Effects of Exchange Rate Uncertainty on Turkish Foreign Trade: Wavelet Analysis

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Abstract

In this paper, wavelet method used to analyze the effects of Exchange Rate (ER) on Foreign Trade Rate (FTR) for the period of 1991 to 2011. Data based on monthly records of the Turkish treasury. The technical analysis of continuous and 1-D discrete package has been applied in data. Wavelet techniques can help to detect abrupt changes and trends of data. Firstly, deals with an introduction of wavelet technique for its proper understanding. We discuss basic ingredients of the wavelet methodology and data in later. After that correlations of economical parameters are given. Finally, deals with results and conclusion.

Keywords: wavelet transforms, unit-root test, cross correlation, de-noising

1. Introduction

Understanding of economical parameters such as Consumer Price Index (CPI), inflation, Exchange Rate (ER), gross domestic product (GDP), stock exchange rate, etc. that have been the subject of both experimental and mathematical research for a long time. But the use of wavelet and fractal methods has begun recently for better understanding of the economic fluctuations and for the planning of future development.

Analysis of Foreign Trade Rate (FTR) and Exchange Rate (ER) may provide valuable information about the pressure forces on developing economy. Application of wavelet method may help to discuss foreign trade rate analysis of Turkey.

Wavelet methodology is comparatively a new area of human knowledge which has been found very useful for analyzing signals that are a periodic, noisy, intermittent and transient. Wavelet analysis has been applied by now in the study of a multitude of diverse physical phenomena from climate analysis to analysis of financial indices, from heart monitoring to the oil exploration and sensing technologies.

For many time series wavelet packets may be of more use as they provide a wider choice of decomposition of the frequency domain. Wavelet packets (WP) transforms are a generalization of the discrete wavelet transform. It is a wavelet transform where the signal is passed through more filters than the discrete wavelet transform (DWT). In DWT, each level is calculated by passing the previous approximation coefficients thorough a high and low pass filters (Yang et al, 2009). However in the wavelet packet transform or wavelet packet decomposition, both the wavelet and scaling coefficients are decomposed for n levels of the decomposition the WPD procedures $2\ n$ different sets of coefficients as opposed to $(n+1)$ sets for DWT (Razaz, 2011)

Wavelet package is one of the alternative methodologies to Fourier Transformations. This study coves some applications of 1-D Wavelets and Wavelet Packages (Barton, 2002; Haung et al, 2004; Puplava, 2004; Manchanda et al, 2005).

Wavelets are basis functions which are derived from mother wavelet by translations and dilations, $\psi(t)=\sqrt{2}\sum_{k} g_k \phi(2t-k)$, in function space. The basis function in turn can be derived from a scaling function $\varphi(t)$ of a multi-resolution analysis through the wavelet equation.

The scaling function φ and the basic wavelet are ψ the two lowest order functions of a family of function generated by the recursions $w_{2n}(t)=\sqrt{2}\sum_{k} h_k w_n(2t-k)$ and $w_{2n+1}(t)=\sqrt{2}\sum_{k} g_k w_n(2t-k)$ where the coefficient $\{g_k\}$ and $\{h_k\}$ are used in wavelet transform and they are called filter coefficients or simply filters. The filter $\{h_k\}$ corresponds to a low pass filter, $\{g_k\}$ to a high pass filter. Their Fourier transforms are called frequency response functions or transfer functions. The functions $w_{2n}(t)$ and $w_{2n+1}(t)$ are called wavelet packets.

2. Materials and Methods

2.1 Data: Turkish Foreign Trade Rate and Exchange Rate Fluctuations

After 1980, Turkey has its economic development policy of "industrialization of import substitution" is replaced by "export-oriented growth strategy," in the period 1980-2011, exports from Turkey increased by 2.9 billion to $134.9 billion. It was not only a quantitative change of exports, but the composition of the exported goods has also changed significantly.

The integration of the Turkish economy on the global markets has been gradually increased.

The share of external trade in the economy has increased considerably since 1980, the volume of external trade consisted of 8.3 per cent of GDP in 1970, whereas this proportion has increased to 1980, 1990 and 2000 15.3h 23.2 and 30.8 per cent respectively. In 2011, the volume of external trade to GDP has increased to 48.6 %.
In 2000, the volume of external trade was of 82.2 billion dollars, while the ratio of exports / imports was 51 %, and at the end of 2011, the volume of external trade has increased to $375.748 billion, while the ratio exports / imports was 47.8 %. Consequently, the ratio of exports / imports of Turkey in 2011 lower than the 2000.

In developing countries there has been an actual discussion on eligible ER policy that focuses on fluctuations amount of external and internal effects. These fluctuations in ER directs the amortization of expenses of imports for national products and presumably change the economic performance (Kandil et al, 2009).

