The Relationship between Portfolio Return Volatility and Stock Return Volatility Based on Wavelet Analysis

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Abstract

This study examined the relationship between portfolio return volatility and the volatility of stock returns using wavelet analysis on the Tehran Stock Exchange The data for this study from 58 companies member of the Tehran Stock Exchange, the pharmaceutical, food and automotive cluster sampling method in the period 2008-2013 using the Novin software, Tadbir Pardaz software, and stock sites such as www.rdis.ir, through calculating portfolio return volatility and the volatility of stock returns have been collected , and Using wavelet analysis tools in MATLAB software was evaluated. .The results show that, in the short and medium term than long-term relationship between stock returns and the level portfolio return is so severe that the stock market in the short and medium term is more efficient than in the long run.

Keywords: portfolio returns volatility, stock return volatility, wavelet, time scale, the Stock Exchange

- **Introduction**

Today, investing is a major element of economic activity and one of the requirements to progress in any society is investment; investors seek to invest their funds in where gives the highest returns and few signs of risk. Any investor also consider to several important factors, most notably are the return of investment, the expected return of the investment. Among many cases of investment (suppose their risk has been proved) the investor usually chooses the case that will have to be more efficient. The return that an investor would consider is only a forecast of future realreturns.Therefore, it is concluded that the anticipation of return on investment is very important and every investor, to predict the outcome, considers several factors (Hamrita, M.E., & Trifi,2011).Harvey (1995) reports that emerging markets have high average returns, low overall volatility, low exposure to world risk factors, and little integration. He concludes that emerging markets are less efficient than developed markets and that higher return and lower risk can be obtained by incorporating emerging market stocks in investors' portfolios. From a U.S.-based investor's point of view, it is important to understand the potential portfolio implications of investing in stocks in these countries. Additionally, it is desirable to understand the behavior of the major equity performance indicators for these countries over time.

Risk and return are two important and influential factors on investment decisions. In order to reduce risk and increase efficiency, the observation of time series, which their changes can be mark of changes in securities prices, is helpful. Regard to the fact that investors and financial analysts apply return as one of the basic criteria to assess the company's stock, they tend to measure future returns amount, to make decisions about whether invest in shares or hold and sell shares (Bound, Shaun A. & Patel Kanak,2002).

In 1909, Haar was the first person who cited wavelets. In1930, mathematicians, intended to analyze the singularity structure of matter, began to think of the base modification. After 1970, a French geophysics mannamed Jean Morleh, Fourier bases are not the best possible tool for underground exploration. The issue in a laboratory belonging to Akilen led to the discovery of wavelets.

Wavelet analysis is one of the relatively new and exciting achievements in pure mathematics which is based ondecades of research in harmonic analysis. The clear wavelet function is base on mean zero and its amplificationis done in terms of the transfer of this function.In contrast to the trigonometric polynomials, wavelets are considered locally in space and thus closer connection between the coefficients of some functions is possible. Each set of wavelet coefficients covers different time series in the time scale and using the wavelet basis functions suggests a time-series transformed into frequency space and then a time series on different time scales. Analysis wavelet, also, makes analyze data at different scales of time and the idea behind wavelet and the decomposition of a time series of scale to scale feasible.

In such a context, where the strength and direction of relationships between economic and financial variables may differ according to the time scale of the analysis, wavelet techniques are of particular interest. Wavelet analysis is a comparatively new, at least in finance, and powerful tool for signal processing that takes into account both time and frequency domains. The main advantages of wavelets are their ability to decompose any signal into their time scale components, their flexibility to handle non-stationary data and their capacity to provide an alternative representation of the variability and association structure between variables on a scale-by-scale basis.

The primary aim of this paper is to examine the relationship between portfolio return volatility and the volatility of stock returns by using wavelet methods. The application of wavelet decomposition enables us to study the dynamic linkages between portfolio return volatility and the volatility of stock returns in time, as well as frequency domains, opening the path to a deeper understanding of the true relationship between these variables. Specifically, three alternative and complementary wavelet tools are utilized, namely wavelet variance, correlation and cross-correlation. Knowledge of the relationship between portfolio return volatility and the volatility of stock returns at different time scales is of undoubted interest for investors, portfolio managers, corporate managers and policy makers, as it provides critical information for risk management, asset allocation, portfolio management or policy making decisions.

