Return Dynamics and Volatility Forecast of Foreign Currencies: USD, Euro, GBP& Yen

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The foreign exchange market is dominant by major four currencies European (Euro), United States Dollar (USD), Great Britain Pound (GBP) and Japanese (YEN). It was observed from their inception that due to multiple factors, these currencies come across various fluctuations whose frequency varies. This study forecast the volatility of USD, Euro, GBP and YEN. Forecasting plays a significant role in the decision making process of foreign currency traders, exporters, importers and associated financial institutions. An accurate forecast of currency volatility will help them in designing appropriate hedging mechanism. We analyse the trend of foreign currencies movements to identify the reasons for abrupt troughs and peaks and to measure the historical volatility. An effective hedging requires historical as well as implied volatility. This study forecast the currency volatility using univariate and multivariate time series models. The precision of these forecasting models is examined by applying statistical and econometric measures of accuracy.

Keywords: Foreign Currency, Volatility Forecast; EWMA; ARMA; ARIMA; GARCH

1. Introduction

Forex market or the foreign exchange market is the largest traded market in the world which even overwhelms the stock markets of US, Japanese and Euro. The market mainly functions to act as mechanism for cross- border payments. According to Bank for International settlements, the trading for foreign exchange has increased to \$5.3 trillion as a daily average which comes about to be an hourly average of \$220 billion(Gregory Mcleod ,2014). A forex trade is carried out by simultaneous buying of a certain currency and selling of the other currency. This trade is carried out in pairs known as currency pairs. All over the world there are many official currencies that are being traded, but only a handful of currencies are actively traded in the Forex market.

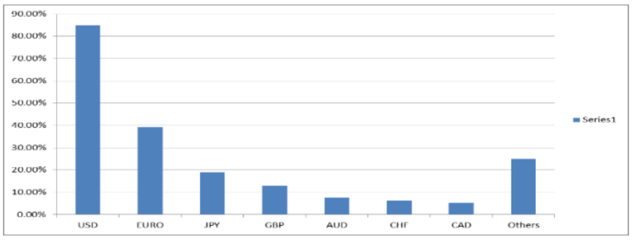

Figure 1.1 *Currency Distribution in the Forex Market*

1.1 Global Forex Market

In 1944 with the establishment of the Bretton Woods Agreement, national currencies were fixed against the dollar and the dollar rate was set at 35USD per ounce of gold. The agreement was done in order to prevent the money flight across the countries. All the participating countries agreed to maintain their currency value within a narrow margin against dollar and an equivalent rate of gold as needed. With dollar gaining a premium position as a reference currency, the global economic dominance was seen to be shifting from Europe to USA. In order to benefit the foreign trade, countries were not allowed to devalue their currencies more than 10% (Yang, n.d.). Later, when the Bretton system broke down, the world adopted to the use of floating exchange rates under the Jamaica Agreement, 1976 which permanently abandoned the use of gold standards. Severe criticisms were encountered for the foreign exchange markets when the Nobel Prize winner Professor James Tobin in 1972 proposed the Tobin Tax. (Lamichhane, 2013)

The major criticism as per James Tobin was for the market's speculative nature and its volatility. He noticed that speculators were easily able to trade in and out of the currencies by taking advantage of the different interest and exchange rate fluctuations amongst various countries. The Tobin Tax was applied in order to stabilize a country's currency. However, the tax turned out to be controversial as the opponents of the Tax stated that the tax would eliminate the profit potential of the currency markets, whereas on the other side proponents stated that the Tax would help in stabilizing currency and interest rates as many country central banks would not have much of the cash in reserve in order to balance a currency selloff (Hemalatha, 2012). Lastly, the Tobin tax system was proven out to be a non-starter as much of the administrative costs were seen to be incurred in context to its implementation which finally gave way to the proposal for a Global Forex Currency Exchange System. By 1995, the daily trading volume of currency was estimated to be US \$1.25 trillion (Flassbeck, n.d.).

The foreign exchange market was seen to be unique in various ways such as its huge trading volumes which made the highest asset class in the world leading to a high liquidity, its low relative profit margins as compared to other fixed markets and enabled it as a market of perfect competition. Foreign currency markets help countries to carry out their business operations among different countries (imports/exports). It also helped in direct speculation and evaluation relative to the value of the currencies and carry out speculation based on the difference in the interest rates amongst currencies (Mendez, 2016).
The eight most traded currencies in the forex markets are USD, Canadian Dollar (CAD), Euro (EUR), British Pound (GBP), The Swiss Franc (CHF), The New Zealand Dollar (NZD), The Australian Dollar (AUD) and Japanese Yen (JPY).

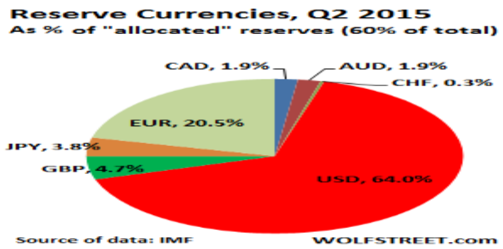

Figure 1.2 *Currency Distributions in the Forex Market*

Currencies are always traded in pairs. The currency pair states the quotation and pricing structure of the currencies being traded in the forex market. The first currency of the pair is known as the base currency and the second currency is known as the quote currency (Investopedia.com). The pair indicates how much of the quote currency is needed to purchase one unit of base currency. There are 27 different currency pairs that are derived from the most actively traded currencies. However, only 18 pairs are quoted by the forex market on the basis of currencies overall liquidity.

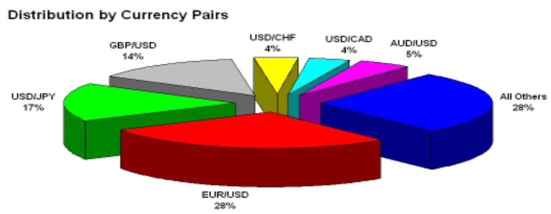

Figure 1.3 *Distributions by Currency Pairs*

The research has been done on four major currencies USD, EUR, GBP and YEN. As per Figure 1.2 USD, EUR, GBP and YEN are found to be the currencies having a major percentage in the foreign exchange markets globally. Moreover various other economic and political factors such as Balance Of Payments, Monetary Policies, Inflation, etc. are seen to be impacted by these four currencies. Hence, the four currencies are seen to be a major area for research and therefore an analysis has been performed to check their volatility and return dynamics and accordingly a forecasting model has been built up. Various associated factors which give a dominant platform to USD, GBP, EUR and YEN.

1.2 Objectives

- To analyse the trend of returns of USD, EURO, GBP and YEN
- To identify the reasons for abrupt troughs and peaks in the trend.
- To forecast the volatility of these foreign currencies by using univariate and multivariate models.

