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RESEARCH PAPER

Interdependence of Tehran Stock Exchange upon the Oil Price and USD Exchange Rate Return Using Quantile Regression and Time-Frequency Domain Analysis

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Abstract
Compared to GARCH, ARDL, VAR, and similar methods that are commonly used for stock market analysis and portfolio pricing, the quantile regression has proven to be more advantageous. In this study, we combine the quantile regression with wavelet decomposition to analyze different investment horizons in Tehran Stock Exchange. The discrete wavelet decomposition is used to divide the indices time series into short-term (2-16 days), mid-term (16-128 days), and long-term (128-512 days) horizons. The investment horizons are then accurately studied in a bear, normal, and bull market. Since Iran is an oil-exporting country and its economy is highly impacted by fluctuations in the USD exchange rate return, it is of crucial importance to analyze the effects of oil price and free-market USD exchange rate return on the stock market for investment policy-making and portfolio management. The results demonstrate how the exchange rate return volatility and the OPEC basket price fluctuation affect the stock market. The results illustrate strong evidence on the assumption of a long-term strong positive correlation between TSE and the USD exchange rate return increase.

Keywords: Comovement, Tehran Stock Exchange, Quantile Regression, Wavelet Decomposition.
JEL Classification: C32, C53, F47, G11.

Introduction

The comovement of world equity markets is often used as an indicator of economic globalization and financial integration. Sun et al. (2008), Mensi et al. (2014) and Chiang and Chen (2016) studied the impact of various factors, e.g. oil prices, exchange rate returns, interest rates, and gold prices, on the comovements among stock markets. Their study of GCC Arab stock markets indicated that they were more sensitive to global changes than the regional factors (Hammoudeh and Li, 2008). A quantile regression approach was employed by Zhu et al. (2016) and Xiao et al. (2018) to investigate the impact of global crude oil prices on the Chinese stock market. Jiang and Yoon (2020) studied the impact of volatility in oil prices on the stock market by using discrete and continuous wavelet decomposition. They showed that there was a strong level of comovement between oil price fluctuations and stock rates in 16 to 128-week time windows. That is a significant dependence between stock prices and oil market volatility in the long-term investment horizon.

Several studies have been conducted to investigate the interdependence between foreign

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exchange rate returns and stock markets for different affluent economies and developing countries. The linkage between stock price and exchange rate return in the developed countries has been scrutinized in Caporale et al., 2014; Chen and Chen, 2012; Ndako, 2013. The same case has also been studied in a plethora of articles (Chkili and Nguyen, 2014; Hatemi-J, 2003; Lin, 2012; Pan et al., 2007; Sui and Sun, 2016; Tang and Yao, 2018; Yang, 2017).

There are few studies written by Iranian scholars to investigate the problem. Rostami et al. (2016) concluded with a significant relationship between the returns of different industry indices on the TSE with returns in the crude oil, gold, and foreign exchange (USD and EUR) markets.

Fattahi et al. (2017) studied the spread across Iranian financial markets and the transfer of positive and negative shocks across different markets. The results indicated an interesting pattern in this relationship, showing a negative relationship between the stock and foreign exchange markets. This relationship becomes apparent when the exchange rate return is exceptionally high or low.

Nademi and Khochiany (2017) investigated the comovement of the stock market with foreign exchange and gold in Iran. Having applied the wavelet coherency analysis, they showed that although in the short and medium time horizons the stock market is in the opposite phase with the other two markets, the stock return is a lagging variable for a longer investment horizon.

We study the interdependence of TSE and the USD exchange rate return and the rate of OPEC oil basket price. Our contribution has two folds. Firstly, we decompose the financial time series in this study in three different time windows to study the price changes in three desired investment horizons, the short-, mid-, and the long-term. The next contribution of our work is due to apply the methodology on the closing prices of the US Dollar exchange rate return in the free market rather than using the rates announced by the central bank of Iran.

The rest of this paper is organized as follows. Section 2 discusses the basics of wavelet transform as a basis of the methodology used in this study. Section 3 provides an elaboration on why we use quantile regression to get more insight into the investment horizons. Section 4 illustrates the descriptive statistics, and discuss the results of applying the selected methodology on the dataset. Finally, we provide the reader with a conclusion on the whole work in Section 5.

