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Application of ARIMA and ARCH/GARCH models to test the foreign exchange market efficiency

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Abstract: The main purpose of this dissertation is to test the weak form market efficiency of the foreign exchange market. Several analytical methods have been implemented to test the daily and weekly currency returns data. The Augmented Dickey-Fuller, run and serial autocorrelation tests are used to ascertain the presence of random walk. Further analysis is done by comparing time series models including Autoregressive Moving Average (ARMA); Autoregressive Integrated Moving Average (ARIMA); Generalised Autoregressive Conditional Heteroskedasticity (GARCH); Exponential Generalised Autoregressive Conditional Heteroskedasticity (E-GARCH); and GARCH-in-Mean (GARCH-M) models. Maximum Likelihood Estimation (MLE), Log-Likelihood Function (LLF), Akaike's Information Criterion (AIC) and Ljung-Box Test have been used to examine various models. The result of our analysis has supported the random walk for all weekly currency pairs. However, the random walk has not been supported for the daily currency pairs except for pound and dollar (GBP/USD) and euro, dollar (EUR/USD). The actual values compared with the predicted values seem very similar. However, because of the limited scope of this research there is not enough evidence to confirm profitability of trading technique. The presence of ARCH is indicated in the proposition of ARMA (p, q). The ARMA (p, q) for squared returns is equivalent to the GARCH (p, q) for the original series. When comparing the forecasting ability between GARCH and EGARCH model, EGARCH model has been found to be the superior model. Based on the lowest Akaike's Information Criterion for the exchange rates, EGARCH model has outperformed all other models used in the analysis. The possible reason for this is that EGARCH model deals with the asymmetric effect of negative returns over positive returns, a phenomenon typically observed in the foreign exchange markets.

Keywords*: efficient market hypothesis, heteroscedasticity, GARCH, exchange range volatility*

Introduction

The Efficient Market Hypothesis (EMH) is an extremely important intellectual concept that guides a lot of theories in finance and forms the main focus of this research. This hypothesis suggests that markets are efficient if current market prices of securities instantaneously and fully reflect all the available information. Any difference between the fundamental and observed value is quickly be bid away by speculation and arbitrage, therefore market forces always bring the market into equilibrium (Koller *et al*., 2010).

On the other hand technical analysis uses historical data and graphs in order to forecast future prices. That goes against the view of EMH supporters, who are very sceptical about it. They

find it irrational and argue vehemently that no prediction can be made based on historical data and that it is only by taking excessive risk that one can make abnormal returns. In spite of these statements many traders, international companies, importers, exporters and speculators continue to use historical data to make decisions. These decisions are based on the assumption that patterns in data exist. An advanced computer technology, twinned with modern mathematical tools, has given birth to the development of various forecasting models to help identify these patterns (King *et al*., 2011). The application of past price behaviour patterns as a guide in trading decisions has been an issue discussed among the public, business professionals and economists for a long time. Although their opinions vary they could be divided onto one of two sides. On one side, there are supporters of the technical analysis and on the other the proponents of the EMH.

The main focus of this paper is to develop a suitable method to examine the weak form of efficiency for six foreign exchange markets; pound and dollar (GBP/USD), euro and dollar (EUR/USD), yen and dollar (JPY/USD) Canada dollar and US dollar (CAD/USD), euro and Czech crown (EUR/CZK), and euro yen (EUR/JPY). Shiller (2014) has observed that that the evolution of financial markets does not follow a random walk; the objective of this paper is as to whether that applies also to the analysed foreign exchange data. Therefore, the main hypothesis tested is as to whether that daily and weekly log returns follow a random walk.

Weak Form of Efficiency and Exchange Rates

The market efficiency of an exchange rate has been researched within the financial literature for several decades. The foreign exchange market, analysed in this research, is the world's largest financial market. The estimated average daily value traded in April 2013 was $5.3 trillion (Economist, 2013). Since Britain's adoption of a flexible exchange rate system, in the autumn of 1992, the Bank of England is not involved in the intervention of the currency markets to obtain a desired exchange rate. The purpose of this system is to bring about an equilibrium exchange rate and a balance of payments. The efficiency of foreign exchange markets is important for economic development, as it implies that the value of exchange rates and volatility are determined by underlying economic fundamentals. Thus, it is understandable that a lot of time has been spent by financial economist to investigate this issue. Levich (2001) suggests that the exchange rate's value and volatility are determined by fundamental factors and not by the misreading of those factors by private investors.

Many early studies of the financial asset behaviour are based on assumption that the variance is constant. However, based on empirical research, foreign exchange rates exhibit volatility clustering, where periods of high volatility are followed by periods of low volatility, a condition referred to heteroscedasticity. It is a condition when autocorrelated and unequal variance (autoregressive structure) is observed over time, phenomena frequently found in the financial time series data. To deal with this phenomena Engle (1982) introduced ARCH, highlighted in this research, frequently discussed in literature and commonly used in studies of market efficiency and rationality. Bollerslev (1986) and Taylor (1986) both independently developed generalised ARCH (GARCH) model. Nelson (1991) developed the exponential GARCH (EGARCH), another model used in this paper deals with asymmetric effect of negative return over positive returns for financial markets. Based on empirical evidence negative returns affect future volatility more that positive returns do. The exchange rate time series commonly exhibit a period of high volatility in down market, but not so much in a bull market. Engle *et al*. (1987) developed the GARCH in mean (GARCH-M) model with main focus on a theoretical assumption that a risky asset has higher expected returns.

Literature Review

Extensive research has been done in order to understand the market efficiency. The efficiency of financial markets represents the degree to which prices of financial assets fully and instantaneously reflect all publicly available and relevant information. This implies that there is perfect competition in the market, so that any change in the exchange rate would only be affected by new information. If all prices in the efficient market respond instantly to any new information, then speculators can quickly bid away any patterns in prices. It is imperative for the market to operate efficiently as it allows for meaningful trade and investment transactions (Brealey *et al*., 2011).

One of the most prominent theories on this topic is Efficient Market Hypothesis (EMH) (Fama, 1970, 2014). According to EMH, efficient market prices reflect all available and relevant information, which implies that prices cannot be predicted, based on publicly available information and therefore participants cannot earn abnormal returns. He classifies market efficiency into three distinct categories depending on the degree of available information. Firstly, the weak form hypothesis, which forms the main focus of this paper, suggests that the information, such as trends in past prices, is already reflected in security prices. Therefore, it is impossible to outperform the market consistently over a long period of time. Secondly, the semi-strong hypothesis stipulates that all publicly available information, such as historic prices, quality of management, state of balance sheet and other publicly available information are all reflected in the price of a financial asset. Thirdly, the strong form of hypothesis states that not only publicly available information, but also privately available information is reflected in the price of an asset.

In contrast Shiller (2014), a Nobel Prize winner, suggests that markets are far from being perfect and refers to EMH as being "half-true". The theory is true in the sense that markets are very fast and prices reflect all available information, however the EMH does not explain certain patterns which are found in financial markets. He expresses the influence of human psychology on the behaviour of investors and believes that some can earn abnormal long-term returns.

Whereas the EMH assumes that all investors are rational wealth-maximising decision makers, at the study on the behavioural finance the main focuses is on investors' irrational behaviour. Behavioural finance investigates the pricing mistakes that investors are likely to make when they invest. Although in the efficient market, rational investors would take the advantage of such mispricing caused by irrational behaviour and through arbitrage activities, the price of stock would be forced to reach its intrinsic value. The behavioural finance argues that such activities are in practice limited and therefore not adequate to adjust prices correctly (Bodie *et al*., 2009).

Moreover, Malkiel (2003) in his seminal work concluded that prices within financial markets reflect each innovation and quickly move from one market equilibrium to another. The fact that news arrives randomly, makes it impossible for investors to outperform the market. Furthermore, buyers and sellers base their decisions depending on news arriving randomly, prices are therefore, determined by economic fundamentals and the market equilibrium.

The initial research of the EMH was mainly focused on the equity market. With the introduction of a free-floating exchange rate, the research has also developed in the foreign exchange market. Similar methods of testing efficiency have been applied as those developed in equity markets (Fama, 1991). The investigation of foreign exchange market efficiency became a prominent area of research within the international finance literature (Copeland, 2000, Hallwood and McDonald, 2000). The main reason for its popularity is that any movement in exchange rate is inevitably translated into price level, affecting the economic

welfare (Kenel 1986). This means that the foreign market efficiency is a fundamental issue for economic development.

Associated with the EMH is the occurrence of the 'the random walk' theory, which argues that all available information would increase or decrease the value of the financial asset at random and without pattern. Malkiel (2003) in his seminal work suggests that prices must be random because they react to news that is wholly random and unpredictable.

