MODIFICATION OF ACCURACY ESTIMATION USING STOCK MARKET DATA

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

Abstract. It is well known that the simplest way of estimation of statistical parameters is the method of least squares using linear functions. However, the problem with this method is in how to find out a linear observations. estimation accuracy is very important concept in many field such that; medicine, humanities, engineering, industry, economics and others since an unbiased vision is crucial in order to support the industry for decision making, also suitable data to obtain is, how estimates are completed, what factors encourage the choice of estimation methods and the current level of estimation accuracy. Therefore, this article purposes a novel technique in field of improving inference about population characteristic estimation, mathematical models were implemented in content of stock market data are collected from Amman stock exchange (ASE). Estimation accuracy directly will be implemented and Daubechies Wavelet transform (DWT) combined with interval estimation accuracy will be calculated also. As a result, the DWT combines with traditional estimation accuracy is better than traditional estimation accuracy directly. The results are implemented using (SPSS) and MATLAB.

Keywords: estimations accuracy, wavelet transform, amman stock exchange.

1. Introduction

Inferential statistics focused on sketch correct inferences about population characteristic using sample information. drawn a sample from a population , evaluated sample statistics on variable (X) and then make inference about variable (X) in the population from witch the sample drawn ([10]).

Stock market sample is drowning to realize the performance of the entire population. For example, the familiar stock market averages are samples designed to show the broader stock market and indicate its performance return. For the domestic publicly-traded stock market, populated with at least 10,000 or more companies, the Dow Jones Industrial Average (DJIA) has just 30 representatives; the S&P 500 has 500. Yet these samples are taken as valid indicators of the broader population ([3, 4]).

Recently, very important to comprehend the mechanics of sample estimation, especially with stock market data and have the insight to analysis the quality of research derived from sampling efforts. Therefore, recently the estimation accuracy and processes become very important topics. Consequently, in this article the estimation accuracy will be improved using one of the most popular spectral analysis functions which are called by Daubechies Wavelet Transform (DWT) by reducing the bound of error.

This study attempts to employ the proposed method to the daily stock market data from ASE. Selected estimation models are used in the proposed method comparison to assess its performance. Experimental results show that the modified method which is interval estimation with DWT is superior to existing method in terms of some accuracy estimation error measure. Section 2 introduces the literature of necessary used term. In section 3 the research methodology and its mathematical models will be presented. In section 4, the dataset, results and discussion will be presented. Finally, in section 6 the conclusion will be presented.

2. Literature review

In [1] discussed the efficiency of Islamic banks in the Middle East and North Africa region. For adjusting the estimation and estimating confidence intervals for the estimated efficiency scores at desired levels of significance ([2]). Has proved that the point estimate can be confusing, therefore, the interval estimation is better than the point estimation and they discussed maximum likelihood point estimates and confidence intervals depended on delta. The researcher improve model studies using both positive factor analysis and standard errors models ([3]) have found that the interval estimates can suitable for the irritation parameters in content of artificial price time series. [4] Explain confidence intervals for the single coefficient of variation and the variance of coefficients of variation using exponential distributions ([5]). Have found that the realistic likelihood process to give suggestion on the bivariate subsistence job of paired failure times by estimating the subsistence job of cut time with the Kaplan–Meier estimator ([6]). Have discussed the Analytical tools that for the parameter estimates using residual analysis and the Cook space for worldwide influence ([7]). Have focus on joint maximum estimation and semi-parametric estimation of copula parameters in a bivariate t-copula.

One of the most important paper is Bruzda in 2015 ([8]) since he discussed nonparametric estimator of random signals established on the Wavelet Transform (WT), he discussed stochastic signals rooted in white noise and abstractions with wavelet de-noising procedures using the non-decimated discrete wavelet transform and the awareness of wavelet scaling. He assesses properties of these estimators through extensive computer simulations and partially also analytically. WT estimator strong benefits over parametric maximum likelihood approaches as far as computational subjects are concerned.

Has transformed regression models to multiple linear regression models by discrete wavelet transformation ([9]). In case the number of analytical curves is huge. They also apply correlation established sparse regression technique to the caused high dimensional regression model. The original feature of sparse technique is the researcher execute sparsely consequence on the way of the estimate of the coefficient course in its place of the estimate itself and only the direction of the estimate is determined by an optimization problem. Comparing method with both functional regression methods and other WT grounded sparse regression approaches on together simulated data and four real data sets has evaluated, with the cases of single and multiple predictive curves. The results indicate that sparse wavelet regression methods are enhanced in removing local features and method.