2. Literature Review

2.1 Historical Trends in Major Forex Currencies

In 2008 the Yen appreciated steadily against the US dollar due to factors such as the appreciation of the real exchange rate over 20 percent during the global financial crisis, a large jump in VIX was seen due to high market distress about peripheral European sovereigns (Chellasamy, 2013). On 25th February 2013 the outcome of the Italian elections led Yen to an appreciation of 5.25 percent against Euro and 4 percent against the dollar (Popovici, n.d.). Indian Rupee growth in context to other currencies such as Dollars, Pound, Euro and Yen has been seen at a fluctuating trend in 1989-1990 to 1990-1991. A positive growth in the Indian Rupee and Yen was seen during this period as compared to other currencies. In 1979- 1980 to 1990-1991 was a positive growth for dollar and 1982-1983 to 1990-1991 was a positive growth for Sterling Pound. The growth of exchange rates in Indian Rupee vs Dollar, Pound, Euro and Yen from 1990-1991 to 2012-2013 were seen as the highest rupee value but the lowest growth from 1997-1998 to 2003-2004 in Indian Currency, 1991-1992 to 2001-2002 in US Dollar, 1991-1992 to 1999-2000 in Pound Sterling and Euro was in 1991-1992 to 1996-1997 and 2006-2007 to 2012-2013 The exchange rates of Indian Rupee in context to dollar seem to be rising above roof since the past years. In 2009 -2010 the exchange rate was 43-45. However, in the last quarter of 2011 the Indian Rupee has depreciated enormously resulting in the reduction of net inflows for 2011 under US$300 million. Also as per the previous researches it has been proved that there is no relation between the Indian currencies growth pre and post period of liberalization (Kumar, 2015). The USD-INR exchange from 2006-2011 has been seen at a nearly stable phase (44.86 on April 24th 2006 and 44.34 on April 15th 2011) .However, a high volatility was seen from March 2008 to March 2009 i.e. 40 to 51.50 within a period of 12 months (Kamruzzaman, 2004).

2.2 Return Dynamics in Forex

The analysis performed tells us the volatility skews of JPY and GBP over a 3 months period and it has been observed that the JPY skew remains negative the majority of time in contrast to which the GBP is seen to be symmetrically zero. Also it has been tested whether the skew is positively correlated to the underlying currency level. The results of JPY and GBP respectively are seen to be positively correlated to the underlying currency i.e. dollar. The skew regression for JPY yields an R-squared of 64.5% and the GBP yields an R-squared of 9.6%. Moreover, a test on whether the skew is positively correlated to the underlying currency trends has also been performed. Both the currencies been positively correlated to the trend implies that implied volatility of calls will increase relative to the implied volatility of puts.

The hedging of volatility in foreign currencies has been achieved with an efficient use of an option pricing model i.e. Black Scholes. As speculators mostly prefer in investing in the volatile currency environment, Black -Scholes helps them in justifying their portfolio insurance which estimates that volatility would be constant or would vary in a predictable manner (T Harvey, 2016). The currency volatility index is seen to be another challenge as there is no such index yet designed which could estimate the volatility of the entire currency market and hence is based on the pair of currencies. Also, certain statistical procedures need to be used in order to smooth the noise element and achieving a reliable estimate of the volatility changes. Also, to make a reliable volatility index it is inferred that an overall volatility index could be made with the US dollar in context to all other currencies.

2.3 Factors Impacting the Forex Markets

Technical and fundamental analyses are the two major financial forecasting methodologies. In recent times, technical analysis has drawn particular academic interest in context to the evidence that markets are less efficient as initially thought. Currency rate predictions are the most challenging application of the modern day forecasting. The rates are inherently noisy, non-stationary and chaotic. As per these characteristics it is assumed that no complete information could be obtained from the past market behaviors and a general assumption is made that the historical data is incorporated with all such behavior (Joarder Kamruzzaman and Ruhul A. Sarker, 2004).

Exports are one global factor apart from other which create fluctuations in currencies. Since 1990, India is the largest processor of diamonds. Other items include Jewelry, Handicrafts, Textiles, Industrial Machinery, Leather products, etc. During the period when dollar was high against rupee exports gained at conversion rate of ($1= Rs. 48). However, in 2007 the rupee appreciated by 10% and exports profits came down to ($1= Rs. 39.35)(Ralph et al., 2000). Bearing in mind Import on the same line as of exports, the importers used to make better profits since 2007 as now he had to pay Rs. 39.35 instead of Rs. 48 for every dollar. This gain on foreign exchange market helped in saving more costs which could be passed on to consumer’s thereby controlling inflation (Lavanya and Parveentaj, 2013). Inflation was at high and the CPI was seen to be increased by 10.88% in 2009 and 13.19% in 2010. All the measures taken by the government in regulating the monetary policy were seen to be ineffective. On the basis of the evaluations made the Indian currency was been expected to depreciate by 22-30% which in turn will get the exchange rate at 55-60 to USD1 (Singhal, 2012)

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Noise trading and central intervention are the two reasons that are been seen for the inefficient currency markets. A hypothesis has been tested whether the noise traders make their investment decisions based on the prior currency movements dominate the foreign exchange market. Secondly, the central banks lack profit motive for trade. The motive for any central bank is not to generate profits, rather to ensure the currencies at politically acceptable values. To overcome this technique of moving averages has been used considering 354 moving averages for 8 different currencies from January 1980 to June 2000.

A long/short strategy is used wherein which the currency with the maximum previous month return is given a long position and the one with the least return is given a short return.

It is been assumed that short term currency markets are seen to be quite inconsistent and hence the economists must shift towards long run. However, the Post Keynesian approach used here is confined towards focusing on the psychology of the market rather than the long -term profitability. It has been suggested that the economists shift towards long run is unnecessary and premature.

2.5 Forecasting Models

For more than two decades, ARIMA model has been widely used for time series forecasting (G.E.P. Box and G.M. Jerkins, 1990). However, the model is a univariate model and is based on the assumption that the time series being forecasted are linear and stationary (L. Cao and F.Tray, 2001). Hence ARIMA is not considered to be the right technique for forecasting of data. Artificial Neural Networks (ANN Model) was found out to be a well-known function approximator and assists multivariate analysis (S.Yaser and A.Atiya 1996;J.Yao ,Y. Li and C.L. Tan,2000). ANN is universal function approximators that can map any nonlinear function without a priori assumption of data.

The Exponentially Weighted Moving Average (EWMA) was developed in 1959 by Roberts. The EWMA uses the most recent and past observations. The EWMA control procedure can be made more sensitive to a small shift by choosing the weighing factor. The main disadvantage of EWMA is that it only relies on moving averages and the recent data. Hence the dependency of the previous factors on the current scenario cannot be determined (Kalgonda A.A, Koshti V.V, Ashokan. K.V, 2011).

The original work of Engle (1982) and Bollerslev (1986) introduced that generalized autoregressive conditional heteroskedastic (GARCH) models are handy if we model the time – varying volatility. The advantage of GARCH model is that it is easy to be estimate in addition allowing performing diagnostic tests (Drakos et al, 2010). However, the model captures some of the skewness and leptokurtosis. Alexakis and Xanthakis (1995) found that if the observed conditional densities were non-normal, it was higher than that were forecasted by normal GARCH (1, 1). Hence, numerous non-normal conditional densities had been introduced in the GARCH framework. GARCH models involve an estimate of the long run volatility. GARCH model cannot account for leverage effects. Lastly, in spite of all such developments the conditional variance impact on normal distribution stood null and hence the normal GARCH model could not explain the entire leptokurtosis and the model was found better for the non-normal distributions. The EGARCH model created by Nelson (1991), helps to estimate the conditional variance which helps us to determine a one period ahead estimate for the variance. The EGARCH model allows for testing of asymmetries. The conditional variance helps to capture the leverage effect of volatility (CHANG SU, 2010)

3. Research Methodology

A daily data for four currencies (USD, GBP, EURO, and YEN) has been taken for a period of 5 years. The reason for considering a period of 5 years (2010-2015) is because a lot of volatility was seen during this period due to the various factors which impacted the trends of the following currencies. Also the vast period helped in understanding that a certain fluctuation in a particular currency had its impact on the subsequent currencies as well. After plotting the data sudden rise and fall were been encountered in certain time zones that were seen to be common for all the currencies considered.

