



THE USE OF THE SHRINKAGE WAVELET TRANSFORMS IN ESTIMATING THE INTEREST RATE ON LONG-TERM LOANS USING DIFFERENT THRESHOLD RULES WITH APPLICATION

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Article history:	Abstract:
<p>Received: July 1st 2022 Accepted: August 1st 2022 Published: September 11th 2022</p>	<p>Wavelet transform applications began to enter the field of statistics as a powerful tool in the field of data smoothing. Considering the wavelet method in statistical estimations is one of the very powerful methods that were spread by the Estimators Wavelet Shrinkage (where wavelet shrinkage is a method or method for removing signal distortion (Signal) based on On the idea of performing Thresholding for the wavelet coefficients and resulting by applying the wavelet transformation, Donoho and others suggested estimation methods for the wavelet regression function. On long-term loans, these methods are the soft threshold, Carrot threshold, and the first improved threshold, in addition to taking the value of the Visushrink threshold, where simulation experiments were used using three test functions at a sample size (64) and noise ratios (5), in general, it shows the superiority of the estimation methods using the value of The visu soft threshold is followed by the improved visu garot method using the visu threshold value. Lamy uses a soft threshold rule and it is more explanatory because the data has a non-linear model.</p>

Keywords: Shrinkage Wavele ,Wavelet Transformation. Threshold Value. Thresholding Rules

INTRODUCTION

Since the beginning of the nineties of the last century, applications of wavelet transformation began to enter the field of statistics as a powerful tool in the field of data smoothing. Considering the wavelet method in statistical estimates is one of the very powerful methods that have been spread by the Estimators Wavelet Shrinkage (where wavelet shrinkage is a method or method to remove Signal distortion is based on the idea of performing a Thresholding of the resulting wavelet coefficients By applying a wavelet transformation, the goal is to retrieve an unknown function, for example, g , based on the noise-polluted data samples. Make very general assumptions about g such that it belongs to a particular class of functions Donoho and Johnstone (1994) Donoho et al. (1995) Nonlinear wavelet estimators have been introduced into the nonparametric regression by thresholding that usually amounts to an evaluation of each term for estimates of coefficients in the expansion Experimental wavelet for the unknown function If the parameter estimate is large enough in absolute terms - that is, if it exceeds a predetermined threshold - then it is celebrated. Keep the corresponding term in the experimental wavelet expansion (or reduce it to zero by an amount equal to the minimum); Otherwise, it was deleted. Therefore, the use of a general threshold

usually disintegrates with great difficulty in providing an appropriate threshold value for the wavelet threshold coefficients at all desired levels. This prompted the researchers to find functions and threshold values that suit that problem to obtain efficient wavelet estimations using deflated wavelet regression and different threshold rules.

2. Wavelet Transformation

Wavelet transform is a mathematical tool that can be used to split functions and data into different frequencies Wavelet transform has been a popular research topic in much technical research: mechanical, electronics, communications, computers, biology, medicine, astronomy, etc. In the field of signal and image processing, it is an alternative transformation to the previous transformations that were suffering from some weaknesses and shortcomings, such as the transformation of sparklers and sparklers for short time, which were limited to the representation of the signal on the time domain and neglecting the frequency or vice versa, and not taking the change in the window width and contented with a fixed window, so These wavelet transformations, which are characterized by the representation of the signal in both time domains - frequency and bandwidth vary with the nature of the data. The wavelet is used as a window function (wavelet transformation) a flexible

window of time, which automatically narrows when observing high-frequency phenomena and widens when studying low-frequency phenomena. [1]

The wavelet transform has advantages over a sparkler transform for representing functions with discontinuities and sharp peaks, for accurately deconstructing and reconstructing finite, non-periodic or non-stationary signals and being of high efficiency and better results. In order to perform any information conversion process, the conversion process must be equal in the amount of information after performing the conversion and avoid losing part of it. Wavelet transformations are classified into Discrete Wavelet Transform and DWT Continuous Wavelet Transform