The success of the devaluation of the currency in the promotion of the trade balance depends largely on transfer of the request in the right direction and the quantity and on the export power to compensate demand for extra products (Guitian, 1976; Dombusch, 1988).

In devaluation of the currency decreasing prices of export goods and raising prices of import goods.
If there is trade balance and the trade structures are stable, these situation make gaps in prices.
In summary devaluation, increases both net exports and the cost of production, in contrary decreases the net exports and the cost of production.

The results of the various impacts of changes expected and unexpected in ER clearly illustrate on the macro-economic environment in Turkey (Bahmani-Oskooee, 2009).

Forecasting relies on a predictive function (a predictor) which uses a known part of a time series to generate a future prediction. References (Nason and Saptines, 2002; Manchanda et al, 2005; Wong, 2003) are devoted to wavelet and wavelet.

The data from Turkish treasury recorded between1991-2011 is processed. Each data are examined by using MATLAB Wavelet Package program.

Time series forecasting is use of model (Mathematical model or other type of models) to forecast future events based on known past events, that is to forecast future data points before they are measured. Methods for time series analysis are often divided into two classes: frequency domain methods and time domain methods. The former centered around methods spectral analysis and recently Wavelet analysis, and can be regarded as model price analysis well-suited to exploratory investigations. Auto–Correlation and Cross Correlation are important notions for time series analysis of a single and two series. The cross-correlation is a measure of similarity of two signals of ER and FTR series.

2.2 Materials and Methods

2.2.1 Wavelet Analysis

In this section we shall give some basic definitions about wavelet transform. Wavelet is families of small waves generated from a single functions $f(t)$ which is called mother wavelet. A sufficient condition for a function $f(t)$ to qualify as a mother wavelet is given as (Huang, et al, 2004).

$$\int_{-\infty}^{\infty} |f(t)|^2 dt < \infty \tag{1a}$$

The Fourier transform F of f(t) is defined as

$$F(w) = \int_{-\infty}^{\infty} f(t) e^{iwt} dt < \infty \tag{1b}$$

A function $\Psi(t)$ satisfying the following condition is called a continuous wavelet [3]:

$$\int_{-\infty}^{\infty} |\Psi(t)|^2 dt = 1 \tag{2a}$$

and

$$\int_{-\infty}^{\infty} |\Psi(t)| dt = 0 \tag{2b}$$

Higher order moments may be zero, that is,

$$\int_{-\infty}^{\infty} t^k \Psi(t) dt = 0 \quad \text{for } k = 0,1,\ldots,N-1$$

The wavelet transform of $f(t)$ denoted by W_f (a,b) is defined as:

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \Psi\left(\frac{(u-b)}{a}\right) f(u) du = \int_{-\infty}^{\infty} f(u) \Psi_{a,b}^{(u)} du \tag{3}$$

Where

$$\Psi_{a,b}^{(u)} = \frac{1}{\sqrt{a}} \Psi\left(\frac{(u-b)}{a}\right) \tag{4}$$

Here “a” is a scaling parameter, b is a location parameter and $\Psi_{a,b}^{(u)}$ is often called continuous wavelet (or daughter wavelet) $\Psi(u)$ is the mother wavelet.

If $\Psi_{j,k}^{(u)} = 2^j \Psi\left(2^j u - k\right)$ is an orthonormal system, that is;

$$\int_{-\infty}^{\infty} \Psi_{j,k}^{(u)} \Psi_{m,n}^{(u)} du = \delta_{j,m} \, \delta_{k,n} \tag{5}$$

Then Ψ is a wavelet and the admissibility condition

$$C_\Psi = 2\pi \int_{-\infty}^{\infty} \frac{|\Psi(w)|^2}{w} dw < \infty \tag{6}$$

is satisfied.

$|W_f(a,b)|^2$ is called the scalogram of the function f and it can also be interpreted as energy density.

$$\int_{-\infty}^{\infty} |W_f(a,b)|^2 \, db = W(a) \tag{7}$$

which is called the wavelet variance or wavelet spectrum. It may be observed that the scalogram can be represented either as three-dimensional plot or as a 2-dimensional grey scale image. In the following sections $f(t)$ will be considered as pressure height or air temperature deviations from mean values.

2.2.2. Correlation and Cross Correlation

Concept of cross correlation and auto correlation functions which are closely related to real world systems.

The cross-correlation coefficient r, which is a measure of linear association between two variables, is defined as

$$r = \sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y}) \ / \ \sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

where for the positive value of the coefficient r indicates that as one value increases, the other tends to increase whereas a negative value indicates that as one variable increases the other tends to decrease.

