

# **POUND STERLING (GBP) EXCHANGE-RATE VOLATILITY IN THE BREXIT CONTEXT USING THE EGARCH MODEL**

## **A COMPARISON BETWEEN THE EFFECTIVE GBP VOLATILITY AND THE EGARCH ESTIMATION FOR THE PERIOD JUNE 2016 - SEPTEMBER 2019**

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**Abstract:** *This study investigates whether different specifications of univariate GARCH models can usefully forecast volatility on the foreign exchange market. The study uses only forecasts from an asymmetric GARCH model, namely Exponential GARCH (EGARCH) for GBP/USD exchange-rate and compares the estimates with the volatility for the period June 2016 to September 2019. The dataset is obtained from “Investing.com” and covers the period between June 2016 - September 2019. The data encompasses the slump of the GBP to a 31-year low due to a major political crisis in the United Kingdom. Besides averting the decision-making factors about the worrying consequences of Brexit, this paper reaches the conclusion that the EGARCH model could be used to predict volatility of the currencies in the future.*

**Key words:** *EGARCH, modelling and forecasting, volatility, exchange-rates*

### **1. Introduction and Objectives**

Volatility is widely recognized as a measure of the dispersion of returns for a market index or security; the importance of volatility on the current financial markets has been addressed by a large number of studies (Alexander, 2001).

Although the standard deviation has its limitations as a measure of risk, this approach is used most frequently to assess an investment's risk (Emmer et al., 2013). The main disadvantage of making use of the Standard Deviation to measure the risk is the absence of suitable weightings that occur at a specific time ascribed to the errors. In other words, the weightings of the errors that occur closer the present time ( $t_0$ ) have the

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same impact and significance as the weightings of errors arising at ( $t_n$ ). Moreover, using the Standard Deviation as a measure of risk provides little response on skewed datasets (Calvet and Fisher, 2008). The mean can be influenced substantially by outliers in the data, which would imply that the datasets are skewed. Therefore, Standard Deviation depends considerably on outliers from the datasets.

Two phases are involved in the estimation of historical correlation and volatility: the unbiased estimates of unconditional variance which are based on weighted averages of squared returns and the conversion into volatility and correlation estimates.

The historic volatility is built on the weighted average of squared returns. Therefore, most of the financial classical theories have to be based on the primary assumption of multivariate normal independent identically distributed (i.i.d) return distributions. Under the assumption of most financial classical theories, volatility does not depend on time. Therefore, in case volatility does not remain constant over a period of time, all the changes attributed to estimations of volatility are considered white noise. Particularly, traditional models assume that the variance of errors is constant over a period of time. This process is known as homoscedasticity. However, according to an article published by Wiley Online Library (2012), the variance of errors does not remain constant over a period of time which implies that the volatility depends on the time period in the majority of financial markets. This process is known as heteroscedasticity.

Most of the financial markets do not show shapes that are identically distributed. On the contrary, most of the financial markets indicate that volatility depends on the time span. Therefore, the development of the GARCH (General Autoregressive Conditional Heteroskedasticity) model in 1982 by Engle and the ARMA (Autoregressive Moving Average) model developed by Whittle in 1951 were introduced to adjust the issue presented above.

The pound sterling has dramatically dropped to a record low since the UK voted to leave the European Union in June 23, 2016 referendum. The result of this referendum severely impacted global markets worldwide and the major currencies such as the US dollar (USD), British Pound (GBP), the Japanese Yen (JPY) and the Euro (EUR). However, since June 2016, the greatest emphasis has been put on the GBP movements against the US dollar due to post-Brexit uncertainty (Bloomberg, 2016).

Furthermore, the speculation about Hard Brexit has also caused a disruption in the correlation between the UK assets and the pound. Until October 2016, the gilt yields and the pound moved in tandem which is very much in line with what had been seen historically for this market, but since the flash crash and the days leading up to the flash crash the correlation between these two markets, two-year yields and the pound against the dollar rate have dropped. Moreover, amid growing fears that the UK will take a major economic hit, the correlation between the sterling and an emerging market currencies index has significantly increased (Bloomberg, 2016).

