Review: Price and Volatility Estimation models with a special reference to ARMA-GARCH Model in equity market

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The estimation of future prices based on historical data is quite natural in today's world. However, for accurate estimation of future price it is important to understand price volatility. Thus, this issue leads to development of many models for estimation of price volatility and at the end short-term forecasting of price. This conceptual paper tries to cover different model of price and volatility estimation namely: MA-Model, AR- Model, ARIMA- Model, ARMA- Model, ARCH- Model, GARCH- Model, EWMA- Model (Specific case of GARCH (1, 1)), EGARCH- Model, and mixture of AR-GARCH Model and at last mixture of ARMA- GARCH- Model. Each model is developed in such way that gives results more near to practical situation. However, they always have some basic assumptions and limitation in practical situation. In present study, based on literature survey it's tried to identify that is ARMA-GARCH model works for price and volatility estimation in equity market or required some more strong model of estimation.

Keywords: ARMA-GARCH Model, Volatility, Estimation, Equity Market

INTRODUCTION

In today's world, due to cut throat competition different mutual fund managers, portfolio service providers, brokers etc. are always trying to find out best-fit model for estimating price for better performance. There are some models and ways available for predicting returns of different financial assets. The estimation of future prices based on historical data is quite natural in today's world. In fact, different models that support price and volatility estimation for different financial instruments are considered under the purview of technical analysis. However, for accurate estimation of future price of any financial instrument, it is important to understand price volatility of that instrument. Thus, this issue leads to development of different models for estimation of price volatility and at the end short-term forecasting of price.

In volatile financial markets, both market participants and market regulators need models for measuring, managing and containing risks. Market participants need risk management models to manage the risks involved in their open positions. On the other hand, market regulators must ensure the financial integrity of the stock exchanges and the clearing houses by appropriate margining and risk containment systems (Varma, 1999). These understanding of volatility estimation motivate the different research to understand the applicability of different econometric models for the purpose of volatility estimation of financial instruments. Price trend and its fluctuation around mean works differently for different financial instruments.

For estimating volatility and price, following models are widely used in the literature namely: (Moving Average) MA- Model, (Autoregressive) AR- Model, (Autoregressive Integrated Moving Average) ARIMA- Model, (Autoregressive Moving Average) ARMA- Model, (Autoregressive Conditional Heteroskedasticity) ARCH- Model, (Generalized Autoregressive Conditional Heteroskedasticity) GARCH- Model, (Exponential Weighted Moving Average) EWMA- Model (Specific case of GARCH (1, 1)), (Exponential Generalized Autoregressive Conditional Heteroskedasticity) EGARCH- Model, and mixture of AR-GARCH Model and at last mixture of ARMA- GARCH- Model and understanding their limitations and applicability for the volatility and price estimation in equity market in India. However, from literature review it is found that ARMA-GARCH model works better than other models when one want to estimate volatility for equity markets. So, in present study price and volatility estimation models with a special reference to ARMA-GARCH model in equity market is reviewed.

LITERATURE REVIEW

In financial applications, model base first try to get price prediction through historical price trend done through simple moving average. In statistics, moving average is a type of finite impulse response filter used to analyze a set of data point by creating a series of averages of different subsets of the full data set (Chou, 1975). In addition to this, Varma (1999) provided a support indicating simple moving average is used for price prediction. However, AR- model tried to find relationship of historical price trend to current price trend due to its auto regressive characteristic. If so, that may be considered as weak form of market efficiency. The results of Mobarek and Keasey (2000) with parametric test auto-regression provided evidence that the share return series do not follow random walk model and the significant autocorrelation co-efficient at different lags reject the null hypothesis of weak form efficiency in Dhaka Stock Market (Mobarek and Keasey, 2000). Furthermore, same results when checked with ARIMA/ARMA models were not consistent with weak form of market efficiency.