The historical volatility was estimated with the help of VAR and CVAR. The daily data was sorted from oldest to newest starting from 2010 to 2015. The returns were calculated on the daily data and further confidence level was been estimated at 95% and 99% using PERCENTILE () which is an in-built excel function.

Value at Risk (VAR)

Value at Risk is a statistical technique which can be used to measure and quantify the level of risk. It helps to estimate the worst expected loss at a given confidence level.

$$1 - c = \int_{-\infty}^{-VAR} f_{\Delta p}(x)dx \tag{3.4.1}$$

Where c= confidence level
To obtain the VAR number we can do a standard transformation α= (Z- μ)/ (σ)
Where Z =- VAR and α= -α, thus

$$VAR=\alpha\sigma-\mu \tag{3.4.2}$$

$F_{\Delta p}$(x) Being the cumulative distribution function ofΔp, the equation could be written as

$$1 - c = \int_{-\infty}^{-VAR} f_{\Delta p}(x)dx = F_{\Delta p}(\text{-VAR}) \tag{3.4.3}$$

The information collected from various articles and e-papers helped in understanding the factors such as local governmental regulations, inflation, etc. which had caused volatility in the currencies. The Knimbus database, Bloomberg along with other news articles helped in getting an understanding of the above factors. The pre financial crisis market encountered a lot of sudden fluctuations at subsequent time intervals as compared to post financial crisis market. The volatility has been forecasted for a period of 1 year .The techniques used for forecasting are ARMA, ARIMA, GARCH, and E-GARCH along with stationary test, correlogram analysis and ADF-Test.

Auto Regressive Moving Average (ARMA)

The ARMA model comprises of an Auto Regressive process AR (p) and a Moving Average process MA (q). As the model is only applicable for stationary data a stationary test has to be done on the data set before establishing the model. The stationary test is named as ADF test. On knowing the stationary of the process, to determine the order of the model an auto correlation function and a partial auto correlation is performed.

$$\mathbf{Y}_{t}=\theta+\alpha_1 Y_{t-1}+\beta_0 u_t+\beta_1 u_{t-1} \tag{3.4.6}$$

Where θ= constant term, u= white noise stochastic error term

Auto Regressive Integrated Moving Average (ARIMA)

ARIMA stands for Auto Regressive Integrated Moving Average. The model is a univariate model and is based on the assumption that the time series being forecasted are linear and stationary.

ARIMA (p,d,q)

$$Y_t=\mu+\beta_1 u_{t-1}+\beta_2 u_{t-2} \tag{3.4.8}$$

Where μ= constant term, u = white noise stochastic error term

Generalized Auto Regressive Conditional Heteroskedasticity (GARCH)

GARCH stands for Generalized Auto Regressive Conditional Heteroskedasticity. GARCH model involve an estimate of the long run volatility. GARCH model cannot measure leverage effects.

$$\sigma^2=\gamma V_L+\alpha U_{n-1}^2+\beta\sigma_{n-1}^2 \tag{3.4.9}$$

Variance, V_L = long run variance, U^2_{n-1} = lagged squared return, σ^2_{n-1} = lagged variance
® = gamma, α = alpha, β = Beta

Jarque Bera Test

Jarque Bera test is a goodness of fit measure used to determine whether the sample data follows normal distribution. The test determines whether the sample data have the skewness and kurtosis. The t-test tests the significance of null hypothesis that states the data forms normal distribution. A normally distributed data set have skewness and excess kurtosis equal to zero and JB statistic asymptotically has a chi-square distribution with two degrees of freedom. Any deviation from this increases the Jarque Bera Statistic.

Where JB = Jarque Bera Statistic, n = number of observations, S = Skewness, K = Kurtosis

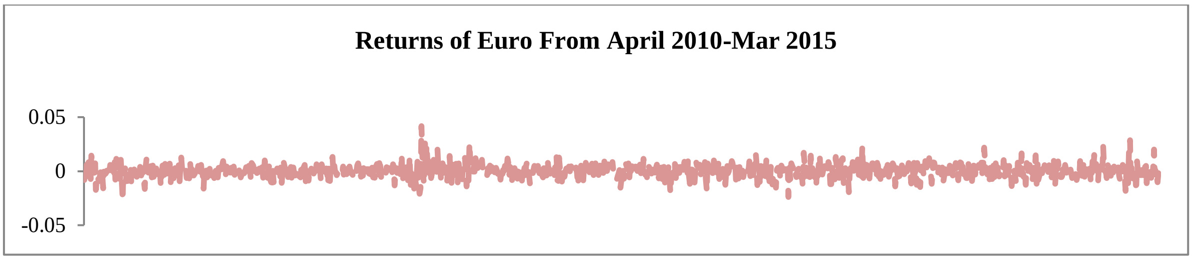
Bound of Stationary: the absolute value of $\Phi < 1$, $(-1 < \Phi < 1)$.

If $\Phi = 1$, it becomes ARIMA (0, 1, 0) which is non-stationary. If $\Phi > 1$, the past values of Y_{t-k} and e_{t-k} have greater and greater influence on Y_t, it implies the series is non-stationary with an ever increasing mean. To sum up, If Bound of Stationary does not hold, the series is not autoregressive; it is either drifting or trending, and first-difference should be used to model the series with stationary.