The sterling dramatically dropped from \$1.26 to \$1.18 almost instantly during Asian trading hours before slightly recovering to stand at \$1.24 against the dollar. The sterling fell by 6 per cent in two minutes after crashing through key support levels which triggered its sell-off. The flash crash was thought to be triggered by trading algorithms which caused sharp movements in pound and French President Francois Hollande's

speech, in which he stated that the UK would not have access to the EU's single market unless it accepts the free movement of labour (CityAM, 2016).

This paper analyses the fluctuations of the GBP from June 2016 when the UK voted to leave the European Union to September 2019. The study uses only forecasts from an asymmetric GARCH model, namely the Exponential GARCH (EGARCH) model introduced by Nelson, for the GBP/USD exchange-rate pair and compares the estimates with the realized volatility for the period mentioned. In other words, the objective is to verify to what extent the trend calculated by the EGARCH model can be compared to the realized volatility recorded during the period mentioned.

## 2. Methodology and Data

This chapter aims to present the nature of GARCH models from both statistical and financial perspectives. The leverage effect and volatility clustering are both part of the GARCH framework by basically extending the linear regression model with another equation known as the conditional equation. This chapter presents the only asymmetric GARCH model used to investigate characteristics of the volatility. The estimation using the maximum likelihood approach highlight the stability of the EGARCH model, the choice of data period and the way it affects long-term volatility.

In a generalized autoregressive conditional heteroscedasticity (GARCH) model, returns are assumed to be generated by a stochastic process with volatility varying according to the time at which it is measured. A GARCH model introduces more detailed assumptions about the conditional distributions instead of modelling the data after they have been collapsed into a single unconditional distribution. Since the conditional variance is an autoregressive process, these conditional distributions change over time in an auto-correlated manner (Alexander, 2001).

As already mentioned in the introduction, this paper will make use of only asymmetric GARCH, namely the EGARCH model. The EGARCH model presents two important advantages over the symmetric GARCH model, specifically the ability to allow for asymmetries in order to capture the leverage effect and the usage of log returns to obtain a positive conditional variance although the parameters are negative. A symmetric GARCH models means that a symmetric response of volatility to both negative and positive shocks will be illustrated when a shock occurs, while the asymmetric GARCH models allow for an asymmetric response showing that positive shocks will lead to lower volatility than negative shocks. There are different mathematical interpretations of the EGARCH model and to facilitate the numerical estimation of these models, the version of Alexander (2001) presented below has been adopted.

The exponential GARCH equation used within this research paper is presented below:

$$\ln(\sigma_t^2) = \omega + g(z_{t-1}) + \beta \ln \sigma_{t-1}^2$$

$$g(z_t) = \theta z_t + \gamma \left( |z_t| - \sqrt{\frac{2}{\pi}} \right)$$

$$z_t = \frac{u_t}{\sigma_t}$$

Where  $\sigma_t$  represents the conditional variance as an asymmetric function of lagged disturbances;  $u_{t-1}$ ,  $g(z_t)$  is a linear asymmetric response function in  $z_t$  with slope coefficient  $\theta+1$  in case  $z_t$  is positive while  $g(z_t)$  is linear with  $z_t$  with slope coefficient  $\theta-1$  in case  $z_t$  is negative. As a result, large innovations increase the conditional variance in case  $|z_t| - E|z_t| > 0$  and decrease the conditional variance in case  $|z_t| - E|z_t| < 0$  only while  $\theta = 0$ . On the other hand, the innovation in variance  $g(z_t)$  is positive in case the innovations  $z_t$  are less than  $\frac{(z_t)^{1/2}}{\theta-1}$ . Thus, the negative returns  $u_t$  cause the innovation to the conditional variance to be positive in case  $\theta$  is much less than 1.

According to Alexander (2001), GARCH models are frequently estimated on intraday and daily data in order to capture volatility clustering effects in the returns of financial assets as it disappears when returns are observed over long time periods. The estimation of GARCH parameters is done by maximizing the value of the log likelihood function using time varying mean and variance. Thus, maximizing the GARCH (1, 1) likelihood comes to solving the problem of maximizing:

$$\ln L(\theta) = -\frac{1}{2} \sum_{t=1}^T (\ln(\sigma_t^2) + \frac{u_t^2}{\sigma_t^2})$$

where the parameters of conditional variance equation are represented by  $\theta$ .

Maximization of the log likelihood function for univariate GARCH models should encounter few convergence problems. Changes in the coefficient estimates will be induced by changes in the data. However, unless there are real structural breaks in the data generation process, the parameter estimates should not change majorly as new data arrive.