The serial autocorrelation and Augmented Dickey-Fuller test are common tools used to assess the randomness of data. The Augmented Dickey-Fuller test is commonly used to examine the Random Walk Hypothesis of exchange rates. Meese and Singleton (1982) described the main characteristic of exchange rate as non-stationary. The problem with non-stationary data is that it is not suitable for econometric analysis as the results might be misleading. (Stavarek, 2007), however, referred to exchange rates as being 'difference stationary', which means that the exchange rates at the first difference tend to be stationary. Another common tool harnessed when assessing the randomness of data is serial autocorrelation. Granger and Morgenstern (1963), Fama (1965) take a credit for being first to apply this test.

The Efficient Market Hypothesis declares that the exchange rates adjust to all information preventing traders from any excess return. However, the technical analysis suggests that past price changes can be used to achieve profitable trading. Technical analysis looks at past price and transaction in order to predict future price of a financial asset. There are several methods to predict the economic time series data. Box and Jenkins (1976) introduced one of them, technically known as the ARIMA (Autoregressive Integrated Moving Average) but commonly referred to as Box Jenkins methodology. The main purpose of this method in the analysis is to analyse the stochastic properties of time series data.

Another method to analyse the weak efficiency is the application of ARCH/GARCH models. In his seminal paper, Engle (1982) advocates the autoregressive conditional heteroscedasticity (ARCH) model; an advanced forecasting technique commonly applied to forecast the price of a financial asset, including prices of stock and currency. Many financial assets, including foreign exchange rates, share common characteristics described as volatility clustering; common phenomenon of periods of high volatility being followed by periods of low volatility. Such phenomenon relate to heteroscedasticity, when autocorrelated and unequal variance (autoregressive structure) is observed over time. However, early studies of financial asset behaviour were based on the constant variance assumption; Engle (1882) proposed to model the time series variance, which would vary over time.

Bollerslev (1986) suggested a useful generalisation and refinement of ARCH model by developing GARCH. He proposed that the conditional variance was a function of previous period squared errors as well as its past conditional variances. Later Bollerslev (1992) declared that returns need to be serially uncorrelated for markets to be efficient. Many studies that focus on return dependencies of assets have been documented where autocorrelations were found to be small and economically insignificant. Concurrently, however, most high frequency data asset returns exhibit volatility clustering; where periods of large volatility tend to be followed by periods of relative tranquillity and large changes tend to be followed by large changes (Engle, 1982). Time series observations exhibit a dependence on their own past value (autoregressive), on past information (conditional) and the error term variances that change over time (heteroscedasticity).

Engle *et al*. (1987) developed GARCH-M model to deal with a theoretical assumption about the risk-premium, which suggests that risky assets have higher expected returns. A typical characteristic of a financial market is that an era of high volatility is observed in a down market, but less volatile market is observed in a bull market (Black, 1976). To deal with this

issue Nelson (1991) developed another form of GARCH model, the Exponential GARCH (EGARCH). This model is designed to deal with an asymmetric effect of negative returns over positive returns for financial markets. Moreover, Baillie and Bollerslev (1989) argued that the time dependent hetersocedasticy as well as the degree of kurtosis are more obvious in daily than weekly timeframes.

Engle (2001) argued that instability of financial returns exhibit a degree of autocorrelation. The empirical evidence indicates that variance changes over time, but also changes to certain predictable patterns. He also argued that rather than considering a heteroscedasticity as an issue to be rectified, both the ARCH and GARCH models are designed to deal with this issue, as their main focus is to model the stochastic variance. Moreover, 'Volatility clustering' implies that changes are not random, thus invalidating the random walk hypothesis (Wang, 2006).

Kisinbay (2003) analysed the time series forecasting ability of asymmetry models. He applied several models to one capital and two currency markets. The asymmetry models showed clearly better forecasting performance when applied to the capital market. Furthermore, all asymmetry models, except EGARCH, showed better results also in terms of currency markets. However, he concluded that although the asymmetry models perform better compared to the GARCH (1,1) when forecasting, the gains do not seem to be economically significant. After exploring the relationship between share volatility and exchange rates, Karla (2008) concluded that the most suitable model was GARCH (1,1).

Research Methodology

Previous empirical research suggests a random walk model is a description of foreign exchange series. However, Wang (2006) observed exchange rates series share common characteristics referred to as 'volatility clustering' suggesting that foreign exchange rates do not follow random walk. In the context six exchange rates are analysed and the results are used to answer following question: are currency markets efficient?

Research Hypotheses

To fulfil the aim of this research following hypothesis will be tested:

Hypothesis 1: $\gamma = 0$ If γ equals zero, x_t contains a unit-root, the data is non-stationary.
Hypothesis 2: $\rho_1 = \rho_2 = \rho_3 = ... = \rho_m = 0$, the correlation coefficient of our sample equals to 0, the time series is a white noise.
Hypothesis 3: Conditional Heteroscedasticity is not present in the data
Hypothesis 4: The negative asymmetry is not exhibited in the data.

Sampling and Instrument:

The philosophy which drives the research design is positivism. Positivism tends to be linked to deduction and this research approach is also taken in this paper. The data is of secondary type as it has been already been collected. Technical analysis works mainly on daily and weekly data, therefore data for this research is divided into a series of logs of daily and weekly returns of the exchange rates between pound and dollar (GBP/USD), euro and dollar (EUR/USD), yen and dollar (JPY/USD) Canada dollar and US dollar (CAD/USD), euro and Czech crown (EUR/CZK), and euro yen (EUR/JPY). All series are spot rates covering the period from 12th October 2009 to 12th October 2012. The main data source is accessed through the Bloomberg terminal

Data preparation

Meese and Singleton (1982) described the main characteristic of time serried data, such as exchange rates, to be non-stationary. The problem with non-stationary data is that econometric analysis might lead to misleading results. However, Nelson and Plosser (1982) referred to exchange rates as being 'difference stationary', which means that the exchange rates at the first difference tend to be stationary. The logarithmic return for the time series data is defined below.

$$x_t = \ln(\frac{P_t}{P_{t-1}})$$

xt = continuously compounded returns,
P_t = exchange rate value at time t
P_{t-1} = exchange rate value in the preceding time period
ln = natural logarithm

Market Efficiency and Random Walk

Prior to discussing the forms of analysis, it is essential to mention the notion of the Efficient Market Hypotheses. In efficient markets, prices do move fully and instantaneously to all new information, therefore a pattern in past prices cannot be used to predict movement of exchange rates (Fama, 1970, 2014). Furthermore, all prices incorporate all past, public and foreseen future information; that is to say, prices follow a random walk. The random walk theory is closely linked to EMH and suggests that the price today only depends on unpredictable events in the future. Extensive research has been done to test the weak form of the EMH implying that prices should follow the random walk. A time series data is referred to random walk if

$$x_t = x_{t-1} + \varepsilon$$

x_t = the logarithm of returns at time t
ε_t = the independent white noise process

The concept of the random walk hypothesis and the weak form of market efficiency are understood to be the same. However, the concept of efficiency seems larger complex and therefore, during this analysis we refer to random walk. Rahman and Saadi (2008) suggested that stationary does not mean predictability. Cootner (1964) concluded that although the prices can be predicted in the short term, does not necessarily mean the market is inefficient. Because forecasting can be lengthy process and is neither costless nor instantaneous.

Randomness tests

Augmented Dickey-Fuller Test

The purpose of this test is to analyse as to whether the unit root is present in the data and therefore the data is non-stationary (Baillie and Bollerslev, 1989). The ADF test process is applied to the following model:

$$\Delta x_t = \alpha + \beta_1 t + \beta_2 t^2 + \gamma x_{t-1} + \phi_{p-1}\Delta x_{t-p+1} + \varepsilon_t$$

Δ= the dependent variable is the first difference
x_t = the logarithm of returns
γ = a constant
β_1 = a time trend coefficient
β_2 = a squared time trend coefficient

ε_t = the white noise trend.
The hypothesis tested is that x_t has a unit-root, so it is non-stationary.

The stationary data is an assumption for ARIMA modeling; any regressing using non-stationary data would give us misleading results (Box and Jenkins, 1976). Therefore, if data is non-stationary, we model the first differential fort which time series data tend to be stationary.

Autocorrelation Function (ACF)

When returns follow a random walk, the correlation between any two returns should be zero. That is correlation e_t, $e_{t-1} \approx 0$. The correlation coefficient can be calculated as follows:

$$\rho_k = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2}$$

x_t = the logarithm of returns at time t
k = the lag order
n = number of values in the time series data

Volatility Models – Forecasting – Linear Models

Autoregressive Moving Average Models (ARMA)

The combination of the autoregressive process with the moving average process is commonly referred to as ARMA (p,q) model. An example of ARMA (2,3) is illustrated below

$$x_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \beta_3 e_{t-1} + \beta_3 e_{t-2} + \beta_3 e_{t-3} + \varepsilon_t$$

x_t = the logarithm of returns at time t

The Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA model can be used as a useful tool to understand and possibly predict future values in the time series. The main purpose of this model is to analyse relationship between Y_t and lagged values of Y itself, and use this information to forecast. ARIMA modeling requires time series data to be stationary. If data is non-stationary we can model the first differential form in which financial data tends to be stationary (Stavarek, 2007).