(CWT).), and it is preferable to use (DWT) as it is mathematically easier and better in interpreting the wavelet coefficients and a better way to deal with it than CWT)), Mathematically when performing any wavelet transformation by means of what is known as Thresholding, the wavelet is compressed with the first two functions called the mother wavelet function, so we get The wavelet coefficients to get the detailed coefficients (Detail $D(s,t)$, and the second is called the wavelet function the father or the measurement function to get the coefficients Approximation coefficients $A(s,t)$. Figure (1) shows the rapid wavelet transformation decomposition and reconstruction process. [2],[3]

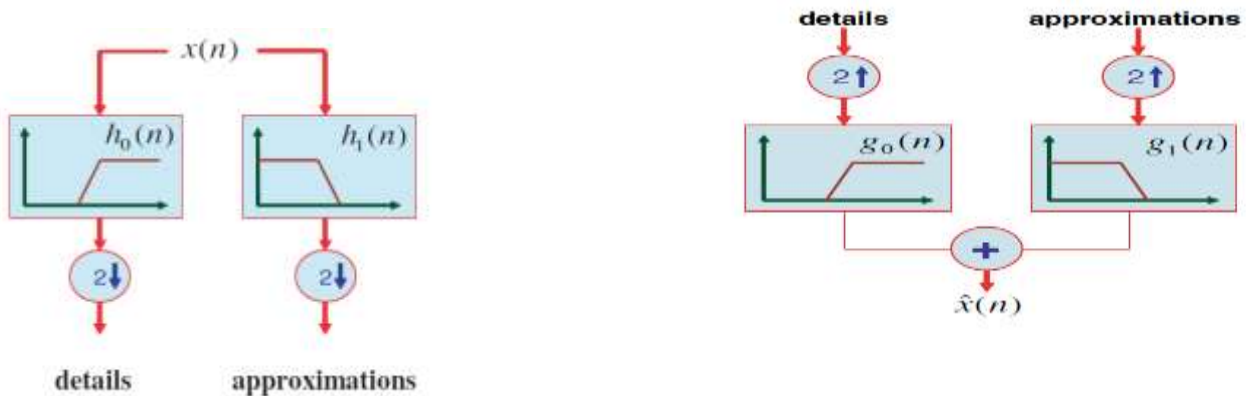


Figure 1 shows the decay and reconstruction of the fast wavelet transform [4]

Function Thresholding

The wavelet threshold is one of the fundamentals of wavelet transformation, whether it is discontinuous or continuous, and the threshold technique is a modern non-linear method used to reduce wavelet noise. Using what is known as wavelet shrinking, the wavelet shrinking process was introduced in (1995) by Donho, which works On the Moygi modulus one at a time in its simplest form, each coefficient is the threshold. By comparison with the threshold, there are several types of frequently used thresholding functions such as, Soft Thresholding, Garrote Thresholding, Improved Thresholding (1) and as It is explained below: [5]

Soft Thresholding

Also proposed by Dohono, this method is a nonlinear, solid-threshold-like function that sets the coefficients below the τ threshold to zero while the significant coefficients are reduced by an absolute threshold value. That is, (round it to zero) to get rid of anomalous values and get the best estimator as shown in equation (2-30), the low-noise signal is smooth and regular like the original signal, and the decay

coefficient is coherent, but it loses part of the high-frequency coefficients above the threshold. Continuous function, but it has a constant deviation. In contrast to the solid threshold, the variance of the estimated function is greater and the amount of bias is small, but it is greater than in the solid threshold, and the average error squares is as large as possible and is expressed by the following formula: [7],[8] ,[6]

$$Th_{soft} = \begin{cases} sgn(Y) (|Y| - |\tau|) & \text{if } |Y| > \tau \\ 0 & \text{if } |Y| \leq \tau \end{cases} \dots\dots(1) \quad [17]$$

is a representation of the estimated wavelet coefficients, (Y) is a representation of the fuzzy wavelet coefficients, τ is the threshold, and sgn is a symbolic multi-sided Signum function which returns 1 if the element is greater than 0, 0 if it is equal to zero and -1 if it is less than 0?[8],[6]