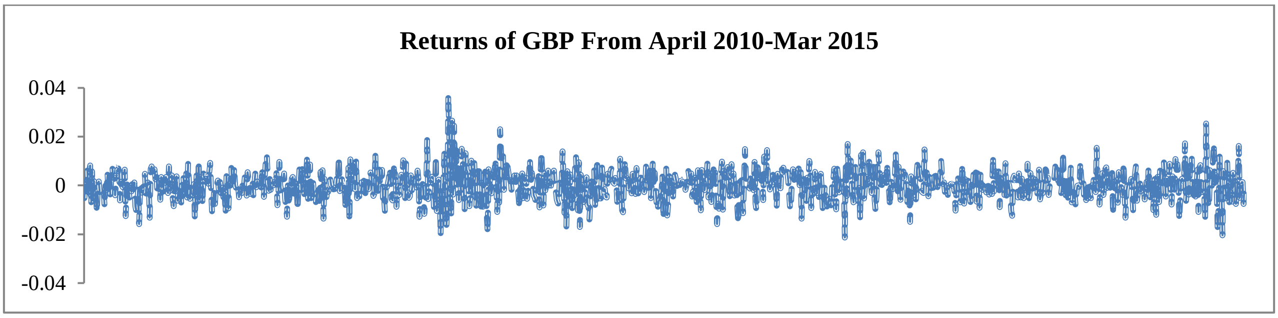
4. Data Analaysis

4.1 Trend Analysis in Forex

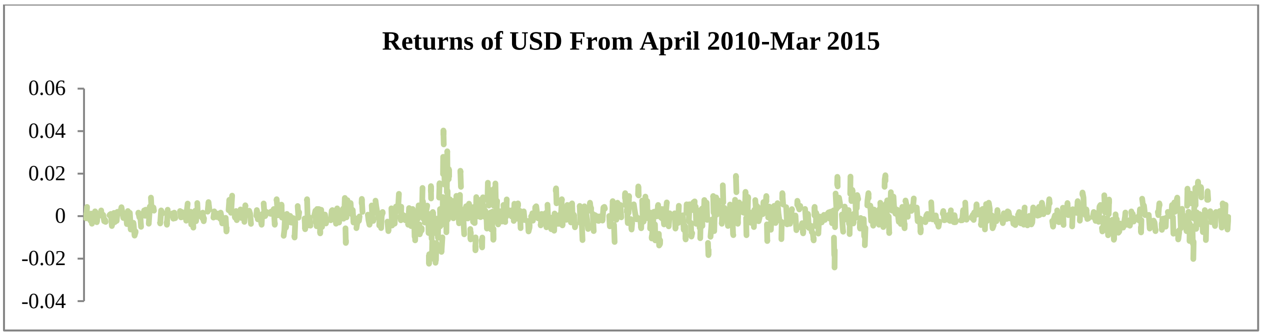
Euro in 2010 slid 1.7 percent to dollar and showed a decline by 1.9 percent against the Yen, the weakest level in 9 years. However, also on June 7 Euro was seen rebounding since its four year low. Also euro's rally slowed as Portugal's debt grade was cut two notches on July 13. Exports fell by1.5 percent in July. Euro underperformed Yen in 2010 where Yen was seen gaining 13.8 percent. As per the correlation-weighted indexes it was seen that Euro slid 10 percent while dollar went 1.5 percent higher. Estimation was made that euro depreciation will gain pace next year due to reduced government spending to shrink budget deficits. Euro in 2014 fell to a two year low against dollar due to inflation. Euro on 11th March 2015 lost more than 1 % against dollar the most rapid fall in the currency since been incorporated from 1999. The three factors i.e. increase in the US interest rates, the deepening Greek crisis and the effect of the ECB's quantitative easing programme launched in the preceding month , combined have led EURO to a 12 year low. The volatile currency was seen reviving a little in the same month giving high daily percentage returns such as 224.30% on 17th of March, 296.71% on 20th March, and 203.79% on 27th March respectively. As per Goldman Sachs, Euro is expected to reach parity with US Dollar. Since 2002 it would be now when Euro would be seen in parity with US Dollar.



The pound fell the most in 2010 since the UK banking crisis .Sterling drop was seen at a seven year low level against the dollar and weakened by about 1 percent amongst its all 16 peers. The GBP during 2011 recorded a loss of 25 percent against dollar in its last 6 months due to the collapses of 1981, 1992 and 2008. Since 2010, the currency tumbled the most during the first quarter of 2011.Pound on September 30, 2015 lost its longest quarterly return gains against euro due to the inception of Europe’s shared currency which clearly signs the U.K. economy to slow. The tighten policies of ECB has caused uncertainty in the UK currency. After the deal at the EU summit failed to alleviate the pound began to tumble.



US dollar in 2010 climbed the most in six years as the Federal Reserve considered rising interest rates. During this period it was fairly hard for nearly any currency to strengthen in a kind of environment as the dollar did. In 2012 monthly deficits averaging to $125 billion, dollar is reducing its position to 60% or even lower. USD in 2013 was seen loosing market due to its three fold balance of payments since 1980 and was between 2.5 percent to 5 percent of the GDP. America encountered a current account deficit of $426 billion in 2012. However, Euro had a surplus of $ 208 billion during the same period.



In 2012 more deflation was encountered rather than inflation. Real exports of japan fell by 40 percent during this period and industrial production fell by 35 percent. Nikkei index suffered a decline of nearly 80 percent. Even though globally measures such cut down of interest rates, flooding in the money in economy, etc. were tried but the Japanese Yen continued its decline .Bad debts continued to accumulate and unemployment situation was seen to be worsening .Astounding bank failures were seen in Japan, USA. Also the impact of Tohoku Earthquake in 2011 had tumbled the economy.

Yen in 2013 declined the most against dollar in the third quarter of the year. In order to save the deflation the Bank of Japan was seen buying nearly 60 to 70 trillion yen a year. The goal for the policy makers was to increase inflation to nearly 2 percent. In context to Euro, Yen was seen gaining 13.8 percent during the period. The total debt for japan reached a mark of 1 quadrillion. Moreover, the debt to country's GDP was 230%.Nearer in time as we could see the graph raising the economy was Japan was seen to be reviving in terms of inflation, wage growth. Also the exports were seen to be bouncing back. But still Japan was seen to have less money to spend on needy resources. Estimates were drawn that if the working population declines by 1%, the productivity needs to be increased by 3% which Japan was not able to meet up.

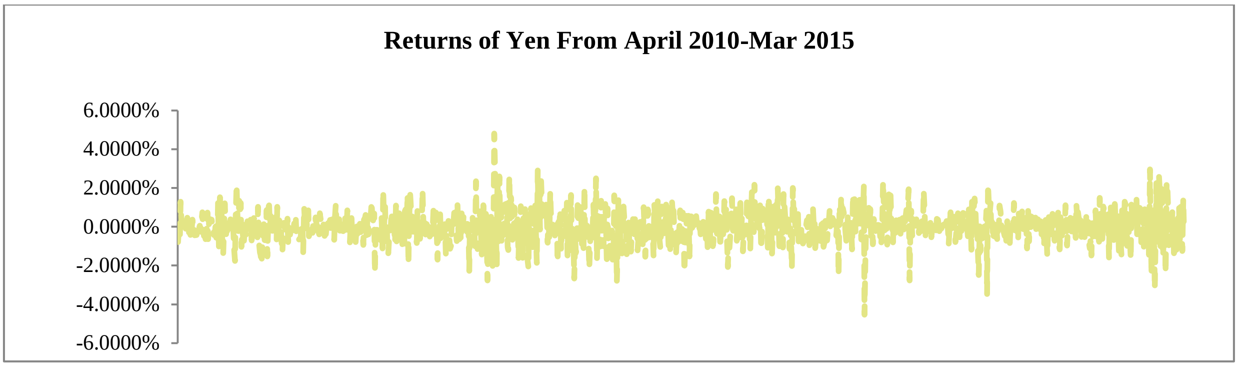


Figure 4.1 *Currency Return Fluctuations between the Period of 2010-15a) Euro; b) GBP; c) USD; d) Yen*

Variety of algorithms are been tested such as Back Propagation, Conjugate Gradient, Quasi- Newton and Levenberg Marquardt. Networks such as feed forward and feedback networks are taken for reference and a proposed system has been designed. The results finally indicate that Levenberg Marquardt is the best training algorithm. The research proves that neural networks could be used for predicting the FOREX rates thereby reducing the risk of unreasonable decisions.