- **Literature Review**

The study of wavelets as a distinct discipline started in the late 1980's. Wavelet theory has since inspired the development of a powerful methodology, which includes a wide range of tools such as wavelet transforms, multi resolution analysis, time-scale analysis, time-frequency representations with wavelet packets. Signal processing, data compression, medical imaging, turbulence and numerical analysis are only a few from a long list of disciplines in which wavelets have been successfully employed. Among others, the wavelet transforms and their modifications are becoming increasingly popular in diverse areas of applied and theoretical science. However, wavelet analysis has received little attention in time series analysis of economic and financial data.

Some recent papers in economic application include Goffe (1994), Gilbert (1995), Nason (1995), Ramsey and Zhang (1995, 1996), Wang (1995) and Wong *et al.* (1997). Goffe (1994) illustrated the application of wavelets to nonstationary economic time series, and Gilbert (1995) examined the stability of economic relationships. Ramsey and Zhang (1995, 1996) used waveform dictionaries to examine the timefrequency distributions of financial data. Nason (1995), Wang (1995) and Wong *et al.* (1997) discussed the wavelet detection of jump points in economic and financial data.

Applications of wavelet analysis in financial markets analysis have been recently performed by E. Capobianco (2004), M. Gallegati (2008), and T. Kravets (2012). E. Capobianco applied wavelet techniques to the multiresolution analysis of the high frequency Nikkei stock index data, showing the use of the wavelet matching pursuit algorithm in uncovering the hidden periodic components. M. Gallegati investigated the relationship between stock market returns and economic activity, applying the maximum overlap discrete wavelet transform to the Dow Jones Industrial Average and the USA industrial production indices. The application of discrete and continuous wavelet techniques for crisis detection by the analysis of the European stock indices is offered in the paper of Kravets and Sytienko (2012). A comparative analysis of the local peculiarities of crisis deployment in Ukraine and Poland has also been performed in the research.

The wavelet application using the macroeconomics indicator aspect is considered in the works of S. Kim (2005), A. Rua, L.C. Nunes (2009), P.M. Crowley (2007), R. Gencay (2001), H. Lee (2004). P.M. Crowley used a wavelet as a tool of the explanatory analysis, time scale decomposition of relationships, and destiny estimation in the US. He also analyzed the frequency components of the European business cycle by the wavelet multiresolutional analysis. R. Gencay investigated the foreign exchange rate scaling properties by the wavelet techniques. H. Lee studied international transmission effects among the US, Japan, Germany and two emerging markets, including Turkey and Egypt. He states that developing markets are strongly affected by developed markets but not vice versa. S. Kim studied the interdependence of the economic and financial 80 time series using the wavelet variance, correlation, and cross-correlation. Rua and Nunes tested changes in the indices' comovements over time, using monthly data from the US, Germany, UK, and Japan. However, most of the mentioned researches were based on the discrete wavelet transform.

A.A. Subbotin (2008) studied the multiscale stock volatility coefficients using wavelet techniques in the portfolio analysis. R.H. Abiyev (2012) used a combination of the wavelet techniques and neural networks for a time series prediction (we proposed the alternative forecasting method in our research).

There are, however, a few recent papers examining the interest rate-stock market link through the wavelet multiscaling approach (Kim and In, 2007; Çifter and Ozun, 2008; Hamrita and Trifi, 2011; Tiwari, 2012). These studies are based on national stock markets of various countries and conclude that the connection between interest rates and share prices is scale dependent, increasing in importance at coarser time scales. All these works, with the only exception of Tiwari (2012), utilize a variant of the discrete wavelet transform, which is known as

the maximal overlap discrete wavelet transform (hereafter referred to as MODWT).

Gencay, &Whitcher.(2002), In a study entitled Systematic risk and time scales, the study of Dell's shares on the Stock Exchange America, a new approach for the estimation of systematic risk (beta assets) based on the Capital Asset Pricing Model were put forward. Scalable Wavelet method proposed approach is based on a specific time scale, the scale breaks is based. Each scale Wavelet variance of market returns, and the covariance Wavelet, the market return and portfolio in order to obtain an estimate of the beta of the portfolio is calculated. Results indicate that the relationship between portfolio return and beta as standard Wavelet grows, becomes stronger. Thus the predictions of the CAPM in the periods of time when compared with short-term prospects are more favorable.