Garrote Thresholding

_GaoHong Ye proposed the Garrote threshold function in order to overcome the shortcomings of the previous threshold functions as it treats the discontinuity in the



hard threshold function and the bias in the soft threshold function and presents the resulting wavelet threshold estimators, in small samples, and has the advantages of both the hard threshold function and the soft threshold function, which is In which the effect of noise reduction is better than the previous threshold functions and better continuity with expressions, and it is expressed in the following formula:[9],[7]

$$Th_{Garrote} = \begin{cases} Y - \frac{\tau^2}{Y}, & \text{if } |Y| > \tau, \\ 0, & \text{if } |Y| \leq \tau \end{cases} \quad \dots\dots(2)$$

Improved Thresholding(1)(M1)

This method was also proposed by Lu Jing-yi et al., to address the remaining weaknesses of the previous functions by adding a tuning operator which consists of a complex exponential function $[\exp] \wedge 3 [\alpha(|Y| -$

$\tau)/\tau$, which has greater adaptability; α is the natural number that can be freely modified and the values of α vary with different sign, the improved threshold function has the characteristics of a soft threshold function when, $\rightarrow \infty$ $[[Th] _ (Improved(1)) \rightarrow Y|Y|$, the improved threshold function is based on $[[Th] _ (Improved(1)) = Y$ as an asymptote, the improved threshold function has continuity, the improved threshold function overcomes the shortcomings of continuous and discontinuous skew, taking advantage of the advantages of the previous functions so, in theory, the noise reduction effect is better. Which is expressed in the following formula: [7]

$$Th_{Improved(1)} = \begin{cases} sgn(Y) \{ |Y| - \frac{\tau}{\exp^3[\alpha(|Y| - \tau)/\tau]} \}, & \text{if } |Y| > \tau \\ 0, & \text{if } |Y| \leq \tau \end{cases} \quad \dots\dots(3)$$

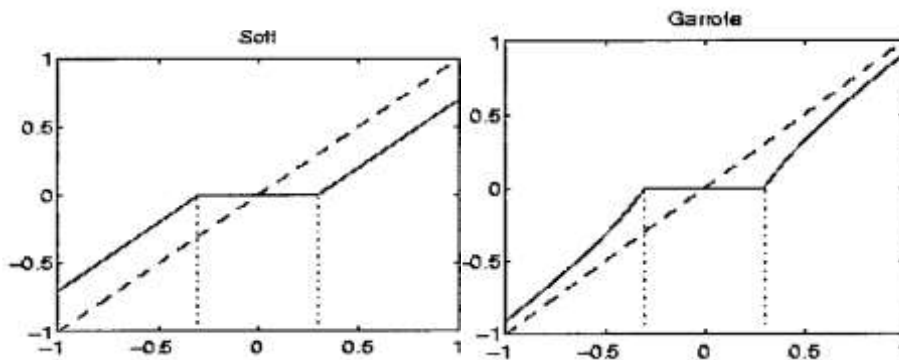


Figure 2 shows the Soft Threshold Function and the Garrote Threshold Function

(Threshold Value)

There are various ways to choose the threshold value τ , which is an important parameter in the wavelet reduction algorithm to reduce signal noise and is very important and necessary in the wavelet conversion process. If the threshold value is too small, there will still be a lot of noise and the estimator will be oscillating, and if the threshold value is too large, some important features of the signal may be filtered, for this reason the appropriate selection of the threshold value has a role in the accuracy of the estimation because the wavelet coefficients pass through the threshold limit, Therefore, optimization of the threshold value is an important criterion for obtaining a minimum MSE. There are many methods presented by (Jonston & Donoho) to determine the threshold value, among these methods: [10] , [6]

(Sure Thresholding)

This method was introduced by Donoho and Johnstone, which is achieved by the principle of Stein Unbiased Estimation (SURE) Estimation (Stein Unbiased Risk) for each j-wave level, which is

indicated at the threshold-dependent level, and the amount of this bias is expressed by the following formula :[10]

$$) = N - 2 \sum_{k=1}^N I(|djk| \leq \tau_j) + \sum_{k=1}^N \min (|djk| \leq \tau_j)^2 \cdot (\tau_j SURE, d_{j,k} \dots\dots(4)$$

djk They represent the wavelet coefficients, which are orthogonal, as they result from the wavelet transformation, which is orthogonal, and the final formula for calculating the value of the Sure Thresholding threshold is as in the following formula:

$$\dots\dots(5) \tau_{j,sure} = argmin_{0 \leq \tau \leq \sqrt{2 \log(N)}} SUR(\tau_j, dj_k)$$

where τ is the value that underestimates the amount of Stein's unbiased risk. Sure Shrink reduces mean squared error