Model Identification

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(x_t - \mu) = \left(\sum_{j=1}^{q} \theta_i L^j\right)\alpha_t$$

x_t = the logarithm of returns at time t
μ = mean of the model
p = the order of AR component
$\phi_1 \ldots \phi_p$ = autoregressive parameters
q = the order of MA component
$\theta_1 \ldots \theta_q$ = moving average parameters
α_t = residual at time t

NumXL program is used for the analysis, modelling and forecasting of the past return time series. The first step is to identify an order of the autoregressive component using the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The second

step is to estimate the parameters of the ARIMA terms in the model. That follows with the third step in which the answer as to whether the model is satisfactory or not is identified. The third step is a calibration of the model and the fourth step is forecasting. In case the model is not satisfactory we go back to step one and set different model parameters. We continue this process until the model fit satisfies our needs.

Volatility Models – Forecasting – Conditionally Heteroscedastic Models

Autoregressive Conditional Heteroscedasticity (ARCH)

The purpose of all ARCH models is to capture dependence in the return series, as they deal with the evolution of variance. The following is the ARCH (q) process with q legs firstly suggested by Engle (1982).

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_m a_{t-m}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2$$

a_t^2 = past-squared shock
σ_t^2 = estimate of variance

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Three time-varying volatility models are used to assess the predictability of exchange rates the GARCH, the asymmetric EGARCH and GARCH-M model. The conditional variance of GARCH is commonly written as follows.

$$x_t = \mu + \alpha_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

$$a_t = \sigma_t \times \varepsilon_t$$

$$\epsilon_t \approx P_v(0,1)$$

x_t = the time series value at time t
μ = the GARCH model mean
α_t = the residual of the model at time t
σ_t = the conditional standard deviation
p = the order of ARCH component with its parameters α_0, α_1, α_2... αp
q = the order of GARCH component with its parameters β_0, β_1,β_2... βp
ϵ_t = standardised residuals

The main assumption of GARCH models is that positive and negative errors effect volatility symmetrically. However, empirical evidence shows that this assumption in practice may not hold and that volatility reacts asymmetrically. As Black (1976) argued, negative news tends to increase the volatility more than good news. The Exponential GARCH (EGARCH) model deals with this issue and therefore is also used in this analysis. For comparison we also employ GARCH-M model which focuses on the risk premium, suggesting that risky asset have higher expected returns.

Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) Model

It is a very typical characteristic of financial markets that negative returns tend to affect the future volatility more than positive returns (Black, 1976). A period of volatility in a down market is observed to be higher than volatility in a bull market.

$$x_t = \mu + \alpha_t$$

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i(|\epsilon_t| + \gamma_i \epsilon_{t-1}) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

$a_t = \sigma_t \times \epsilon_t$

$$\epsilon_t \approx P_v(0,1)$$

Generalized Autoregressive Conditional Heteroskedasticity In-Mean (GARCH-M) Model

Engle, Lillian and Robins (1987) advocated the ARCH-M model. ARCH-M model as many financial models suggest a relationship between risk (volatility) and returns.

$$x_t = \mu + \lambda\sigma_t + \alpha_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

$$a_t = \sigma_t \times \varepsilon_t$$

$$\epsilon_t \approx P_v(0,1)$$

λ = the volatility of the mean

The Maximum Likelihood Estimation (MLE)

Model calibration is a process of identifying the Maximum Likelihood Estimation of model parameters. To calibrate the Excel solver is be used and it is employed to test the reliability of all the ARMA, GARCH, EGARCH AND GARCH-M model parameters.

Log-Likelihood Function (LLF)

Log-Likelihood Function deals with parameters of the specific statistical model. The mathematical representation is of the likelihood function is described as follows:

$$\ln L* = \sum_{n-1}^{N} \ln f\ (y_t | y_{t-1}, y_{t-2}, \dots, y_1,\ \theta_1, \theta_2, \dots, \theta_k)$$

L* = the likelihood function
ln L* = the logarithm of the likelihood function, larger number suggests better fit
f = conditional probability function
ln f = the logarithm of the conditional probability function
yt = the value of time series at time t
θ1, θ2,.., θq = the parameters of the model

Akaike's Information Criterion (AIC)

Akaike's information criterion is another probabilistic measure that computes the goodness of fit of the sample data. The purpose of this test is to provide comparison between models. The AIC model can be defined as follows:

$$AIC = 2k - 2\ x \ln(L)$$

k = the number of parameters in the model
ln(L) = the log likelihood function for the model

Findings

Data Description

The time series data examined in this analysis comprises of daily and weekly currency pair returns from October 2009 to October 2012. The currency pairs analysed in this paper are GBP/USD, EUR/USD, JPY/USD, CAD/USD, EUR/JPY and EUR/CZK.

Table 1. Descriptive statistics for daily and weekly time series

	AVERAGE	P-Value	SIG?	Median	STD DEV:	SKEW	P-Value	SIG?	EXCESS Kurtosis	P-Value	SIG?
Daily											
EUR/USD	0.0001694	0.24	FALSE	-0.0000458	0.007	0.04	0.32	FALSE	0.36	0.02	TRUE
GBP/USD	0.0002414	0.45	FALSE	0.00015688	0.006	0.04	0.32	FALSE	0.37	0.02	TRUE
CAD/USD	0.0000709	0.38	FALSE	0.0000000	0.006	-0.24	0.00	TRUE	1.42	0.00	TRUE
JPY/USD	0.0001728	0.21	FALSE	0.0001064	0.006	-0.59	0.00	TRUE	3.40	0.00	TRUE
EUR/JPY	-0.0003166	0.14	FALSE	0.0002893	0.008	0.15	0.04	FALSE	1.78	0.00	TRUE
EUR/CZK	0.0000404	0.38	FALSE	0.0001076	0.004	0.16	0.03	FALSE	0.70	0.00	TRUE
Weekly											
EUR/USD	0.0008804	0.24	FALSE	-0.0014417	0.015	-0.26	0.09	FALSE	-0.01	0.46	FALSE
GBP/USD	0.0000606	0.47	FALSE	-0.0001598	0.011	-0.38	0.03	FALSE	0.19	0.35	FALSE
CAD/USD	0.0292062	0.09	FALSE	0.0021881	0.276	10.41	0.00	TRUE	113.98	0.00	TRUE
JPY/USD	0.0009502	0.18	FALSE	0.0021580	0.013	-0.26	0.10	FALSE	0.14	0.40	FALSE
EUR/JPY	0.0003179	0.00	TRUE	0.0001635	0.001	7.69	0.00	TRUE	77.51	0.00	TRUE
EUR/CZK	-0.0003166	0.14	FALSE	0.0002893	0.008	0.15	0.04	FALSE	1.78	0.00	TRUE

For all the currency pair except the EUR/JPY weekly the mean is not significantly different from zero. The median and the mean should equal to the same value. Any significant difference between these two values implies skewness. Skewness demonstrates the level of asymmetry of distribution around the mean. A symmetric distribution is when mean equals median. To be normally distributed skewness should be equal to zero. All distributions except for GBP/USD daily and JPY/USD daily are skewed. EUR/USD daily log returns exhibits a positively skew, while the rest of the currency pairs have their asymmetric tail skewed towards more negative values, which indicates that the standard deviation underestimates the risk. Kurtosis represents the tendency of a distribution to stretch (its peakedness or flatness) compared to the normal distribution. The Excel indicates normal (mesocurtic) distribution when kurtosis equals zero. There is evidence that the kurtosis for all of daily and weekly currency distributions are above zero except for CAD/USD and JPY/USD weekly. This excess kurtosis suggests that they are taller density distributions (Leptokurtic) with fatter tails compared to the normal distribution. Therefore, the standard deviation is likely to underestimate the risk and the possibility of achieving higher returns or higher losses. A substantial amount of financial literature suggests an excess kurtosis for exchange rates (Phillips and Peron, 1988; Baillie and Bollerslev, 1989).

