > 0$) and bad news ($\varepsilon_{t-i} < 0$) have different predictability for future volatility, because the conditional variance depends not only on the magnitude but also on the sign of ε_t.

In the influential paper of Engle (1982), the density function of z_t, $f(.)$ was the standard normal distribution. Failure to capture fat-tails property of high-frequency financial time series has led to the use of non-normal distributions to better model excessive third and fourth moments. The most commonly used are the Student-*t* distribution and the Generalized Error Distribution (GED). Bollerslev (1987) tried to capture the high degree of leptokurtosis that is presented in high frequency data and proposed the Student-*t* distribution in order to produce an unconditional distribution with fat tails.

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Half-Life Measure of Volatility

Mean reversion means that current information has no influence on the long run forecast of the volatility. In stationary GARCH-type models, the volatility mean reverts to its long run level, at a rate given by the sum of ARCH and GARCH coefficients, which is usually close to one (1) for financial time series.

The average number of time periods for the volatility to revert to its long run level is measured by the half-life of the volatility shock. One measure of volatility persistence is the volatility half-life (*HL*), Engle and Patton (2001) defined half-life as the time required for the volatility to move half way back towards its unconditional mean. For example, the persistence parameter in the EGARCH model is defined as $P = \sum_{j=1}^{q} \beta_j$. If $P<1$, then the return series exhibit mean reversion. However, if $P=1$, then the series follow the random walk. Another related concept is the half-life (*HL*) parameter. The latter is defined as the period that it takes the returns to reach half the long-term average values. The half-life is given by (Gbenro and Moussa 2019:4):

$$HL = \frac{-\ln(2)}{\ln(\mathrm{P})} \quad (7)$$

DATA AND EMPIRICAL RESULTS

The section shows the empirical results of models. The closing prices of USD/KZT exchange rates are analyzed and interpreted. The characteristics of the data are presented in the first subsection. The second subsection shows the estimated results of asymmetric GARCH-type model under alternative probability distributions. The EGARCH (1,1)-GED model produced highly significant test statistics than other asymmetric models.

Data

The paper considers the USD/KZT exchange rates for the period from August 20, 2015 to September 13, 2019 (1,063 observations) because the National Bank of Kazakhstan switched to a floating rate on August 20, 2015. Hence, analysis period started from the date of regime change. However, the analysis period is divided into three sub-periods in order to differentiate the effects of devaluation on the return volatility of USD/KZT exchange rate. The first sub-period covers the period from the announcement of devaluation to September 13, 2019 and represents the whole period of the analysis. The second sub-period neglects the first six months after the announcement of the devaluation and covers February 23, 2016 - September 13, 2019 period. The third sub-period neglects the year following the announcement of devaluation and covers the period of August 22, 2016 – September 13, 2019. The main purpose of the policy change was to minimize its involvement in the currency market. For the USD/KZT exchange rates, the continuously compounded rate of return was estimated as $r_t = \ln(p_t / p_{t-1})$ where p_t is the closing price on day *t*. The usual descriptive statistics for USD/KZT exchange rates return series (RUSDKZT)

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are summarized in Table 1.

Table 1. *Descriptive Statistics of USD/KZT Return Series*

	RUSDKZT (1st Sub-Period)	RUSDKZT (2nd Sub-Period)	RUSDKZT (3rd Sub-Period)
Observation	1,063	931	801
Minimum	-0.071430	-0.017344	-0.017344
Maximum	0.055450	0.027839	0.018936
Standard Deviation	0.007523	0.004548	0.004143
Skewness	0.564191	0.383801	-0.001702
Kurtosis	23.61967	6.690080	5.418561
Jarque-Bera (Prob.)	18,897.92 (0.000)	551.07 (0.000)	195.23 (0.000)
ARCH LM (p-value)	125.46 (0.000)	7.281695 (0.007)	19.65229 (0.000)
		Unit Root Tests	
ADF-Test	-31.35319[a]	-27.91354[b]	-23.96037[b]
PP-Test	-31.35225[a]	-27.83488[b]	-23.76133[b]
KPSS-Test	0.222973[a]	0.317725[a]	0.236011[a]

a indicates that there is a constant but no trend and *b* indicates that there is no constant and no trend in the regression model with lag=0. MacKinnon's critical value at the 1% significance level for ADF and PP tests are -3.436290 (with constant), for KPSS test critical value is 0.739000 (with constant) at the 1% significance level.