[11](Visushrink Thresholding)

This method is considered an improvement of the comprehensive threshold method, as it addresses the weakness of this method through its good

performance even with an increase in the sample size, as it gives a more homogeneous and preparatory estimate. For n , which leads to a loss of many wavelet coefficients with noise, and therefore the threshold does not perform well at interruptions in the signal, and Visu Shrink does not deal with reducing the mean square error. This method can be explained according to the following formula:

$$\sigma_n \sqrt{2 \log(n)} \tau_{\text{Visushrink}} = \dots\dots\dots(6)$$

σ_n It is the standard deviation of the noise level, which can be found through the following relationship:

$$\hat{\sigma}_n = \text{MAD}(Y) / 0.6745 \dots\dots\dots(7)$$

Where MAD is the absolute median of the wavelet coefficients

(Signal to Noise Ratio)(SNR)

It is a method of comparison between the value of the signal and the value of the noise associated with the signal, and it is often used to know the quality and accuracy of some methods in removing noise to

improve the signal. that accompanied the signal removal process, and in order to raise the level of improvement of the signal-to-noise ratio in general, it is necessary to either raise the signal power or reduce the level of noise, or both, and sometimes pre-values for the noise-to-signal ratios are assumed in simulation experiments, often equal to SNR = 3 , SNR=5 and SNR=7. Or calculate it through the following formula:

$$\text{SNR} = \frac{\sigma_{\text{signal}}}{\sigma_{\text{noise}}} \dots\dots\dots(8)$$

Test Function

:[12](Doppler function)

$$\text{sin} \{2\pi(1 + \epsilon)\}, \epsilon = f_1(x) = \{x(1 - x)\}^{\frac{1}{2}} \dots\dots\dots(9)$$

:[12](Heavisine function) دالة -2

$$f_2(x) = 4\sin 4\pi x - \sin(x-0.3) - \sin(0.72-x)k \dots\dots\dots(10)$$

:[12](Blocksfunction) دالة -3

$$f_3(x) = \sum h_j k(x-x_j), \quad k(x) = \{1 + \text{sgn}(x)\} / 2 \dots\dots\dots(11)$$