For the log likelihood function to be well defined, a certain minimum amount of data is necessary. Frequently, numerous years of daily data are needed to ensure proper convergence of the model. Thus, the data within this study covers the period from June 2016 to September 2019 resulting in a total of 858 daily observations.

### 3. Empirical Results and Analysis

Autocorrelation is the early evidence to support the use of ARCH/GARCH models. Therefore, the Box-Pierce or the Q test was used to identify whether autocorrelation within the dataset exists (Alexander, 2001). The test is applied to the residuals of the time series after fitting an ARCH (p, q) model to the data. The formula used to identify autocorrelation is presented below:

$$Q = n \sum_{k=1}^h r_k^2$$

Where  $Q$  represents the Box-Pierce statistic,  $n$  represents the total number of observations,  $m$  is the number of parameters and  $h$  represents the maximum lag considered.

Generally, the Box-Pierce test is defined as:

$H_0$ : Prices do not have any significant historic dependence

$H_1$ : Prices do have significant historic dependence

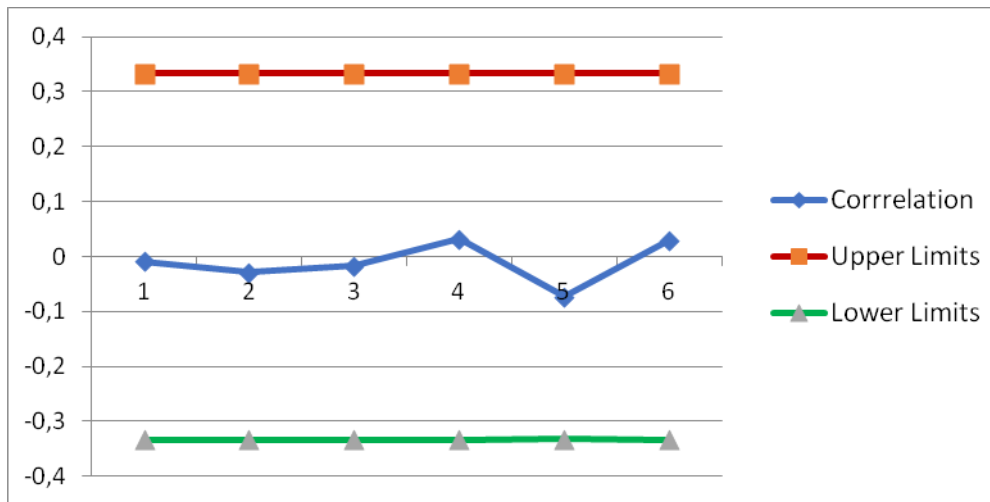


Fig 1. GBP/USD Autocorrelation for the period June 2016 to September 2019 (elaborated by the authors)

Figure 1 presented above shows that autocorrelation in returns does not exist for the GBP/USD exchange rate for the period June 2016 to September 2019.

Since the correlation line is between the upper limit and the lower limit, the existence of autocorrelation in returns does not exist. Furthermore, in order to be certain, the application of the Box-Pierce test or the Q test is also made.

Essentially, the Q test statistic shows that in case that residuals are white noise, the Q statistic follows a  $\chi^2$  distribution with  $(h-m)$  degrees of freedom. In case each  $r_k$  value is close to 0 then Q statistic is very small; otherwise, in case some  $r_k$  values are large then Q is relatively large. Then a comparison between the Q statistic with  $\chi^2$  distribution will be made.

Since six lags were plotted, this paper only focuses on the  $r_k^2$  values for the first 6 observations. As a result, the full Q test process for the GBP/USD exchange-rate between June 2016 and September 2019 is presented below:

$$Q = 858 \sum_{k=1}^6 r_k^2 = 7.2205$$

As a result, the Q statistic for the above-mentioned period is compared with Chi-squared critical value of 12.6 for a 5% significance level. Thus, the Q statistic is lower

than 12.5 for a 5% significance level, leading to the conclusion that returns do not have significant historic dependence. Therefore,  $H_0$  is the accepted hypothesis.

Table 1 presents how the likelihood function was calculated and how to maximize the log likelihood function using Excel Solver.

