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FORECASTING THE TIME VOLATILITY OF EMERGING EUROPEAN STOCK MARKET INDEX

Dr. M. Sheik Mohamed., M.Com.,M.Phil.,Ph.D.,
PGDCA.,FICWA.,FMSPI.,PGDFM.,Dip.MA.,MBA.,M.Phil
Professor and Vice Principal (SF),
Jamal Institute of Management,
Jamal Mohamed college (Autonomous),
Tiruchirapalli – 620 020.
prince@jmc.edu

Dr. M.A.Shakila Banu.,
M.Com.,M.Phil.,MBA.,M.Phil., HDCA., PGDFM.,PGDFT.,
Assistant Professor in Management Studies,
Jamal Institute of Management,
Jamal Mohamed College (Autonomous),
Tiruchirapalli- 620 020.
rspazila@yahoo.com

ABSTRACT

Generally the term” volatility” is simplify synonymous with “risk”. The estimation of market volatility is important for different people for different reasons, Merton Miller (1991), the winner of the 1990 Nobel Prize for economics, defined the term Volatility thus “By volatility, public seems to mean days when large market movements, particularly down moves, occur.

These precipitous market wide price drops cannot always be traced to a specific news event. The public takes a more deterministic view of stock prices; if the market crushes, there must be a specific reason”.

Stock market volatility responds differently to the arrival of positive and negative news in the market. This asymmetric nature of volatility exerts an impact on stock prices. Hence its implications are important for traders in the market place to chalk out different trading strategies under different conditions.

In the literature, time varying conditional volatility is modeled through the Seminal Autoregressive Conditional Heteroskedasticity (EXPONENTIAL SMOOTHING) mode of Engle (1982) and its subsequent parsimonious representation through the Generalized ARCH (EXPONENTIAL) of Bollerslev (1986). But these two models do not capture the asymmetric nature of volatility. Hence (EXPONENTIAL SMOOTHING) is used in this study for forecasting future volatility. This EXPONENTIAL SMOOTHING model incorporates the asymmetric volatility of the component exactly.

The exponential growth in the European derivatives markets raised the question, “Have the Asian market indices become more volatile?”. In order to answer this question, one has to examine the partial volatility in the European markets. Hence the present study is an attempt to forecast the volatility of stock market indices with the help of EXPONENTIAL SMOOTHING model.

Key Words: EXPONENTIAL SMOOTHING, volatility, Normality Distribution

1. INTRODUCTION OF THE STUDY

A statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index. Commonly, the higher the volatility, the riskier the security.

A variable in option pricing formulas showing the extent to which the return of the underlying asset will fluctuate between now and the option's expiration. Volatility, as expressed as a percentage coefficient within option-pricing formulas, arises from daily trading activities. How volatility is measured will affect the value of the coefficient used.

The relative rate at which the price of a security moves up and down. Volatility is found by calculating the annualized standard deviation of daily change in price. If the price of a stock moves up and down rapidly over short time periods, it has high volatility. If the price almost never changes, it has low volatility.

2. MEANING OF VOLATILITY

In words volatility refers to the degree to which financial prices fluctuate. Large volatility means that returns (that is: the relative price changes) fluctuate over a wide range of outcomes.

Volatility is a theoretical construct. Models for volatility often use an unobservable variable that controls the degree of fluctuations of the financial return process. This variable is usually called the volatility. Generally, two different volatility models, will lead to different concepts of volatility.

In finance, **volatility** is a measure for variation of price of a financial instrument over time. Historic volatility is derived from time series of past market prices. An implied volatility is derived from the market price of a market traded derivative (in particular an option). The symbol σ is used for volatility, and corresponds to standard deviation.

Each bullet below treats a different volatility definition.

- Conditional variance / conditional standard deviation

Given the information up until now \mathcal{F}_n , what is the variance of the financial return r_{n+1}

$$\text{var}(r_{n+1}|\mathcal{F}_n)$$

The square root of this quantity is the conditional standard deviation. Note that this variance depends on the information set. To obtain an explicit number, one has to make model assumptions for the returns. If one assumes that the financial returns are iid Normal, then the volatility is constant and the usual variance estimator is appropriate:

$$\hat{\sigma}^2 = 1/(N - 1) \sum_{n=1}^N (r_n - \bar{r})^2$$

Here \bar{r} denotes the average of the returns. Time series models are designed to deal with the situation of time varying volatility.

