

## **Co-movement among industry indices of Tehran Stock Exchange, Wavelet Coherence approach**

Somayeh Mohammadi<sup>1</sup>, Ebrahim Abbasi<sup>1\*</sup>, Gholamreza Mansourfar<sup>2</sup>, Fahimeh Beiglari<sup>3</sup>

1. Faculty of Social sciences & Economic, Alzahra University, Tehran, Iran
2. Faculty of Economic & Administration, Urmia University, Urmia, Iran
3. Department of Science, Urmia University of Technology, Urmia, Iran

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### **Abstract**

Co-movement analysis has a significant role in recourse allocation, risk management, etc. This study uses the novel approach of wavelet coherence in continuous wavelet transform framework to investigate the correlation dynamic and spillover effect of 10 main sector indices of Tehran Stock Exchange, in time and frequency domains. Analyzing the data indicates that correlation structure among TSE sectors is dynamic and varies over time. Besides, co-movements of industry indices have a multi-scale character. In other words, investors with different investment horizons would benefit differently if they diversify their portfolios via the same industries. In addition, results indicate that the spillover effect pattern is a scaled based phenomenon. This study suggests time scales of 2-32 days as the best time horizon for portfolio diversification.

### **Keywords**

Co-movement, Continuous wavelet transform, Sector returns, Volatility spillover, Wavelet coherence.

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\* Corresponding Author, Email: [abbasiebrahim2000@yahoo.com](mailto:abbasiebrahim2000@yahoo.com)

## Introduction

Studying the interdependence among different sectors of capital markets as a measure of sensitivity of one-sector relatives to shocks originating in other sectors of the market is curial for every individual involved in the market (Bordoloi, 2009). Dynamic behavior of the return correlations over time has been the subject of numerous studies (Gallali & Abidi, 2012; Lean & Teng, 2013). Besides the time dimension of the market dynamics, such dynamics are influenced by different types of investors as well. The spectrum of investors ranges through noise traders with investment horizon of several minutes to pension funds with the investment horizon of several years. Thus, apart from the time domain, there is a frequency domain which represents various investment horizons (Barunik, Vacha & Krištoufek, 2011).

In co-movement studies, the difference amongst investors should be taken into consideration. From the perspective of portfolio diversification, since investors with short investment horizons prefer to analyze the co-movement of stock returns at the higher frequencies<sup>1</sup> which correspond to short-term deviations, long-term investors are interested in the relationship at lower frequencies, which correspond to long-term fluctuations (Rua & Nunes, 2009). In this regard, even though financial and economical analysts consider different time scales in decision-making, due to the lack of appropriate analytical instruments, most of the empirical studies are limited just to two-time scale and long and short terms. (Farzinvash, Farmanara & Mohammadi, 2013)

One of the financial time series features is their multi-scale behavior which indicates that an observed time series may include numerous structures, each occurring on a dissimilar timescale (Ranta, 2010). Using modern mathematical tools in financial market studies makes the analysis of complex behavior of the time series possible. Wavelet transform, one of the mathematical approaches, is a powerful

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1. In Finance and Economy, it is common to use the word "Scale" interchangeably for the word "Frequency," yet the terms are inversely related here.  $\text{Scale} = 1/\text{Frequency}$

technique which has the ability to split different timescales from primary data. Wavelets allow researchers to study the frequency elements of the time series at the same time as saving the time information (Barunik, Vacha & Krištoufek, 2011).

The innovation of this study lies in the use of wavelet coherence tool in sector level co-movement analysis, which leads to understanding the relationship among the major sector returns of TSE (nearly 80% of the market value) in a different way. This research contributes to the current risk management literature by using a model-free novel approach which facilitates researchers to explore the co-movement structure of different sectors both in time and in scale domains. Moreover, by using this new view through co-movement analysis, the spillover effect among sectors can be studied in time and scale domains simultaneously.

The paper, hence, is organized as follows. A brief background of the study is provided in Section 2. The data and the methodology of the study are described in Section 3. Section 4 reports the results of co-movement analysis by the wavelet coherence function in this empirical study. Finally, a conclusion and some suggestions for further studies are presented in section 5.