Methodology

Wavelet Transform

A wavelet is a wave function with an average value of zero. Unlike sinusoidal functions, wavelets have a finite period, that is they have a start and an end (Gençay et al., 2002). Wavelet functions are useful for extracting key features from signals for reproduction without requiring the entire wave to be stored. Moreover, wavelets are effective tools for overcoming the non-stationary nature of financial time series. The capacity of wavelet analysis for breaking time series down to basic functions containing information are major advantages of the tool.

By definition, a wavelet analysis imitates Fourier dynamics. The difference is that the functions used to identify the local behavior of time series offers better performance. Although the Fourier transform can transfer information from the time domain to the frequency domain, the wavelet transform offers the advantage that it can display data in both domains so that it makes the wavelet transform a reliable tool for the analysis of financial time-series (Aguiar-Conraria et al., 2008; Roueff and von Sachs, 2011).

The wavelet transform of g(t) with finite energy is defined as an integral transform with a family of functions in the form of $\eta_{\lambda,t}(u) \equiv \frac{1}{\sqrt{\lambda}}\eta(\frac{u-t}{\lambda})$.

$$Wg(\lambda,t) = \int_{-\infty}^{\infty} g(u)\eta_{\lambda,t}(u)du \quad \lambda > 0 \tag{1}$$

where λ is the scale parameter, t is the location parameter, and $\eta_{\lambda,t}(u)$ functions are the wavelets. In the case of an imaginary wavelet function, the imaginary complex $\bar{\eta}_{\lambda,t}(u)$ is used in Equation 1. The normalization factor $1/\lambda$ is adjusted to ensure that Equation 2 holds for any scale parameter.

$$\|\eta_{\lambda,t}(u)\|^2 \equiv \int |\eta_{\lambda,t}(t)|^2 du = \int |\eta(t)^2 dt = 1 \tag{2}$$

The choice of the wavelet $\eta(t)$ is neither arbitrary nor unique. The wavelet function must satisfy the following conditions:

1. Has unit energy, $\|\eta(t)\|_{L^2}^2 = 1$;
2. Rapidly attenuates;
3. Has a zero average, $\int \eta(t)dt = 0$.

Wavelet transforms can be continuous or discrete. Given that financial time series are discrete, the discrete wavelet transform (DWT) is much more fitting for this type of data. Groups of wavelets are generated by the scale function ϕ and a wavelet function η. Scale functions are utilized to discover smooth and low-frequency features. Wavelet functions, however, are used to reveal details and high-frequency features in data. The integral of a scale function sums up to 1, whereas that of a wavelet function adds up to 0.

$$\int \phi(t)dt = 1 \quad \text{and} \quad \int \eta(t)dt = 0 \tag{3}$$

While using wavelets, “scale” is often used rather than the “frequency”. Orthogonal decomposition of the time-series wavelet $X_t\,; t = 1, \dots, n$ is defined as Equation 4.

$$\begin{aligned} X_t = &\sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\eta_{J,k}(t) + \sum_k d_{J-1,k}\eta_{J-1,k}(t) + \cdots \\ &+ \sum_k d_{1,k}\eta_{1,k}(t) \end{aligned} \tag{4}$$

The J[th] level represents the number of scales (frequencies) for the orthogonal wavelet decomposition of the time series X_t, and k can assume any value from 1 to the number of coefficients corresponding to the component. Through shifting and scaling based on powers of 2, $\phi_{J,k}(t), \eta_{J,k}(t), \eta_{J-1,k}(t), \dots, \eta_{1,k}(t)$ functions are created from the scale function $\phi(t)$ and the wavelet function $\eta(t)$.

$$\begin{aligned} \phi_{J,k}(t) &= 2^{-\frac{J}{2}}\phi\left(\frac{t - 2^J k}{2^J}\right), \\ \eta_{j,k}(t) &= 2^{-\frac{j}{2}}\eta\left(\frac{t - 2^j k}{2^j}\right), \quad j = 1, \dots, J. \end{aligned} \tag{5}$$

Where $2^j k$ and 2^j are the shift and scale parameters, respectively. Wavelet functions are shorter and spread-out for large j values but narrow and longer for smaller scales. The discrete wavelet transform of the time series X_t comes down to the coefficients $s_{J,k}$ and $d_{J-1,k}$ for

$j = J, J-1, \dots, 1$ in the time-series orthogonal wavelet decomposition relation. In some orders of approximation, Equation 6 can be rewritten for the two coefficients.