2.2.3 Auto-Correlation Function

We say that a data set exhibits auto-correlation if value X_t at time t_t is correlated with a value $X_t + d$ at time $t_i + d$ where d some time increment is in the future. In a long memory process the autocorrelation decays over time following a power law namely, $p(k) = Ck^{-\alpha}$ where C is a constant and p(k) is the autocorrelation function with lag k. For a given $X_1, X_2, ..., I_B$ at time $t_1, t_2, ...,t_n$ the k-lag auto correlation function is defined as,

$$r_k = \sum_{i=1}^{n-k}(X_i - \bar{X})(X_{i+k} - \bar{X}) / \sum_{i=1}^{n}(X_i - \bar{X})^2 \ \text{ where } \ \bar{X} = \frac{X_1 + X_2 + ...+ X_n}{n}$$

It may be remarked that in the above definition, the observations are uniformly sampled. Unlike cross-correlation, the autocorrelation results in a correlation coefficient indicating the degree of similitude between two values of same variable at time t_i and t_{i+k}.

Augmented Dickey-Fuller Unit Root Test on FTR

Null Hypothesis: FTR has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.827750	0.0031
Test critical values:	1% level	-3.462737	
	5% level	-2.875680	
	10% level	-2.574385	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FTR)
Method: Least Squares
Date: 06/27/11 Time: 18:59
Sample (adjusted): 1991M03 2011M12
Included observations: 250 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FTR(-1)	-0.196248	0.051270	-3.827750	0.0002
D(FTR(-1))	-0.349274	0.066251	-5.271954	0.0000
C	0.123560	0.032749	3.772933	0.0002

R-squared	0.255711	Mean dependent var	-0.000649
Adjusted R-squared	0.248230	S.D. dependent var	0.075348
S.E. of regression	0.065331	Akaike info criterion	-2.603975
Sum squared resid	0.849347	Schwarz criterion	-2.554843
Log likelihood	266.0015	F-statistic	34.18459
Durbin-Watson stat	2.003137	Prob(F-statistic)	0.000000

Figure 1: Unit Root Test Result for FTR

Augmented Dickey-Fuller Unit Root Test on USD

Null Hypothesis: USD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.741977	0.8324
Test critical values:	1% level	-3.462574	
	5% level	-2.875608	
	10% level	-2.574346	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(USD)
Method: Least Squares
Date: 06/27/08 Time: 19:08
Sample (adjusted): 1991M02 2007M12
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USD(-1)	-0.003922	0.005286	-0.741977	0.4590
C	0.008349	0.004831	1.727990	0.0855

R-squared	0.002731	Mean dependent var	0.005757
Adjusted R-squared	-0.002230	S.D. dependent var	0.047496
S.E. of regression	0.047549	Akaike info criterion	-3.244291
Sum squared resid	0.454450	Schwarz criterion	-3.211649
Log likelihood	331.2956	F-statistic	0.550530
Durbin-Watson stat	1.694515	Prob(F-statistic)	0.458967

Figure 2: Unit Root Test Result for ER

The autocorrelation function is being used to detect non-randomness in data and to identify an appropriate time series model if the data are not random. When autocorrelation is used to detect non-randomness, it is usually only the 1-lag autocorrelation that is of interest. When the autocorrelation is used to identify appropriate time series model, the k-lag autocorrelation is plotted.

3. Results

In our research, first of all, we applied unit root test for both series using e-views package program. After that, we found Lag Length as 1 for FTR and we evaluate r_k = 0.6988 (k=1) and also cross-correlation calculated as 0.25023 between both series.

In figure 3 and 4, discrete wavelet analyses of decomposition of ER and FTR values recorded between January 1991 and December 2011 have been presented. In both series there are some large scale effects; especially ER variation in 2001 corresponds to from fixed rate to variable (changeable) rate.