### **Review of literature**

In 1952, Markowitz proved that portfolio variance partly depends on the covariance of assets within the portfolio, and one can reduce the investment risk through portfolio diversification (1952). Hence, maximum benefit of investors from holding portfolios depends on the possibility of diversification. In many empirical studies, diversification possibility is examined through price and returns co-movement by enormous methods such as: Correlation coefficient, Vector Auto Regressive models, multivariate GARCH models, Regime switching models, and Wavelet analysis (Dajcman, Festic & Kavkler, 2012).

For many decades, the most common method in co-movement analyzing tool was Pearson correlation coefficient, but Xiao & Dhesi (2010) indicated that the use of linear correlation is not unconditional;

this method is a symmetric, linear dependence metric that conceals the time-varying nature of correlations. Fifteen years before Xiao & Dhesi (2010), Allen & MacDonald (1995) illustrated that the correlation coefficient shows the short-term dynamics of the variables. However, price time series may have different behaviors in the end and become co-integrated.

Because of these limitations, using more advanced econometric models became vital. In 1980, the Vector Auto Regressive (VAR) model was introduced by Christopher Sims (1980). Beside many advantages of VAR model in econometric and finance, this model is not much applicable in portfolio selection, and since portfolio optimization is performed on the basis of MPT<sup>1</sup>, correlations of assets are needed. Furthermore, co-integration of stocks does not necessarily imply high correlation because two co-integrated time series may have very low correlation and move in different directions and vice versa (Onay & Ünal, 2012).

Additionally, Multivariate GARCH models were proposed to model and study the variability of two or more variables all at once. Although these models can handle some key characteristic of stocks such as leptokurtosis, leverage effects, and volatility clustering, they suffer from many parameters that should be estimated. Furthermore, the results of these models just cover two short- and long-term scales and do not consider other scales.

In this regard, wavelets are powerful mathematical functions that are applied in time series analysis as well. Morlet was the first scientist who named these functions 'wavelet' (Behradmehr, 2008). The base of wavelet transform lays in Fourier transform. A wavelet means a small wave (the sinusoids used in Fourier analysis are big waves) and, in brief, a wavelet is an oscillation that decays quickly (Sifuzzaman, Islam & Ali, 2009).

In general, there are two different approaches toward time series: time domain and frequency domain (which are typically represented by Fourier transform). However, the biggest deficiency of both of

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1. Modern Portfolio Theory

them is that by analyzing one domain, the information in the other domain is excluded from the analysis. This happens for the reason that one cannot achieve simultaneous time and frequency resolution because of the Heisenberg uncertainty principle. In the field of particle physics, an elementary particle does not have a precise position and a precise momentum simultaneously. The better one can determine the position of a particle, the less precisely the momentum is known at that time (Gencay, Selcuk & Whitcher, 2002: 99). In order to overcome this problem, a new set of functions (wavelets) is proposed that facilitates the study of the frequency module of time series without losing the time information. Figure 1 shows the different approaches to time series analysis.

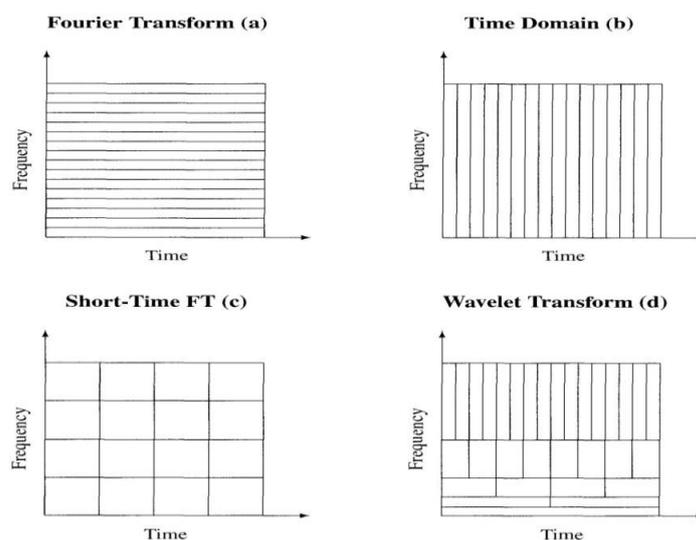


Fig. 1. A comparison of different approaches to time series analysis  
(Gencay, Selcuk & Whitcher, 2002: 98)