Gencay (2005) in a study titled Wavelet analysis of stock markets in Africa, concluded that the variance and correlation of stock returns in the stock market, African countries will vary according to the scale.

Ben Ammou and Ben Mabrouk (2007) used wavelet analysis to examine the relationship between stock returns and systematic risk in the capital asset pricing model, the French stock market have different time scales. A new approach based on Wavelet analysis in order to explain the relationship between share returns and systemic risk in the capital asset pricing model proposed in different time scale. The results show that the relation between stock returns and the level of systemic risk in the short-term scale It is long and more severe, so that the French stock market is efficient in the short-term and long-term.

Kim (2007) research as the relationship between changes in stock prices and yields of bonds in the G7 based on analysis Wavelet concluded that, bond yields and stock change with the scale of change and the changes from country to country is also true.

Hypothesis

Since the present study, the relationship between portfolio return volatility and stock return volatility based on wavelet analysis is proposed hypotheses are as follows:

1 - the volatility of portfolio return and volatility of stock returns over shorter time scale of 2-4 days, and significant negative relationship exists.

2 - the volatility of portfolio return and volatility of stock returns over shorter time scale of 4-8 days, and significant negative relationship exists.

3 - the volatility of portfolio return and volatility of stock returns over the medium term time scale of 8-16 days, and significant negative relationship exists.

4 - the volatility of portfolio return and volatility of stock returns over the medium term time scale of 16-32 days, and significant negative relationship exists.

5 - the volatility of portfolio return and volatility of stock returns for long-term time scale of 32-64 days, and significant negative relationship exists.

6 - the volatility of portfolio return and volatility of stock returns for long-term time scale from 64-128 days, and significant negative relationship exists.

Confirmed the research hypothesis in each period represents the relation between stock returns and beta in different time scales will be. Verify if the first and second hypothesis is the concept that short-term CAPM model is more predictability. But if confirmed hypotheses third, fourth, fifth and sixth contrary suggests that longer period of time will cause the predicted CAPM model would be more appropriate. In other words, the relationship between stock returns and beta wavelet becomes more severe with increasing scale.

Variables and their measurement

The purpose of this study, independent research, volatility portfolio return and dependent variables, the expected stock return volatility of individual stock portfolios is. Beta as unchangeable risk of an asset, relative to the stock market, CAPM return on investment in the form of equation (1) defines:

$$E(R_i) = r_f + \beta_i E(R_m - r_f) \qquad \textbf{(1)}$$

CAPM two parts can be risk-free rate of return (R_f) and the risk premium is split. The equity risk premium investors demand returns in excess of risk-free interest rate to offset the risk that the investment unchangeable as Beta, in equation (2) is calculated as:

$$\beta_i = \frac{cov(R_i ; R_m)}{var(R_m)} \qquad \textbf{(2)}$$

Market risk premium, the returns (E (R_m)- R_f) is considered. Greater than the risk-free rate returns for investors, to keep the stock market.Since the risk premium on individual assets, the market risk premium multiplied by the

beta of it. Equation (1) can be related to (3) to be rewritten:

$$E(R_i)-R_f = \beta i\ [E(R_m)- R_f] \qquad (3)$$

Beta suited to parse the variance of an asset, especially as R_i variance equation (4) shows.

$$\partial\ _i = \beta_i\ \partial\quad + \partial \qquad (4)$$

So, ∂_i can be decomposed into two parts, the first part of the firm's systematic risk ($\beta i\ \partial$ m) that part of the variance attributable to the asset market volatility shows. The second component, unsystematic risk firms (∂) and the firm-specific volatility is concerned. If all asset prices are related to market movements, the error (itε) is always zero, $\partial\ \varepsilon_{it}\ =0$ is.