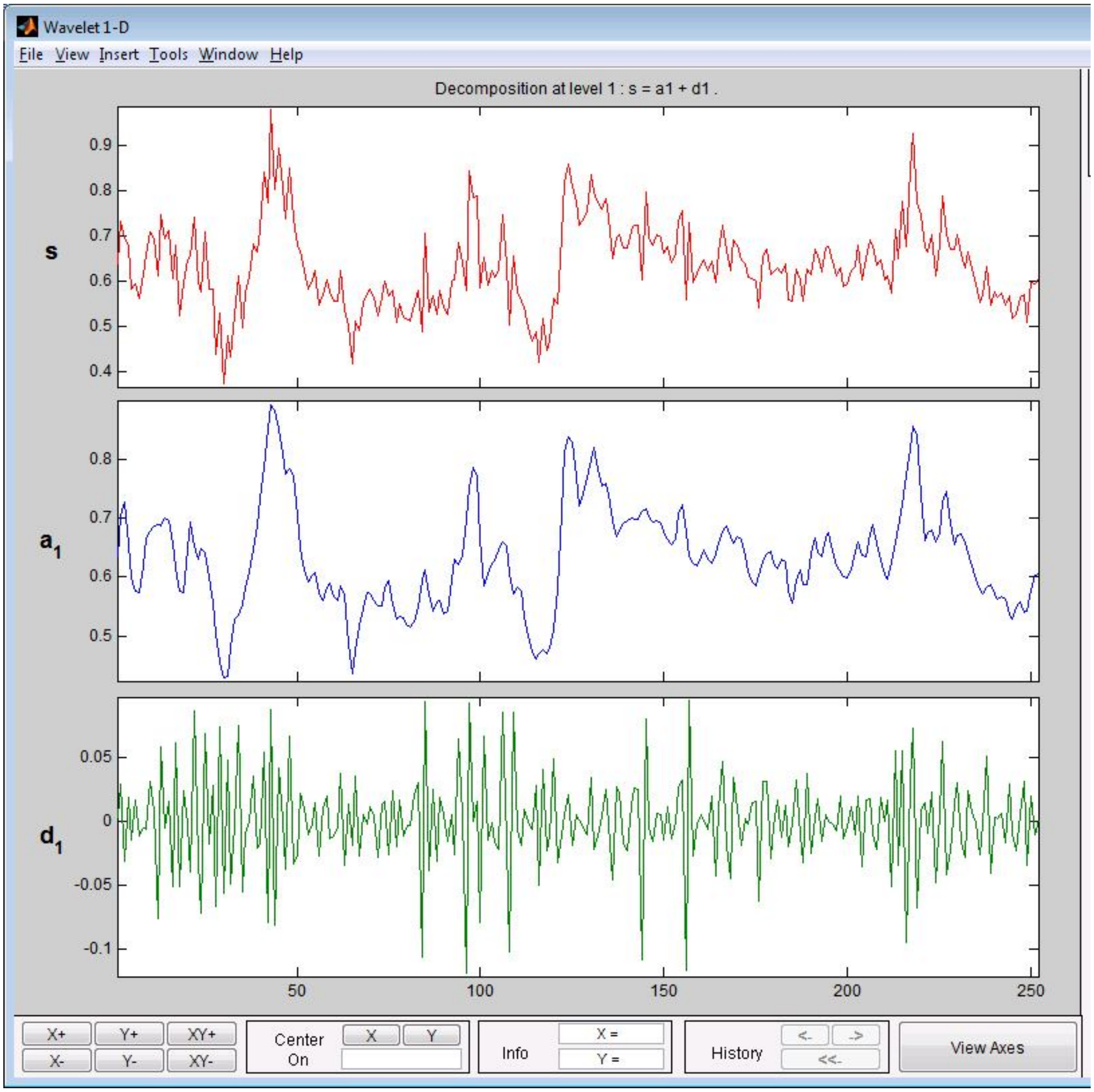

Figure 3: Decomposition of data for FTR using DB5

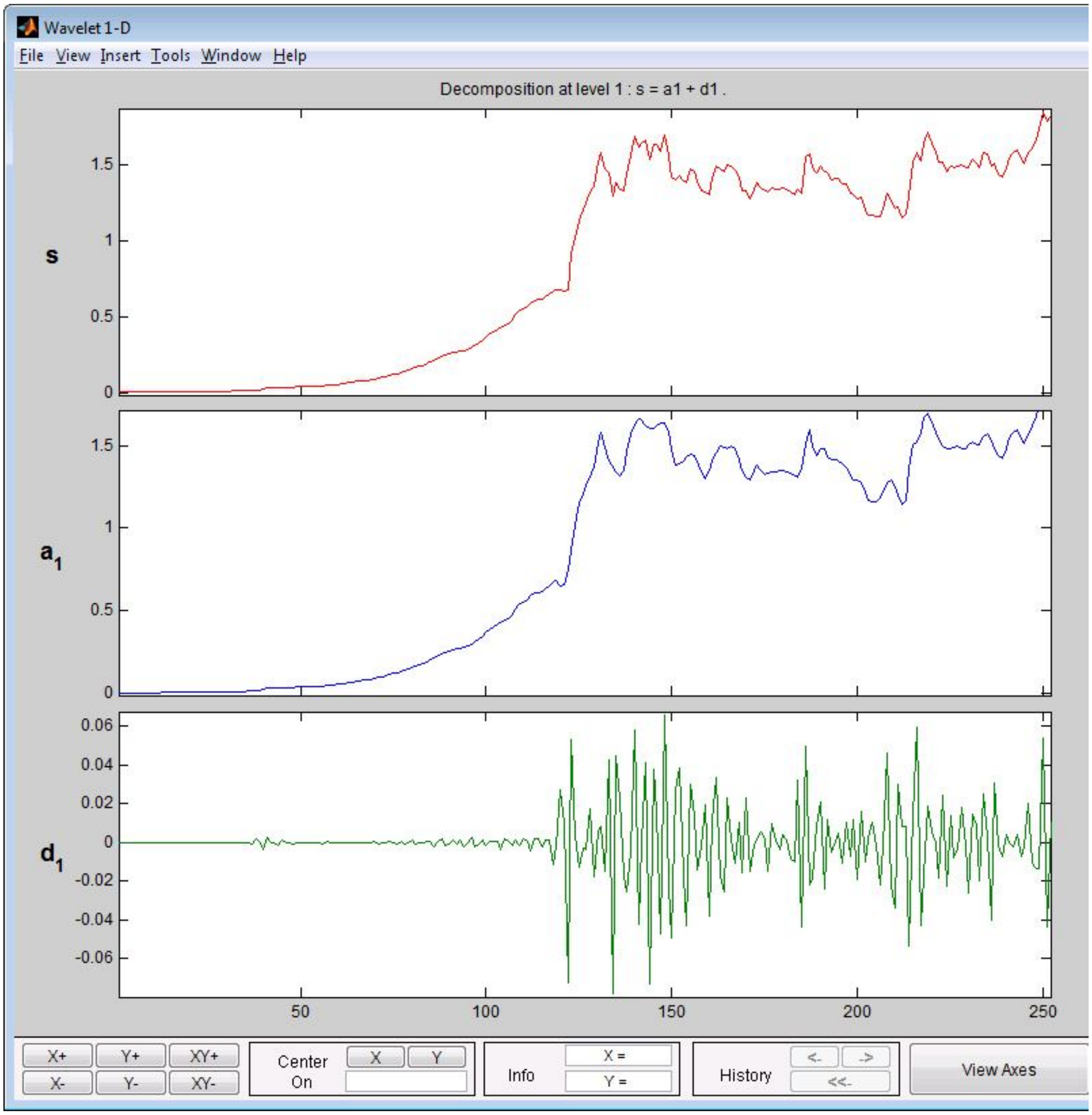

Figure 4: Decomposition of data for ER using DB5

3.1 Wavelet Continuous and Wavelet De-noising

Figures 5 and 6 are exhibited the wavelet de-noising of FTR and ER. Each figure contains original details coefficients, but not de-noised signals.