Considering the limitation of correlation methods, many studies used econometric models (VAR, multivariate GARCH, etc.) in international stock markets co-movement investigations (such as You & Daigler, 2010; Ali, Butt & Rehman, 2011; Lahrech & Sylwester, 2011; Gallali & Abidi, 2012; Mansourfar, 2013; Lean & Teng, 2013; Narayan, Sirananthakumar & Islam, 2014; Chen, Chen, & Lee, 2014;

Teulon, Guesmi & Mankai, 2014). In addition to international portfolio diversification research studies, some other studies examined returns co-movement in sector level within a specific country's capital market (like: Bordoloi, 2009) or among various countries (such as Guerrieri & Melicani, 2005).

Wavelet transform can be divided into two main parts: discrete and continuous wavelet analysis. In recent years, wavelet transform is widely used in Economic and Finance and Discrete Wavelet Transform (DWT) as a simplified and compact version of Continuous Wavelet Transform (CWT) and is supposed to be the main body of studies in Finance, (e.g., Gallegati, 2008; Dajcman, Festic & Kavkler, 2012; Dajcman, 2013; Saiti, Dewandaru & Masih, 2013; Kravets & Sytienko, 2013). However, continuous wavelet transform is a new approach in this field of science, and just a small number of studies gained its advantages. The DWT is useful for noise reduction and data compression whereas the CWT is better for feature extraction purposes (Madaleno & Pinho, 2010).

Rua & Nunes (2009) used continuous wavelet transform and wavelet coherence approach in co-movement analysis of the United State, United Kingdom, Japan, and Germany stock markets. Their findings reveal that the strength of the co-movement of international stock returns depends on the frequency. In addition, co-movement among markets is stronger at lower frequencies (higher scales). Madaleno & Pinho (2010), by analyzing international stock markets, indicated that the relationships among sample indices are strong but vary over scales. Barunik, Vacha & Křištoufek (2011) studied Central Europe stock markets interdependence using high-frequency financial market data in a time-scale space. Their finding illustrates that the interconnection between all stock markets changes significantly in time and varies across scales. Rua & Nunes (2012) explore the beta behavior in emerging markets using continuous wavelet transform. They explained that beta in emerging markets varies over time and scale.

Regarding the aforementioned information, the majority of studies are dedicated to time domain rather than frequency (scale) domain. In

addition, studies in frequency domain are limited to international markets co-movement analysis. Domestic markets including many industries with special characters are exceptionally important for the numerous investors of a country. Therefore, in domestic sector indices co-movement analysis (as the fundamental step in portfolio construction), the dissimilarity of investors should be considered; a fact which has received a smaller amount of concentration. The present study attempts to fill this gap by exploring co-movement behavior among returns of TSE sector indices in time-scale space using wavelet coherence approach within the continuous wavelet transform framework.

Stock returns are influenced by many different factors, such as monetary policy, gold, oil and Basic metal global price changes, currency ratios, financial crises, etc. These Factors impact directly on some industries, where other sectors are affected due to their correlation with the first group. Therefore, co-movement structure analysis in different years is essential in order to control the destructive shocks transferred from one sector to others. On the one hand, if the correlation structure changes during several years, market control policies should be updated continuously. On the other hand, for investors who want to reduce their investment risk by portfolio diversification, the awareness of correlations change over time is vital, so that they can verify their portfolio in time and reduce their portfolio risk. Hence, the first hypothesis is developed as:

**H1:** Co-movements among sector returns (industry indices return) of Tehran Stock Exchange (TSE) vary over time.

In 1991, Peters proposed Fractal Market Hypothesis (FMH) suggesting that the dynamics of the market price might be caused by the interaction of the agents with different time horizons and differing interpretations of information (Anderson and Noss, 2013). Each of these agencies with different time horizons uses dissimilar transaction strategies; thus, they need different co-movement information related to their own horizon separately. Accordingly, it is expected that the correlations among sector returns have a multi-scale nature. As a result, it is critical to test whether co-movements among TSE sector

returns have multi-scale behavior. In addition, if so, what industries combination in each scale leads to better portfolio diversification? Hence, the second hypothesis is developed as:

**H2:** Co-movements among sector returns of TSE vary over scales.

### Data and Methodology

The data used in this study are the daily closing prices of the ten industry indices of TSE from 23 August 2006 to 5 November 2013, which have been acquired from Fipiran (Financial Information Processing of Iran) official website. The industry indices with the highest share of market value, which has been in TSE active industry list for at least 9 years, were selected as the study sample. Afterward the returns of industry indices were calculated as differences of logarithmic daily closing prices. Table 1 shows the chosen sectors and their share of market value.

Table 1. The selected sample of study

industry index	market share
Chemical products	16.67%
Basic metals	13.00%
Financial intermediation	12.95%
Refined petroleum products	11.91%
Banks	10.34%
Metal ores	7.65%
Cement, Plaster & lime	2.68%
Investment Companies	2.03%
Motor vehicles	1.92%
Pharmacy	1.55%
Total	80.7%

The wavelet transform was introduced to solve problems related to the Fourier transform, when evaluating non-stationary data or signals with localized behavior in time and frequency (Sharkasi, Ruskin & Crane, 2005). The wavelet transform uses a basic function called “mother wavelet” in order to capture the features that are local in time and in frequency by translation and dilation.

When capturing low frequency events, the time-frequency separator of the wavelet transform is long in time which leads to good frequency resolution for these events, and once capturing high

frequency components, the time-frequency separator of transform is long at frequency; hence, good time resolution of these elements would be achievable (Gencay, Selcuk & Whitcher, 2002: 99).

### Continuous wavelets transform (CWT)

The continuous wavelet transform is a function of two variables  $W(u, s)$  and is gained by simply projecting the function of interest  $x(t)$  onto a particular wavelet  $\psi$  using:

$$W_x(u, s) = \int_{-\infty}^{+\infty} x(t) \overline{\psi_{u,s}(t)} dt \quad (1)$$

where  $\overline{\psi_{u,s}(t)}$  is the complex conjugate of  $\psi_{u,s}(t)$ .

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) \quad (2)$$

$\psi_{u,s}(t)$ , can be stated as the function of time position  $u$  (translation parameter) and the scale  $s$  (dilation parameter), which is interrelated with the frequency. However, the original function was only a function of one parameter. By applying shifted and translated versions of the mother wavelet to every function (time series), the complicated structure of the function could be broken down into simple components (Gencay, Selcuk & Whitcher, 2002; Rua & Nunes, 2009).

Every mother wavelet should fulfill some conditions like:

1. Zero mean  $\int_{-\infty}^{+\infty} \psi(t) dt = 0$  (3)

2. Unit energy  $\int_{-\infty}^{+\infty} |\psi_{u,s}(t)|^2 dt = 1$  (4)

3. Admissibility condition  $0 < c_\psi = \int_0^{+\infty} \frac{|\hat{\psi}(w)|^2}{w} dw < +\infty$  (5)

where  $\hat{\psi}(w)$  is the Fourier transform of  $\psi(t)$ . Condition number 3 allows the reconstruction of a time series from its continuous wavelet transform (Rua & Nunes, 2009; Barunik, Vacha & Kriřtoufek, 2011).