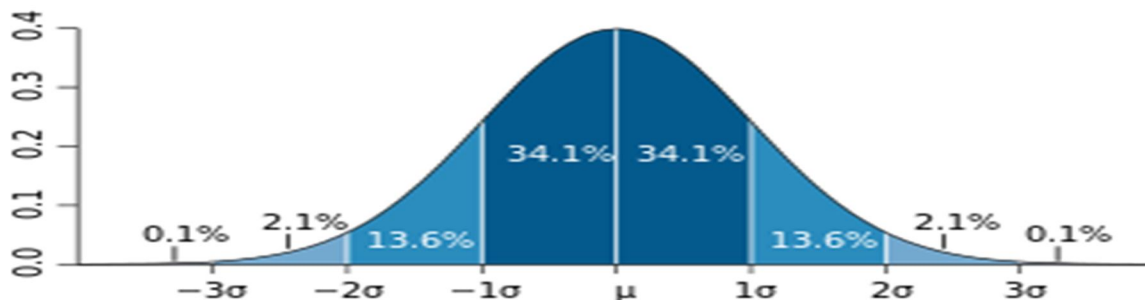
- Time series volatility

Discrete time models for time varying volatility often have a product structure,

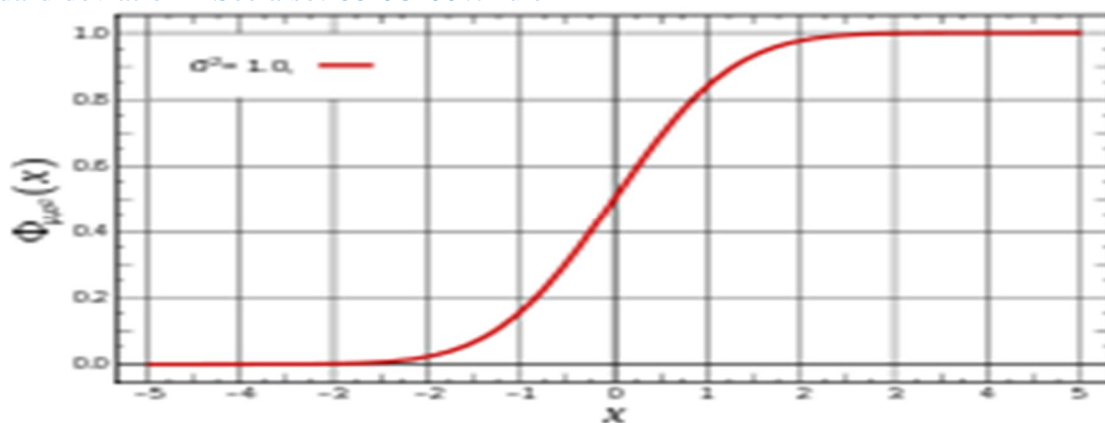
$$r_n = \sigma_n \varepsilon_n.$$

3. STANDARD DEVIATION

In statistics and probability theory, **standard deviation** (represented by the Greek letter sigma, σ) shows how much variation or dispersion exists from the average (mean), or expected value. A low standard deviation indicates that the data points tend to be very close to the mean; high standard deviation indicates that the data points are spread out over a large range of values.



A plot of a normal distribution (or bell-shaped curve) where each band has a width of 1 standard deviation – See also: 68–95–99.7 rule



3.1 MEAN

The arithmetic mean (or simply "mean") of a sample x_1, x_2, \dots, x_n is the sum the sampled values divided by the number of items in the sample:

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

Exponential smoothing is a technique that can be applied to time series data, either to produce smoothed data for presentation, or to make forecasts. The time series data themselves are a sequence of observations. The observed phenomenon may be an essentially random process, or it may be an orderly, but noisy, process. Whereas in the simple moving average the past observations are weighted equally, exponential smoothing assigns exponentially decreasing weights over time.