4.2 Summary of Factors Creating Volatility in Currencies

Table 4.1 *Factors Creating Volatility in Various Currencies*

Year	Date	Event Occurred	Reason	Currency
2013	July	slide down	Due to twin deficits, where current account deficit reaching to $ 88.2 billion .Also Indian exports had slowed down. The foreign investors pulled down RS 620bn from the Indian debt and equity markets.(Kamruzzaman, 2004)	Yen
2011	January	slide down	Inflation is impacting currency. The rupee fell down by 20 percent making it the least performing currency in Asia. Also due to the global strengthening of dollar the rupee is falling. The growing trade deficit is another reason for the sharp decline in rupee(Gopalkrishnan, 2013)	Yen
2013	1-May	Slide Down	Annual Inflation was reported at 1.4% and the unemployment rate was at 12.2% high which was a 36 year high.(Leonard, 2003)	Euro
2014	August	Slide up	Inflation Rate was seen coming down at 0.4% and the unemployment rate reduced from 12.2% to 11.5 percent. (Popovski et al., 2000)	Euro
2013	May	Shift down	Egypt sworn 10 new cabinet members to improve the economic conditions in the country ,which further planned to use 60 percent of the US dollar reserves to pay off their debts .The budget planned for investments in fixed assets and other investments gave a deficit of 167.7 bn. (Dunis and Huang, 2002)	GBP
2013	September	Shift down	Prices for food have risen 2% since 2009 ,gold standards have increased by 70%,commodity index increased at 8.1% compounded yearly.(Bloom et al., 2007)	GBP
2013	July	Slide Down	GDP is down by 11%,BOP deficits have multiplied 3 folds, ports had become very little.(Manikyam, 2014)	USD
2012	February	Slide Down	Monthly deficits averaging to $125 billion, dollar is reducing its position to 60% or even lower. (Lamichhane, 2013)	USD

4.3 Historical Volatility Analysis

4.3.1 VAR analysis The yearly Volatility at Risk for the currencies YEN , EURO,GBP,USD for Table 4.2.1 at 95% confidence level and 99 % confidence level. In 2008, Yen at 95% as well as 99% is been seen as the least volatile currency, whereas GBP is the currency indicating the maximum volatility. Whereas in 2009, USD at both 95% and 99% is seen to be the most stable amongst the four currencies whereas GBP continues to be the most volatile currency market. In 2010, USD continues its stability at both 95% and 99% whereas GBP though being the most volatile amongst all has yet revived slightly. In 2011, USD retrains its stability at both the confidence levels (95% and 99%), whereas GBP is seen to be highly volatile as compared to 2010. In 2012, it is seen that USD is the only currency which has been able to maintain its volatile stability in context to its previous year's performance whereas GBP had seen a sudden jump and has turned out to be a risky market. EURO and Yen on the other end are experiencing slight variances in their market performances which are nearly predictable. In 2013, GBP is seen to continue its high volatile trend. In comparison to 2008 the currency has seen to be nearly 10% high volatile. USD continues its stable volatile and is seen to be the safest market for trade for the consecutive years. Euro and Yen are the markets that could be seen for the medium level risk takers. In 2014, Yen is seen to be the most stabilized currency followed by USD, EURO. GBP showed a tremendous increase of 15% which changed the market psychology for the year 2013-2014 and predictions for 2015.

Table 4.2 *Volatility at Risk for (a) YEN (b) EURO (c) GBP (d) USD*

Currency	Currency Year	95%	99%		Currency	Currency Year	95%	99%
YEN	2008	36.638	35.84		EURO	2008	57.779	57.4063
	2009	49.232	48.4344			2009	63.044	62.3224
	2010	47.5775	47.2635			2010	56.85	56.1945
	2011	54.0675	51.9692			2011	61.129	58.7897
	2012	60.9905	60.1733			2012	65.05117	64.47304
	2013	54.659	53.5715			2013	70.49338	69.84365
	2014	52.5125	51.6035			2014	76.73635	85.6673
Currency	Currency Year	95%	99%		Currency	Currency Year	95%	99%
GBP	2008	72.84634	70.72979		USD	2008	39.379	39.27
	2009	70.04576	68.47577			2009	46.328	46.1152
	2010	67.50593	65.89793			2010	44.3525	44.2545
	2011	71.04977	70.12615			2011	44.3	44.07884
	2012	77.75271	77.18763			2012	49.24502	48.95031
	2013	82.06091	81.15382			2013	53.77138	53.20664
	2014	97.08703	96.6162			2014	59.12313	58.57866

4.2.2 Cumulative Value at Risk (CVAR)

Cumulative Value at Risk helps to understand whether a particular currency has cumulatively performed in the same manner in its consecutive years. As per table 4.2.2 it could be clearly seen that the Volatility at Risk for the four currencies YEN, EURO, GBP, USD it is interpreted that GBP showed the most volatile market for the period 2008-2014 whereas USD was seen as a stable market for a majority of period. EURO and Yen are seen to be the average performers. For risk-free investors USD, GBP and YEN are seen as the considerable markets whereas the high risk takers bend would be more towards the GBP market.

Table 4.3 *Cumulative Value at Risk for (a) YEN (b) EURO (c) GBP (d) USD*

Currency	Currency Year	95%	99%		Currency	Currency Year	95%	99%
YEN	2008-2009	36.988	35.9156		EURO	2008-2009	58.156	57.5784
	2008-2010	37.193	36.0266			2008-2010	57.591	56.5976
	2008-2011	38.47	36.3502			2008-2011	57.81	56.7568
	2008-2012	38.908	36.6404			2008-2012	58.196	56.85
	2008-2013	39.188	36.6744			2008-2013	58.418	56.9248
	2008-2014	39.486	36.822			2008-2014	58.884	56.9736
Currency	Currency Year	95%	99%		Currency	Currency Year	95%	99%
GBP	2008-2009	71.08316	69.15225		USD	2008-2009	39.478	39.2876
	2008-2010	68.0526	67.01095			2008-2010	39.816	39.29
	2008-2011	68.35845	67.37679			2008-2011	39.961	39.3086
	2008-2012	68.61234	67.50162			2008-2012	40.14	39.38
	2008-2013	68.95424	67.6212			2008-2013	40.45	39.3948
	2008-2014	69.37952	67.65702			2008-2014	41.44	39.4168