Expected rate of return kj using the D-CAPM is:

$$K_{j=Rf+\beta d(Rm-Rf)} \qquad (5)$$

Beta-reduction (mitigation beta) is calculated by the following equation:

$$(6)$$

$$\beta = \frac{S_{covRi,Rm}}{S_{var\ Rm}}$$

R_i is calculated from the following equation:

$$(7)$$

R_f calculated using data from the Central
Bank of Iran to sites of interest rate investment deposits
Term to consider.

The following equations are used to calculate the rate of return.

$$R_m = \frac{I_2-I_1}{I_1}*100 \qquad (8)$$

In the above equation, we have:

(Table 1): Description of the variables

	Variables	Proxies
1	E(R$_i$)	Volatility expected return on assets
2	R$_f$	risk-free premium rate
3	E(Rm)	Volatility expected market shares
4	β	Risk assets
5	k$_I$	Expected rate of return
6	α	Percent increase in the capital
7	P$_0$	First, the stock price
8	P$_1$	The final price of the stock
9	DPS	Benefit split between shareholders
10	I$_2$	Month-end market price index
11	I$_1$	First prices month market index
12	R$_M$	The market rate of return

In this study wavelet coefficient beta, the sixth time scale used. while the scale of one movements time 2-4 days, scale of two movements time 4-8 days, scale of three movements time 8-16 days, scale of four movements time 16-32 days, scale of five movements time 32-64 days, scale of six as the highest scale is connected with the movements of the day 128-64. Because the scale of six is considered as the highest scale, the scale of 7 is associated with a period of 256-128 days. It is estimated that nearly one year, we will be away from the main purpose.

Research Methodology
Since this study sought to examine the relationship between portfolio return volatility and stock return volatility based on wavelet analysis is, Methods for the study of correlation and regression analysis was used to examine

the relationship between these variables.

The study of listed companies in Tehran Stock Exchange for the pharmaceutical, food and automotive industries, was selected as the target population. Among these firms, firms that are eligible under the cluster sampling method in the period 2008-2013 were selected from the 58 participants who were selected as samples.

1. The beginning of 2008 have been a member of the Tehran Stock Exchange.

2. Courses leading to the end of March is financial.

3. During the research period, interrupted their stock trades have been more than 6 months.

4. The information you need to research available.

5. Component industry companies are not investing in financial intermediation.

Required data through observation and analysis of documents and information have been collected from company financial statements. In this study, the research literature to develop a library of methods has been used. To test the hypothesis of a company's financial statements and information contained in the Site and the Information Exchange Bank and mash the New Deal program, has been used.

In this study, the statistical methods used are descriptive statistics and regression.

In order to test the research hypotheses, the beta of the sample companies, the annual breakdown of the different time scales of a capital asset pricing model adjusted (DCAPM) was calculated. Then using the wavelet time-series of returns and beta, firms were evaluated in the study. Optimized based on the time period is introduced. Well as to determine the significance of the relationship between the independent variables and the dependent, t - test was used. Finally, the primary data file format of the Excel spreadsheet software was designed and completed.

And then analyzed in order to EVIEWS software is used to perform statistical tests.

Statistical hypothesis test

The first hypothesis test(Short term 2-4 days)

The results in Table (1) The F-statistic is equal to 44.1, which was significant at a confidence level of 95, which represents an estimate is good. In addition, the coefficient of determination and the adjusted coefficient of determination for models with 0.44 and 0.43. Also, the value of the independent variable portfolio return., and the dependent variable expected rate of return, the first scale is equal - 0.149, which is significant at 95% confidence.

Table (1): short term (2-4 days)

Dependent variable: ER2		Method: Panel Least Squares		
Includes: 6 time periods	Sample range:2008-2013			
Number of companies: 158	Total sample: 58			
Variables	**Coefficients**	**Standard deviation**	**t-statistics**	**Probability of statistic t**
C	0.071284*	0.009346	7.627282	0.000
B1STDRM	-0.149063*	0.000739	-6.641353	0.000
R Square	0.440	Mean of the dependent variable		0.035
Adjusted R Square	0.430	Standard deviation of the dependent variable		0.076
Standard deviation of the regression	0.057	AIC		-2.831
Not justify the sum of squared error	0.186	SBC		-2.760
LOG	84.115	HQ		-2.803
Durbin- Watson	1.729	F		44.107
		VIF		0.000

The second hypothesis test (Short term 4-8 days)

The results in Table (2) The F-statistic is equal to 31.68, which was significant at a confidence level of 95, which represents an estimate is good. In addition, the coefficient of determination and the adjusted coefficient of determination for models with 0.34 and 0.36. Also, the value of the independent variable portfolio return., and the dependent variable expected rate of return, the second scale is equal – 0.01, which is significant at 95% confidence.