Exponential smoothing is commonly applied to financial market and economic data, but it can be used with any discrete set of repeated measurements. The raw data sequence is often represented by $\{x_t\}$, and the output of the exponential smoothing algorithm is commonly written as $\{s_t\}$, which may be regarded as a best estimate of what the next value of x will be. When the sequence of observations begins at time $t = 0$, the simplest form of exponential smoothing is given by the formulae:

$$s_0 = x_0$$

$$s_t = \alpha x_t + (1 - \alpha)s_{t-1}, \quad t > 0$$

where α is the smoothing factor, and $0 < \alpha < 1$.

3.2 L-JUNG BOX

The Ljung–Box test (named for Greta M. Ljung and George E. P. Box) is a type of statistical test of whether any of a group of autocorrelations of a time series are different from

zero. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags, and is therefore a portmanteau test.

This test is sometimes known as the Ljung–Box Q test, and it is closely connected to the Box–Pierce test (which is named after George E. P. Box and David A. Pierce). In fact, the Ljung–Box test statistic was described explicitly in the paper that led to the use of the Box-Pierce statistic, and from which that statistic takes its name. The Box-Pierce test statistic is a simplified version of the Ljung–Box statistic for which subsequent simulation studies have shown poor performance.

The Ljung–Box test is widely applied in econometrics and other applications of time series analysis

3.3 FORMAL DEFINITION

The Ljung–Box test can be defined as follows.

H_0 : The data are independently distributed (i.e. the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process).

H_a : The data are not independently distributed.

The test statistic is:

$$Q = n(n+2) \sum_{k=1}^h \frac{\hat{\rho}_k^2}{n-k}$$

where n is the sample size, $\hat{\rho}_k$ is the sample autocorrelation at lag k , and h is the number of lags being tested. For significance level α , the critical region for rejection of the hypothesis of randomness is

$$Q > \chi_{1-\alpha, h}^2$$

where $\chi_{1-\alpha, h}^2$ is the α -quantile of the chi-squared distribution with h degrees of freedom.

The Ljung–Box test is commonly used in autoregressive integrated moving average (ARIMA) modeling. Note that it is applied to the residuals of a fitted ARIMA model, not the original series, and in such applications the hypothesis actually being tested is that the residuals from the ARIMA model have no autocorrelation. When testing the residuals of an estimated ARIMA model, the degrees of freedom need to be adjusted to reflect the parameter estimation. For example, for an ARIMA($p,0,q$) model, the degrees of freedom should be set to $m - p - q$.

3.4 SKEWNESS AND KURTOSIS

Skew, or skewness, can be mathematically defined as the averaged cubed deviation from the mean divided by the standard deviation cubed. If the result of the computation is greater than zero, the distribution is positively skewed. If it's less than zero, it's negatively skewed and equal to zero means it's symmetric. For interpretation and analysis, focus on downside risk. Negatively skewed distributions have what statisticians call a long left tail (refer to graphs on previous page), which for investors can mean a greater chance of extremely negative outcomes. Positive skew would mean frequent small negative outcomes, and extremely bad scenarios are not as likely.

A non symmetrical or skewed distribution occurs when one side of the distribution does not mirror the other. Applied to investment returns, non symmetrical distributions are generally described as being either positively skewed (meaning frequent small losses and a few extreme gains) or negatively skewed (meaning frequent small gains and a few extreme losses).

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case.

A normal distribution has kurtosis exactly 3 (excess kurtosis exactly 0). Any distribution with kurtosis $\neq 3$ (excess $\neq 0$) is called mesokurtic.

A distribution with kurtosis < 3 (excess kurtosis < 0) is called platykurtic. Compared to a normal distribution, its central peak is lower and broader, and its tails are shorter and thinner.

A distribution with kurtosis > 3 (excess kurtosis > 0) is called leptokurtic. Compared to a normal distribution, its central peak is higher and sharper, and its tails are longer and fatter.

Let X be a random variable. Let μ_n to the n th central moment.

$$\mu_n = E(X - \mu)^n$$

In words this says the n th central moment is the expectation of the difference between the random variable X and its mean to the n th power.

The first central moment is $\mu_1 = 0$

The second central moment is μ_2 is the variance.

The skewness is found by the equation $(\mu_3) / [(\mu_2)^{3/2}]$.

It is a measure of the lack of symmetry of the probability density function.

The kurtosis is a measure of the peakedness of the density function and is the ratio between the fourth central moment and the square of the second central moment.

$$= \mu_4 / [(\mu_2)^2]$$

Both the skewness and the kurtosis are unitless.