Table

GBPUSD	EGARCH
June 16 – September 2019	
$\omega$	-0.49527
$\alpha$	–
$\beta$	0.95108
$\alpha + \beta$	–
$\theta$	0.08098
$\gamma$	0.24739
$\lambda$	–
LT Vol	10.02%
LogLikelihoodFunction	3988.75

Note:

$$\ln(\sigma_t^2) = \omega + g(z_{t-1}) + \beta \ln \sigma_{t-1}^2; g(z_t) = \theta z_t + \gamma(|z_t| - \sqrt{\frac{2}{\pi}}) - \text{parameter estimation}$$

The estimates of the parameters, the long-term volatility and the maximized value of the log likelihood for the GBP/USD exchange-rate volatility using the EGARCH model between June 2016 and September 2019 are shown in Table 1. Note that the unconditional volatility that is estimated using an equally weighted average of all the squared return mean deviations (10.14%) does not differ significantly from the long-term volatility estimate given by the EGARCH model (10.02%).

Parameters within the EGARCH models are optimally estimated using the maximum likelihood function. Furthermore, the persistence coefficient  $\beta$  shows a value that illustrates high persistence in volatility since the Brexit vote in June 2016. Moreover, the long-term average volatility in an EGARCH model can be forecasted from the estimated parameters. However, the EGARCH volatility forecasts are not constant, so the term structure of volatility that is forecasted from an EGARCH model will mean-revert to the long-term average volatility.

Any EGARCH parameter estimates, especially the estimate of the GARCH constant ( $\omega$ ), are very sensitive to the historic dataset used for the model. In case the sample covers approximately 2 years during which some extreme market movements were recorded, the estimate of the EGARCH constant ( $\omega$ ) and the long-term volatility is not extremely high but large enough to emphasize the Brexit shock. Furthermore, this can occur even in the case of the market being stable for some time. There is a trade-off between having too much data and enough data for parameter estimates to be stable so that the

long-term GARCH forecasts reflect as good as possible the current market condition as well as possible, but not exactly

The  $\gamma$  parameter measures the asymmetry or the leverage effect. Such a parameter is vital to the analysts who use the EGARCH model. Since  $\gamma$  shows a value greater than 0, more specifically 0.24739, then negative shocks (bad news) generate much more volatility than positive shocks (good news).

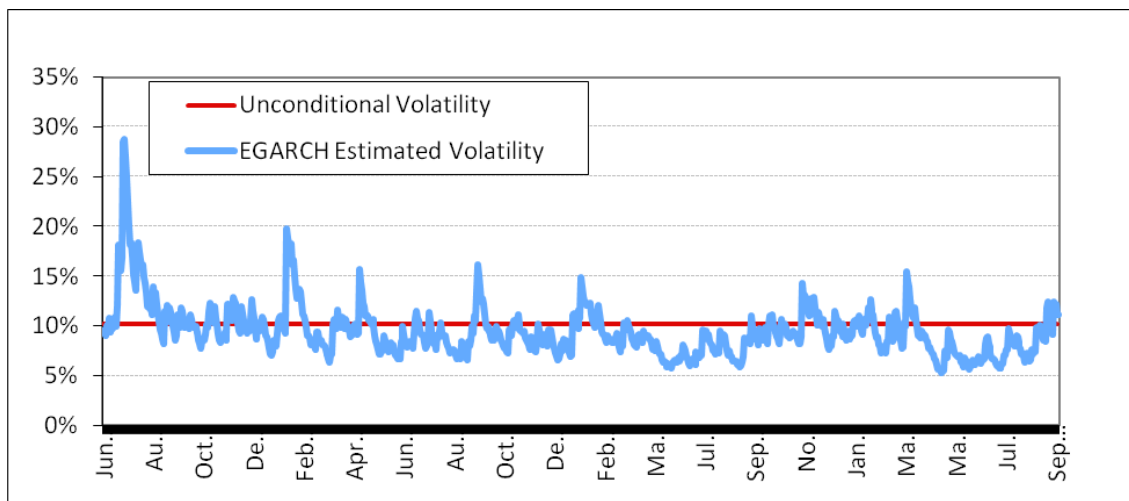


Fig 2. Comparison between EGARCH Estimated Volatility versus Unconditional Volatility for the GBP/USD exchange-rate from June 2016 to September 2019 (elaborated by the authors)

Figure 2 presents that the i.i.d unconditional volatility estimate of 10.14% is approximately the same as the unconditional EGARCH volatility of 10.02%. However, it is not unusual to find differences between the i.i.d volatility and the long-term EGARCH volatility since the EGARCH model does not assume that returns are i.i.d. Figure 2 also illustrates that between June 2016 and September 2019, a massive spike in volatility occurred after the result of the Brexit vote announcement and as the vote on UK's withdrawal deal from the European Union looms, volatility is expected to persist.

