Modeling the volatility insurance time series data using Wavelet transform

Ahmed Atallah Alsaraireh
The University of Jordan
Department of Computer Information Systems
Aqaba
Jordan
ah_8545@yahoo.com
a.alsarairah@ju.edu.jo

Mohammad Salameh Almasarweh
The University of Jordan
Department of Business Administration
Aqaba
Jordan
m.almasarweh@ju.edu.jo

S. Al Wadi*
The University of Jordan
Department of Risk Management and Insurance
Aqaba
Jordan
Sadam_alwadi@yahoo.co.uk

Mahmoud Barakat Alnawaiseh
The University of Jordan
Department of Business Administration
Aqaba
Jordan
m.alnawaiseh@ju.edu.jo

Abstract. Nowadays, the volatility of stock market data have contributed an essential section in risk study. Volatility is measured by standard deviation of the return. This study explores volatility event for the insurance time series data from Amman Stock Exchange (ASE). Wavelet models (WT) have used in order to study the events in the volatility data that collected from 2010 to 2018. Therefore, the researchers found that WT is a suitable model in studying the volatility data.

Keywords: volatility, insurance time series data, wavelet transform.

1. Introduction

Statistical science has widely applications in various application such as forecasting and operation research (Alsaraireh, et al., 2018; Mohammad Almasarweh

*. Corresponding author

et al., 2018; Al Wadi, 2018) volatility is one of the concerning points for many researchers in financial institutions. Therefore, they have focus in the volatility field such as forecasting, detecting and modeling volatility since the volatility plays an significant part in risk management. For example, the financial markets use the forecasting to predict the future risks which will effect in the decisions regarding the financial institutions (Bollersley, et al. 2016). Nowadays, many models of volatility models have been proposed in the literature reviews in order to make testing the fundamental trade-off between return and risk of financial assets.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is the first and famous model in volatility field. This model is usually implemented for approximating and predicting volatility for the financial time series data for more details refer to (Babu and Reddy, 2015).As a new contribution in this article the volatility data will be modeled using WT in order to detect the events (such as outlier values) in the insurance section in content of ASE from the period between 2010-2018.

The organization of this article as the following. In section 2 the mathematical review will be presented. Section 3 the statistical data description will be presented also. While section 4 signs the results.Finally, section 5 is the conclusion.

2. Literature review

2.1 Volatility model

As we mentioned previously, many researchers have focused on the volatility data since all the Financial time series data are highly volatile. Therefore, the data trend and accuracy necessities can be met simultaneously (Babu and Reddy, 2015) this reason force the researchers to improve many methods for modeling for forecasting volatility data such as (Bentes, 2015) discuss the GARCH model in describing the gold volatility behavior. (Joukar and Nahmens, 2015) implemented ARCH and GARCH models to determine the persistency volatilities, for more details about the volatility data in content of modeling and predicting refer to (Kambouroudis and McMillan, 2015; Kristjanpoller and Minutolo, 2015; Abounoori, et al.,2016; Byun , 2016; Bollerslev et al., 2016). The definition of volatility WT methods will be storied in this section. In literature , volatility is the variance of the continuously compounded return per day (Baillie and DeGennaro, 1990). A variable's volatility, σ_t,is defined as the standard deviation of $R_i's$ at time t.

$$\sigma_t = \sqrt{\frac{\sum_1^n (R_i - \overline{R})^2}{n-1}}.$$

$\overline{R}$: arithmetic mean of $R_i's$. for more details refer to (Hull, 2012; Jaber, 2017).

$$\psi^{H}(t)=\begin{cases}1, & 0\le t\le \frac{1}{2}\\ -1, & \frac{1}{2}\le t\le 1\\ 0, & \mathit{Otherwise}\end{cases}$$

Where:

$$l_k=\sqrt{2}\int_{-\infty}^{\infty}\phi(t)\phi(2t-k)dt=\begin{cases}1, & 0\le \mathrm{t}\le 1\\ 0, & \text{otherwise}\end{cases},$$

$$\int_{-\infty}^{\infty}\psi(t)dt=0,\ \int_{-\infty}^{\infty}|\psi(t)|<\infty,\ \int_{-\infty}^{\infty}\frac{|\psi_1(\omega)|^2}{|\omega|}d\omega<\infty.$$