3.5 NORMALITY TEST

In statistics, normality tests are used to determine whether a data set is well-modeled by a normal distribution or not, or to compute how likely an underlying random variable is to be normally distributed.

More precisely, they are a form of model selection, and can be interpreted several ways, depending on one's interpretations of probability:

- In descriptive statistics terms, one measures a goodness of fit of a normal model to the data – if the fit is poor then the data are not well modeled in that respect by a normal distribution, without making a judgment on any underlying variable.
- In frequentist statistics statistical hypothesis testing, data are tested against the null hypothesis that it is normally distributed.
- In Bayesian statistics, one does not "test normality" per se, but rather computes the likelihood that the data come from a normal distribution with given parameters μ, σ (for all μ, σ), and compares that with the likelihood that the data come from other distributions under consideration, most simply using a Bayes factor (giving the relative likelihood of seeing the data given different models), or more finely taking a prior distribution on possible

models and parameters and computing a posterior distribution given the computed likelihoods.

3.6 OBJECTIVES:

- To study the profile of selected countries in European.
- To evaluate the distribution of equity share price of the selected countries.
- To find out the normality of equity share price of the selected countries.
- To compute the stationery position of equity share price of the selected countries.
- To identify the Volatility position of equity share price of the selected countries.
- To provide necessary finding and suggestion & conclusion.

4. REVIEW OF LITERATURE

“Determinants of stock exchange integration: evidence in worldwide perspective Ekaterina Dorodnykh”, (2014)¹, Vol. 41 Iss: 2, pp.292 – 316 explain, that the paper contains an empirical analysis of determinants of international integration projects over the time period 1995-2010. After a broad discussion of the existent literature, the investigation combines a large number of potentially relevant determinants for the explanation of whether stock exchanges are participating in formal integration projects. The paper aims to discuss these issues The methodology is based on multistage statistical data analysis, using correlation and cluster analyses to investigate the presence of integration trend between existing stock exchange projects, while multivariable logit regression examines the determinants of stock exchange integration. The paper confirms empirically the set of drivers of financial integration. Moreover, the paper provides quantitative estimations of probability of stock exchange integration estimated for different explanatory variables. The paper demonstrates that financial harmonization, cross-membership-agreements, for-profit corporate structure, trading engine and regional integration are important drivers of stock exchange integration. By contrast, high size of stock exchange market has negative impact on the likelihood of successful merger. This result is, especially, important in terms of financial regulation. Results highlight the importance of stock exchange market in terms of exposure to systemic shocks and the linkages with the overall size of the economy. The paper contributes to the existing literature and extends the analysis of determinants of stock exchange integration. In particular, the existence of de jure stock market integration projects suggests to design a special regulatory framework in order to benefit the important consequences of the integration phenomenon and to decrease the risk of financial contagion.

“Volatility interdependence in European real estate securities markets: Who is the most influential?” By Kim Hiang Liow, (2013)², Vol. 6 Iss: 2, pp.117 – 138 explain, that the paper aims to investigate the interdependence of daily conditional volatility in seven FTSE-NAREIT-EPPRA European developed real estate securities markets – the United Kingdom, France, Germany, The Netherlands, Italy, Sweden and Switzerland, from January 1990 to December 2011. This paper employs the multivariate GARCH and the generalized VAR volatility spillover index methodologies. The author finds that each of the seven European developed real estate securities markets is relatively endogenous and interacts well with the other markets. In particular, the French real estate securities market has the most dominant volatility impact on

other markets over the full sample period. The introduction and implementation of the euro is associated with a moderate increase of the total volatility spillovers around the three-year (January 1999-January 2002) period among the sample markets. Moreover, these markets have experienced an increase in their volatility correlation, as well as becoming more open around the GFC period. Around this crisis period, the German real estate securities market emerges as the “volatility leader” in transmitting the conditional volatilities to other markets in the European region. This is the first paper to examine whether each of the sample European real estate securities markets has influenced or has been more influenced by others from the conditional volatility spillover perspective in the context of economic globalization, monetary integration and financial crisis. Since international investors incorporate into their portfolio selections not only the return correlation structure but also the market volatility interaction, the results of this study can shed light on the extent to which investors can benefit from international real estate securities diversification in the European developed countries.