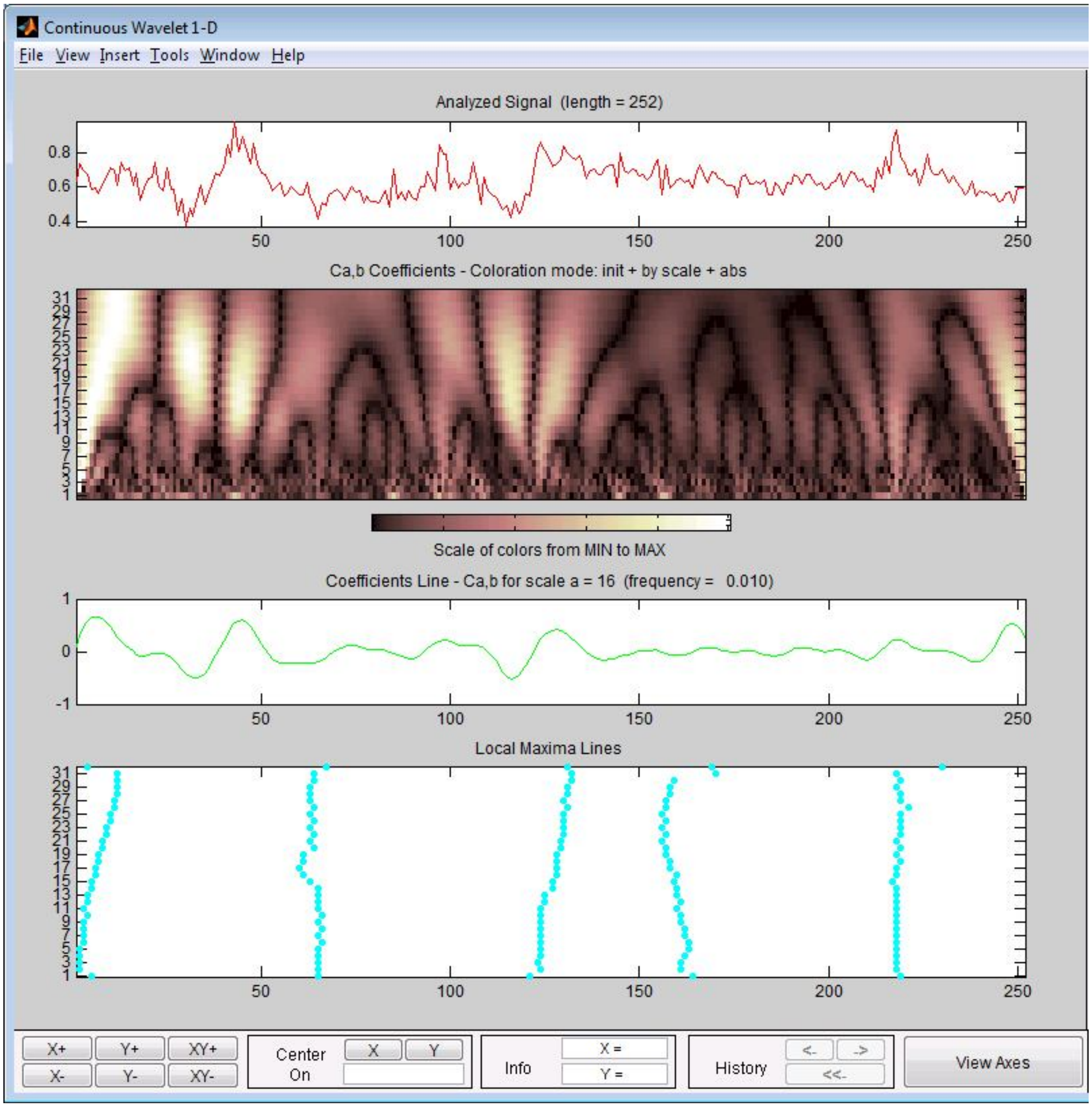

Figure 5: Denoising of data for FTR using DB5

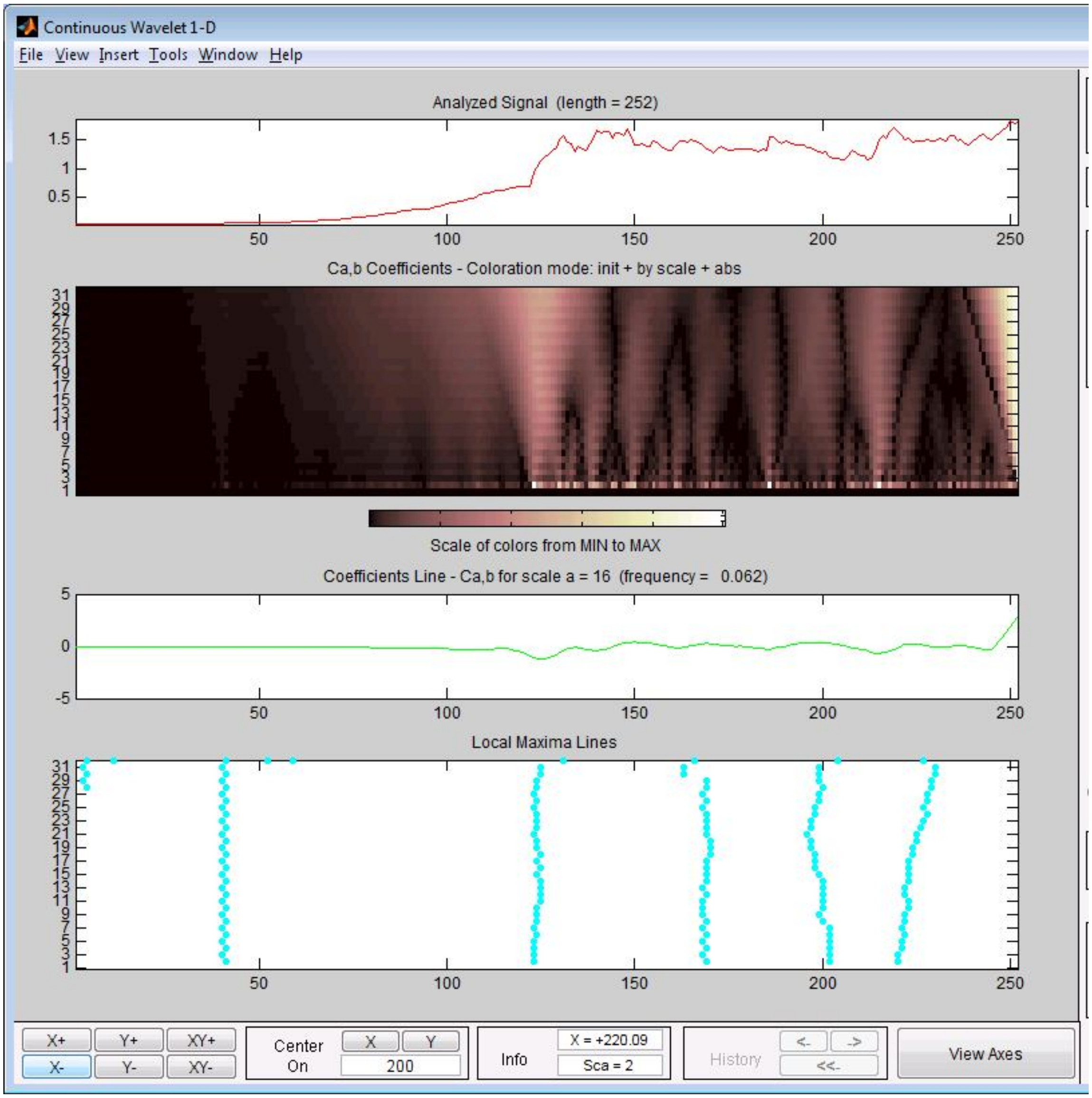

Figure 6: Denoising of data for ER using DB5

Wavelet packets and a special class of Haar wavelet transform (Renaud et al, 2005) could be tried for predicting economical data. Wavelet and wavelet packet transforms of data are also used in classical statistical method for prediction in place of data.

Figures 7 and 8 are exhibited the wavelet de-noising of FTR and ER. Each figure contains original details coefficients, but not de-noised signals.