2.2 Wavelet transform

Wavelet transform was defined as:

$$\psi_{i,j}(t)=2^{j/2}\psi(2^{j}t-k),i,k\in Z,Z=0,1,2,...$$

ψ:is the real-valued function having compactly supported (Chiann and Moretin, 1998), (Gencay et al, 2002). Generally, WT were calculated by using dilation equations and defined as:

$$\phi(t)=\sqrt{2}\sum l_k\phi(2t-k),\psi(t)=\sqrt{2}\sum h_k\phi(2t-k).$$

$\phi(2t-k),\psi(t)$:are the father and mother wavelets respectively, these two functions are producing the approximation and details coefficients respectively (Gencay et al, 2002). In this research the simplest and oldest WT will be used which is Haar WT (HWT) this model is defined as: In HWT the mother WT should stratifies: Where $\phi_1(\omega)$ presents WT (Gencay et al, 2002). For more details about WT and its application refer to (Al Wadi and Tahir Ismail, 2011; Al Wadi, 2017; Al Wadi et al., 2011; Al Wadi, 2013).

3. Methodology and results

In order to modeling the volatility data for the insurance time sereis data the daily time series data from the insurance sector is used from 2010-2018. HWT transforms the time series data into two sets; approximation and details coefficients. The details coefficients will be adopted in this research since this series has the fluctuations and the behavior of the data used.

3.1 Volatility data decomposition

The volatility data is decomposed as presented using HWT in Fig.1 for Jordanian insurance sector. It is noticeable that, S= a5+d1+d2+d3+d4+d5 where a5 represents the approximation coefficients while from d1 to d5 represent the details coefficients which will be used in this article. Therefore, we can adopt d1 since the fluctuations are very clear so stating from the first observations (2010) then the data is very fluctuated, nonlinear, non-stationary. Therefore, the percentage of volatility is high in this year because the crisis 2009. The high fluctuations are continued until the observation number 700 which means the year number 2013 since the political situation in the neighbor's countries. Then the sector become more stable and the volatility is less than before. In general, Insurance sector is a main mechanisms of the financial system. It protects properties and individuals from risks, also plays a main record in supporting economic development. This sector contributes the GDP to reach about 2.14% in 2016.Since this sector is important , therefore many regulations in year 2016 have approved as follows: Apprising the supervisory frameworks of the insurance business, developing the financial solvency of the insurance companies, establishing regulatory requirements, applying the prudential regulatory requirements for the investment policies of the insurance companies and improving corporate governance requirements for the insurance companies. Therefore, the mentioned regulations help the sector to be more stable with less fluctuations.

4. Conclusion

In this paper, the volatility of the insurance time series data is modeled using Haar wavelet transform (HWT). Therefore, the especial event, outlier values abrupt change and regime shits were detected and discussed based on the HWT's transforms decompositions. As a result the authors have found that HWT is suitable method for decomposition and studying the volatility behavior.

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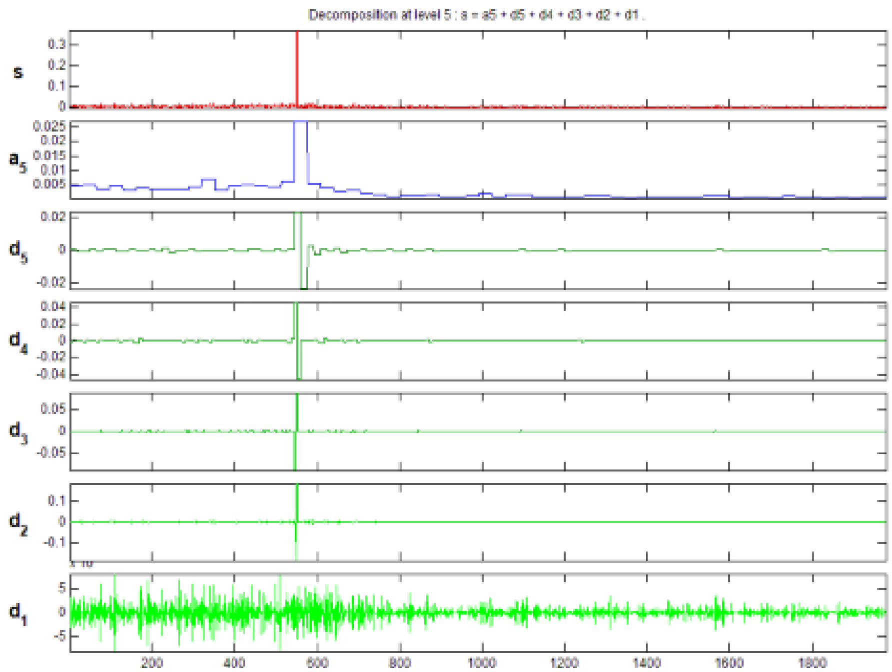

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