Table 1 Distribution of the Equity share prices

Index	Mean	Skewness	Kurtosis	Standard deviation
FCHI	3432.6	-0.19514	-1.06	242.57
GDAXI	7122.7	-1.0868	-0.26805	546.61
MSCI	32.599	-0.84468	-0.25013	3.0909
RTSI	1466.3	-0.22171	-0.68727	100.70
TRI	29.046	-0.78982	-0.33728	1.1929

Table 2 Test of Normality BIC

Indices	12 months	6 months	3 months
FCHI	7.535	7.806	7.874
GDAXI	8.718	9.021	9.191
MSCI	-0.493	-1.303	-1.092
RTSI	6.179	6.591	6.701
TRI	-2.241	-1.994	-1.826

Table No.3. L-jung box Q for France stock index

Period of Analysis	No of predictors	Model fit Statistics	L-jung box Q-(18)		
		Stationary R-squared	statistic	DF	Sign.

12 Months	0	.021	18.966	17	.330
6 Months	0	.004	15.200	17	.581
3 Months	0	.019	17.815	17	.401

Table no: 4. L-jung box Q for Germany stock index

Period of Analysis	No of predictors	Model fit Statistics	L-jung box Q-(18)		
		Stationary R-squared	Statistic	DF	Sign.
12 Months	0	.000	19.329	17	.310
6 Months	0	.000	14.362	17	.641
3 Months	0	-.007	12.923	17	.741

Table No:5 L-jung box Q for Italy stock index

Period of Analysis	Model fit Statistics	L-jung box Q-(18)		
	Stationary R-squared	Statistic	DF	Sign.
12 Months	.024	8.798	17	.946
6 Months	.002	17.012	17	.454
3 Months	2.840E-5	20.927	17	.230

Table No:6 L-jung box Q for Russian 12 months stock index

Period of Analysis	No of predictors	Model fit Statistics	L-jung box Q-(18)		
		Stationary R-squared	Statistic	DF	Sign.
12 Months	0	-.001	19.732	17	.288
6 Months	0	-.003	17.388	17	.428
3 Months	0	-.033	15.255	17	.577

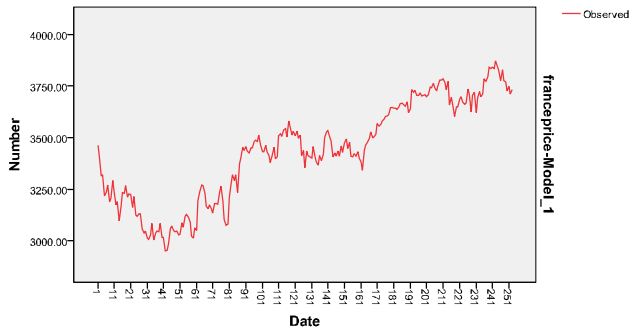
Table No:7. L-jung box Q for Uk 12 months stock index

Period of Analysis	No of predictors	Model fit Statistics	L-jung box Q-(18)		
		Stationary R-squared	Statistic	DF	Sign.
12 Months	0	-.001	33.565	17	.010