WT is a well-known method in estimation, forecasting and other fields ([16, 17]). However, still some caps in the WT' literature is not fill up until today. Therefore, after intensive review in the estimation literature especially with WT, the researcher has found no paper has improved the estimation accuracy using DWT in content of stock market data. Therefore, this research is different from others because the researchers gathered stock market data from website of (ASE) using the closed price dataset from 1992 until 2017 in order to draw right inferences about population characteristic (mean, variance, stander deviation) through computing confidence interval using standard formula directly then computing and comparing the results confidence interval combined with DWT.

3. Methodology and mathematical models

3.1 Research framework

DWT is a good model in decomposing and it can notice much real fluctuation. Therefore, it will be used in this article to improve the accuracy of estimation process. The following figure will be presented the flowchart diagram for this article with its methodology:

Referring to the upper research framework, the methodology of this article can be summarizing as follows:

1. Decomposing the stock market data based on DWT.

2. Using the details coefficients in order to detect the fluctuations and outlier values from the data used.

3. Combining the smoothed coefficients with the standard confidence interval estimation to improve the estimation accuracy.

4. Comparing the results that generates from DWT with standard interval estimation with the results that generates from the standard interval estimation directly.

5. Selecting the best method that reduces the error term.

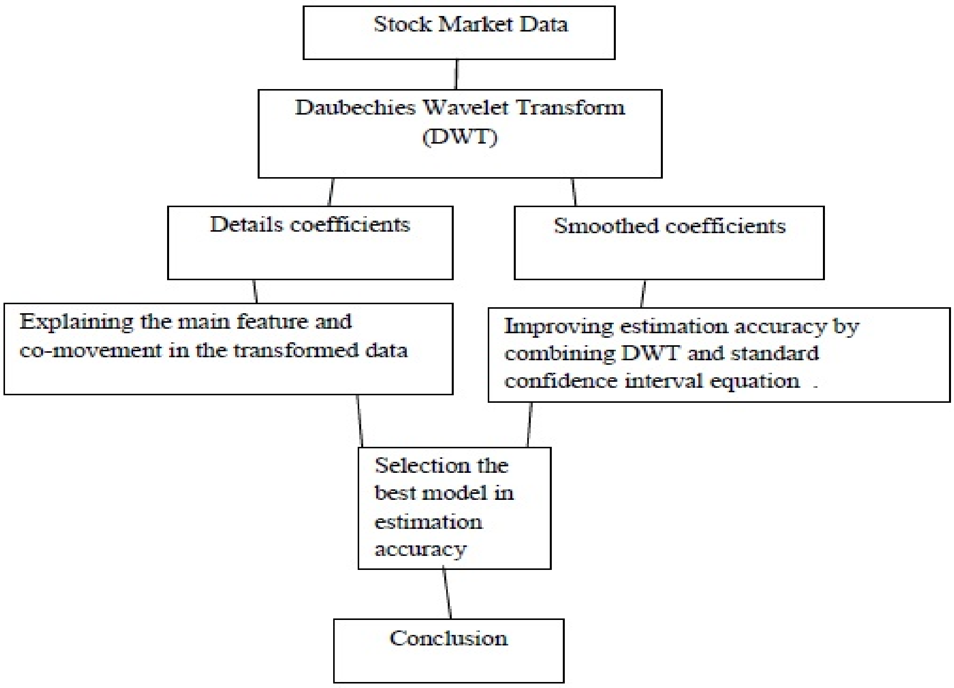

Figure 1: Research framework.

3.2 Interval estimation

One Population Mean can be estimated as $(\overline{x} \mp z_{\alpha,2}\sqrt{\frac{s}{n}})$ the interval estimate offered an estimation range where in which true population parameter might fall in statistics, interval estimation is the habit of sample data to compute an interval of likely values of an unidentified population parameter, in difference to point estimation, which is a single number. For more details about the interval estimation please refer to [1].

3.3 Wavelet transform

WT is used in many fields for prediction and estimation. The key aspect of DWT for financial analysis is decomposition by time scale. Wavelet transform (WT) is based on Fourier Transform (FT), which characterizes any function as the sum of the sine and cosine functions. WT is function of time t that obeys a basic condition ([11, 12, 13, 14, 15]):

$$C_\varphi = \int_0^\infty \frac{|\varphi(f)|}{f} df < \infty.$$

Where $\varphi(f)$ are the FT and a function of frequency f. WT is a mathematical tool that which has much application, such as image analysis and signal processing. WT has good dealing with non-stationary signals, or when dealing with signals that are localized in time, space, or frequency. There are two types of WT within a given family. Father wavelet defines the smooth and low-frequency parts of a signal, and mother wavelet defines the detailed and high-frequency components. In the following equations, (2a) represents the father wavelet and (2b) represents the mother wavelet, with $j = 1...J$ in the J-level wavelet decomposition ([14],[15])

$$\phi j,k = 2^{-j/2}\phi(t - 2^j k/2^j)\varphi j,k = 2^{-j/2}\varphi(t - 2^j k/2^j).$$