Source: Authors' estimates

It is not surprising that USD/KZT return series exhibit asymmetric and leptokurtic (fat tails) properties. Thus, the return series of USD/KZT exchange rates are not normally distributed. The USD/KZT exchange rates return series are positively skewed except for the 3rd sub-period. Moreover, by Jarque-Bera statistics and corresponding p-value we reject the null hypothesis that returns are well approximated by the normal distribution. The USD/KZT return series is subjected to three unit root tests to determine whether stationarity I(0). All Augmented-Dickey–Fuller (ADF), Phillips–Peron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test statistics are rejected the hypothesis of a unit root at the 1% level of confidence. ARCH LM statistics highlight the existence of conditional heteroskedastic ARCH effect.

From the descriptive graphics presented in Figure 1, several volatility periods can be observed. These graphical expositions show that USD/KZT exchange rates return series exhibit volatility clustering which means that there are periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes.

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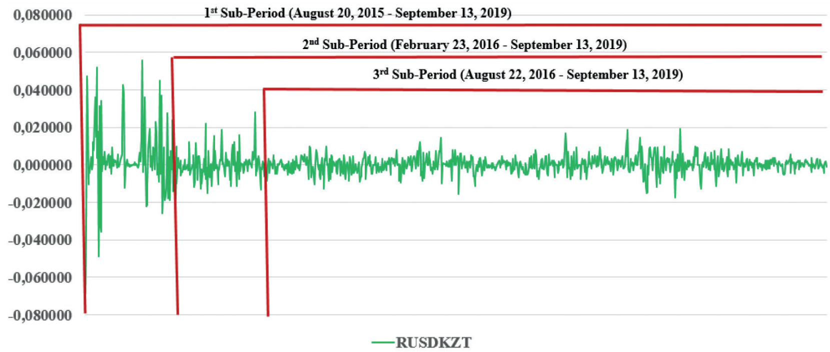
Figure 1. *Daily Log-Returns for USD/KZT Exchange Rates Return Series*



Source: Authors' estimates

Estimation Results

In this subsection, for the volatility analysis the EGARCH, GJRGARCH and APGARCH models are performed for return series under Gauss, Student-*t* and GED (Generalized Error Distribution) distributions. The standard of model selection is based on in-sample diagnosis including Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hannan-Quinn Information Criterion (HIC), log-likelihood (LL) values, and Ljung-Box Q and Q^2 statistics on standardized and squared standardized residuals respectively. Under every distribution, the model which has the lowest AIC, SIC and HIC or highest LL values and passes the Q-test simultaneously is adopted.

In summary, ranking by AIC, SIC, HIC and LL favors the EGARCH (1,1)-GED distribution specification with the first order lags in USD/KZT return series. Table 2 reports the estimation results of the asymmetric GARCH-type models under GED distribution. To conserve space the results of the models with other distributions declined to present, but they are available upon request.

Because of the ranking by AIC, SIC, HIC and LL favors the EGARCH (1,1)-GED distribution specification in USD/KZT return series, only coefficients related to EGARCH model were interpreted. Table 2 presents the results of this estimation procedure and from this table one can see that all of the ARCH and GARCH coefficients are statistically significant at the 1% level for three sub-periods. Further, the GARCH (β) coefficients were lower than 1 indicating that the models are stationary and the shocks to the model are transitory rather than permanent. Also β indicates a high degree of volatility persistence. β takes values between 0.892163 to 0.956806 suggesting that there are substantial memory effects.

As all asymmetric GARCH models the EGARCH model also includes a leverage term (γ) which allows positive and negative shocks of equal magnitude to elicit an unequal response from the market. Table 2 presents details of this EGARCH model leverage term (γ) and reveals that for all sub-periods fitted; the estimated coefficient was positive and statistically significant. Leverage term (γ) is 0.083199, 0.057809 and 0.077764 for three sub-periods respectively. This means that positive shocks lead to higher subsequent volatility of USD/KZT returns than negative shocks.

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The EGARCH model results for three sub-periods given in Table 2 show that it succeeds in taking into account all the dynamical structure exhibited by the returns and volatility of the returns as the Ljung-Box statistics for up to 20 lags on the standardized residuals (Q) (except 3rd sub-period) and the squared standardized residuals (Q^2) are non-significant at the 5% level. There is also no evidence of remaining ARCH effects according to the ARCH-LM test statistic with lag 1. According to the AIC, SIC, HIC and LL statistics the EGARCH (1,1)-GED distribution specification in USD/KZT return series for 3rd sub-period has been determined as the most successful model.