The degree of stock market volatility can help forecasters predict the path of an economy's growth and the structure of volatility can imply that "investors now need to hold more stocks in their portfolio to achieve diversification" (Krainer, 2002). The ARCH models introduced by Engle (1982) and its extension, the GARCH models (Bollerslev, 1986) have been the most commonly employed class of time series models in the recent finance literature for studying volatility. The appeal of the models is that it captures both volatility clustering and unconditional return distributions with heavy tails. The estimation of GARCH model involved the joint estimation of a mean and a conditional variance equation. The findings of research had some implications for the investors in Fiji as volatility in the stock return of a firm stems from the fact that stock returns may no longer be seen as the true intrinsic value of a firm and thus the investors might start losing confidence in the stock market (Mala and Reddy, 2007).

One of the principal empirical tools used to model volatility in asset markets has been the ARCH class of models. Following Engle's (1982) ground-breaking idea, several formulations of conditionally heteroscedastic models (e.g. GARCH, Fractional Integrated GARCH, Switching GARCH, Component GARCH) have been introduced in the literature (Bollerslev *et al*., 1992 and Bollerslev *et al*., 1994). These models form an immense ARCH family. Many of the proposed GARCH models included a term that can capture correlation between returns and conditional variance. Models with this feature were often termed asymmetric or leverage volatility models. One of the earliest asymmetric GARCH models was the EGARCH (exponential generalized ARCH) model of Nelson (1991). In contrast to the conventional GARCH specification, which requires non-negative coefficients, the EGARCH model did not impose non-negativity constraints on the parameter space since it models the logarithm of the conditional variance.

Although the literature on the GARCH/EGARCH models was quite extensive, relatively few papers have examined the moment structure of models where the conditional volatility is time dependent. Karanasos (1999) and He and Ter¨asvirta (1999) derived the autocorrelations of the squared errors for the GARCH (*p*,*q*) model, while Karanasos (2001) obtained the autocorrelation function of the observed process for the ARMA-GARCH-in-mean model. Demos (2002) studied the autocorrelation structure of a model that nests both the EGARCH and stochastic volatility specifications. In extending this literature, He *et al*. (2002) considered the moment structure of the EGARCH (1,1) model.

Despite its simplicity and versatility in modeling several types of linear relationship such as pure autoregressive, pure moving average and autoregressive moving average (ARMA) series (Kwok et al., 1998), such type of models was constrained by its linear scope. The nonlinear serially dependent ARCH/GARCH and EGRACH group of models is widely accepted among econometricians and time series statisticians as the premier model of stock market returns, especially so for the GARCH(1,1) model. This wide acceptance rests on two bodies of empirical evidence.

First, a number of statistical tests easily reject the null hypothesis of a linear process; this evidence against a linear process has been accumulating since the mid-1980s. Second, the parameter estimates of a GARCH (1,1) process are statistically significant when a model is estimated on various examples of realized stock market returns and individual stock issues. This statistical significance of the parameter estimates is apparently sufficient evidence for the vast majority of empirical investigators to accept these models as true. Thus, it seems that historical price data followed partial linear and nonlinear characteristics. So, many researchers tried to applied mixture of ARMA-GARCH model for the purpose of volatility estimation like Kumar and Mukhopadyay (2002), Ling and McAleer (2003), Sparks and Yurova (2006), Wang et at. (2009) and Hossain et al. (2011)

OBJECTIVES

Present study aims to cover following objectives:

- To understand different models of volatility estimation with special focus on ARMA-GARCH model
- To analyze whether ARMA-GARCH model is appropriate for equity market volatility estimation or not based on empirical support from past literature

THEORETICAL FRAMEWORK

Volatility forecasting is an important area of research in financial markets and lot of effort has been made in improving volatility models since better forecasts translate into better pricing of options and better risk management. In this direction, this paper attempts to evaluate the ability of ten different statistical and econometric volatility forecasting models in the context of equity market.

A Moving average is a type of finite impulse response filter used to analyze a set of data point by creating a series of averages of different subsets of the full data set. An AR model is also known in the filter design industry as an infinite impulse response filter (IIR) or an all pole filter and is sometimes known as a maximum entropy model in physics applications. There is "memory" or feedback and therefore the system can generate internal dynamics. However, these internal dynamics are used with moving average of historical equity price known as ARIMA model for volatility prediction. When historical price trend used for volatility predictions, ARMA model become more applicable than ARIMA. These models used as parametric test for Auto-regression provide evidence whether the share return series do follow random walk model or not and the significant autocorrelation co-efficient at different lags accept or reject the null hypothesis of weak form efficiency.