Where: J denotes the maximum scale sustainable by the number of data points. WT should stratify the following conditions: $\int \phi(t)dt = 1$ and $\int \varphi(t)dt = 0$

Time series data, i.e., function $f(t)$, is an input represented by WT, and can be constructed as a sequence of projections onto father and mother wavelets indexed by both {k}, $k = \{0, 1, 2,. \ . \ .\}$ and by {S}=2^j, {j=1,2,3,. . .J}. Mathematically, it is convenient to use a dyadic expansion. The expansion coefficients are given by the projections [15]:

$$Sj,k = \int \phi j,kf(t)dt, \quad dj,k = \int \varphi j,kf(t)dt. \tag{3.1}$$

The WT series approximation to $f(t)$ is defined by:

$$\begin{aligned} F(t) &= \sum Sj,k\phi j,k(t) + \sum dj,k\varphi j,k(t) \\ &\quad + \sum dj-1,k\varphi j-1,k(t) + ... + \sum d1,k\varphi 1,k(t) \end{aligned} \tag{3.2}$$

$$\begin{aligned} Sj(t) &= \sum Sj,k\phi j,k(t), \\ Dj(t) &= \sum dj,k\varphi j,k(t). \end{aligned} \tag{3.3}$$

The WT is used to evaluate the approximation and details coefficients based on equation 3.3.

The HWT was improved and developed the frequency–domain characteristics by DWT. However, there is no specific formula for this method of wavelet transform. Thus, we tend to use the square gain function of their scaling filter, it is defined as:

$$g(f) = 2\cos^l(\pi f)\sum_{l=0}^{\frac{l}{2}-1}\begin{pmatrix} \frac{l}{2}-1+l \\ l \end{pmatrix}\sin^{2l}(\pi f). \tag{3.4}$$

Where l : Positive number and represents the length of the filter ([11]).

4. Dataset, results and discussion

In order to illustrate the effectiveness of WT in estimation the Daubechies function is applied for daily closed price for the time period from 1992 until 2017

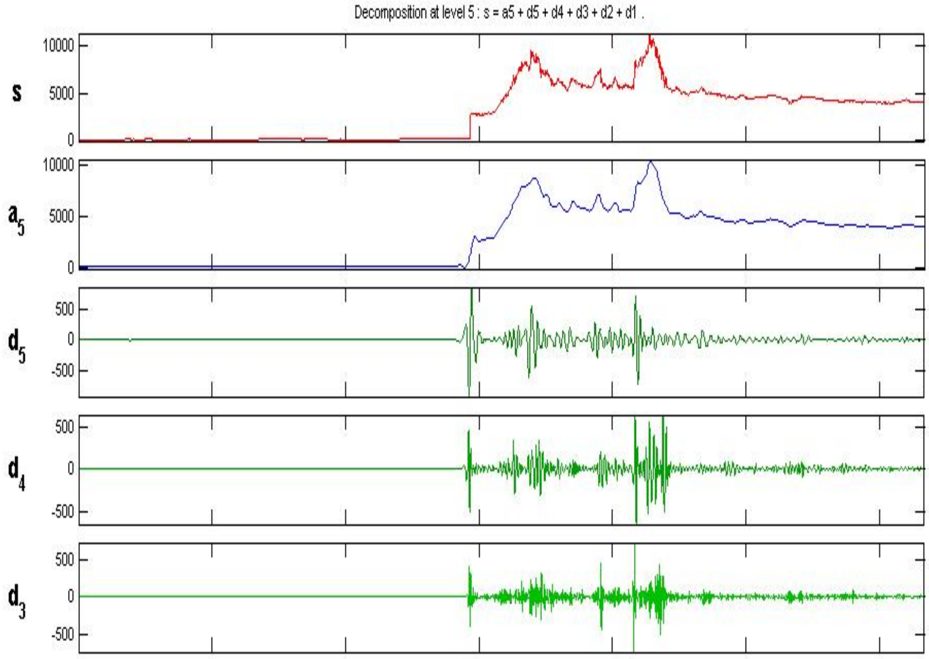

Figure 2: DWT analysis until level3.

were selected from ASE. The analysis with its behavior for the dataset using the mentioned models will be presented.

Referring to the up Figure, then notice the following:

1. In this article the decomposition for level 3 has used. However, the author can use any other level since the smoothed data only is used estimation accuracy. Therefore, the level of decomposition is unjustified.

2. DWT function is used in this article since it is well known that Daubechies function is the best function in the WT field.