Table 2. *Model Estimation Results for Three Sub-Periods of the USDKZT Exchange Rate Returns*

Table 2. *Model estimation results for three sub-periods of the USDKZT exchange rate returns*

	1st Sub-Period August 20, 2015 to September 13, 2019 (1,063 Obs.)			2nd Sub-Period February 23, 2016 - September 13, 2019 (931 Obs.)			3rd Sub-Period August 22, 2016 – September 13, 2019 (801 Obs.)		
	EGARCH(1,1) Model	GJRGARCH(1,1) Model	APGARCH(1,1) Model	EGARCH(1,1) Model	GJRGARCH(1,1) Model	APGARCH(1,1) Model	EGARCH(1,1) Model	GJRGARCH(1,1) Model	APGARCH(1,1) Model
μ	0.000000^{*} [0.000]	0.000000^{*} [0.000]	0.000000^{*} [0.000]	0.000129^{*} [1.294]	0.000007^{*} [0.658]	0.000120^{*} [1.190]	0.000209^{b} [1.940]	0.000175^{*} [1.587]	0.000192^{b} [1.753]
ϖ	-1.556653 [-6.238]	0.000001 [4.056]	0.000163^{*} [0.799]	-0.653767 [-3.018]	0.000008^{a} [2.287]	0.000063^{*} [0.491]	-0.835948 [-3.048]	0.000001^{a} [2.380]	0.000018^{*} [0.369]
α	0.579064 [8.085]	0.510781 [5.584]	0.352868 [6.048]	0.248145 [4.739]	0.174471 [3.925]	0.136674 [4.389]	0.265005 [4.900]	0.232920 [3.954]	0.144841 [4.195]
β	0.892163 [40.527]	0.551938 [12.389]	0.644513 [13.216]	0.956806 [52.323]	0.833746 [23.507]	0.860148 [26.360]	0.942459 [40.587]	0.783414 [16.445]	0.832208 [21.501]
γ	0.083199^{b} [1.819]	-0.148762* [-1.262]	-0.173622^{b} [-1.764]	0.057809a [2.056]	-0.068856^{*} [-1.441]	-0.236016^{b} [-1.903]	0.077764^{a} [2.537]	-0.125590^{a} [-2.133]	-0.258935^{a} [-2.105]
δ	-	-	1.237961 [5.113]	-	-	1.182959 [3.204]	-	-	1.447759 [3.053]
LL	**4,214.56**	4,212.12	4,214.37	**3,815.70**	3,813.68	3,815.81	**3,341.11**	3,340.55	3,341.11
AIC	**-7.918271**	-7.913674	-7.916024	**-8.184104**	-8.179762	-8.182196	**-8.327361**	-8.325973	-8.324880
SIC	**-7.890225**	-7.885628	-7.883304	**-8.152936**	-8.148594	-8.145833	**-8.292261**	-8.290873	-8.283930
HIC	**-7.907644**	-7.903046	-7.903625	**-8.172217**	-8.167875	-8.168328	**-8.313878**	-8.312490	-8.309150
ARCH-LM (Prob.)	**1.801734 (0.1795)**	0.492921 (0.4826)	1.802578 (0.1794)	**1.282117 (0.2575)**	0.534277 (0.4648)	1.317168 (0.2511)	**3.275407 (0.0703)**	0.956645 (0.3280)	2.573085 (0.1087)
Q(20)	29.311 (0.082)	30.594 (0.061)	30.386 (0.064)	29.067 (0.086)	29.000 (0.088)	28.619 (0.096)	37.011 (0.012)	35.396 (0.018)	36.155 (0.015)
Q^2(20)	20.829 (0.407)	18.142 (0.578)	20.804 (0.409)	17.248 (0.637)	16.876 (0.661)	17.741 (0.604)	24.996 (0.202)	24.262 (0.231)	25.481 (0.184)

a, b denote 5% and 10% significance level respectively; * denotes insignificancy; t-statistics of corresponding tests in brackets. AIC-Akaike Information Criterion, SIC-Schwarz Information Criterion, HIC-Hannan-Quinn Information Criterion, LL is the value of the maximized log-likelihood. The ARCH-LM denotes the ARCH test statistic with lag 1. Q(20) and Q2(20) are the Ljung-Box statistics for remaining serial correlation in the standardized and squared standardized residuals respectively using 20 lags with p-values in parenthesis.