However, ARMA model may results in error of estimation due to underlying assumption of linearity of data set that is difficult to realize through any statistical tool. The basic version of the least squares model assumes that the expected value of all error terms, when squared, is the same at any given point. ARCH/ GARCH models followed the assumption of homoskedasticity that covers nonlinear characteristic of data set. Now, this ARCH/GARCH models have family of different regressive based models focusing on the volatility predictions. EWMA is a specific case of GARCH (1,1) model. However, many of researcher have used GARCH (4,1) and GARCH (5,1) models. These competing models are evaluated on the basis of two categories of evaluation measures – symmetric and asymmetric error statistics. Based on an out of the sample forecasts and a majority of evaluation measures we find that GARCH (4, 1) and EWMA methods will lead to better volatility forecasts in the Indian stock market and the GARCH (5, 1) will achieve the same in the forex market (Kumar, 2006). The same models perform better on the basis of asymmetric error statistics also.

For the purpose of getting better prediction of equity volatility, many researchers used AR-GARCH and ARMA-GARCH models. These models with appropriate mixture of two derived different parametric tests for the best results of prediction with least error in volatility estimation. In next section detail of ARMA-GARCH model discussed with implications and limitations. At last different empirical evidence of best fit of ARMA-GARCH model for the equity volatility prediction is shown.

ARMA-GARCH Mixture for volatility prediction

a. ARCH model:

In econometrics, an autoregressive conditional heteroscedasticity (ARCH) (Engle, 1982) model considers the variance of the current error term to be a function of the variances of the previous time periods' error terms.

Specifically, let ε_t denote the returns (or return residuals, net of a mean process) and assume that,

$\varepsilon_t = \sigma_t z_t$

where $z_t \sim$ iidN(0,1) and where the series σ^2 are modeled by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots\ldots + \alpha_q \varepsilon_{t-q}^2$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0$, $i > 0$.

b. GARCH model:

GARCH model has become an important in time series data analysis, particularly in financial applications when the goal is to analyze and forecast volatility (Bollerslev, 1986; Ling and McAleer, 2002).

If an ARMA model is assumed for the error variance, the model is a GARCH model.

The GARCH model is an extension of the ARCH model. A GARCH model with order $p \geq 0$ and $q \geq 0$ is defined as:

$Z_t = \varepsilon_t / \sigma_t$

In that case, the GARCH (p, q) model (where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ε^2) is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots\ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots\ldots + \beta_p \sigma_{t-p}^2$$

Generally, when testing for heteroskedasticity in econometric models, the best test is the White test. However, when dealing with time series data, the means to test for ARCH errors and GARCH errors (Davis and Brockwell, 2002).

c. ARMA-GARCH model:

The mixture of ARMA-GARCH model is similar to the mixture of AR-GARCH model proposed in Lanne and Saikkonen (2007). We can see each component of the mixture model can be denoted as a normal ARMA series:

$$y_{t,j} = \sum_{r=1}^{R} b_{rj}\, y_{t-r,j} + \sum_{s=1}^{S} a_{sj}\, \varepsilon_{t-s,j} + \varepsilon_{t,j}$$

Furthermore, each residual term $\varepsilon_{t,j}$ is assumed Gaussian white noise with variance denoted by the GARCH model.

$$\sigma^2_{t,j} = \delta_{0\,j} + \sum_{q=1}^{Q} \delta_{qj}\, \varepsilon^2_{t-q,j} + \sum_{p=1}^{P} \beta_{pj}\, \sigma^2_{t-p,j}$$

where, δ_{0j} ψ>ψ0 for qψ=1, Qψ and β_{pj} >ψ0 for pψ=1 ψP.

EMPIRICAL SUPPORTS OF USE OF ARMA-GARCH MIXTURE FOR VOLATILITY PREDICTION

Wang et al. (2009) used GARCH model and ARMA-GARCH model for the index volatility prediction and provided empirical evidence with the help of R software. Output of parameters and coefficient of ARMA-GARCH model is shown in Table 1 and Table 2 respectively.