Augmented Dickey-Fuller Test

Table 2: Augmented Dickey-Fuller Test daily and weekly time series

Stationary Test	**Stat**	**P-Value**	**C.V.**	**Stationary? (5.0 %)**
GBP/USD daily	-8.07	1.0%	-1.2	TRUE
GBP/USD weekly	-12.27	1.0%	-3.3	TRUE
EUR/USD daily	-28.27	1.0%	-1.2	TRUE
EUR/USD weekly	-12.40	1.0%	-3.3	TRUE
JPY/USD daily	-30.25	1.0%	-1.2	TRUE
JPY/USD weekly	-14.72	1.0%	-3.3	TRUE
CAD/USD daily	-30.74	1.0%	-1.2	TRUE
CAD/USD weekly	-14.23	1.0%	-3.3	TRUE
EUR/JPY daily	-3.8	1.0%	-1.2	TRUE
EUR/JPY weekly	-10.7	1.0%	-3.3	TRUE
EUR/CZK daily	-3.6	1.0%	-1.2	TRUE
EUR/CZK weekly	-12.6	1.0%	-3.3	TRUE

The table above represents all the observed ADF statistics for all the daily and weekly currency pairs. The NumXL software is used for the analysis; we choose the significance level 5% and ten legs. As a result of this test there is enough evidence to reject H_0 hypothesis stating the presence of unit root. The results indicate that the first difference of exchange time series data is stationary and therefore exhibit a random walk. Rahman and Saadi (2008) suggested that stationary does not mean predictability. The presence of random walk in this stage does not necessarily mean that time series data is unpredictable. Only when data behave as White noise, it can be concluded that data exhibits random walk. Taking in consideration purely the Augmented Dickey-Fuller test it can be concluded that the exchange rate time series data are weak efficient. The reason behind that is that although ADF test examines the stochastic trend it can't identify the predictability of time series data.

Table 3. Ljung-Box, Jarque–Bera and Arch effect test for normal log returns

	White noise?		Normal Distributed?		ARCH Effect?	
	P-Value	**SIG?**	**P-Value**	**SIG?**	**P-Value**	**SIG?**
EUR/USD Daily	80.93%	TRUE	12.56%	TRUE	25.85%	FALSE
GBP/USD Daily	10.95%	TRUE	10.39%	TRUE	10.83%	FALSE
CAD/USD Daily	10.20%	TRUE	0.00%	FALSE	0.00%	TRUE
JPY/USD Daily	9.23%	TRUE	0.00%	FALSE	2.41%	TRUE
EUR/JPY Daily	11.18%	TRUE	0.00%	FALSE	0.08%	TRUE
EUR/CZK Daily	13.51%	TRUE	0.01%	FALSE	0.00%	TRUE
EUR/USD Weekly	75.83%	TRUE	0.00%	FALSE	97.98%	FALSE
GBP/USD Weekly	15.81%	TRUE	15.86%	TRUE	17.77%	FALSE
CAD/USD Weekly	18.88%	TRUE	0.45%	FALSE	27.69%	FALSE
JPY/USD Weekly	21.86%	TRUE	41.38%	TRUE	84.53%	FALSE
EUR/JPY Weekly	45.54%	TRUE	0.01%	FALSE	34.58%	TRUE
EUR/CZK Weekly	100.00%	TRUE	0.00%	FALSE	100.00%	FALSE

Table 4. Ljung-Box, Jarque–Bera and Arch effect test for normal squared returns.

	White-noise		Normal Distributed?		ARCH Effect?	
	P-Value	**SIG?**	**P-Value**	**SIG?**	**P-Value**	**SIG?**
EUR/USD Daily	25.85%	TRUE	0.00%	FALSE	0.00%	FALSE
GBP/USD Daily	10.83%	TRUE	0.00%	FALSE	0.02%	TRUE
CAD/USD Daily	0.00%	FALSE	0.00%	FALSE	0.28%	TRUE
JPY/USD Daily	2.41%	FALSE	0.00%	FALSE	57.06%	FALSE
EUR/JPY Daily	0.08%	FALSE	0.00%	FALSE	0.56%	TRUE
EUR/CZK Daily	0.00%	FALSE	0.00%	FALSE	0.02%	TRUE
EUR/USD Weekly	75.83%	TRUE	0.00%	FALSE	97.98%	FALSE
GBP/USD Weekly	17.77%	TRUE	0.00%	FALSE	83.39%	TRUE
CAD/USD Weekly	33.87%	TRUE	0.00%	FALSE	99.92%	FALSE
JPY/USD Weekly	84.53%	TRUE	0.00%	FALSE	95.65%	FALSE
EUR/JPY Weekly	69.50%	TRUE	0.00%	FALSE	99.96%	FALSE
EUR/CZK Weekly	34.58%	TRUE	0.00%	FALSE	0.02%	FALSE

White Noise – Ljung-Box Test

The Ljung-Box passed for all daily and weekly currency pairs. Looking at the white-noise for the daily and weekly squared returns, the white noise did not fail, indicating that there is no evident correlation in the time series data. The EUR/USD, GBP/USD and all weekly exchange rates do not show any serial correlation neither in log return data nor the squared log return data. That indicates that they act like a random noise rather that an ARMA or GARCH process.

Normal Distribution - Jacques-Bera Test

Although the weekly data sets are smaller than 500, this test is included as the result can give us an indication. The normality test failed for all four currency pairs exhibiting ARCH. That is expected because the presence of ARCH in the data indicates fat-tailed distribution. However, fat-tailed distribution does not necessary mean there is ARCH in the data. There is also no evidence of normal distribution in the other currency data pairs except for EUR/USD daily, GBP/USD daily and weekly and JPY/USD weekly.

ARCH Effect Test – Ljung-Box test (for the squared log returns)

The main purpose of the ARCH test is to examine the hypothesis that at least one of the autocorrelation values (for the squared returns) is not zero and thus there is a conditional heteroscedasticity present in data. The process is the same as for white test but is applied to squared time series. The table 3.1 above indicates that four out of 12 currency pairs (CAD/USD, JPY/USD, EUR/JPY and EUR/CZK) exhibit and ARCH in the data. That is confirmed, in the daily square returns summary statistics, as the white noise test fails, therefore a correlation in square returns is evident. That indicates a proposition of ARMA (p, q). The ARMA (p, q) for squared returns, is the equivalent to a GARCH (p, q) for the original series. In the weekly squared return for CAD/USD, EUR/JPY, EUR/CZK and the daily squared returns for GBP/USD and EUR/USD, there is no evidence of significant serial correlation but rather a fat-tailed distribution random variable. It is important to make a distinction between a simple fat tailed distribution (i.e. excess-kurtosis), and the presence of an ARCH effect. The first indicate a non-normal distribution (but still random and not serially correlated), while an ARCH effect implies presence of dependency between the

return on second order (squared) or volatility. In summary, the ARCH tests the assumption that the volatility is serially correlated.

Based on the above analysis the daily EUR/USD, GBP/USD and the weekly GBP/USD, JPY/USD looks like a Gaussian white noise, which means no ARMA or GARCH is needed or can model this time series. CAD/USD, JPY/USD, EUR/JPY and EUR/CZK daily passed the white-noise test, so we can't use ARMA/ARIMA to forecast the mean. The squared-returns are used for the analysis, so we can figure out the GARCH order (p,q). In GARCH-type of process, the mean is constant throughout the time, but the daily volatility is changing over time, typical phenomena for a daily financial time series. In the following section the ACF and PACF are used to analyse the best suitable model for these exchange rates.

ARIMA

The common characteristic of financial time series data, including exchange rate, is that price levels tend to be non-stationary. Unfortunately, most of econometric analysis can be applied only to data which is stationary. The ARIMA model can be used to deal with this issue. It is an extension or ARMA model, but applied to differenced time series data. The main purpose of differencing is to convert non stationary data into stationary. The weak form hypothesis suggests that the information, such as trends in past prices, is already reflected in prices. Thus, it is impossible to predict future prices based on past information. Cuthbertson (1996) concluded that the absence of weak efficiency suggests that returns are not only dependent on previous returns but also on forecasted errors. Thus, if prices are a function of previous prices or error terms, it can be concluded, that time series data is not weakly efficient.

Based on the previous analysis, the random walk has not been rejected for all weekly data, and two daily currency pairs EUR/USD and GBP/USD. Thus, ARMA and GARCH are not appropriate for these data sets. Furthermore, Box and Jenkins (1976) suggested that serial dependency, stationary and normality are the main assumptions of ARIMA models. The null hypothesis for unit root has been rejected for all currency pairs. The random walk has been rejected for CAD/USD, JPY/USD EUR/JPY and EUR/CZK and they are used for ARIMA, GARCH modelling.

For ARIMA and GARCH modelling we begin the analysis with plotting a graph. Graphs for all log returns seem to be centred on the X axis suggesting there is no trend over time. Using the ACF plot we identify the moving average component and using the PACF function we identify the order of the autoregressive component. The ARMA model consists of three parts, the model parameters, goodness of fit and residuals. The initial parameter values are not optimal; therefore they need to be calibrated. The Excel solver used for this process finds different combinations of parameters in order to maximize the LLF and those values are automatically copied into the table. The residual diagnosis table explains how satisfying the proposed model is.