6 Months	0	.000	30.978	17	.020
3 Months	0	0.002	24.397	17	0.109

CHART

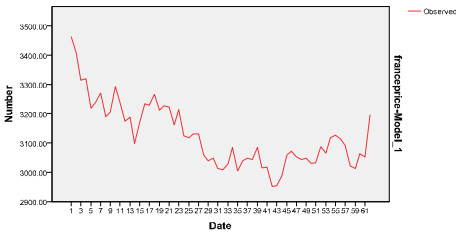
FRANCE 12 MONTHS STOCK INDEX



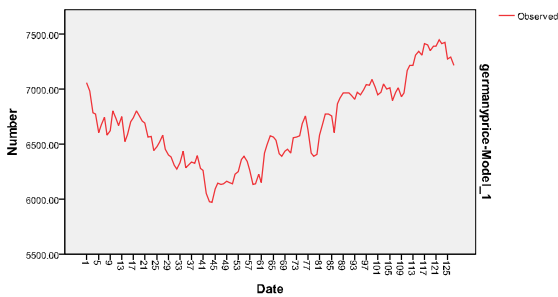
FRANCE 6 MONTHS STOCK INDEX



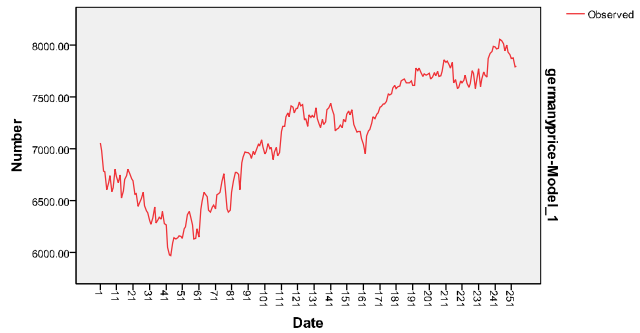
FRANCE 3 MONTHS STOCK INDEX



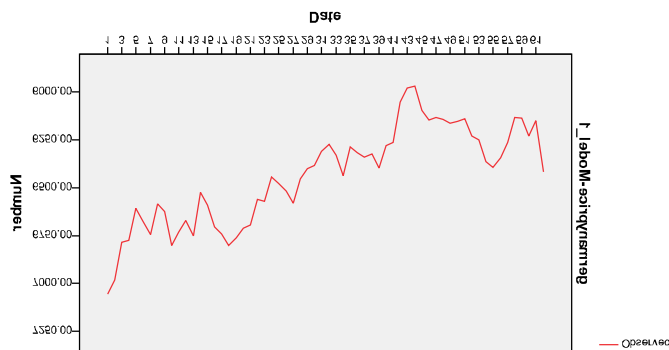
GERMANY 12 MONTHS STOCK INDEX



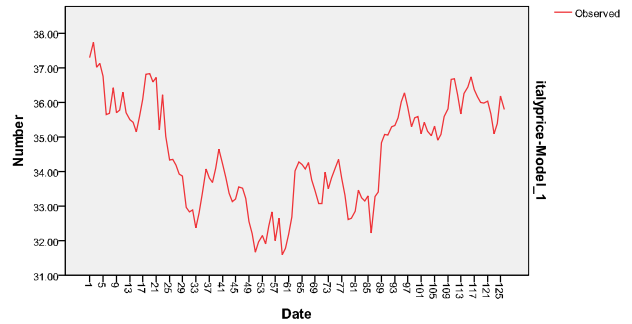
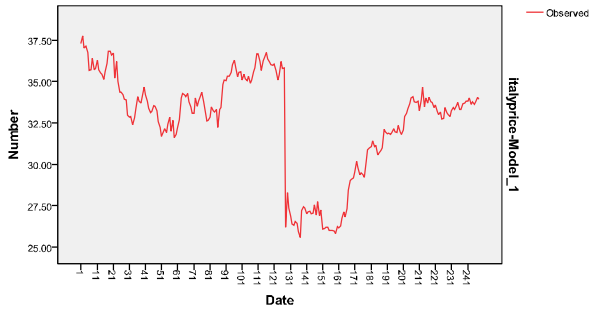
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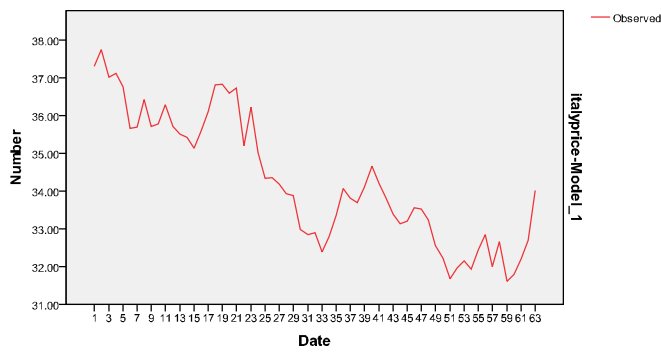
GERMANY 3 MONTHS STOCK INDEX