### Morlet wavelet

There are several wavelets available for continuous wavelet transform (i.e., Morlet, Mexican hat, Shannon, etc.) with different characteristics useful for various purposes. Morlet wavelet is the most common

complex<sup>1</sup> wavelet in continuous wavelet analysis (Addison, 2002: 35). This wavelet has Gaussian envelope with good time-frequency localization. The wavelet contains both real and imaginary parts which allows studying amplitude and phase components of the time series together. This is applicable to wavelet coherence and wavelet phase discussions (Barunik, Vacha & Kriřtoufek, 2011; Vavrina, 2012). This common wavelet in Economic and Finance studies is defined as:

$$\psi^M(t) = \frac{1}{\pi^{\frac{1}{4}}} e^{iw_0 t} e^{-\frac{t^2}{2}} \quad (6)$$

where  $w_0$  is the wave number. In practice,  $w_0$  is set to six as it provides a good balance between time and frequency localization. Owing to the aforementioned capability of Morlet wavelet and following Rua & Nunes (2009), Ranta (2010), and Barunik, Vacha & Kriřtoufek (2011), this study utilized Morlet wavelet in empirical analyses.

### Wavelet coherence

The wavelet coherence (WTC) is a powerful and efficient mathematical tool that can represent the linkage of two time series and investigate their co-movement from the frequency and the time points of view at the same time. A richer picture of interdependence between returns would be available by clearly indicating when and at which scale the two examined time series co-move (Vavrina, 2012).

Wavelet coherence could be described as:

$$R^2(u, s) = \frac{|S(s^{-1}W_{xy}(u, s))|^2}{(S(s^{-1}|W_x(u, s)|^2))(S(s^{-1}|W_y(u, s)|^2))} \quad (7)$$

where  $S$  is a smoothing operator<sup>2</sup>.  $W_{xy}(u, s)$  is the cross wavelet transform which is defined as:

$$XWT: W_{xy}(u, s) = Wx(u, s)\overline{W_y(u, s)} \quad (8)$$

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1. Complex or analytic wavelets are the kind of wavelets with both real and imaginary parts whose Fourier transforms for negative frequencies are zero.
  2. Smoothing operator is  $(w) = S_{scale}(S_{time}(w_n(s)))$ ,  $S$  time represents smoothing in time and  $S$  scale is smoothing along the wavelet scale. For more details see: Grinsted *et al.* (2004) and Torrence & Compo (1998).

$W_x$  and  $W_y$  are wavelet transforms of the original time series  $x$  and  $y$ . Character  $\overline{W_y}$  indicates complex conjugate.  $|W_{xy}(u, s)|^2$  corresponds to the local covariance between the time series ( $x$  &  $y$ ), and  $|W_x(u, s)|^2$  is the local variance of  $x$  at each scale (Rua & Nunes, 2009; Barunik, Vacha & Krištoufek, 2011).

The value of  $R^2(u, s)$  is between zero and 1. Higher rates indicate strong co-movement; however, lower amounts of  $R^2(u, s)$  show weak interdependence. In WTC plots, color code for power ranges from blue (low power) to red (high power). A significant level for wavelet coherence was estimated by Monte Carlo methods. In wavelet coherence figures, the black contour designates the 5% significance level. Since co-movement of time series in wavelet coherence method is reported by  $R^2(u, s)$ , the model never demonstrates the negative correlations. To overcome this concern, (Torrence & Webster, 1999) proposed the concept of phase differences. Mathematical definition of phase difference is as follows:

$$\phi_{xy}(u, s) = \tan^{-1} \left( \frac{\Im\{s^{-1}W_{xy}(u, s)\}}{\Re\{s^{-1}W_{xy}(u, s)\}} \right) \quad (9)$$

In the mentioned formula,  $\Re$  and  $\Im$  correspond for smoothed real and imaginary parts. In figures, phase differences are represented by phase arrows. If the arrows points to the right, the examined time series are in phase, and opposite direction means anti-phase. If they point down, the first time series is leading the second one, and if they point up, the second one is leading the first one. Therefore, that spillover effect can be investigated simultaneous with the co-movement study (Grinsted, Moore & Jevrejeva, 2004). In our empirical study, we test for the existence and strength of co-movement among returns of TSE sector indices in time and frequency (scale) domains. All computations have been done using Matlab (R2012a).

## Results

### Descriptive analysis

Descriptive analyses of daily returns of ten major industry indices are performed to find out the properties of the data; the results are presented in Table 2.