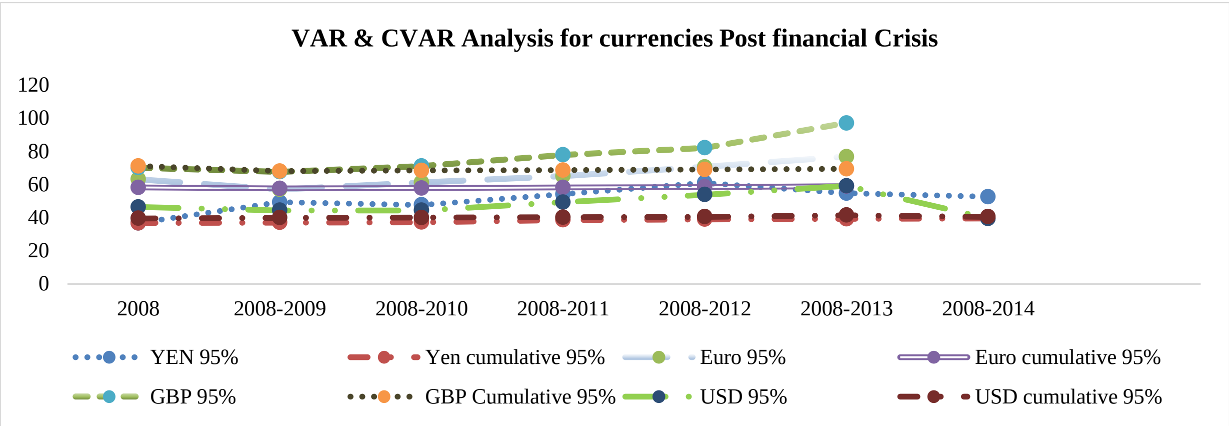


Figure 4.1 *VAR & CVAR Comparison for Four Currencies*

4.4 Forecasting Volatility FOREX

4.4.1 Scores for Normality & Stationarity Test

Normality is a prerequisite before any kind of time bound forecasting, in this area several tests are required to check the stationarity of data. The variables shows either the univariate, bivariate or multivariate behavior. On procedure. Some of the formal statistical tests for checking normality are Anderson–Darling test (1952), Cramér–von Mises criterion (see Anderson, 1962), Shapiro–Wilk test (1965), Jarque–Bera test (1987), etc. for univariate normality test Shapiro and Wilk's (1965) considered to be good. Razali (2011) showed that Shapiro-Wilk test has the best power, followed closely by Anderson-Darling when comparing the Shapiro-Wilk, Kolmogorov-Smirnov, and Anderson-Darling tests. For univariate case, Jarque and Bera (1987) proposed a test using skewness and kurtosis for checking normality. Improved Jarque-Bera test have been discussed by many authors (see e.g. Urzúa, 2007).The below mentioned table no 4.1 & 4.2, mentioned the normality and stationarity of available data set. For normality three difference set of test- jarque-Bera, Shapiro-wilk and Doornick Chi-square tests were applied. It is observed from the table among all the test mentioned below the all currency data falls under the ground of normality. Close look over p values of all the currencies also proves the data normal.

Table 4.1 *Normality Table for Currencies*

	EURO	GBP	USD	YEN
Jarque-Bera	287.33	203.39	876.72	278.68
Shapiro-Wilk	0.98	0.98	0.95	0.97
Doornick Chi-Square	151.62	116.81	349.91	167.10

4.4.2 Forecasting Using ARMA (1, 1)

Table 4.2 *Forecasting using ARMA*

	EURO	GBP	USD	YEN
$\boldsymbol{\beta_0}$	0.000171	0.000137	0.000281	0.000802
$\boldsymbol{\beta_1}$	0.000000	0.000000	0.000000	0.000000
$\boldsymbol{\theta}$	0.000000	0.000000	0.000000	0.000000
α	0.007047	0.007411	0.005978	0.008521

$$Y_{euro} = 0.007047 - 0.000171u_t$$
$$Y_{GBP} = 0.007411 - 0.000137u_t$$
$$Y_{USD} = 0.005978 + 0.000281u_t$$
$$Y_{YEN} = 0.008521 + 0.000802u_t$$

4.4.3 Forecasting Using ARIMA (1, 1)

Table 4.3 *Forecasting using ARIMA*

	EURO	GBP	USD	YEN
$\boldsymbol{\beta_0}$	-0.000001839309	-0.000001877200	0.000004677198	0.000006142716
$\boldsymbol{\beta_1}$	0.000000000000	0.000000000000	0.000000000000	0.000000000000
$\boldsymbol{\theta}$	0.000000000000	0.000000000000	0.000000000000	0.000000000000
α	0.008960796154	0.008508555432	0.008144450349	0.012134971749

$$Y_{euro} = 0.008960796154 - 0.000001839309u_{t-1}$$
$$Y_{GBP} = 0.008508555432 - 0.000001877200u_{t-1}$$
$$Y_{USD} = 0.008144450349 + 0.000004677198u_{t-1}$$
$$Y_{YEN} = 0.012134971749 + 0.000006142716u_{t-1}$$

Table 4.4 *Summary of Stationary of Various Currencies*

	Daily Variance	Daily Volatility	Volatility(Annualized)
Euro	0.0045%	0.6716%	10.6192%
GBP	0.0040%	0.6355%	10.0487%
USD	0.0020%	0.4436%	7.0132%
YEN	0.0067%	0.8191%	12.9509%

4.4.4 Forecasting Using GARCH (1, 1)

In order to find a proper model for the data collected and the forecasting of its volatility Auto correlation (ACF) and partial auto correlation (PACF) was done. The results are as follows in table 6. The graphs show no significant auto correlation in the data so an ARMA model is not justified to take out the volatility of the stocks. This being said the data does possess fat tails and the taking out exponential weighted moving average will be ideal. Therefore the use of E-GARCH from the Garch family would be ideal in this case. ***Harrison & Moore, 2012***

Table 1.5 *Summary Statistics of Various Currencies using GARCH Tool*

	EURO	GBP	USD	YEN
ɰ	0.000093638582	0.000252304473	0.000278124077	0.000080171004
α	0.000035037184	0.000032085206	0.000027004597	0.000059063856
α	0.095697297769	0.074137531088	0.095380902885	0.092768603231
β	0.095697297769	0.074137531088	0.095380902885	0.092768603231

$$\sigma^2_{euro} = 0.00003V_L + 0.09569\, U^2_{n-1} + 0.09569\, \sigma^2_{n-1}$$
$$\sigma^2_{GBP} = 0.00003V_L + 0.07413\, U^2_{n-1} + 0.09569\, \sigma^2_{n-1}$$
$$\sigma^2_{USD} = 0.00002V_L + 0.09538\, U^2_{n-1} + 0.09569\, \sigma^2_{n-1}$$
$$\sigma^2_{Yen} = 0.00005V_L + 0.092768\, U^2_{n-1} + 0.09569\, \sigma^2_{n-1}$$

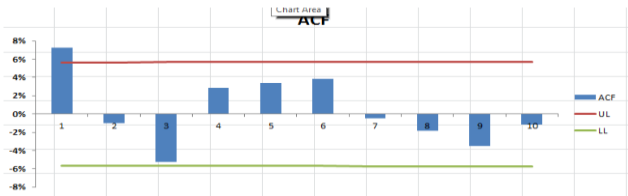
The long run conditional mean for USD is the highest followed by GBP, YEN and EURO Fitness of Good shows that the data is fit for all the volatility forecast As mentioned in the analysis of the currency exchange here the skewness is normal for EURO and USD which mean data is normally distributed and for YEN and GBP it is positively skewed. The kurtosis again is Leptokurtic which means the data has a long tail and is not stable which gives rise to volatility in Currency fluctuations.

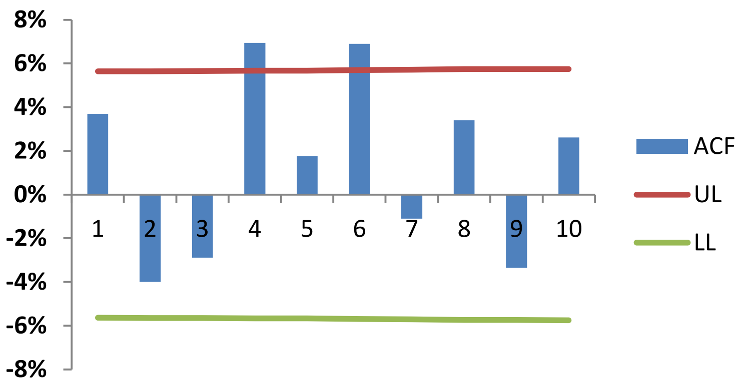
Table 4.6 *ARMA (1, 1), ARIMA (1,1,1) & GARCH (1, 1) Model AIC and BIC Analysis*

	GARCH(1,1)		**ARMA(1,1)**		**ARIMA(1,1,1)**	
Currency	AIC	BIC	AIC	BIC	AIC	BIC
EURO	-8748	4377	-8700	4354	-7948	3978
GBP	-8899	4453	-8872	4440	8073	4040
USD	-9089	4548	-9019	4513	-8179	4093
YEN	-8131	4068	- 8078	4043	-7216	3612

By Table 2, it is visible that GARCH (1, 1) model gets the minimum AIC and BIC value. So, we select GARCH (1, 1) model over ARMA (1, 1) & ARIMA (1, 1, 1). Also, we can get the same result by using ACF and PACF. (i) The kurtosis of sequence {} =6.675589>3, so the fat-tail behavior exists. *k* (ii) From Fig 4-2 we can see that sequence {*ty*} shows volatility clustering.