$$s_{J,k} = n^{-\frac{1}{2}} \sum_{t=1}^{n} X_t \phi_{J,k}(t), \tag{6}$$
$$d_{j,k} = n^{-\frac{1}{2}} \sum_{t=1}^{n} X_t \eta_{j,k}(t) \quad j = J, J-1, \dots, 1.$$

The significance of the wavelet term in describing the behavior of the time series is measured by its corresponding coefficients. The $s_{J,k}$ are smoothness coefficients describing the smoothness of data; Moreover, the $d_{j,k}$ are detail coefficients representing the high-frequency nature of time-series data. For example, one way to measure each level is to find the energy ratios of stock market data collected daily and per minute. The level corresponds to the number scales for the orthogonal wavelet decomposition of the time series. In this example, figures which are larger than the scale show slower and more smooth time-series wave shapes, whereas smaller scales correspond to more rapid and finer motions in the time series.

Quantile Regression

As a statistical tool, the Ordinary Least Squares (OLS) regression is widely used in different disciplines. Unfortunately, despite the simplicity of application, linear regressions must be employed with caution due to their serious weaknesses. Therefore, by modeling the conditional mean function $\mathbb{E}[Y|X]$, the standard linear regression methods reveal a mean relationship between prediction variables and the dependent model output. It is important to note that these methods provide nothing but a brief insight into the relationship at work (for example, it provides no information on the conditional variance $Var[Y|X]$). In contrast, in most cases, more accurate information is required about the relationships across the conditional distribution of Y given X. In these cases, the quantile regression can provide a reliable solution to the problem. Compared with other OLS regression models, quantile regression makes no assumption regarding the parametric distribution of the solution. Besides, it does not assume a constant response variance. The conditional median function $Q_\tau[Y|X]$ is used in quantile regression to represent the relationship between the independent and the dependent variables, while τ is the corresponding quantile in the empirical distributions. The $\tau \in (0,1)$ quantile is the point that divides the dependent variable data into those less than τ and more than $1-\tau$. The τ quantile level is the probability $\Pr[Y \le Q_\tau(Y|X)|X]$, that is the value of Y below which the population ratio of the conditional response sums up to τ. Fitting a series of regression models using a series of $\tau \in (0,1)$ results in the complete description of the conditional distribution of the response. The optimal choice of τ series depends on the training data, as more details can be discovered and recorded on the conditional distribution with a more extensive training dataset. The regression model is written as in Equation 7 for the τ quantile of the response (Koenker & D'Orey, 1987).

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \cdots + \beta_p(\tau)x_{ip}, \quad i = 1 \dots n \tag{7}$$

$\beta_j(\tau)$ is estimated by solving the minimization problem of Equation 8.

$$\min_{\beta_0(\tau),\dots,\beta_p(\tau)} \sum_{i=1}^{n} \rho_\tau \left(y_i - \beta_0(\tau) - \sum_{j=1}^{p} x_{ij}\beta_j(\tau) \right) \tag{8}$$

The function $\rho_\tau(r)$, defined as Equation 9, is the check loss function.

$$\rho_{\tau(r)} = \tau \max(r, 0) + (1 - \tau)\max(-r, 0) \qquad (9)$$

For any arbitrary level of the τ quantile, the solution to the minimization problem provides a separate group of regression coefficients. One of the most significant properties of the quantile regression is its ability to examine both upper and lower tail dependence in addition to the capability of measuring the average or linear dependence between the dependent variable and the regressors (Baur, 2013; Chuang et al., 2009; Lee & Li, 2012). According to the above-mentioned discussion, the independent variables in this study are USD and Oil. Therefore, the model used in this work is as shown in equation 10:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)USD_i + \beta_2(\tau)Oil_i\,, \quad i = 1 \dots 8 \qquad (10)$$

y_i is the return rate of TSE indices while the i stands for each of the eight wavelet decomposition scale bands, i.e. USD_i means the i^{th} scale band of wavelet decomposition for the USD exchange rate return time series.