Generalised Autoregressive Heteroscedasticity (GARCH)

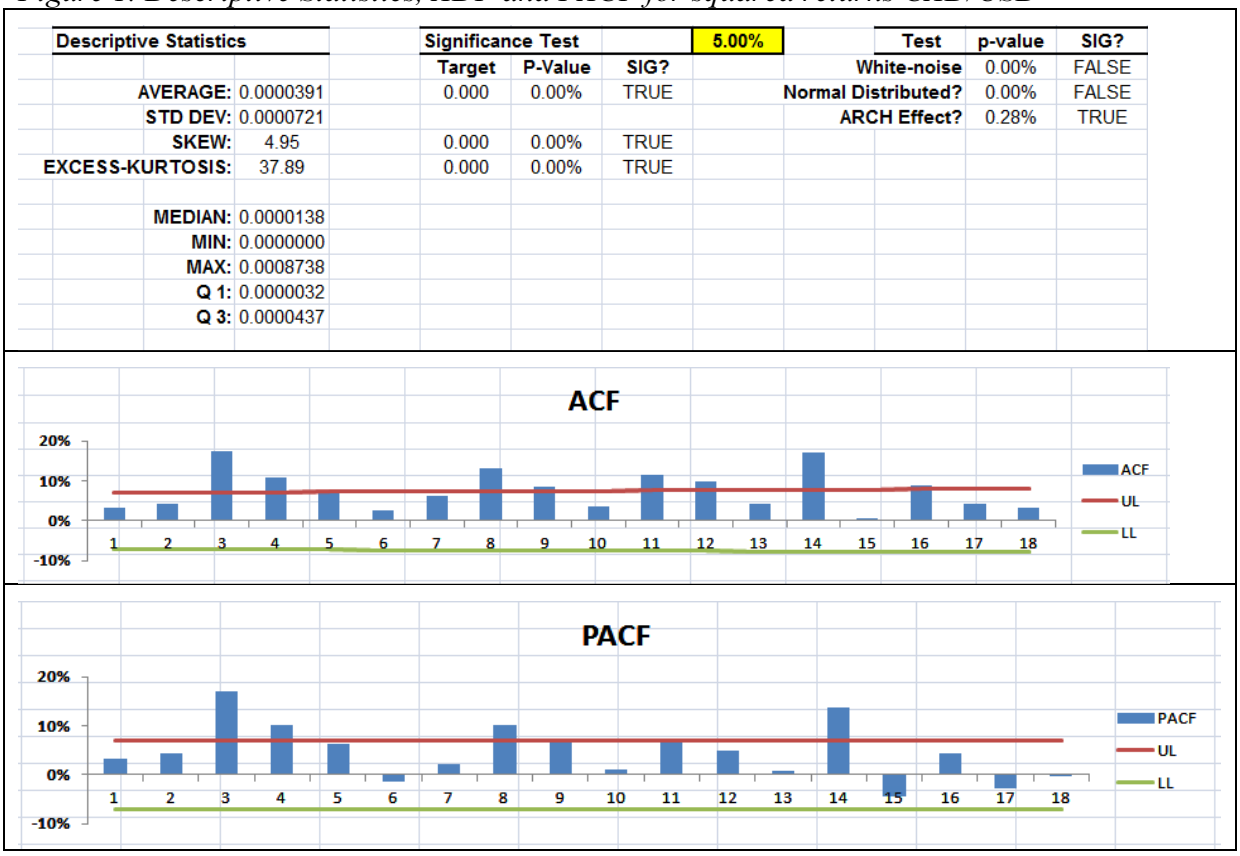
Through this research there is an expectation to gain a better understanding of the six markets and assess which model is most suitable to test the level of heteroscedasticity. Three types of GARCH models are used for the analysis, GARCH, EGARCH and GARCH- M. The EGARCH mainly deals with an asymmetric effect of negative returns over positive returns for financial markets. Based on empirical evidence negative returns affect the future volatility more than positive returns do (Black, 1976). That is typical characteristic of financial markets where an era of high volatility is observed in a down market, but less volatile market is observed in a bull market. The GARCH-M deals with a theoretical assumption about the risk-premium, which suggests that risky assets have higher expected returns. The GARCH model

does not make a distinction between the signs of the return as EGARCH does; therefore, the EGARCH is expected to be the more accurate when compared to GARCH model. However, based on empirical evidence, the gains might be insignificant, (Kisinbay, 2003).

ARIMA and GARCH modeling

CAD/USD Squared Returns Daily

Figure 1. Descriptive Statistics, ADF and PACF for squared returns CAD/USD



The log returns illustrated above are centred on the axis suggesting no trend over time. The volatility (proxy EWMA) runs smoothly compared to returns. The mean for the daily CAD/USD squared returns is significantly different than zero; there is also an evidence of skew and excess kurtosis. Furthermore, in the daily square returns summary statistics, the white noise test fails, therefore a correlation is evident.

Table 5. Goodness of fit CAD/USD

Goodness-of-fit			
	LLF	AIC	CHECK
GARCH(2,2)	2816,94	-5623.89	1
GARCH(3,3)	2823.99	-5633.98	1
EGARCH (2,2)	2827.49	-5644.98	1
EGARCH (3,3)	2831.13	-5648.25	1
GARCH-M (3,3)	2825.44	-5636.87	1

Looking at the ACF, the number of moving average component is determined, in this case 3. Looking at the PACF, the autoregressive component is determined, in this case 3. Therefore

ARMA (3, 3) may be appropriate. This is the same as saying GARCH (3, 3) for non-squared returns. The GARCH model has three part model parameters, goodness of fit and residual diagnosis. The initial parameters are not optimal; therefore it is important to calibrate the model before we continue. We construct several models and compare the goodness the fit to identify which model is more suitable. The solver calculates different combinations of parameters to maximise the LLF. The analysed residuals passed all tests and they look like a Gaussian noise.

Figure 2. EGARCH (3.3) CAD/USD

EGARCH(3,3)	
Param	Value
μ	0.00
α_0	-9.85
α_1	-0.06
α_2	0.06
α_3	0.10
γ_1	5.06
γ_2	3.17
γ_3	-3.03
β_1	0.70
β_2	-0.84
β_3	0.18

Goodness-of-fit		
LLF	AIC	CHECK
2831.13	-5648.25	1
VL		
0.00610809		

	Residuals (standardized) Analysis						
	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
	0.01	1.00	-0.19	0.63	TRUE	FALSE	TRUE
Target	0.00	1.00	0.00	0.00			
SIG?	FALSE	FALSE	TRUE	TRUE			

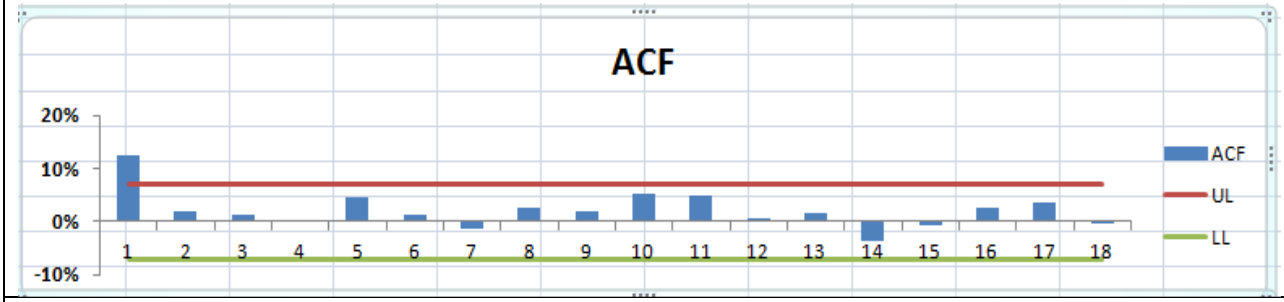
JPY/USD Squared Returns Daily

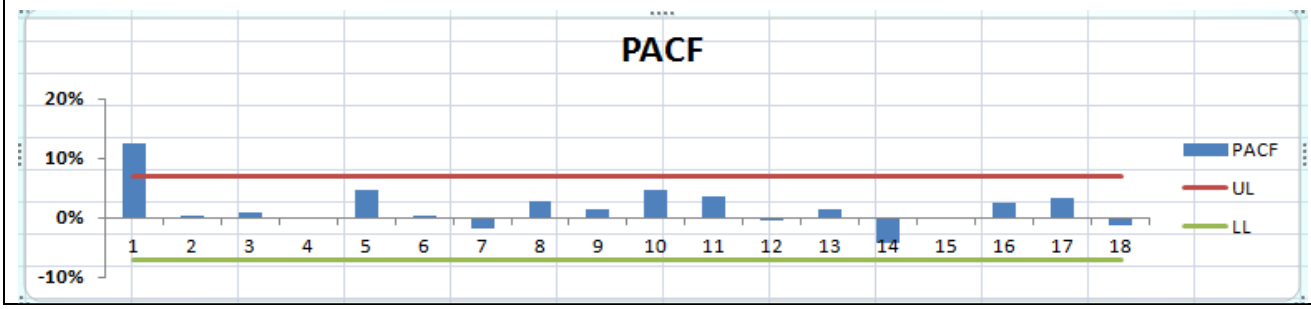
Figure 3. Time series log return, Descriptive Statistics, ADF and PACF for squared returns