(iii) Figure 4-5 shows that the ACF of the squared return sequence exhibits some correlation although the ACF and PACF of sequence {2{}*tyty*} are largely uncorrelated(Fig4.6 and Fig4.7).





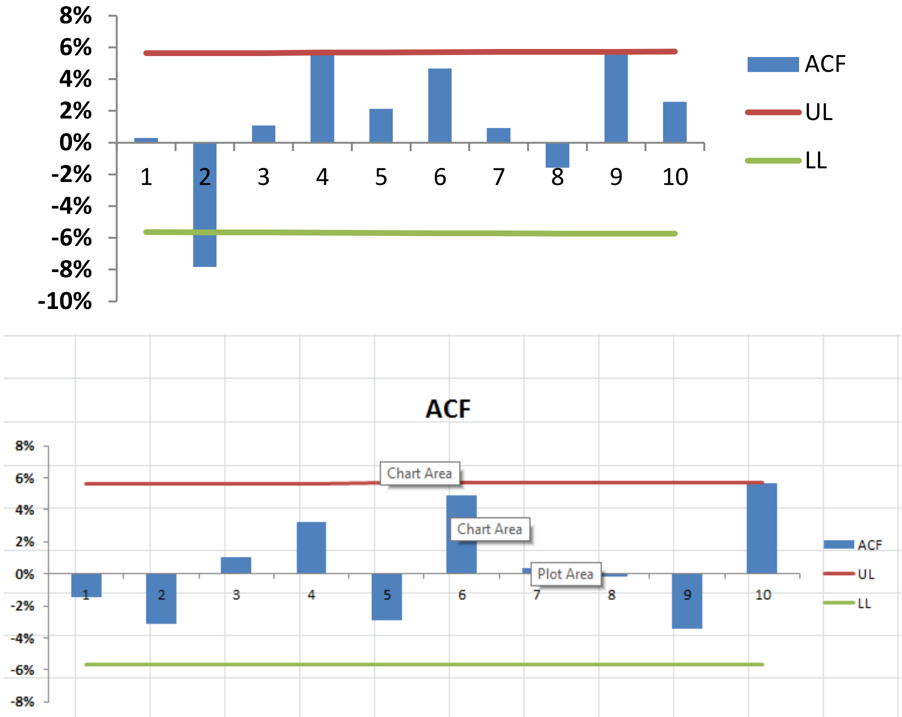
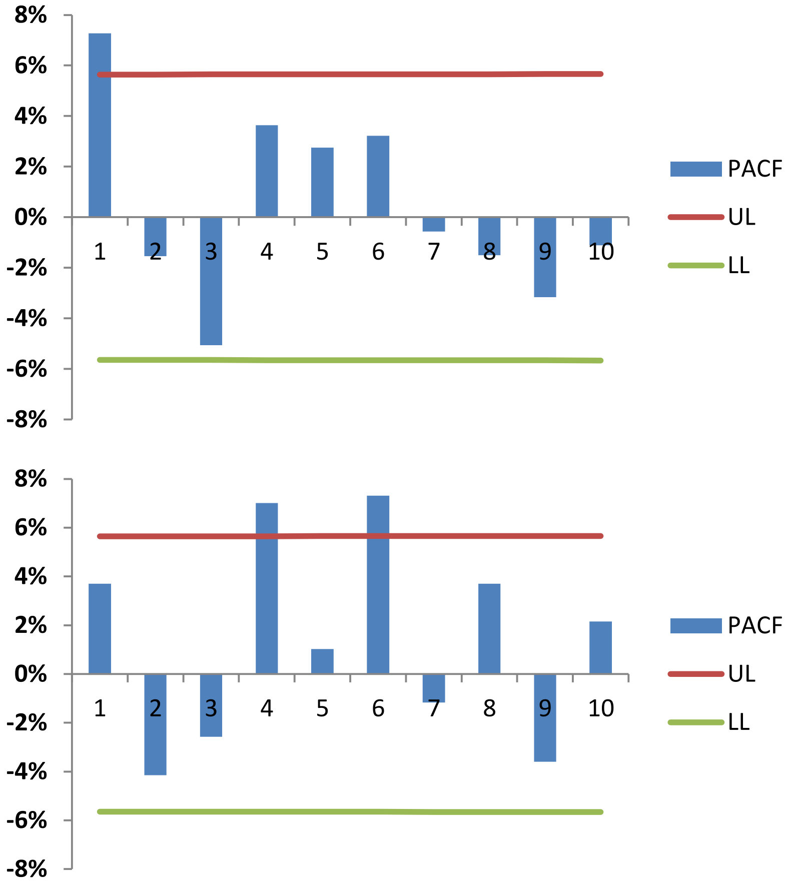


Figure 4.6 *Auto Correlation Diagram of currencies) Euro;b)GBP;c) USD & d) YEN*



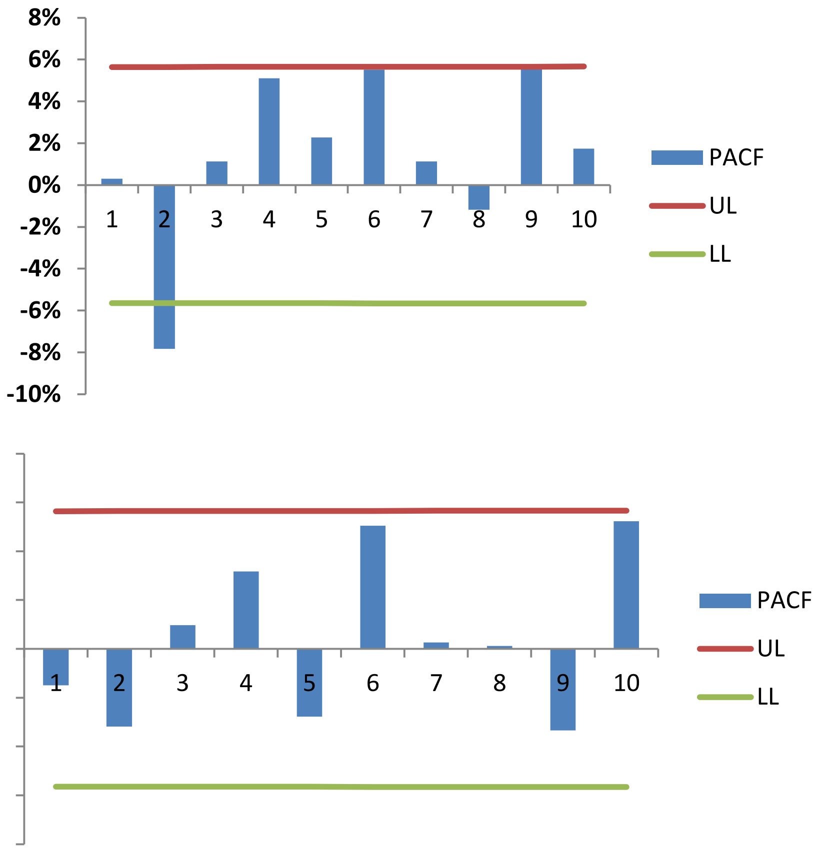


Figure 4.7 *Partial Auto Correlation Diagram of Currencies) Euro; b) GBP; c) USD & d) YEN*