The highest average daily return is observed for Basic metals and

Metal ores industries by 0.165% though; Motor vehicles sector has the lowest average of the daily return (0.047%). Considering standard deviation as a measure of volatility, the industry of Refined petroleum products shows the highest volatility at 1.61%, while Pharmacy industry is the least volatile market with the smallest returns standard deviation at 0.59%. Five TSE industry indices (Financial intermediation, Refined petroleum products, Banks, Cement & Pharmacy) have right skewed return distributions which reveals that there is a superior probability of higher returns in these industries. The other five industries are negatively skewed. The kurtosis in Motor vehicles industry indices is the lowest among sample of study, which implies that this industry is more risky compared to other industries. The hypothesis of normality of returns in all industry indices is rejected by Jarque-Bera tests.

Table 2. Descriptive analysis of the daily returns of ten major industry indices

Industries	Chemical products	Basic metals	Financial intermediation	Refined petroleum products	Banks
Mean	0.00143	0.00165	0.00121	0.00156	0.00149
Std. Dev	0.0121	0.0143	0.0084	0.0161	0.0113
Skewness	-2.97	-0.23	2.27	4.49	5.64
Kurtosis	74.09	64.07	22.93	69.28	100.66
Jarque-Bera	352798	258616	28980	310221	670130
Prob	0.0001	0.0001	0.0001	0.0001	0.0001
Industries	Metal ores	Cement	Investment Companies	Motor vehicles	Pharmacy
Mean	0.00165	0.00073	0.00096	0.00047	0.00124
Std. Dev	0.0153	0.0082	0.0086	0.0137	0.0059
Skewness	-0.37	2.21	-0.83	-0.14	3.72
Kurtosis	17.92	32.72	24.61	13.76	36.07
Jarque-Bera	15470	62582	32558	8038	79656
Prob	0.0001	0.0001	0.0001	0.0001	0.0001

### **Wavelet coherence results**

Linkage of TSE major industry indices are investigated by wavelet coherence approach, which presents a depiction of the co-movement between pairs of sectors in time-scale space. Figure 2 addresses wavelet coherence and phase difference calculation results between Chemical products industry and other sectors.<sup>1</sup> The horizontal axis implies time, whereas the vertical axis represents scale in days. Sections surrounded by the black lines plotted in warmer colors represent areas with significant dependence. The colder colors stand for the areas with less dependence. Concentrating on the results acquired from the wavelet coherence, it is apparent that co-movement of Chemical products and other sectors amplify by moving from lower scales toward higher ones, in a way that scales of 1 to 32 days report weaker co-movement in comparison with scales of 128 to 512 days. In 128-512 days periods, the estimated local correlations are high and sectors move in phase (due to phase arrows), which reveals the decrease in the amount of benefits from portfolio diversification for investors with long-term investment horizons. In the term of time, it is understandable that the co-movement of sector pairs vary over time. For example, most of the sector co-movement power was higher during 2007-2011.

In recent years, co-movement between Chemical products industry and some sectors like Banks, Financial intermediation, Cement, Motor vehicles, and Pharmacy was weaker than the co-movement of this industry with industries of Basic metal, Refined petroleum products, and Metal ores.

One interesting and important matter is the spillover mechanism between sector pairs. The spillover effect patterns between sectors vary over time and over scale. As an example, considering wavelet coherence plot of Chemical products and Metal ores, it is observable that, in the scale of 256 days and during 2009-2010 Chemical products

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1. Due to the limitation of journal pages, just ten wavelet coherence results for industry pairs, within two figures, are reported in the article as sample. The other figures are available via Email.

sector was the leading industry. However, during 2011-2013 and at the scale of 128 days, Metal ores industry was the leader sector.