Descriptive Statistics	
AVERAGE:	0.000037
STD DEV:	0.000085
SKEW:	6.43
EXCESS-KURTOSIS:	53.08
MEDIAN:	0.000011
MIN:	0.000000
MAX:	0.000947
Q 1:	0.000002
Q 3:	0.000038

Significance Test			5.00%
Target	P-Value	SIG?	
0.000	0.00%	TRUE	
0.000	0.00%	TRUE	
0.000	0.00%	TRUE	

Test	p-value	SIG?
White-noise	2.41%	FALSE
Normal Distributed?	0.00%	FALSE
ARCH Effect?	57.06%	FALSE





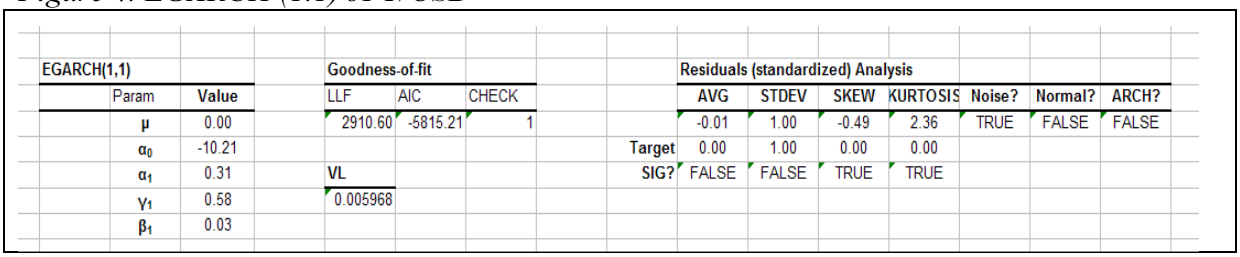
Using the NumXL function we construct the model. In this case 6 different GARCH models are constructed and compared. The goodness of the fit table clearly indicates that the most suitable model is EGARCH (3,3). The mean for the daily JPY/USD squared returns is significantly different than zero; there is also an evidence of skew and excess kurtosis.

Furthermore, in the daily square returns summary statistics, the white noise test fails, therefore a correlation is evident. Looking at the ACF the number of moving average component is determined, in this case one. Looking at the PACF the autoregressive component is determined, in this case also one. Therefore ARMA (1, 1) may be appropriate. This is the same as saying GARCH (1, 1) for non-squared returns. The ARMA model has three part model parameters, goodness of fit and residual diagnosis. The initial parameters are not optimal; therefore it is important to calibrate the model before we continue. The solver calculates different combinations of parameters to maximise the LLF. The analysed residuals passed all tests and they look like a Gaussian noise.

Table 6. Goodness of fit JPY/USD

	Goodness-of-fit		
	LLF	AIC	CHECK
GARCH(1,1)	2904.75	-5803.51	1
EGARCH(1,1)	2910.60	-5815.21	1
EGARCH (2,2)	2899.19	-5792.38	1

Figure 4. EGARCH (1.1) JPY/USD



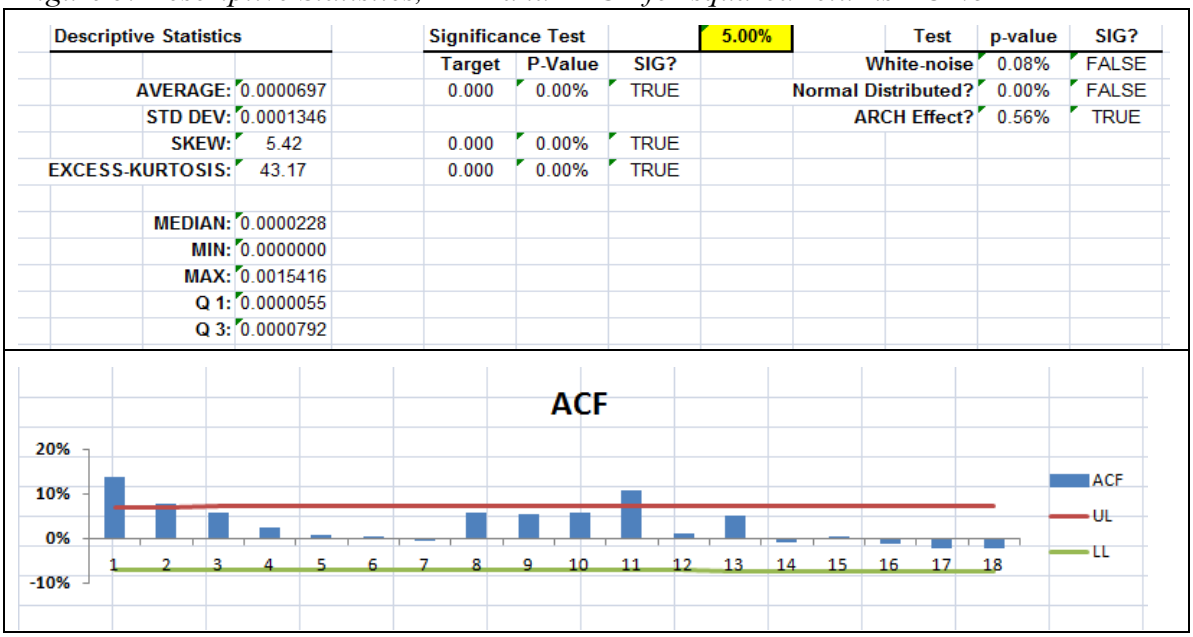
EGARCH(1,1)		
	Param	Value
	μ	0.00
	α_0	-10.21
	α_1	0.31
	γ_1	0.58
	β_1	0.03

Goodness-of-fit		
LLF	AIC	CHECK
2910.60	-5815.21	1
VL		
0.005968		

Residuals (standardized) Analysis							
	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
	-0.01	1.00	-0.49	2.36	TRUE	FALSE	FALSE
Target	0.00	1.00	0.00	0.00			
SIG?	FALSE	FALSE	TRUE	TRUE			

EUR/JPY Squared Returns Daily

Figure 5. Descriptive Statistics, ADF and PACF for squared returns EUR/JPY

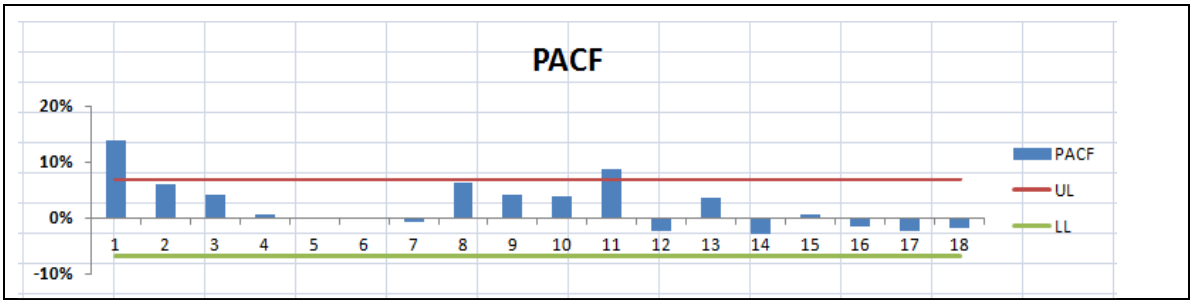


Descriptive Statistics	
AVERAGE:	0.0000697
STD DEV:	0.0001346
SKEW:	5.42
EXCESS-KURTOSIS:	43.17
MEDIAN:	0.0000228
MIN:	0.0000000
MAX:	0.0015416
Q 1:	0.0000055
Q 3:	0.0000792

Significance Test		
Target	P-Value	SIG?
0.000	0.00%	TRUE
0.000	0.00%	TRUE
0.000	0.00%	TRUE

5.00%

Test	p-value	SIG?
White-noise	0.08%	FALSE
Normal Distributed?	0.00%	FALSE
ARCH Effect?	0.56%	TRUE