5. Result & Discussion

Euro in 2010 was seen to be trending at its weakest level of past 9 years. The currency slid 1.7 percent to dollar and 1.9 percent to Yen. The increase in US interest rates, the deepening Greek Crisis led Euro to a 12-year low against the USD in 2015. Yen in 2010 gained 13.8 percent and USD went up by 1.5 percent. USD climbed to a six-year high in 2010 due to rising interest rates. In 2011 the currency was slightly volatile as it was impacted with inflation along with an increase in the Japan trade deficits. Yen in 2013 reported a current account deficit of $ 88.2 billion due to which the Indian exports slowed down. During the time period of 2009-2013 USD has been the least volatile currency with a minimum of 44.3% and 44.08% at confidence levels of 95 and 99 percent respectively. British Pound (GBP) was found out to be the most volatile currency during 2008-2014 with a maximum of 97.09% and 96.61% in 2014 at confidence levels of 95 and 99 percent respectively. Forecasting models for USD, GBP, EURO and YEN have been designed with the help of forecasting tools ARMA, ARIMA, EWMA, GARCH. ACF and PACF helped us to understand that the currencies do not possess a stationary trend. Hence, ARIMA test was found out to be insignificant. The GARCH (1, 1) is the best- fit model for our study as the model indicates the minimum AIC and BIC values which indicates a better stability.

6. Conclusion

Foreign currency transactions are subject to fluctuations. Any minor fluctuations within the tolerance level may not have an adverse impact on foreign exchange exposure. Various factors such import and export demand, interest rate changes and other macroeconomic factors cause volatility in exchange rate movements. The study examines the trend of returns of the major foreign currencies such as USD, EURO, GBP and YEN. It is inferred that major events such as current account deficit and the fall of rupee by 20 % in 2013, has contributed volatility in the rupee – yen movement. The 36-year highest unemployment rate of 12.2 % in Euro has caused abrupt trough and peak in trend of Euro in May 2013. The political developments and economic conditions in Egypt brought volatility to GBP in September 2013. Application of statistical and econometric tools requires the data to be normally distributed. Jarque Bera test, Shapiro –Wilk and Doornick Chi-square tests of normality were applied to examine whether the series of daily returns of foreign currencies are normally distributed. The test results show the returns of all currencies are normally distributed. ARMA, ARMA and GARCH models were applied to forecast the volatility of USD, EURO, GBP and YEN. Goodness of fit test is done to examine the fitness of data to forecast volatility. Application of Auto Correlation and Partial auto correlation tests indicates no significant correlation in the time series data of daily returns. Forecasting volatility by GARCH model shows long run conditional mean for USD is the highest followed by GBP, YEN and EURO. For our analysis and study only 4 currencies i.e. USD, GBP, EURO and YEN have been considered. In future the same study could be carried out on other currencies respectively. The estimations of volatility using VAR and CVAR have only been done on monthly data. Volatility estimations for daily and yearly data can also be performed. Only four Forecasting tools i.e. ARMA, ARIMA, EWMA, GARCH are been used to determine the best-fit model for the currencies. However, other forecasting tools or techniques could also be used in future. The entire analysis has been performed post financial crisis i.e. from 2008-2015. The same analysis could also be performed on pre financial crisis data with the same set of currencies. A comparison could be done in context to the behavior of the current set of currencies pre and post financial crisis.

7. References

1. Alexakis, P, Xanthakis, M, 1995. Day of the week effect on the Greek Stock Market. Applied Financial Economics 5, 43-50
2. Anastassios A. Drapos, Georgios P.Kouretas and Leconidas P.Zarangas, 2010 “Forecasting Financial Volatility of the Athens Stock Exchange daily returns: An application of the asymmetric normal mixture GARCH Model. International Journal of Finance and Economics :1-4
3. Bloom, N.,Bond,S.,Van Reenen, J,2007. Uncertainity and Investment Dynamics. Rev.Econ.Stud. 74, 391-415
4. Chellasamy .P. 2013. Depreciation of Indian Currency Vol 1. Issue-2
5. Chang Su, 2010. Application of EGARCH Model to estimate Financial Volatility of Daily Returns
6. C.Samual Nightingale, 2010. Activity in Global Foreign Exchange Markets
7. Duinis C.L. Huang, X, 2002. Forecasting and Trading Current Volatility: An application of Recurrent Neural Regression and Model Combination. J. Forecast. 354, 317-354
8. Flashbeck, H, n.d. Global Imbalances and destabilizing speculation
9. Fengwang ZHANG, Wengang CHE, Bebei XU, 2013. The Research of ARMA Model in CPI Time Series
10. GEP Box and G.M.Jerkins, 1990.Time Series Analysis, Forecasting and Control
11. Gopalkrishnan, K.V.R.M.M., 2013. Volatility in Indian Stock Market- A study of Post and Pre Recession Period Dr. K.V.Ramanathan Namex Int .J.Manag, Res-3,143
12. Gregory Mcleod, 2014. Forex Market Size: A Traders Advantage
13. Hemalatha , K,2012. Testing on weak form efficiency and volatility of Forex Market Sector: The evidence from National Stock Exchange 2656-2669
14. John .T. Harvey, 2002. The Determinants of Currency Market Forecasts:An Emperical Study Vol.25, No 1, pp 33-49
15. J Yao and C.L. Tan, 2000. “A Case Study on using neural networks to perform technical forecasting of forex,” Neuro Computing, Vol. 34, pp 79-98
16. Kalgonda A.A, Koshti V.V., Ashokan K.V., 2010. Exponentially Weighted Moving Average Control Chart
17. Kamruzzaman, J, 2004. ANN-Based Forecasting of Foreign Currency Exchange Rates Neural Information Process Rev.3, 49-58
18. Lamichhane, B, 2013. Foreign Investment Case: Production of Hydroelectricity in Nepal
19. Lavanya,V, Parveentaj,M,2013. Foreign Currency Exchange Rate (FOREX) using Neural Network. Int.J.Sui.Res.2, 174-177
20. Leonard, T, 2003. Implied Volatility skews in the Foreign Exchange Market Emperical Evidence from JPY and GBP:1997-2002
21. Manikyam, K.R.2014 Indian Banking Sector, Challenges and Opportunity. IOSR J.Bus.Manag 16, 52-61
22. Mendez, R.P., 2016. Debate: Harnessing the Global Foreign Currency Market: Proposal for a Foreign Currency Exchange (FXE) 3, 498-512
23. Popovici, O.C.,n.d. A volatility analysis of the Euro 67-80
24. Singhal, S, 2012.An analytical Study of Indian Currency Rupee Depreciation against the US Dollar and its economic impact
25. S. Yaser and A. Atiya, 1996. “ Introduction to Financial Forecasting “, Applied Intelligence, Vol.6 pp 205-213