Source: Authors' estimates

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Following Nelson (1991), for EGARCH model, a stationary solution of Equation (8) is given by:

$$\sigma = \sqrt{\exp\left\{\omega_0 + \left(\sum_{i=1}^{p}\alpha_i\sqrt{\frac{2}{\pi}}\right)\Big/\left(1-\sum_{j=1}^{q}\beta_j\right)\right\}} \tag{8}$$

Table 3 shows the heteroskedastic (EGARCH) volatility, homoskedastic volatility (standard deviation) and half-life coefficients for three sub-periods.

Table 3. *Volatility and Half-life Estimation Results*

	1st Sub-period	**2nd Sub-Period**	**3rd Sub-Period**
Heteroskedastic (EGARCH) Volatility (HeV)	0,006249	0,005113	0,004398
Homoskedastic Volatility (HoV)	0,007523	0,004548	0,004143
Volatility Comparison	HoV > HeV	HoV < HeV	HoV < HeV
Half-life (HL) (days)	6	16	12

Source: Authors' estimates

According to Table 3 the results show that homoscedastic volatility (HoV) and heteroskedactic (EGARCH) volatility (HeV) are gradually decreasing during sub-periods. However, HoV is bigger than HeV in the 1st sub-period. For the 2nd and 3rd sub-periods, HoV is lower than HeV means that the effect of shocks shrinks and volatility decreased after exchange rate regime change. The persistence parameter (β) in the EGARCH model is lower than 1 that means the return series exhibit mean reversion. However, the half-life (*HL*) was 6 days, 16 days and 12 days for 1st sub-period, 2nd sub-period and 3rd sub-period respectively. Because of the EGARCH (1,1)-GED distribution specification in USD/KZT return series for 3rd sub-period has been determined as the most successful model, after the shocks occurs in the USD/KZT volatility than reverts to its mean in 12 days.

CONCLUSION

Because of the weakening of the Chinese yuan and the decrease in the price of Brent crude oil from early 2015, the pressure on the economy of Kazakhstan was exacerbated. This economic condition forced the National Bank of Kazakhstan to switch to a floating rate in August 20, 2015. Hence, analysis period started from the date of regime change. The paper considers the USD/KZT exchange rates for the period August 20, 2015 to September 13, 2019 (1,063 observations). However, the analysis period is divided into three sub-periods in order to differentiate the effects of devaluation on the return volatility of USD/KZT exchange rate. The main purpose of this paper is to examine the adequacy of the asymmetric GARCH-type models to capture the stylized features of volatility in USD/KZT exchange rate returns. Moreover, the average number of time periods for the volatility to revert to its long run level is measured by the half-life of the volatility shock.

The results suggest that in the presence of asymmetric responses to innovations in the Kazakhstan foreign exchange market, the EGARCH (1,1) - GED model which accommodates the kurtosis of financial time series is preferred. According

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to the AIC, SIC, HIC and LL statistics EGARCH (1,1)-GED distribution specification in USD/KZT return series for 3rd sub-period has been determined as the most successful model. These results also show that the USD/KZT exchange rate returns have strong mean reversion and short half-life. Based on half-life parameter, after the shocks occurs in the USD/KZT volatility than reverts to its mean in 12 days.

Consequently, in Kazakhstan, which shifted from a fixed exchange rate regime to a floating exchange rate regime, the volatility effect was high in the first 6 months and decreased due to the weakening of macroeconomic shocks in the next 6 months. For countries that have similar economic structure, the effects of volatility shocks should be examined comparatively by expanding analyzes at different exchange rates.

REFERENCES

Abdalla, Suliman Z.S. (2012). "Modelling Exchange Rate Volatility Using GARCH Models: Empirical Evidence from Arab Countries". *International Journal of Economics and Finance* 4(3): 216-229.

Ahmed, Rizwan R., Jolita Vveinhardt, Dalia Streimikiene and Zahid A. Channar (2018). "Mean Reversion in International Markets: Evidence from G.A.R.C.H. and Half-Life Volatility Models". *Economic Research-Ekonomska Istrazivanja* 31(1): 1198-1217.