Simulation and Results Analysis

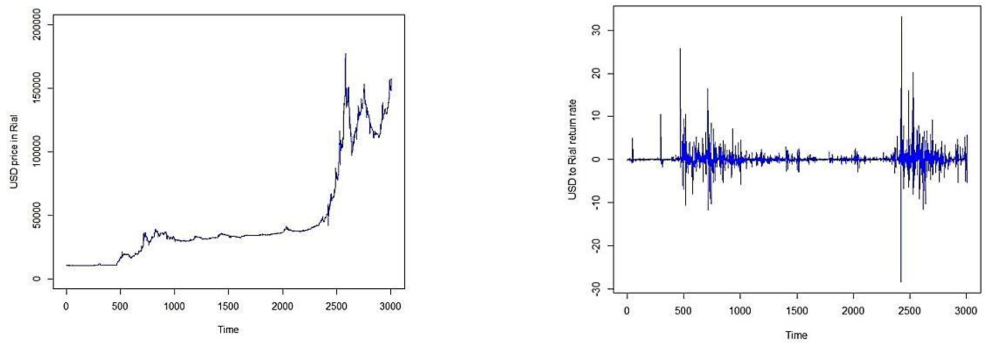
This section reviews the data on the most notable TSE indices to simulate the adopted model. For this purpose, the return of daily closing prices is computed for TSE Dividend and Price Index (TEPIX), top-50 companies (TSE50), industry index (IND), automotive industry index (KHDR), banking index (BNK), industrial metals index (FLZT), chemical companies index (CMCL), cement index (CMNT), drug index (DRG), and food products (except sugar) index (FOD). The raw data was sourced from Tehran Securities Exchange Technology Management website from 15 August 2010 to 18 March 2020. The time series includes 3007 observations. It must be noted that the TSE workdays are different from those of global financial markets. Therefore, the data corresponding to the Iranian and global markets was matched by using the last day's final prices for days when no data was available for the Iranian market. Besides, the USD in this study stands for the US dollar to the Iranian Rial exchange rate and was obtained from TGJU.org[1]. It should be emphasized that the USD exchange rate used in this study is the rate that is used to sell the USD note in the free market. Furthermore, for the OPEC Oil return rate, we use the Oil variable. The data for Oil price was fetched from the OPEC website. Figures 1-3 illustrate the raw and return time series for USD dollar to the Iranian Rial, Oil Price in Us dollar, and TSE overall index respectively.

The time-series data corresponding to each studied variable was divided into eight investment windows using the Daubechies wavelet since it has a preassigned degree of smoothness and compact support and also gives better results than the Haar wavelet. The orthogonal components D1–D8, as scale levels, and the smoothness component *S*, produced by processing the time series data by the discrete wavelet decomposition function, are plotted in Figures 4-6. Since the number of data points in this study is limited to 3007, and on the eighth scale we have 256-512 days, decomposing times series into 8 different scale bands exhausts all data points. To avoid repetitiveness we plot wavelet decompositions of USD return rate, oil price return, and TEPIX return.

Tables 1–3 present the descriptive statistics for the time series studied in this work. According to Table 2, the highest fluctuation among the TSE indices corresponds to oil products,

1. https://english.tgju.org/

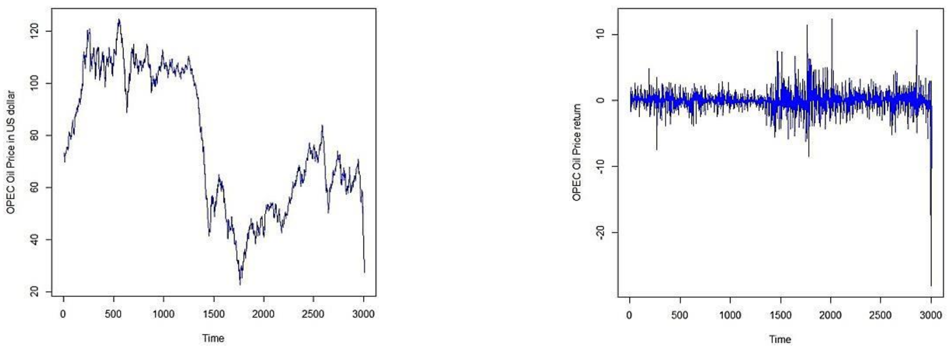
NFTI, followed by the automotive group, KHDR. Meanwhile, TEPIX shows the least fluctuation. Except for NFTI, all studied indices have positive skewness. The statistics show that the TSE was mostly a bull market over the period studied. Given the highly negative skewness of NFTI index, this group is considered mostly bearish. Considering the high skewness and kurtosis of stock market indices, as well as Oil and USD, the probability density of these random variables is fat-tailed and features peaks.