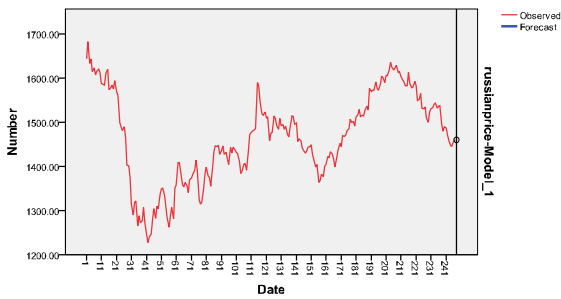
ITALY 12 MONTHS STOCK INDEX ITALY 6 MONTHS STOCK INDEX



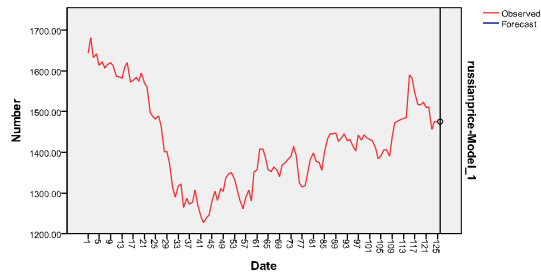
ITALY 3 MONTHS STOCK INDEX



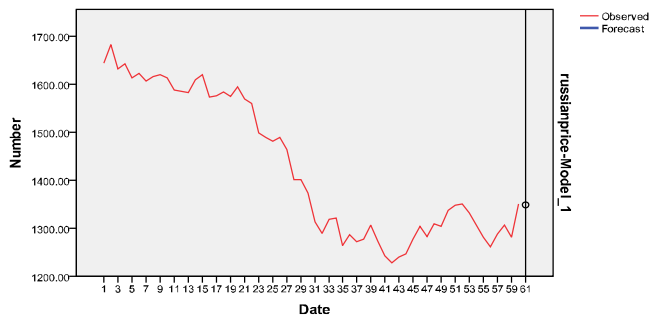
RUSSIAN 12 MONTHS STOCK INDEX



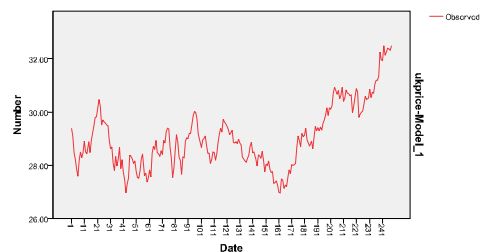
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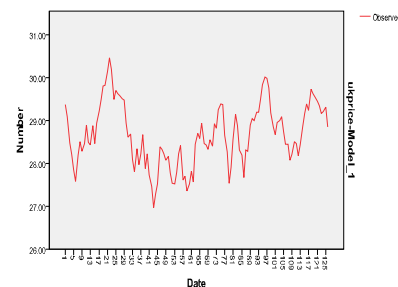
RUSSIAN 3 MONTHS STOCK INDEX