Table (2): short term (4-8 days)

Dependent variable: ER2			Method: Panel Least Squares	
Includes: 6 time periods Sample range:2008-2013				
Number of companies: 158 Total sample: 58				
Variables	Coefficients	Standard deviation	t-statistics	Probability of statistic t
C	0.019067*	0.003805	5.011099	0.000
B1STDRM	-0.015643*	0.000278	-5.628883	0.000
R Square	0.361	Mean of the dependent variable		0.0094
Adjusted R Square	0.349	Standard deviation of the dependent variable		0.032
Standard deviation of the regression	0.025	AIC		-4.434
Not justify the sum of squared error	0.037	SBC		-4.363
LOG	130.590	HQ		-4.406
Durbin- Watson	1.881	F		31.684
		VIF		0.000001

Due to hypothesized relationships between first and second in the 95% confidence level, it can be concluded that the short-run relationship between portfolio return and the expected rate of return there. So the first and second hypothesis is confirmed.

• **The third hypothesis tests (medium-term period 8-16)**

The results in Table (3) The F-statistic is equal to 37.25, which was significant at a confidence level of 95, which represents an estimate is good. In addition, the coefficient of determination and the adjusted coefficient of determination for models with 0.38 and 0.39. Also, the value of the independent variable portfolio return., and the dependent variable expected rate of return, the third scale is equal – 0.039, which is significant at 95% confidence.

Table (3): medium-term period (8-16 days)

Dependent variable: ER2			Method: Panel Least Squares	
Includes: 6 time periods Sample range:2008-2013				
Number of companies: 158 Total sample: 58				
Variables	Coefficients	Standard deviation	t-statistics	Probability of statistic t
C	0.014256*	0.003250	4.387031	0.0001
B1STDRM	-0.039904*	0.000229	-6.103636	0.000
R Square	0.399	Mean of the dependent variable		0.0105
Adjusted R Square	0.388	Standard deviation of the dependent variable		0.031
Standard deviation of the regression	0.024	AIC		-4.562
Not justify the sum of squared error	0.033	SBC		-4.491
LOG	134.311	HQ		-4.534
Durbin- Watson	1.798	F		37.254
		VIF		0.0000000

The fourth hypothesis testing (medium-term period 16-32 days)

The results in Table (4) The F-statistic is equal to 61.44, which was significant at a confidence level of 95, which represents an estimate is good. In addition, the coefficient of determination and the adjusted coefficient of determination for models with 0.51 and 0.52. Also, the value of the independent variable portfolio return., and the dependent variable expected rate of return, the fourth scale is equal – 0.25, which is significant at 95% confidence.

Table (4): medium-term period (16-32 days)

Dependent variable: ER2		Method: Panel Least Squares		
Includes: 6 time periods Sample range:2008-2013				
Number of companies: 158 Total sample: 58				
Variables	Coefficients	Standard deviation	t-statistics	Probability of statistic t
C	0.008692*	0.001079	8.056237	0.0000
B1STDRM	-0.259216*	7.55E-05	-7.838885	0.0000
R Square	0.523	Mean of the dependent variable		0.0032
Adjusted R Square	0.514	Standard deviation of the dependent variable		0.0090
Standard deviation of the regression	0.006	AIC		-7.259
Not justify the sum of squared error	0.002	SBC		-7.188
LOG	212.517	HQ		-7.231
Durbin- Watson	1.815	F		61.448
		VIF		0.000000

Due to hypothesized relationships between third and fourth in the 95% confidence
level, it can be concluded that the mid-term relationship between portfolio return and the expected rate of return
there. So the third and fourth hypothesis is confirmed.
• The fifth hypothesis testing (long-term period 32-64 days)
The results in Table (5) The F-statistic is equal to 10.7, which was significant at a confidence level of 95, which
represents an estimate is good. In addition, the coefficient of determination and the adjusted coefficient of
determination for models with 0.14 and 0.16. Also, the value of the independent variable portfolio return., and
the dependent variable expected rate of return, the fifth scale is equal – 0.01, which is significant at 95%
confidence.