(a) (b)

Figure 1. Time Series Representation for (a) USD to Rial Exchange Price, (b) the Corresponding Return Rate Time Series

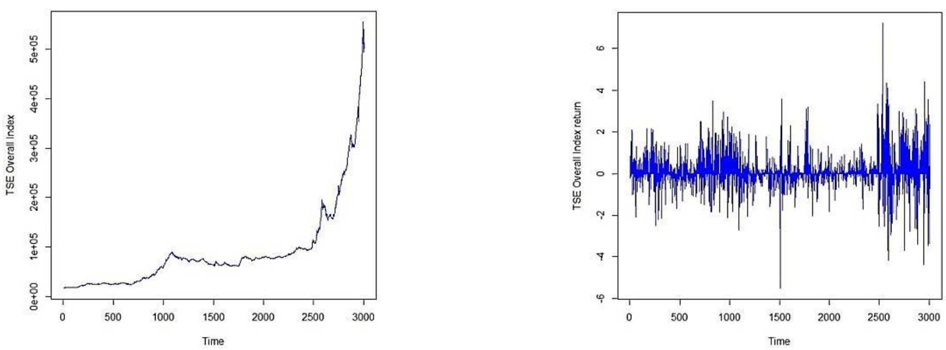
Source: (a) https://english.tgju.org (b) Research finding.



(a) (b)

Figure 2. Time Series Representation for (a) OPEC Oil Price (b) the Corresponding Return Rate Time Series

Source: (a) https://OPEC.org. (b) Research finding.



(a) (b)

Figure 3. Time Series Representation for (a) TSE's Overall Index, TEPIX, and (b) the Corresponding Return Time Series.

Source: (a) http://en.tsetmc.com (b) Research finding.

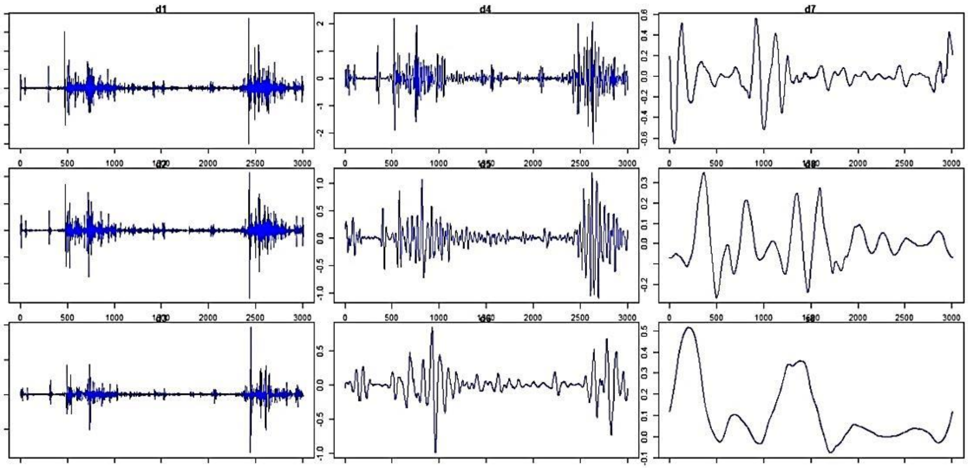


Figure 4. The Wavelet Decomposition of USD at Different Bands
Source: Research finding.

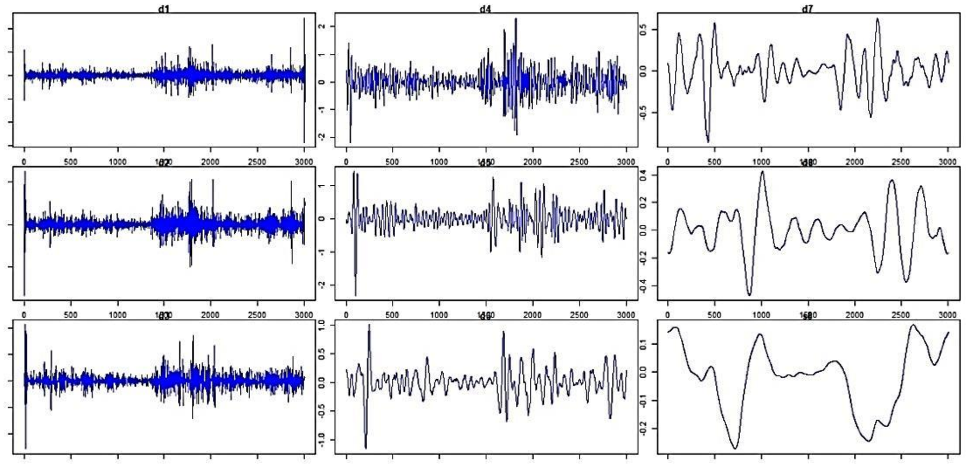


Figure 5. The Wavelet Decomposition of Oil Price Return at Different Bands
Source: Research finding.