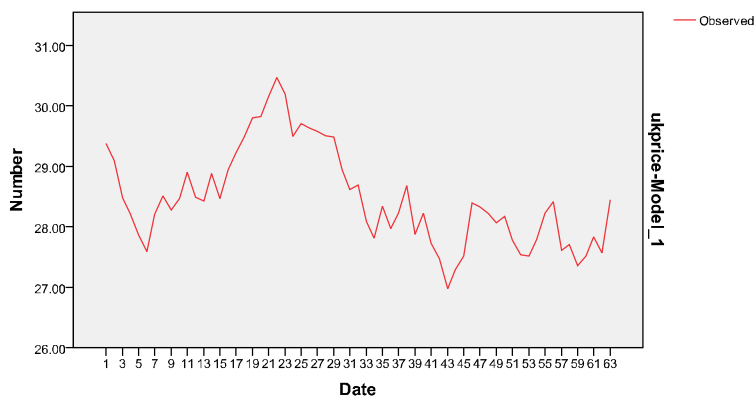
UK 12 MONTHS STOCK INDEX



UK 6 MONTHS STOCK INDEX



UK 3 MONTHS STOCK INDEX



5. FINDINGS

- It can be observed that in case of European countries, the skewness and kurtosis value(-0.19514,-1.0868,-0.84468,-0.22171,-0.78982) has shown negative impact during the in case of European countries aso the skewness and kurtosis value (-1.06,-0.26805,-0.25013,-0.68727,-0.33728) has shown negative impact during the european countries stock index.It is noted the European countries shows only negative impact for the announcement of equity share.
- The test of normality for the selected indices.As for as analysis the normalized BIC is germany indeices is higher as 8.718, 9.021,9.191 for 12, 6, 3 months respectivey.
- The L-jung box-pierce Q-Test the about table 3.3 shows that the R-Squared value is 0.021 which is lower than the statistical value 18.966, which clearly states that there is no heteroskedasticity.
- The L-jung box-pierce Q-Test the about table 3.4 shows that the R-Squared value is 0.004 which is lower than the statistical value 15.200, which clearly states that there is no heteroskedasticity.
- The L-jung box-pierce Q-Test the about table 3.5 shows that the R-Squared value is 0.019 which is lower than the statistical value 17.815, which clearly states that there is no heteroskedasticity
- The L-jung box-pierce Q-Test the about table 3.6 shows that the R-Squared value is 0.000 which is lower than the statistical value 19.329, which clearly states that there is no heteroskedasticity

- The Ljung box-pierce Q-Test the about table 3.7 shows that the R-Squared value is 0.000 which is lower than the statistical value 14.362, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.8 shows that the R-Squared value is - 0.007 which is lower than the statistical value 12.923, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.9 shows that the R-Squared value is 0.024 which is lower than the statistical value 8.798, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.10 shows that the R-Squared value is 0.002 which is lower than the statistical value 17.012, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.11 shows that the R-Squared value is 2.840E-5 which is lower than the statistical value 20.927, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.12 shows that the R-Squared value is - 0.001 which is lower than the statistical value 19.732, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.13 shows that the R-Squared value is - 0.003 which is lower than the statistical value 17.388, which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.14 shows that the R-Squared value is - 0.033 which is lower than the statistical value 15.255 which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.15 shows that the R-Squared value is - 0.001 which is lower than the statistical value 33.565 which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.16 shows that the R-Squared value is 0.000 which is lower than the statistical value 30.978 which clearly states that there is no heteroskedasticity
- The Ljung box-pierce Q-Test the about table 3.17 shows that the R-Squared value is 0.002 which is lower than the statistical value 24.397 which clearly states that there is no heteroskedasticity

6. SUGGESTIONS

It is suggested that when there is normality in equity share price it is safe to the investor to invest their money in the stock price. The investment in short term leads to high risk. It is better to invest in long term period because the investor faces only a limited risk.

7. CONCLUSION

This project in particular addresses the stock market volatility of selected European countries in International stock exchange of European using EXPONENTIAL SMOOTHING model. It can be observed that among the five countries selected, European countries had got more volatility during the study period, mention the reason why the European Countries has more volatility.

8. FURTHER STUDY

- A study on comparative analysis of volatility of equity share price for selected countries in European.
- A study on forecasting time volatility of selected stock market index in Indian country.
- A comparative study on forecasting time volatility of selected stock market index in Indian and European country.

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Author Profile

Dr.M.A.Shakila Banu (b.24th March 1983) working as Assistant Professor in Jamal Institute of Management, Jamal Mohamed College, Trichy-20. She obtained her M.Com in Jamal Mohamed College securing a rank holder, Bharathidasan University, M.Phil (commerce) in Jamal Mohamed College as college First Student, Bharathidasan University, M.B.A in Bharathidasan University, M.Phil (Management) specialization in Finance in Jamal Institute of Management, Jamal Mohamed College, PGDFM in Annamalai University, FGDFM in Annamalai University, HDCA in TNPCS, Dip in Arabic and Dip in Hindi. Ph.D in Bharathidasan University. She has 7 years of teaching experience handling various subjects in Management like International Business Environment, Production Management,



Financial Market, Financial Management, Management Accounting, Accounting for Manager, e-commerce.email: rspazila@yahoo.com

Dr.M.Shaik Mohamed (b. 05.01.1952) working as Professor in Jamal Institute of Management, Vice Principal (SF) Jamal Mohamed College, Trichy-20. He obtained his Haji.CMA.Dr.M.Shefk Mohamed., M.Com., M.Phil., Ph.D., PGDCA., FCMA., FMSPL.,PGDFM., Dip.M.A., M.B.A., M.Phil, from various university..He has 38 years of teaching experience handling various subjects in Management and Commerce like Financial Management, Management Accounting, Accounting for Manager, Principles of Accounts, Cost and Management Accounts.email:drmsheik@jmc.edu