Baltagi, Badi H. (2000). *Econometrics*, Fourth Edition. Springer Press. USA.

Bollerslev, Tim (1986). "Generalized Autoregressive Conditional Heteroscedasticity". *Journal of Econometrics* 31(3): 307-327.

Bollerslev, Tim (1987). "A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return". *Review of Economics and Statistics* 69(3): 542-547.

Box, G.E.P. and David R. Cox (1964). "An Analysis of Transformation". *Journal of the Royal Statistical Society* 26(2): 211-252.

Brooks, Chris (2002). *Introductory Econometrics for Finance*. Cambridge University Press. UK.

Chatfield, Chris (2003). *The Analysis of Time Series: An Introduction*, Sixth Edition. Chapman and Hall/CRC Publishing. USA.

Ding, Zhuanxin, Clive W.J. Granger and Robert F. Engle (1993). "A Long Memory Property of Stock Market Returns and a New Model". *Journal of Empirical Finance* 1(1): 83-106.

Engle, Robert F. and Andrew J. Patton (2001). "What Good is a Volatility Model". *Quantitative Finance* 1(2): 237–245.

Engle, Robert F. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". *Econometrica* 50(4): 987–1007.

Fiser, Radovan and Roman Horvath (2010). "Central Bank Communication and Exchange Rate Volatility: A GARCH Analysis". *Macroeconomics and Finance* *in Emerging Market Economies* 3(1): 25-31.

Gbenro, Nathaniel and Richard K. Moussa (2019). "Asymmetric Mean Reversion in Low Liquid Markets: Evidence from BRVM". *Journal of Risk and Financial Management* 12(38): 1-19.

Glosten, G. Lawrence, Ravi Jagannathan and David E. Runkle (1993). "On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks". *Journal of Finance* 48(5): 1779-1801.

Hafner, Christian M. (1998). "Estimating High-Frequency Foreign Exchange Rate Volatility with Nonparametric ARCH Models". *Journal of Statistical Planning and Inference* 68(2): 247-269.

Hamadu, Dallah and Ismaila Adeleke (2009). "On Modelling the Nigerian Currency (Naira) Exchange Rates Against Major Regional and World Currencies". *NUST Journal of Business and Economics* 2(1): 42-52.

Harris, Richard and Sollis Robert (2003). *Applied Time Series Modeling and Forecasting*. John Wiley and Sons. USA.

Kamal, Yasir, Hammad Ul-Haq, Usman Ghani and Muhammad M. Khan (2012). "Modeling the Exchange Rate Volatility, Using Generalized Autoregressive Conditionally Heteroscedastic (GARCH) Type Models: Evidence from Pakistan". *African Journal of Business Management* 6(8): 2830-2838.

Longmore, Rohan and Wayne Robinson (2004). "Modelling and Forecasting Exchange Rate Dynamics: An Application of Asymmetric Volatility Models". Bank of Jamaica Working Paper WP2004/03.

Nelson, Daniel B. (1991). "Conditional heteroskedasticity in asset returns: A new approach". *Econometrica* 59(2): 347-370.

Olowe, Rufus A. (2009). "Modeling Naira/Dollar Exchange Rate Volatility: Application of GARCH and Asymmetric Models". *International Review of Business Research Papers* 5(3): 377-398.

Thomas, Stuart and Heather Mitchell (2005). "GARCH Modeling of High-Frequency Volatility in Australia's National Electricity Market. Discussion Paper". Melbourne Centre for Financial Studies Discussion Paper.

Ural, Mert (2010). *Yatirim Fonlarinin Performans ve Risk Analizi (Performance and Risk Analysis of Investment Funds)*. First edition. Ankara: Detay Yayincilik.

Wang, Alan T. (2006). "Does Implied Volatility of Futures Currency Option Imply Volatility of Exchange Rates". *Physica A: Statistical Mechanics and its Applications* 374(2): 773-782.

Yoon, Seok and Lee Ki Seong (2008). "The Volatility and Asymmetry of Won/Dollar Exchange Rate". *Journal of Social Sciences* 4(1): 7-9.

Zholamanova, Makpal, Maya Arzayeva, Raikhan Doszhan, Assel Turlybekova and Abai Kukiev (2018). "Devaluation in Kazakhstan: History, Causes, Consequences". *European Research Studies Journal* 21(4): 831-842.