Table 1: Output of R software (parameters for GARCH and ARMA-GARCH model)

	AIC	BIC	SIC	HQIC
S&P GARCH (1,1)	14.13	14.19	14.13	14.16
S&P ARMA (1,1) – GARCH (1,1)	9.08	9.16	9.08	9.11
DOW GARCH (1,1)	18.28	18.33	18.28	18.30
DOW ARMA(1,1)-GARCH(1,1)	13.38	13.46	13.38	13.41

Source: Wang, Weiqiang; Guo, Ying; Niu, Zhendong and Cao Yujuan (2009)

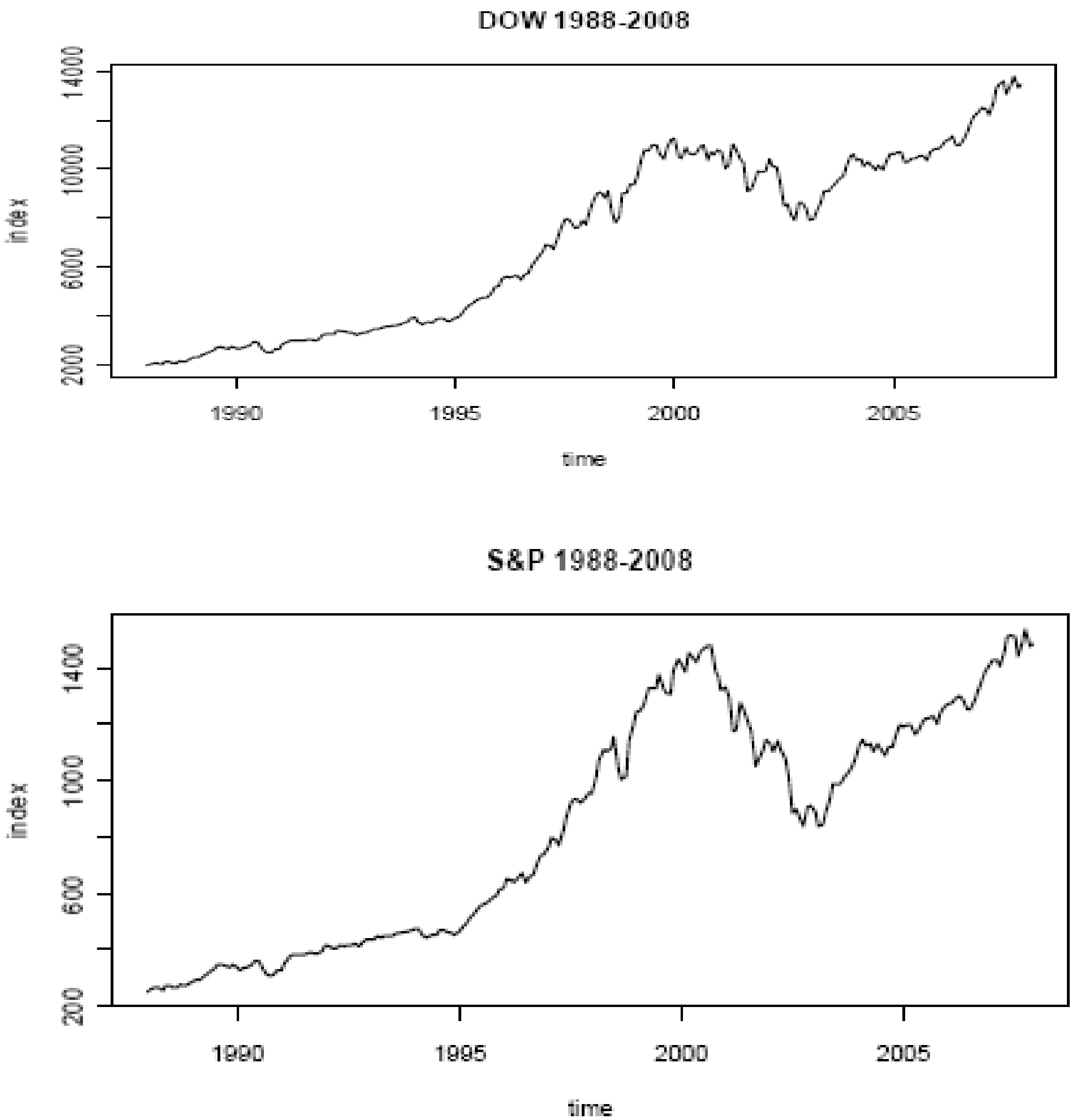
Table 2: Coefficient of ARMA-GARCH model for DOW and S&P