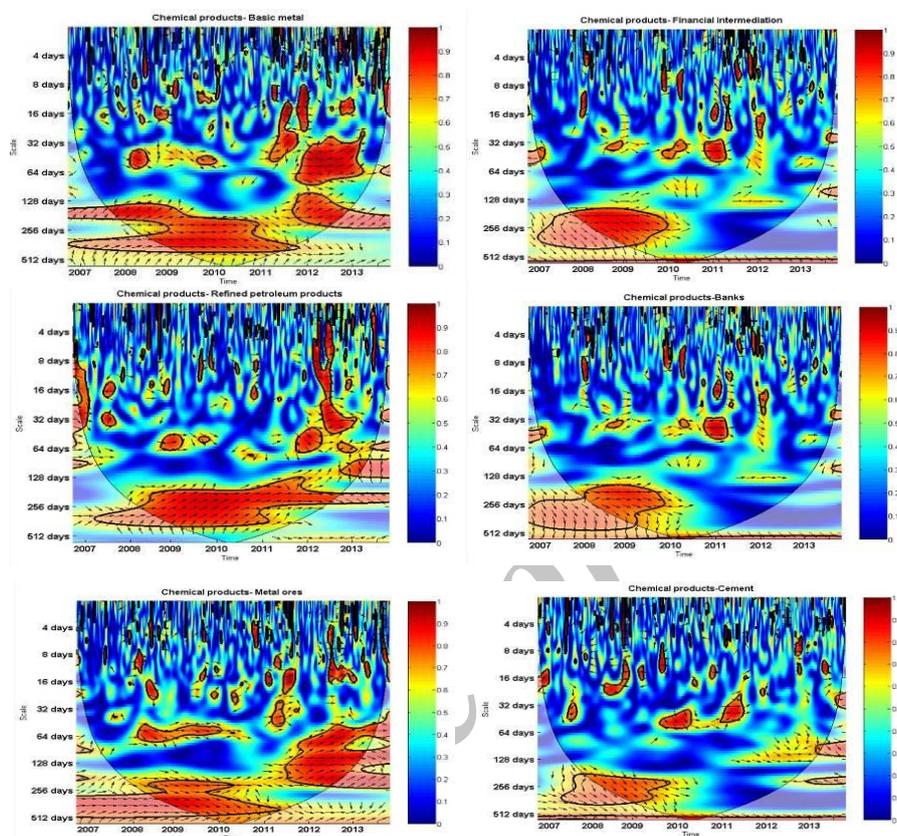


Fig. 2. Wavelet coherence of Chemical products industry and Basic metals, Financial intermediation, Refined petroleum products, Banks, Metal ores, and Cement sector indices pairs

Estimated wavelet coherence between Basic metal industry and four sectors is reported in Figure 3. By inspecting the plots, one can find that co-movements between Basic metal industry and other sectors are time- and scale-based phenomena. This means that time and scale changes lead to different co-movement. There is a strong co-movement between Basic metal industry and Refined petroleum products in various scales, yet without the same distribution form in different years. For instance, in the scales of 256-512 days, strong and significant co-movement is reported during 2007-2010; however, this high linkage could not be found during 2010-2013 in the stated scale.

In other words, investors with investment horizons of 256-512 days could benefit from portfolio diversification advantages during 2010-2013 while it was not possible during 2007-2010. Moreover, in this pair, the benefit of portfolio diversification is less for investors with investment horizon of 16-32 days.

The highest amount of co-movement between returns of Basic metal and Banks industries is related to the scales of 64-128 days during 2008-2012. In this restricted region, the directions of phase arrows indicate spillovers from the Basic metal to Banks industry. In addition, the co-movement behavior of this industry and Metal ores in lower scales shows several changes. Besides, this pair's co-movement is stable for the scales higher than 128 days for all the years.

During 2007-2011, the interdependence of Basic metal and Cement industry returns in the scales of 64-256 days was higher than recent years. An important issue in this pair's wavelet coherence plots was the changes of spillovers' directions in different years. Considering the scales of 128-256 days during 2007-2010, it could be seen that the Basic metal industry was the leader sector, while in 2013, spillovers were from Cement index to Basic metal industry at the same scale.