The application of the DWT to the historical data decomposes them into a variety of resolution levels that expose their essential structure and it generates detail coefficients at each one of the three decomposition levels. In DWT, the three levels of decomposition can be carried out by the DWT using the following equation: S=a3+d3+d2+d1. S refers to the original signal which is represented in the topmost part of Figure 1. Then the next part consists of one approximation level (a3), a3 which shows the plot of the approximation coefficients for the transformed data using DWT. The following parts of d1, d2 and d3 represent the details levels, whereby, d1 is the plot of the first level of the details coefficients, d2 is the plot of the second level of the details coefficients and d3 is the plot of the third level of the details coefficients. Any of these three levels (d1, d2 and d3) can be adopted for explaining the data. Starting with d1 which is the first details level (see Figure 4.3), the transformed data is filtered from d1 until d3 through the details levels. As can be seen the data becomes smoother in d2, since the amount of data will be reduced automatically in the hope of obtaining a suitable level for detecting the stock market behavior. In this regard, we notice that at level d3 most of the fluctuations and high frequencies appear after the observation number 3000, which is from 2004 onwards. The reason of these fluctuations can be refer to the following events:

1. 1n 2003: Publication of annual book “Emerging Jordan 2003” by Oxford Business Group. Also High Performance of public shareholding companies and The California Public Employees’ Retirement System in USA selected Jordan together with 13 other countries as recipients of funds for the development of emerging markets.

2. In 2004, it was a golden year for all ASE performance indicators. We notice that in d3 Fig. 1 there was a spike between the observations 3000 and 3500 which indicates a high volume of trading occurred in this year. Some of the important events that contributed to this were: Inviting foreign and local investors to give some attention to ASE by participating in the specialist meeting “Enhancing the Capacity of Financial Markets to Promote Intra Investment among IDB Member Countries”.

3. In 2005, ASE participated in ‘Workshop on Exchange Technology” in the USA to discuss some issues related to technologies used in stock exchanges also A report on the most attractive 27 emerging stock markets placed the ASE as 10th. And The ASE attracted a lot of visitors and interested people; Arabs and foreign ministers, which motivates the ASE to increase the number of investors.

4. In 2006 the fluctuations are still very high as a result of some events such as: Securities Depository Center in the ASE initiated new services for investments and new instructions for the purchase of share of public shareholding companies. These instructions enhanced the general investment climate. New instructions for dealing with subscription rights in order to preserve the rights of investors; to protect the investors; to provide cash for investors, and to enhance the level of its performance.

5. From 2007 to 2009: Between 2007- 2009, many events occurred in the ASE which effected the stability of the stock market such as: Dow Jones Composite Index currently includes component stocks of 10 of the 32 member states of the Federation of Euro-Asian Stock Exchanges. The exchanges included ASE and other stock markets. The International Organization of Securities Commission selected the Executive Chairman of the ASE as a member of a special committee.

   After the year 2009 and referring to the level d3, then the fluctuations become more stable. However, there are some event such that;

6. 2009- 2017 Signing an Memorandum of Understanding between Amman Stock Exchange and the Egyptian Exchange's has finished stage of preparing the new website. New Version of the Electronic Trading System. The meetings of the Working Committee of the Federation of Euro-Asian Stock Exchanges (FEAS).S&P Indices and Arab Federation of Exchanges Create S&P AFE 40 Index and ASE receives an economic delegation from the French Embassy.

In this article the results of estimation accuracy which was comparing between confidence intervals use standard formula directly and DWT with Confidence intervals using standard formula estimation. The researcher found that the estimation using confidence interval directly gives less information about the population and not very significant While Confidence intervals with DWT representation more exact about population parameter characteristics; the following table shows the results about the estimation process.

Std. Error	interval estimation	Wavelet Transform
Std. Error of mean for one sample	**2.561**	**0.892**
Std. Deviation for one sample	**1.002**	**0.148**

Table 1: represent the standard error for data used using the method used

Refer to Table 1 then it is noticeable that the estimation has improved and the modified method is better that estimation directly this is return to the ability of DWT since the standard error has been reduced from 2.561 to 0.892 and the Std. Deviation also reduced from 1.002 to 0.148 this results implies to the ability of the DWT in improving the estimation accuracy.

5. Conclusion

The overall objective of carrying out this article is to investigate the comparative and contrastive efficiency and accuracy and hence suitability of DWT in the decomposition, processing and estimation of stock market data based on a sample dataset taken from the ASE. Based on the findings of the experiments, the significant contributions of this study can be summarized as follows:

- The experiments have shown that the level of estimation accuracy is improved in ASE when DWT is combined with a suitable standard estimation model compared to using standard estimation model directly.
- The experiments in this study have shown that the DWT is a good model in decomposing the data in content of ASE and detecting the events from

the dataset. Therefore, it would be to its advantage to implement DWT applications to assist in solving some of its financial issues such as uncertainties, volatility and structure breaks which will be suitable for investment sector.

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