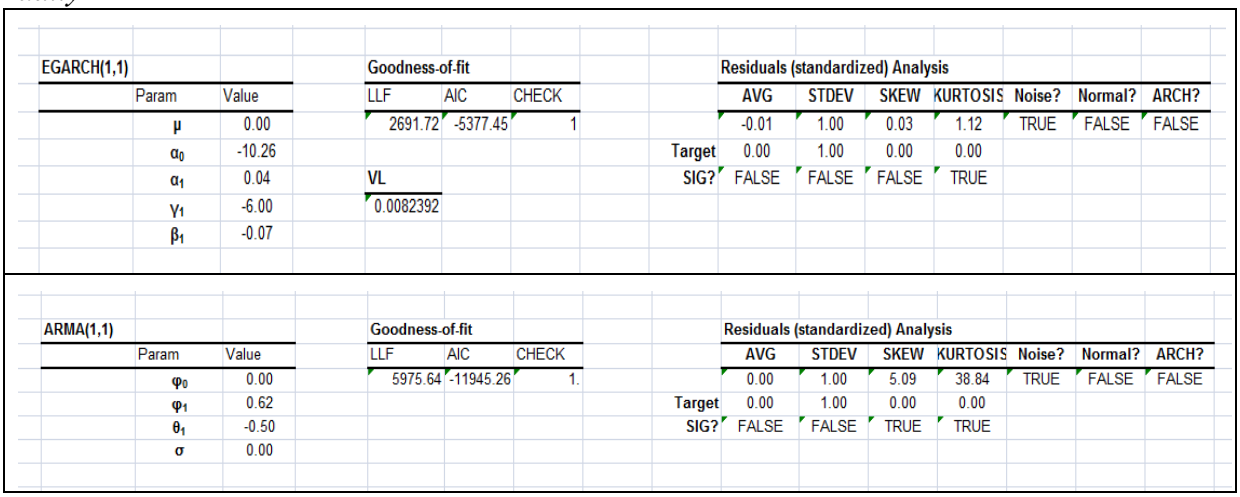
The NumXL function constructs all the models. In this case three different GARCH models are constructed and compared. The goodness of the fit table clearly indicates that the most suitable model is EGARCH (1,1).

The mean for the daily EUR/JPY squared returns is significantly different than zero; there is also an evidence of skew and excess kurtosis. The white noise passed; therefore ARMA model is not suitable. However, ARCH test passed for the original returns. The squared time series correlogram, indicates a GARCH (p, q) process, it looks like GARCH (1, 1) or GARCH (2, 2). Thus, the original p and q value is set up to one (p=q=1) and two (p=q=2). Based on the lowest value of AIC the best model is identified. Although the correlogram gives us a p,q value suggestion, it is only when competing models are compared, the best model can be identified.

Table 7. Goodness of fit EUR/JPY

	Goodness-of-fit		
	LLF	AIC	CHECK
GARCH(1,1)	-2622.19	5250.38	1
EGARCH(1,1)	2691.72	-5377.45	1
GARCH-M(1,1)	2687.50	-5369.00	1
GARCH(2,2)	2687.76	-5365.52	1
EGARCH(2,2)	2689.14	-5368.27	1
GARCH-M(2,2)	2687.30	-5364.61	1
ARIMA (1,1)	5975.64	-11945.26	1

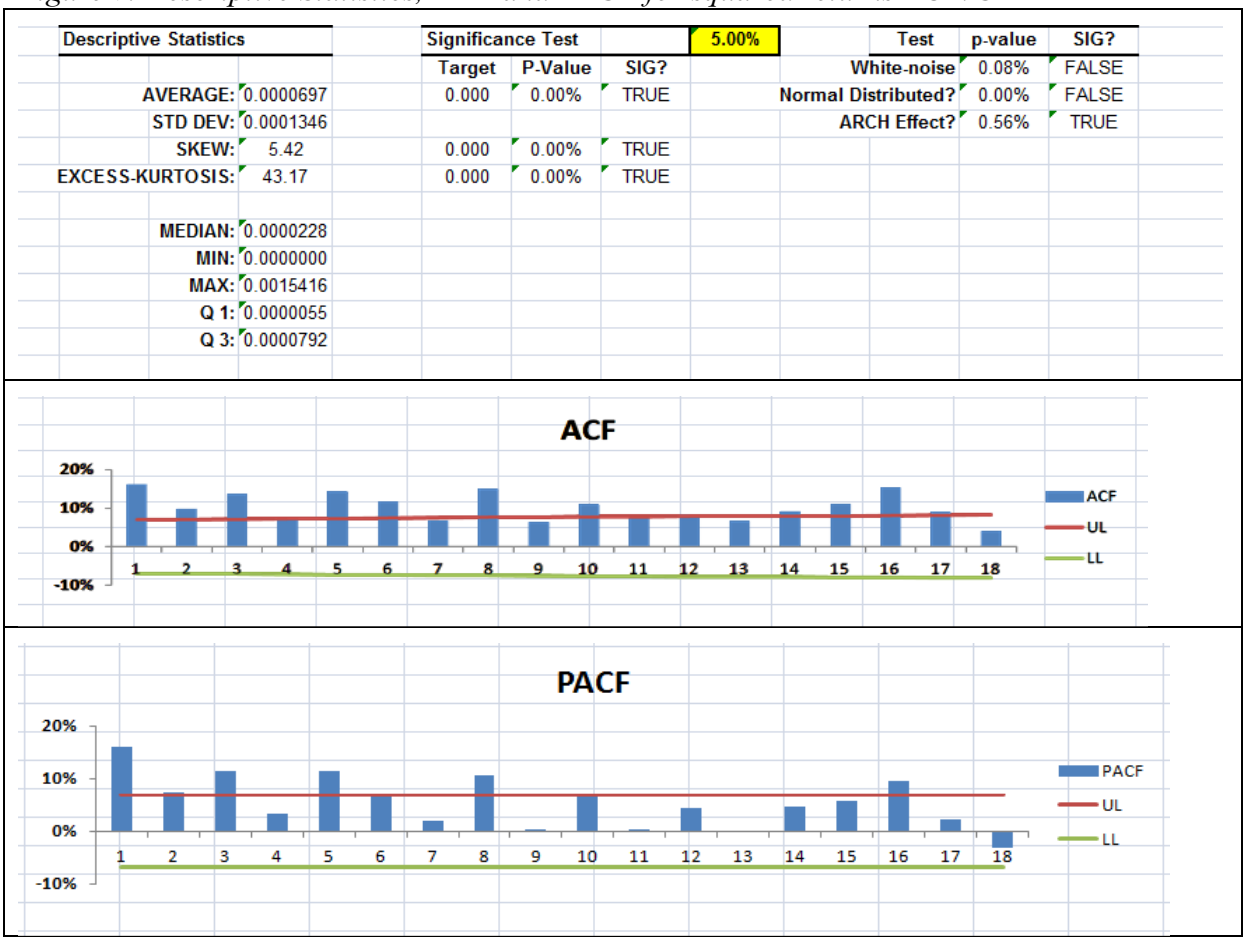
Figure 6. EGARCH (1,1) log returns the same as ARMA (1,1) squared returns EUR/JPY daily



The NumXL function constructs all the models. In this case seven different models are constructed. The goodness of the fit table clearly indicates that the most suitable model is EGARCH (1,1) which is the same as ARIMA (1,1) for squared returns.

EUR/CZK Squared Returns Daily

Figure 7. Descriptive Statistics, ADF and PACF for squared returns EUR/CZK



The mean for the daily EUR/CZK squared returns is significantly different than zero; there is also an evidence of skew and excess kurtosis. The white noise passed; therefore ARMA model is not suitable.

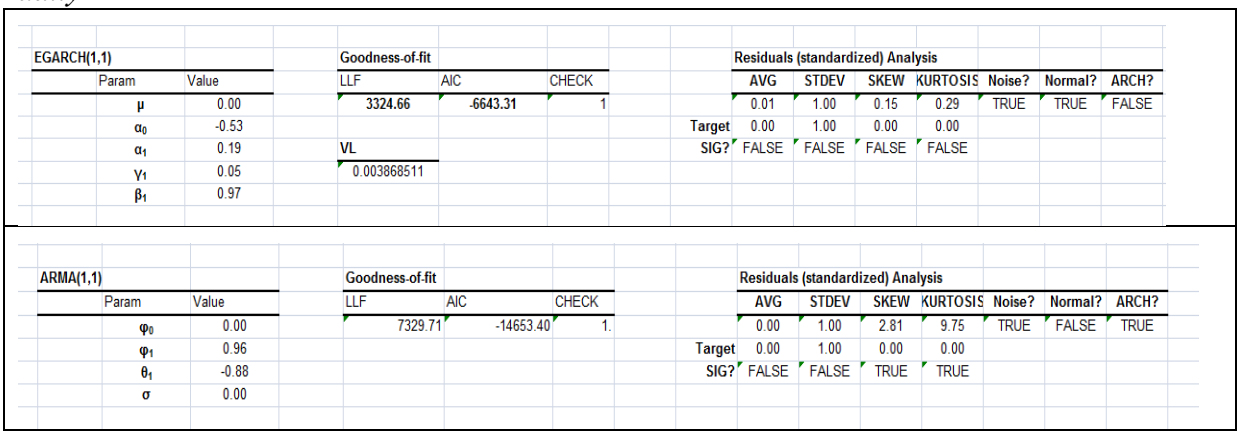
Table 8. A comparison of GARCH models for EUR/CZK

	Goodness-of-fit		
	LLF	AIC	CHECK
GARCH(1,1)	3324.831	-6643.66	1
GARCH(2,2)	3325.080	-6640.16	1
GARCH(3,3)	3324.852	-6635.70	1
GARCH(4,4)	3324.633	-6631.27	1
GARCH(5,5)	3316.407	-6610.81	1
GARCH(6,6)	3306.757	-6587.51	1
EGARCH(1.1)	3324.660	-6643.31	1
GARCH-M(1,1)	3291.660	-6577.32	1

However, ARCH test passed for the original returns. The squared time series correlogram, indicates a GARCH(p,q) process. The original p and q value is set up to one (p=q=1), then we move up to six (p=q=6). Based on the lowest value of AIC the best model is identified. Although the correlogram gives us a p,q value suggestion, it is only when competing models are compared, the best model can be identified.