Table (5): long-term period (32-64days)

• Dependent variable: ER2		Method: Panel Least Squares		
Includes: 6 time periods Sample range:2008-2013				
Number of companies: 158 Total sample: 58				
Variables	Coefficients	Standard deviation	t-statistics	Probability of statistic t
C	0-.002014*	0.000559	-3.606682	0.0007
B1STDRM	-0.016148*	4.94E-05	-3.271403	0.0018
R Square	0.160	Mean of the dependent variable		-0.0006
Adjusted R Square	0.145	Standard deviation of the dependent variable		0.0031
Standard deviation of the regression	0.002	AIC		-8.794
Not justify the sum of squared error	0.0004	SBC		-8.723
LOG	257.029	HQ		-8.766
Durbin- Watson	1.932	F		10.702
		VIF		0.001835

The sixth hypothesis testing (long-term period 64-128 days)
The results in Table (6) The F-statistic is equal to 18.21, which was significant at a confidence level of 95, which
represents an estimate is good. In addition, the coefficient of determination and the adjusted coefficient of
determination for models with 0.23 and 0.24. Also, the value of the independent variable portfolio return., and
the dependent variable expected rate of return, the sixth scale is equal – 0.033, which is significant at 95%
confidence.

Table (6): long-term period (64-128days)

Dependent variable: ER2			Method: Panel Least Squares	
Includes: 6 time periods Sample range:2008-2013				
Number of companies: 158 Total sample: 58				
Variables	Coefficients	Standard deviation	t-statistics	Probability of statistic t
C	0-.005482*	0.000974	-5.626428	0.0000
B1STDRM	-0.033795*	7.92E-05	-4.268227	0.0001
R Square	0.245	Mean of the dependent variable		-0.002
Adjusted R Square	0.231	Standard deviation of the dependent variable		0.005
Standard deviation of the regression	0.005	AIC		-7.721
Not justify the sum of squared error	0.001	SBC		-7.650
LOG	225.918	HQ		-7.693
Durbin- Watson	1.931	F		18.217
		VIF		0.000077

Due to hypothesized relationships between fifth and sixth in the 95% confidence level, it can be concluded that the long-term relationship between portfolio return and the expected rate of return there. So the third and fourth hypothesis is confirmed.

Conclusion and Discussion

The results of the first and second hypothesis suggest that there exists a short-term relationship between portfolio return and the expected rate of return, so the first and second hypotheses are confirmed; also the short-term impacts of the portfolio return in the first scale have been greater than the second scale.

The overall results of the first two hypotheses consistent with the results from the study of Bollywood and others which shows that, in short term, the relationship between market returnsdue to the lack of consensus on the part of analysts and behavioral reasons such as skewness of returns has been over the stock returns. It, also, is inconsistent with the results Gencay, &Whitcher.(2002), which shows that the time period when compared with short-term prospects are more favorable.

The results of the third and fourth hypothesesshow that there has been a significant relationship between portfolio return and the expected rate of return and the third and fourth hypotheses are confirmed. Also, in the medium-term, the impacts of the portfolio return in the third scale are greater than the fourth scale.

In general, the overall results of the third and fourth hypotheses is inconsistent with the results of Gencay, &Whitcher.(2002) who showed the relationship between portfolio return and the return is more , in comparison with short –ranged period of time.

 The results of the fifth and sixth hypotheses indicate that the long-run relationship exists between the portfolio return and the expected rate of return and the fifth and sixth hypotheses are confirmed. Also, over the long term, the portfolio return impacts of the sixth scale are more than the fifth one.

In general, the overall results of the third and fourth hypotheses is inconsistence in comparison with the results of Ben Ammou and Ben Mabrouk (2007) who suggest that the relation between stock returns and the level of short -scale and long-term portfolio return is more intense.