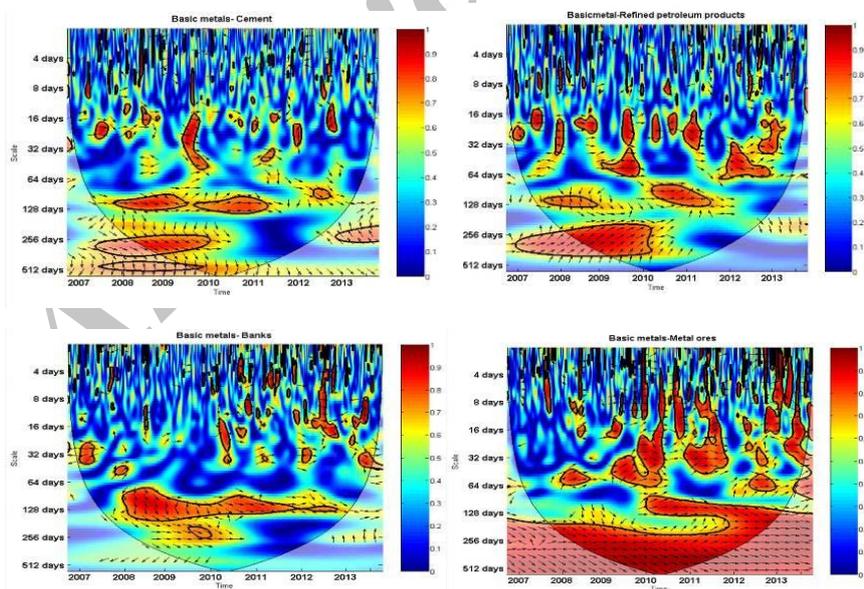


Fig. 3. Wavelet coherence of Basic metals and Cement, Refined petroleum products, Banks, and Metal ores sector indices pairs

## **Conclusion**

This paper examined return co-movement among industry indices of Tehran Stock Exchange using a wavelet coherence method in continuous wavelet transform. This new sight on the co-movement analysis can show the outline of local correlations changes in time and scale domains continuously. Data analysis confirms the correctness of the two developed hypotheses of the study simultaneously in 95% confidence level. As wavelet coherence plots and figures indicate that returns co-movement among different sectors of TSE varies over time and across scales, the investors with different investment horizons would benefit differently if they diversify their portfolios via the same industries. In lower scales (2-64 days) cross correlation of sector returns are unbalanced, while in higher scales (128-512 days) the co-movement of some sectors such as Banks-Cement or Basic metal-Metal ores are high and more stable in the study period. This stability could not be found in the returns co-movement of industry pairs like Basic metal-Motor vehicles and Chemical products-Cement.

Investors having short investment horizons (less than 32 days) could benefit from portfolio diversification advantages using the stocks within most of the industry indices of TSE. Because of the correlation dynamics over time, these portfolios need continual inspecting. Investors with intermediate investment perspectives (64-128 days) can use the low cross industry correlation of some pairs including Chemical products-Banks, Basic metal-Pharmacy, or Refined petroleum products-Investment Companies to construct portfolios.

Even though there is a high amount of interdependence in higher scales, the possibility of portfolio diversification is even provided via some pairs of sectors for investors with long term horizons as well; for example, this opportunity is available through industry pairs like Metal ores-Pharmacy, Metal ores-Motor vehicles, Metal ores-Banks, Investment Companies-Pharmacy, and Chemical products-Investment Companies.

Wavelet coherence and its phase difference concept are perfect and

simple methods in spillover effect analysis. Volatility spillovers are influenced by the changes in time and across scales. Analyzing the spillover effect among domestic sectors is a key issue for market policy makers rather than investors, since policy makers can account for the spillover mechanisms in order to protect some sectors from damaging effects of originating in others by recognizing leader and follower industries. Moreover, the wavelet coherence approach provides facilities to distinguish susceptible scales easily.

This study's findings confirm the results of Rua & Nunes (2009) and Barunik, Vacha & Krištoufek (2011) representing time varying and scale based characters of stock markets.

Taking into account the numerous capabilities of wavelets in time series analysis, further research studies may re-examine other key Economic and Finance issues (i.e., investment utility curves behavior in time-scale space or estimating optimal hedge ratio in different time-scales) using wavelets.

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