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Using Accelerated Failure Time model to Predicting time until Volatility cluster changes in Stock Market

Introduction

Stock market prediction focus on developing approaches to determine the future price of a stock or othere financial products. Stock market predictions is regarded as a challenging task due to the high volatiity and non linear relationship, driven short term flactuations in investment demand. Some researchers have even found that man standard econemetric models are unable to produce better prediction than the random walk model which has also encouraged researchers to develope more predictive models.

Problem statement

In the field of stock market forecasting, most early models were dependant on convectional statistical methods such as time series models and multivariate analysis. In this method the stock movement was modelled as a function of time series and was solved as regression problem. However stock prices are difficult to predict due to their chaotic nature. Furthermore, there are some assumptions about the variables used in statistical methods, which may not be suitable for those dataset that do not follow the statistical distribution.most models have not solved the problem for time untill voltility cluster changes in stock markets.

More generally survival analysis involve the modeling of time to event data. in the context of volatility in stock market forecast , volatility clustering are considered as two events in survival analysis literature. We attempt to answer quetions about volatility changes at different states and what rate will stock prices fall or rise.

Research Objectives

General Objectives

To predict the time until volatility cluster changes which can be used as the indicators to determine the future stock price.

Specific objectives

- To fit K-means algorithm.
- To fit Accelerated Failure Time model.
- To test adequacy of the model.
- To predict time until the volatility clustering change.

- To check the accuaracy of the prediction.

Literature review

Various models have been proposed for investigating volatility; ranging from time series based volatility models such as exponential smoothening, the Garman-Klass model, heteroscedasticity models such as ARCH and GARCH models, options-implied volatility models such as the Classical Black-Scholes equation among others (Onwukwe et al., 2011). The essence is to build volatility model for risk forecasting on the stock market in order to provide investors and policy makers information regarding the future performance of the market. However, the most widely used are the family of heteroscedasticity models where the conditional variance of the distribution is regressed as a function of previous information and such models have become very popular because of their capability in estimating the variance of a series (Enders, 2004). However, since the introduction of heteroscedasticity, there are large number of empirical applications on financial time series in both developed and developing countries to address the concept of volatility of stock market returns using the family of such models known as ARCH and GARCH models (Emenike, 2010; Ahmed and Suliman, 2011). These models require two distinct specifications, namely the mean and variance equations where the mean is the same for every family of the volatility models (Ekong and Onye, 2017). Furthermore, these models are divided into symmetric and asymmetric. Symmetric volatility models are heteroscedasticity models where the conditional variance depends only on the magnitude of the return of an asset and not on its sign. The widely used symmetric volatility models include autoregressive conditional heteroscedasticity (ARCH) model, generalized autoregressive conditional heteroscedasticity (GARCH) model and GARCH-in-Mean (GARCH-M) model. While the asymmetric models include EGAECH, TGARCH and PGARCH designed to capture the issue of asymmetric effect which the symmetric models are not be able to (Ibrahim, 2017). Furthermore, the modelling in this paper include the all share index (ASI) which the market returns will be derived from and the lag of lagged trading volume (logVolumet-1) as well as the structural breaks which both will be incorporated in the conditional variance equation. The rationale for Lamoureux and Lastrapes (1990) to propose the use of the lag of trade volume instead of the contemporaneous trade volume series is that it may not be strictly exogenous to stock market returns. More so, the logic for not using the absolute lag of the trade volume series but its logged lag is to obtain efficient estimate (Ekong and Onye, 2017). Nonetheless, the motivation to argument the lagged lag of the trade volume in the conditional variance equation is to solve for the likely problem of simultaneity bias in the conditional variance specification. Moreover, the rational for accommodating structural breaks in the conditional variance equation to smooth the sudden shifts in the variance due to the fact it is the specification that contains the persistence parameter which ignoring break in the equation could lead to over estimation of the parameter. However, the structural breaks will be added to the equation as dummy variables that take value 1 as the break occurs in conditional volatility onwards and otherwise it takes value 0. Kuhe(2018) model the volatility persistence and asymmetry with breaks in the Nigerian stock returns using daily closing quotations of stock prices from 3rd July, 1999 to 12th June, 2017. The study used GARCH, EGARCH, and GJR-GARCH models with and without structural breaks. The estimates without breaks provide evidence of high persistence of shocks in the returns series but when incorporating breaks the study found significant reduction in shocks persistence. However, there is evidence of asymmetry in the returns series where positive shocks induce a larger increase in volatility when compared to the negative shocks of equal magnitude and the model that best fits the series is the EGARCH (1, 1) model. From the above foregoing it can be seen that there is extensive literature documenting the behaviour of stock exchange market returns but still there are some slits to carry more investigation on. For example, no study incorporates the time until a specific volatility related events happen,while it has been empirically verified that adding the logged lag of trading time until volatility clustering event occurs plays a significant role in studying the market volatility. Moreover, the contribution of structural breaks in the analysis has been neglected while incorporating breaks proved to be important in volatility analysis. In addition, none of the studies incorporate the time until certain volatility related events occur

Methodology

In this work we are addres this problem by adopting Accelerate Failure Time model (AFT) to predict a stock future price changes. We define the problem of volatility cluster changes in terms of survival analysis perspective.

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

$$(x_{\text{centroid}}, y_{\text{centroid}}) = \left(\frac{\sum x_i}{m}, \frac{\sum y_i}{m} \right) \tag{2}$$

$$\ln(T) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \epsilon \tag{3}$$

Data Description

The study is based on data from 4000 observations and four variables, covering companies listed on the NSE20 share prce market from 2003 to 2023. The closing prices of these companies were analyzed during these periods.

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