After the June 2016 referendum, imported goods and holidays for the UK have increased in price while the UK exports have decreased in price. In other words, exporters, such as carmakers, are importers themselves by purchasing raw materials such as copper or oil while the British population drawing a UK pension has been massively impacted by slump in the value of the pound (BBC News, 2019),

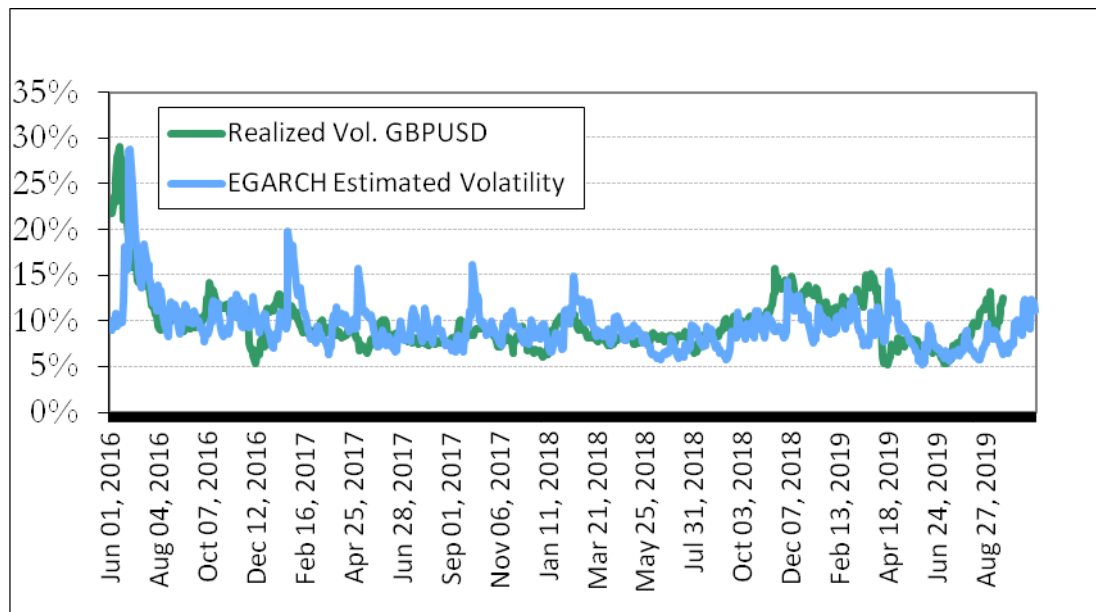


Fig 3. Comparison between EGARCH Estimated Volatility versus Realized Volatility for the GBP/USD exchange-rate from June 2016 to September 2019 (elaborated by the authors)

Based on the EGARCH model and estimate using daily data between June 2016 and September 2019, Figure 3 compares the EGARCH estimated volatility of GBP/USD exchange-rate with the daily realized volatility over almost the same period. Thus, it must be mentioned that even though 30 observations from the data of the realized volatility are missing due to the lack of efficient data, the EGARCH estimates seem to closely mimic the behaviour of the realized volatility. In other words, due to the missing data, the realized volatility trend is a bit delayed compared to the trend provided by the EGARCH model. Furthermore, it must be noticed that the EGARCH model has larger reactions to the negative news compared to the realized volatility. Therefore, each large spike in volatility recorded since June 2016 concerns major political events or decisions within the UK government such as the invocation of Article 50 of the Treaty on the European Union, the release of Brexit transition plans and the EU deal approved by the cabinet (BBC News, 2019).

#### 4. Conclusion

After the Brexit shock, from June 2016, the volatility of the GBP/USD exchange-rate increased massively only to stabilize in November 2016 with normal fluctuations similar to the period before the Brexit vote. Since then, most of the major political events or decisions have caused a dramatic rise in the volatility of the GBP. Therefore, it must be mentioned that the EGARCH model is very close to mimic the volatility trend compared to the realized volatility and it could be used to predict volatility of the currencies in the future.



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