	μ	ar1	ma1	ω	α_1	β_1
DOW	31.1	1.0	0.20	461.3	0.20	0.80
S&P	3.90	1.0	0.22	4.6	0.23	0.81

Source: Wang, Weiqiang; Guo, Ying; Niu, Zhendong and Cao Yujuan (2009)

Appendix 1 shows standardized residual tests and their results. Appendix 2 shows forecasted volatility and mean value of index based on models. Results of study showed that ARMA (1,1)-GARCH(1,1) model provides excellent prediction, and this model is good fitting in stock indices data sets. Furthermore, model based simulation of Dow and S&P is shown in Figure 1.

Figure 1: Simulation of DOW and S&P for 1988-2008



Source: Wang, Weiqiang; Guo, Ying; Niu, Zhendong and Cao Yujuan (2009)

In another study by Munoz et al. (2003) different models of ARMA-ARCH and ARMA-GARCH are developed for the purpose of best fitted model identification in equity market. Table 3 shows coefficients for the different ARMA (0,0)-GARCH(1,1) models. Result of Table 3 and as per Munoz et al. (2003) ARMA-GARCH model work as best for equity volatility estimation.

Table 3: Coefficient for different ARMA-GARCH models

Models	ω	α_1	β_1
1	0.5	0.10	0.40
2	0.5	0.25	0.25
3	0.5	0.40	0.10
4	1.0	0.10	0.80
5	1.0	0.45	0.45
6	1.0	0.80	0.10

Source: Munoz, L.; Olave, P. and Salvador, M. (2003)

Appendix 3 includes the some more studies of ARMA-GARCH model, which indicated significantly better performance for volatility estimation of different companies or indexes.

IMPLICATIONS AND LIMITATIONS

Based on present study, it is found that ARMA-GARCH model is widely used model for estimating volatility of equity markets. However, within the use of ARMA-GARCH model there may be several combination or mixtures that required to further research to find out best fit model for different companies and indexes listed on exchanges. Different empirical research support the argument of best fit of ARMA-GARCH model for different large cap companies listed on NASDAQ and for different indexes like NASDAQ, NIFTY, DOW, S&P 500, DJIA, DAX, PSI20 and SENSEX.

Use of ARMA-GARCH model for volatility estimation reduce the error in residual variance term and gives more accurate estimation. In way volatility estimation indicates price range for said period of volatility and act as measure of risk. One can use model for predicting volatility and based on risk ability can trade to creates appropriate returns through equity market. Furthermore, this estimation of volatility may also helps in determination of option pricing of equity and index which is depend on volatility.

In present study due to time constrain and scope empirical tests are not performed on companies and Indexes listed on Indian equity market. One can use ARMA-GARCH model for volatility estimation of different stocks and Indexes listed on NSE or BSE.

However, this study has its own limitations like Study covers past data for the estimation of future volatility of stocks or index, which may not work for other time span. ARMA-GARCH model required to follow assumption of auto regressive and conditional heteroskedasticity for the applicability of model on the data of stocks or index for the volatility estimation.

CONCLUSION

ARMA and GARCH models have been applied to a wide range of time series analyses, but applications in finance have been particularly successful and have been the focus of this study. Financial decisions are generally based upon the tradeoff between risk and return; the econometric analysis of risk is therefore an integral part of asset pricing, portfolio optimization, option pricing and risk management. This paper has presented an example of risk measurement that could be the input to an equity market related decisions. The analysis of ARMA and GARCH models and their many extensions provides a statistical stage on which many theories of asset pricing and portfolio analysis can be exhibited and tested. However, mixture of ARMA-GARCH model seems to be most fitted model for the volatility estimation in most of the companies and indexes traded in equity market.