REFRENCES

Abiyev, R.H., Abiyev, V.H. (2012). Differential evaluation learning of fuzzy wavelet neural networks for stock price prediction. Journal of Information and Computing Science, Vol. 7, issue. 2, p. 121–130.

Bound, Shaun A. & Patel Kanak. (2002). "Distribution of Real Estate Returns: Are higher moments time varying" The Conditional? www.ssrn.com

Capobianco, E. (2004). Multiscale analysis of stock index return volatility. Computational Economics, Vol. 23. (3), p. 219–237.

Çifter, A. & Ozun, A. (2008). Estimating the effects of interest rates on share prices in Turkey using a multi-scale causality test. Review of Middle East Economics and Finance, 4, 68-79.

Crowley, P.M. (2007). A guide to wavelets for economists.Journal of Economic Surveys, Vol. 21, p. 207–267.

Gallegati, M. (2008). Wavelet analysis of stock returns and aggregate economic activity. Computational Statistics and Data Analysis, Vol. 52 (6), p. 3061–3074.

Gencay, R.F.Selcak & B.Whitcher.(2002). "An Itroduction to wavelets and other Fitering Method in Finance

and Economics". Academic press, san Diego

Gencay, R., Selcuk, F., Whitcher, B. (2001). Scaling properties of foreign exchange volatility. Physica A: Statistical Mechanics and Its Applications, Vol. 289 (1–2), p. 249–266.

Gilbert, S. (1995), "Structural Changes: Estimation and Testing by Wavelet Regression," Discussion Paper (University of California, San Diego).

Goffe, W.L. (1994), "Wavelets on Macroeconomics: An Introduction," in: Computational Techniques for Econometrics and Economic Analysis, D. Belsley (Ed.), 137-149, Kluwer Academic Publishers: The Netherlands.

Hamrita, M.E., & Trifi, A. (2011). The relationship between interest rate, exchange rate and stock price: A wavelet analysis. International Journal of Economics and Financial Issues, 1, 220-228.

Kim, S., & In, F. (2007). On the relationship between changes in stock prices and bond yields in the G7 countries: Wavelet analysis. Journal of International Financial Markets, Institutions and Money, 17, 167-179.

Kim, S., In, F. (2005) The relationship between stock returns and inflation: new evidence from wavelet analysis. Journal of Empirical Finance, Vol. 12 (3), p. 435–444.

Kravets, T., Sytienko, A. (2012). Wavelet analysis of stock indices of Ukraine and Poland in economic crisis and relaxation. Visnyk of Taras Shevchenko National University of Kyiv: Economics. Vol. 132, p. 39–43.

Lee, H.S. (2004). International transmission of stock market movements: a wavelet analysis. Applied Economics Letters, Vol. 11, issue 3, p. 197–201.

Nason, G.P. (1995), "Wavelet Function Estimation using Cross-Validation," in: Wavelets and Statistics, A. Antoniadis and G. Oppenheim (Eds.), 261-280, Springer-Verlag: New York.

Ramsey, J.B. and Z. Zhang (1995), "The Analysis of Foreign Exchange Data Using Wave Form Dictionaries," in Conference on High Frequency Dynamics, Olsen and Associates: Zurich.

Ramsey, J.B. and Z. Zhang (1996), "The Application of Wave Form Dictionaries to Stock Market Index Data," in Predictability of Complex Dynamic Systems, J.K. Brush (Eds.), Springer-Verlag: New York.

Rua, A., Nunes L.C. (2009). International comovement of stock market returns: a wavelet analysis. Journal of Empirical Finance, Vol. 16, issue 4, p. 632–639.

Subbotin, A. A. (2008) Mutli-horizon scale for volatility. CES Working Papers Series, University of Paris-1 (Pantheon-Sorbonne), Vol. 20, p. 1–44.

Tiwari, A.K. (2012). Decomposing time-frequency relationship between interest rates and share prices in India through wavelets. MPRA Paper No. 39693.

Wong, H., W. Ip, Y. Luan and Z. Xie (1997), "Wavelet Detection of Jump Points and an Application to Exchange Rates," Manuscript (Hong Kong Polytechnic University).

http://ivyunion.org/index.php/ajfe/author/index

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