$$x_j = (0.1, 0.13, 0.15, 0.23, 0.25, 0.40, 0.44, 0.65, 0.76, 0.78, 0.81)$$

$$h_j = (4, -5, -4, 5, -4.2, 2.1, 4.3, -3.1, 2.1, -4.2)$$

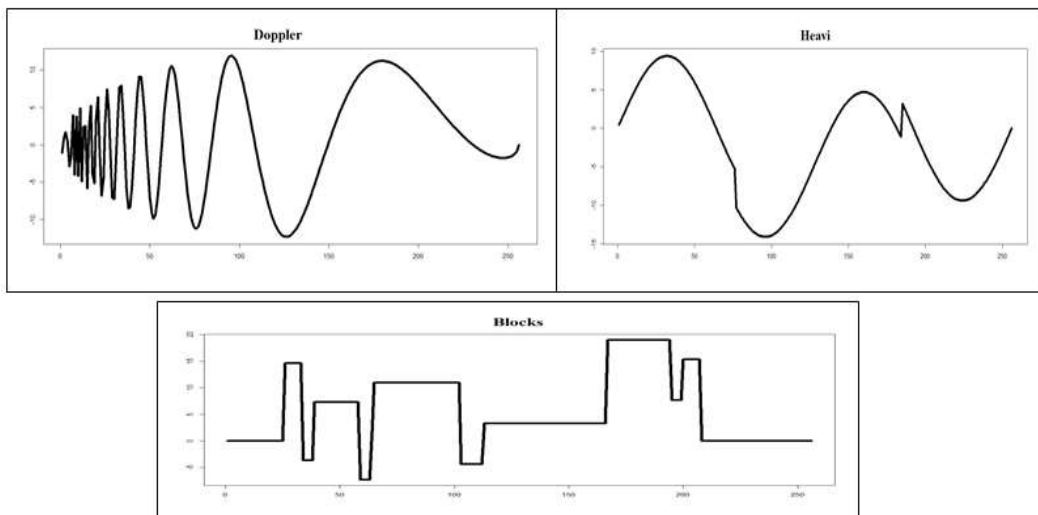


Figure (3) Test function

The practical side of real data:

The data for the research was collected using the data of the Central Bank of Iraq, as we were provided with the monthly rates for both long-term loans as an approved variable from (1/1/2008 to 04/31/2021), as for the explanatory variable, the bank liquidity ratio data was taken, which is One of the factors that effectively affect the amount of long-term loans, as well as being ideal data because they are limited to (0.1) and equal in time, which makes them suitable for

the estimation methods used. According to the study, long-term loans are greatly affected by the amount of the liquidity ratio One of the most important stages of model building is to determine the dependent variable and the explanatory variable based on the nature and type of data under study.

RESULTS:

1. In general, we note the superiority of the estimation methods using the visu soft threshold value, followed

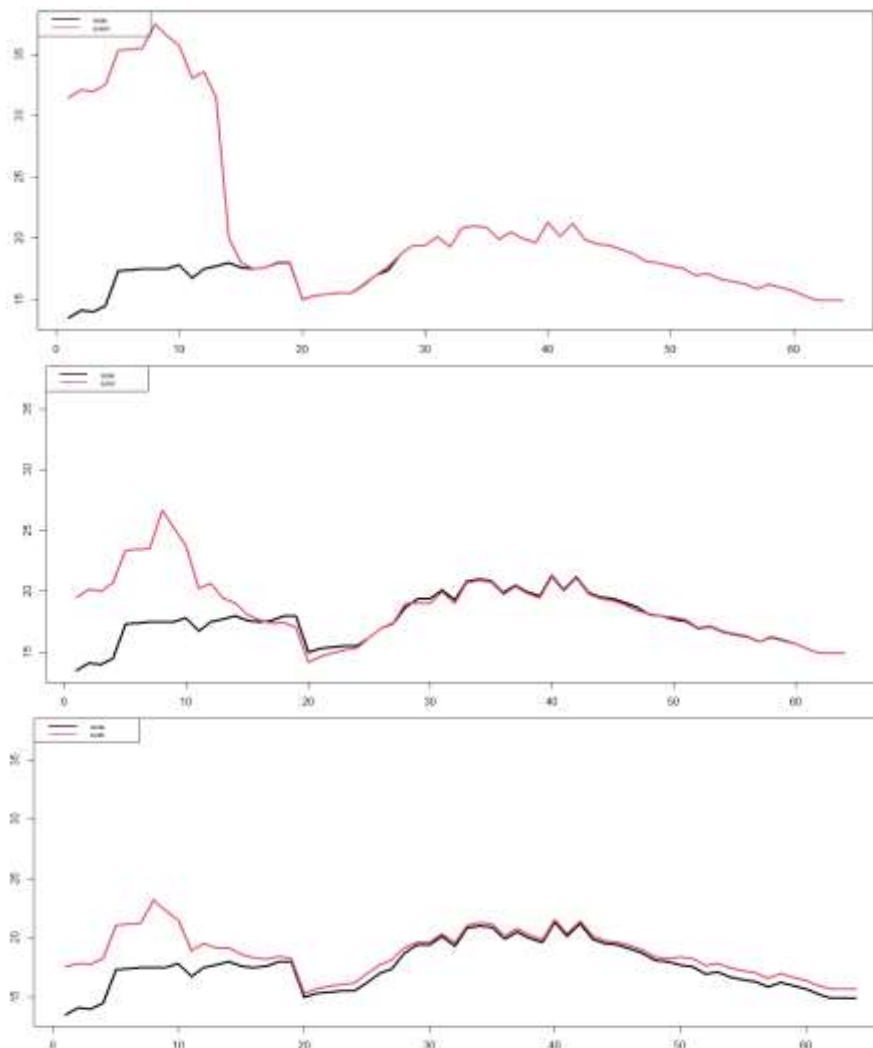


by the improved visu garot method using the visu soft threshold value.
 2. In general, we note the superiority of the non-parametric model using a soft threshold rule and its being more explanatory because the data has a non-linear model.