APPENDIX

Appendix 1: Statistic and p-Values for different test for DOW and S&P 500

DOW		Statistic	p-Value
Jarque-Bera Test	R Chi^2	32.73165	7.80573 e-08
Shapiro-Wilk Test	R W	0.9699429	5.80263 e-05
Ljung-Box Test	R Q(10)	12.66138	0.2432256
Ljung-Box Test	R Q(15)	15.99925	0.3821015
Ljung-Box Test	R Q(20)	26.12278	0.1617951
Ljung-Box Test	R^2 Q(10)	5.925618	0.8214733
Ljung-Box Test	R^2 Q(15)	12.30569	0.6557585
Ljung-Box Test	R^2 Q(20)	16.77428	0.6675783
LM Arch Test	R TR^2	8.500406	0.7449056
S&P 500			
Jarque-Bera Test	R Chi^2	45.12342	1.590645 e-10
Shapiro-Wilk Test	R W	0.967331	3.974364e-05
Ljung-Box Test	R Q(10)	10.14911	0.4275105
Ljung-Box Test	R Q(15)	13.35924	0.5745714
Ljung-Box Test	R Q(20)	21.20197	0.3853318
Ljung-Box Test	R^2 Q(10)	9.062306	0.5262009
Ljung-Box Test	R^2 Q(15)	15.88776	0.3895499
Ljung-Box Test	R^2 Q(20)	18.19338	0.5746709
LM Arch Test	R TR^2	9.176007	0.6878282

Appendix 2: Forecast of DOW and S&P 500 Indices

DOW	MeanForecast	MeanError	SD
1	11845.88	2581.861	1691.019
2	10303.48	3425.319	1688.436
3	10303.48	3425.319	1685.867
4	10303.48	3425.319	1683.313
5	10303.48	3425.319	1680.774
6	10303.48	3425.319	1678.250
7	10303.48	3425.319	1675.740
8	10303.48	3425.319	1673.245
9	10303.48	3425.319	1670.764
10	10303.48	3425.319	1668.297
S&P 500			
1	1292.661	258.0161	207.1376
2	1102.370	347.5169	208.0580
3	1102.370	347.5169	208.9755
4	1102.370	347.5169	209.8902
5	1102.370	347.5169	210.8022
6	1102.370	347.5169	211.7115
7	1102.370	347.5169	212.6181
8	1102.370	347.5169	213.5221
9	1102.370	347.5169	214.4234
10	1102.370	347.5169	215.3222

Appendix 3: ARMA-GARCH model for volatility prediction

Name of author	Study	Company / Index Name
Sparks, John J. and Yurova, Yuliya V. (2009)	"Comparative Performance of ARIMA and ARCH/GARCH Models on Time Series of Daily Equity Prices for Large Companies"	Oracle Systems Corp
		Coca Cola Co
		Coca Cola Bottling Co Cons
		Comcast Corp
		General Electric Co
		General Motors Corp
		International Business Machs Cor
		Pepsico Inc
		Apple Computer Inc
		Hershey Foods Corp
		Boeing Co
		Abbott Laboratories
		Dow Chemical Co
		Pfizer Inc
		Merck & Co Inc
		Hilton Hotels Corp
		Ford Motor Co Del
		Cooper Tire & Rubber Co
		Xerox Corp
		Donnelley R R & Sons Co
		Mcdonalds Corp
		Host Marriott Corp
		Wal Mart Stores Inc
		Southwest Airlines Co
		Century Telephone Entrprs Inc
		Federal Express Corp
		Toys R Us Inc
		New Germany Fund Inc
		Cisco Systems Inc
		Delta & Pine Land Co
		Universal Holding Corp
Kumar, K. Kiran and Mukhopadyay, Chiranjit (2010)	A case of U.S. and India	NASDAQ
		S&P 500
		NIFTY
		SENSEX
Curto, Jose Dias; Pinto, Jose Castro and Tavares Goncalo Nuno (2007)	Modeling stock markets' volatility using GARCH models with Normal, Student's *t* and stable Paretian distributions	DJIA
		DAX
		PSI20

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