The table above represents LLF and AIC values for all different types of GARCH models chosen for the analysis of EUR/CZK. When analyzing GARCH models it is clear that GARCH (2, 2) has the highest value of LLF. However, the LLF value is irrelevant when comparing models as it does not have a term to penalize more complex models. Thus, the most appropriate model is GARCH (1, 1) with the lowest value of AIC. However, when looking at residuals analysis, the White-noise test passed (no serial correlation), and the ARCH test failed (no serial correlation between the squared residuals), but normality test did not passed, it may have picked up on some excess kurtosis (fat tails) in residuals. GARCH-M (1, 1) model also did not pass the normality test. Thus, EGARCH (1, 1) is implemented to see if it adjusts for positive/negative returns and manages to absorb the excess kurtosis in the residuals. The EGARCH (1, 1) analysed residuals passed all tests and they look like a Gaussian noise. It has also the lowest AIC and therefore, it is the most suitable model.

Figure 8. EGARCH (1,1) log returns the same as ARMA (1,1) squared returns EUR/CZK daily



EGARCH(1,1)		
	Param	Value
	μ	0.00
	α_0	-0.53
	α_1	0.19
	γ_1	0.05
	β_1	0.97

Goodness-of-fit		
LLF	AIC	CHECK
3324.66	-6643.31	1
VL		
0.003868511		

Residuals (standardized) Analysis							
	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
	0.01	1.00	0.15	0.29	TRUE	TRUE	FALSE
Target	0.00	1.00	0.00	0.00			
SIG?	FALSE	FALSE	FALSE	FALSE			

ARMA(1,1)		
	Param	Value
	φ_0	0.00
	φ_1	0.96
	θ_1	-0.88
	σ	0.00

Goodness-of-fit		
LLF	AIC	CHECK
7329.71	-14653.40	1.

Residuals (standardized) Analysis							
	AVG	STDEV	SKEW	KURTOSIS	Noise?	Normal?	ARCH?
	0.00	1.00	2.81	9.75	TRUE	FALSE	TRUE
Target	0.00	1.00	0.00	0.00			
SIG?	FALSE	FALSE	TRUE	TRUE			

It can be concluded that the EGARCH model is the most suitable model in the analysis. The typical characteristic of financial markets is that negative returns affect the future volatility more than positive returns do. Therefore, it is according to our expectation that the EGARCH is the most suitable model for the analysis. Furthermore, the level of the time dependent hetersoscedaticiy and a degree of kurtosis is greater for daily rather than weekly data (Baillie, Bollerslev 1989) argued that the time dependent hetersocedasticy as well as the degree of kurtosis are more obvious in daily than weekly timeframe.

Conclusion

Foreign exchange efficiency is fundamental for economic development, as it implies that exchange rate value and volatility are determined by underlying economic fundamentals. The value of an exchange rate is important as any distortion is quickly translated into prices, affecting economic welfare. Although high volatility in foreign exchange market may result in material gains, it can also result in a significant loss, thus, it makes financial planning very difficult. It follows that much financial research focuses on the efficiency of the foreign exchange market.

Empirical results within the social science literature suggest no definitive answers. Fama (2014) suggests reasonably that markets are efficient and prices reflect all available information, while writers such as Shiller (2014) suggest that markets are subject to irrational behaviour resulting in "bubbles" with attendant market crashes. While the focus of this study has been mainly empirical, there is a growing body of related work concerning behavioural economics which is generally outside of the scope of this study. Generally, individuals, institutions and organisations do not react in a rational manner predicted by the well-established theory of Fama (2014) commonly known as the efficient market hypothesis.

While the main objective of the EMH is to explain the nature of investor behaviour in capital markets, the notion of rational investor behaviour must be challenged in the light of further research which examines such phenomena as the "speculative bubble" (Shiller, 2013) significant in foreign exchange time series.

All daily and weekly data except for CAD/USD and JPY/USD exhibit excess kurtosis. The distinction has been made between an excess kurtosis and the presence of ARCH. An excess kurtosis implies non-normal distribution, but still random, while an ARCH effect implies presence of dependency between the returns on second order.

According to Nelson and Plosner (1982), exchange rates tend to be 'difference stationary' and the findings of this paper support this conclusion. The Augmented Dickey-Fuller test rejects the null hypothesis stating the presence of unit root and there also evidence that all daily and weekly exchange rate log returns are stationary. Based on Ljung-Box test all weekly, GBP/USD and EUR/USD data do not exhibit any serial autocorrelation neither in log returns nor in the squared returns, showing evidence of random walk. Through the analysis it became clear that major foreign exchange markets tend to be very efficient and almost impossible to find any serial autocorrelation. However, for CAD/USD, JPY/USD, EUR/JPY and EUR/CZK, the white noise test failed for squared returns. Therefore, correlation and the presence of the ARCH are evident in the data.

Based on these findings, further analysis continued, where different methods including linear modeling ARIMA and conditionally heteroscedastic modeling GARCH, EGARCH and GARCH-M were compared to determine which superior model should be used. The presence of ARCH indicated a proposition of ARMA (p, q). The ARMA (p, q) for squared returns, is the equivalent to a GARCH (p, q) for the original series. When comparing the forecasting ability between GARCH and EGARCH model, the EGARCH model is evidently the superior model. Based on the lowest Akaike's Information Criterion for all four exchange rates it clearly outperformed all other models used in the analysis. The reason for that is because it deals with an asymmetric effect of negative returns over positive returns, typical phenomena foreign exchange markets. Throughout the analysis the most suitable model for CAD/USD was the EGARCH (3,3), for JPY/USD, EUR/JPY and EUR/CZK it was the EGARCH (1,1). The forecasting actual values of the EGARCH compared with the predicted values seem very similar. However, because of the limited scope of this research there is not enough evidence to confirm profitability of this trading technique.

This research is crucial, as it investigates the same markets using different frequencies. The fact that the EMH holds for weekly frequency, rather than daily currency, gives us a better understanding of currency behaviour. It is evident that the market efficiency theory is rejected in daily frequency data, but it holds in weekly frequency data, it suggests that the market is asymmetric and that abnormal returns through speculation may be possible.

In terms of the limitation of the results of this analysis, forecasting can be lengthy process and is not costless (Cootner, 1964). Therefore, a rejection of null hypothesis stating random walk does not necessarily mean a rejection of weak efficiency. Roll (1994) suggested that it is

extremely hard to make profits even if the market efficiency is rejected. Any anomalies in the foreign exchange market are unlikely to appear again in the future as they are probably a matter of chance. Furthermore, the method of testing the EMH for foreign exchange market is based on method used in the equity market. However, because of many differences between these two markets, the concept of efficient market theory may not be appropriate when assessing the efficiency of foreign exchange market (Levich, 1979).

When analysing the overall results it can be concluded that the degree of efficiency differs across markets; some are more efficient than others. In reality all markets have inevitably mispricing errors. Moreover, investors are far from rational. Although inefficiencies and abnormalities exist in the market, the question arises as to whether we can exploit them to gain an advantage. The investors can behave as if markets are efficient, or they can assume that they are inefficient with many pricing errors. However, the transaction cost of exploiting such errors may be too great and investors would probably not be able to benefit from doing so. Thus, the difference of overvalued or undervalued currency cannot be exploited commercially and investors are probably better off behaving as if markets were perfectly efficient and other investors rational.

This research is designed to benefit traders, investors and fund managers by measuring the efficiency and volatility of the foreign exchange market, which is essential when planning any investment. Exchange rate modelling is an important aspect of financial research. This research can be used for investment; assessment of foreign borrowing, hedging and strategic decisions (Levich 2001). In terms of future study only daily and weekly data were used. High frequency data can also be analysed to determine whether the markets are efficient in this time frame. For such analysis however, an advanced types of GARCH model need to be implemented, which is beyond scope of this paper. In addition trading strategy can be designed and its profitability analysed.

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