3. It turns out that bank liquidity explains 40% of the change in the value of long-term loans and 60% is explained by variables that were not included in the model.

Table (1) shows the MASE criterion for comparing estimates of the data for noisy sample sizes $n=64$, and a signal-to-noise ratio $SNR=5$

n=64			
	Visu Soft	Visu garot	visuM1
methods	0.147222067	0.212261112	0.22942102
Mse			



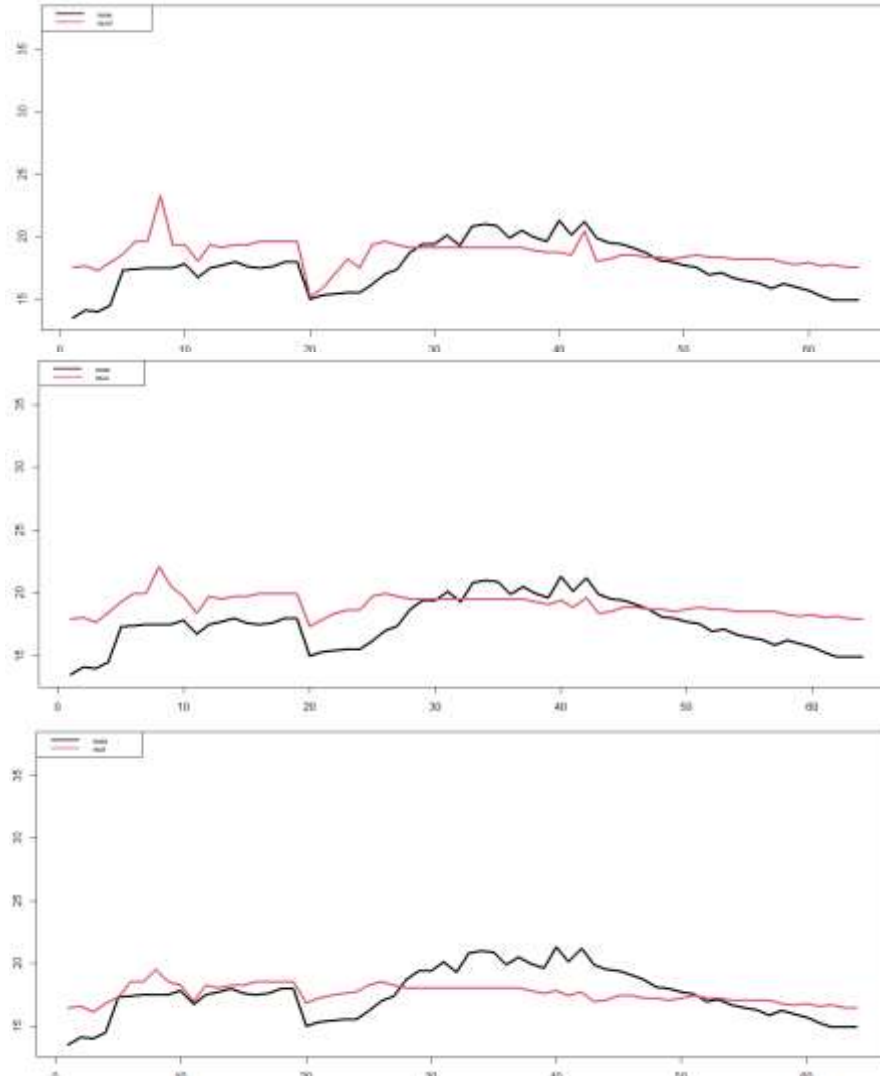


Figure (4) shows the real and estimated values of the dependent variable Y using the distortion ratio (5) and sample size (64)

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