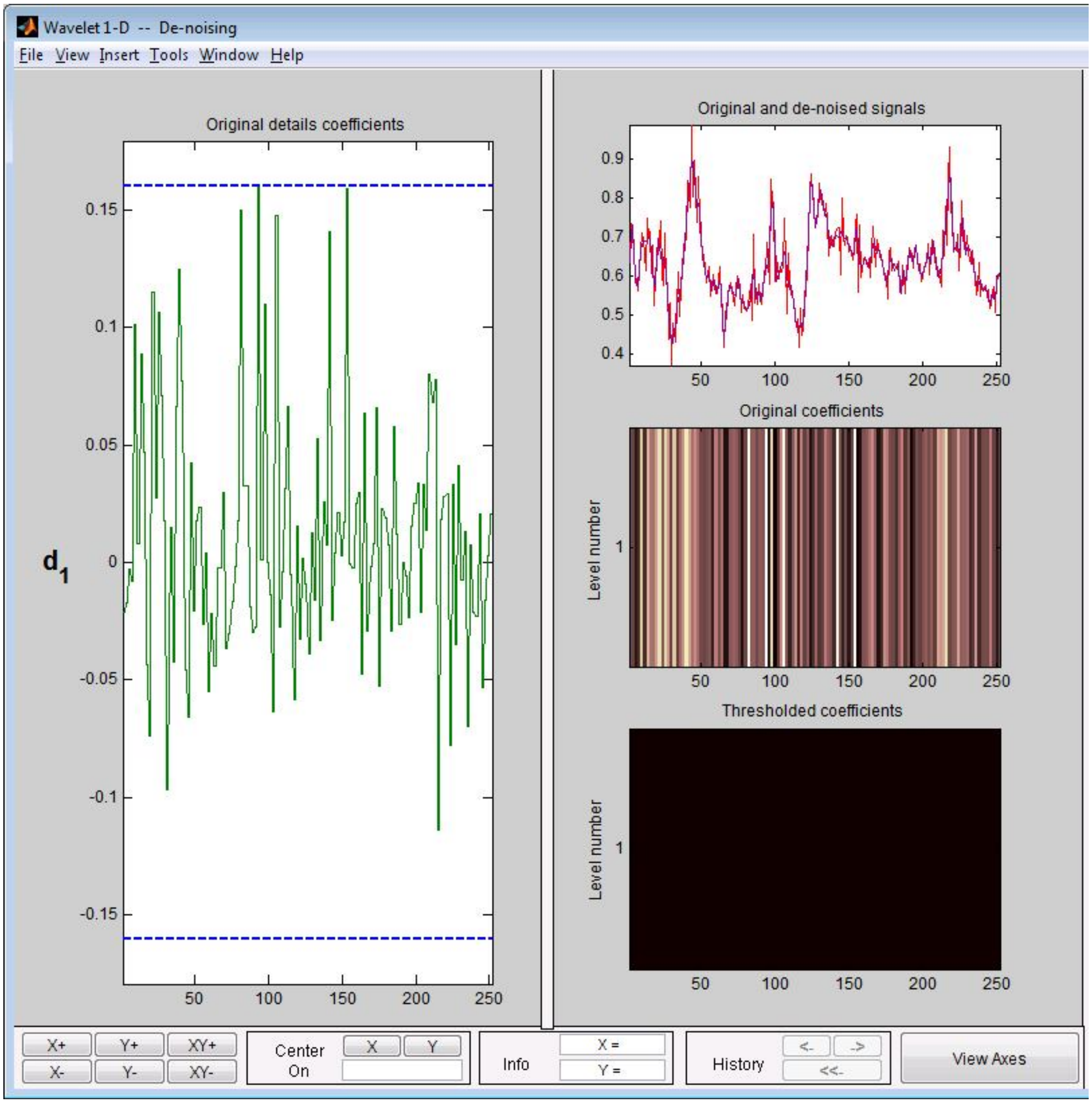

Figure 7: Denoising of data for FTR using DB5

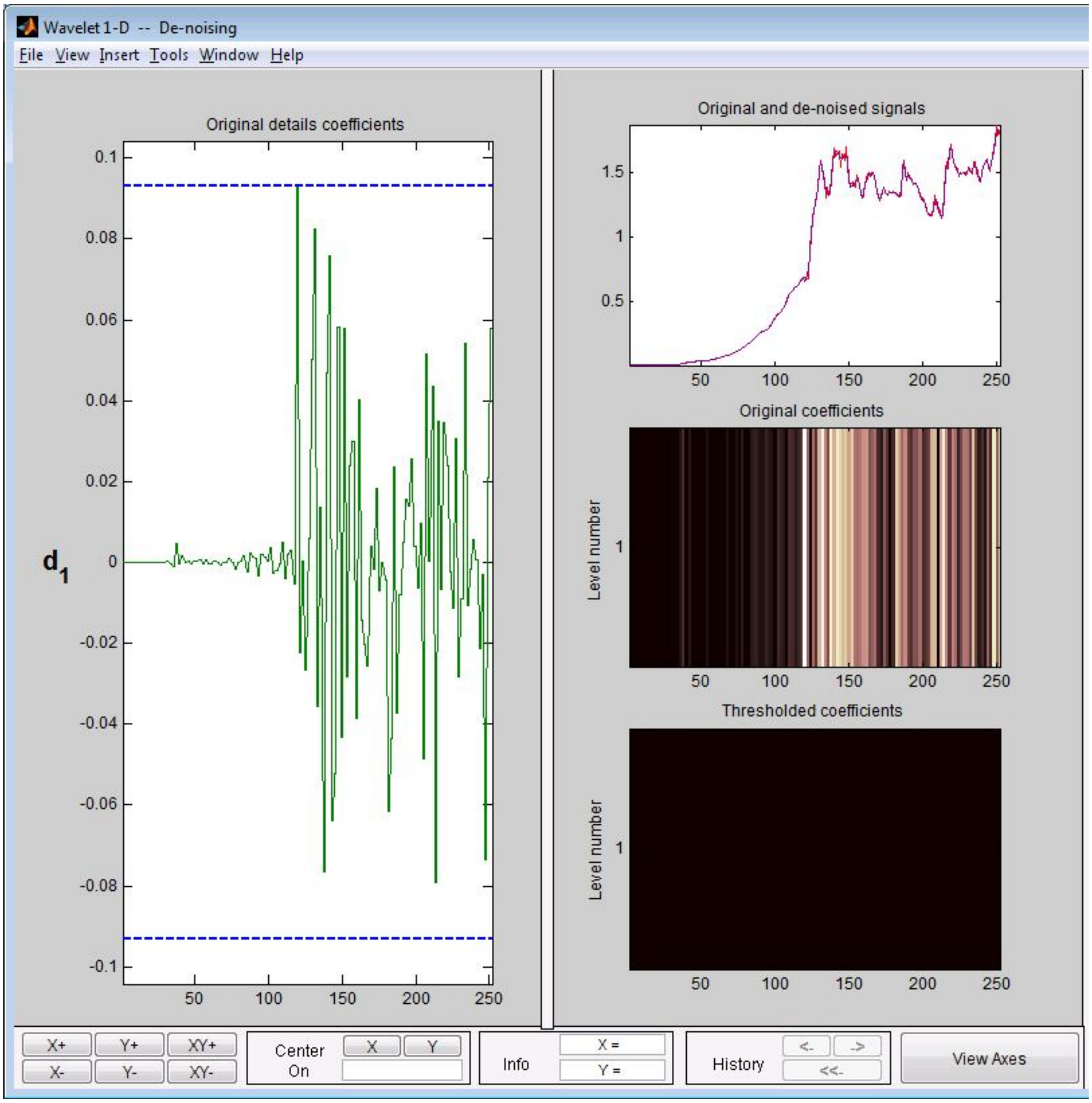

Figure 8: Denoising of Data for ER using DB53.

Conclusions

Statistical method was developed to periodic behavior of a time series on the basis of its known value in the past. Within a limited scope, modern computers mathematics and algorithms give forecasting of time series. On the other hand, long term forecasting is a challenging task. If an underlying deterministic process generated the time series that we are attempting to forecast a forecasting technique may hope for success.

Wavelet compression provides one measure for estimating the amount of determinism in a time series.
The wavelet cross-correlation analysis indicates that there is relation in the period before the financial crisis.
The empirical outcome shows the reciprocal influence between the exchange rate and foreign trade rate, generally finding a positive link between them.

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