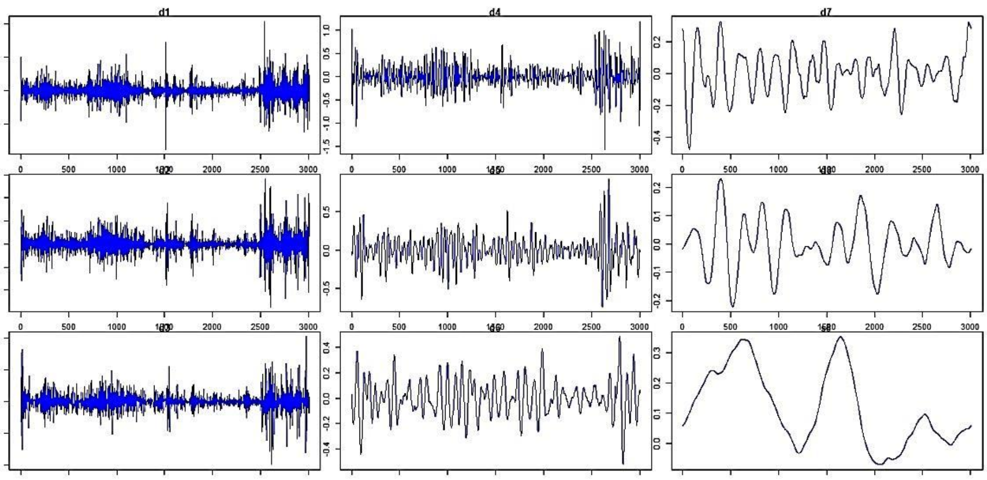


Figure 6. The Wavelet Decomposition of TEPIX at Different Bands
Source: Research finding.

Table 1. Descriptive Statistics for USD Return Rate and Oil Price Return

Statistics	USD	Oil
Mean	0.1051	-0.0204
Maximum	33.1429	12.3319
Minimum	-28.3887	-28.1903
Standard Deviation	1.8493	1.5420
Skewness	2.5425	-1.7964
Kurtosis	82.4425	46.4033

Source: Research finding.

Table 2. The TSE Indices Statistics

	Indices										
	TEPIX	TSE50	IND	FLZT	CMCL	CMNT	DRG	KHDR	BNK	FOD	NFTI
Mean	0.117	0.137	0.123	0.129	0.136	0.115	0.147	0.102	0.086	0.146	0.146
Maximum	7.22	7.34	7.82	11.44	9.75	5.71	6.47	14.47	10.33	22.9	29.25
Minimum	-5.51	-5.54	-6.34	-7.82	-5.84	-3.92	-4.25	-7.27	-11.33	-5.84	-46.43
St. Dev.	0.797	0.823	0.83	1.17	1.0	0.97	0.87	1.7	1.1	1.18	1.72
Skewness	0.58	0.88	0.61	0.89	1.05	1.06	1.59	0.496	0.247	3.125	-4.09
Kurtosis	10.7	13.16	11.41	9.78	11.79	7.18	12.15	5.58	14.68	53.19	214.3

Source: Research finding.

Table 3 shows the Spearman rank correlation coefficient and a choice of indices from Tehran Stock Exchange, USD exchange rate return, and OPEC oil price. As can be seen, the OPEC oil price has a negative correlation with the TSE indices. The strong negative correlation between the OPEC oil price and the stock market indices is suggestive of the negative impact of fear in the crude oil market on the stock market. Therefore, the investors in Iranian stocks must be watchful of OPEC oil price fluctuations. Moreover, the free-market USD shows a strong positive correlation with all stock market indices. In other words, over time, the USD exchange rate return results in positive effects on the rise of the stock prices. The positive correlation matches the empirical evidence on the fluctuations of the Iranian companies' share prices. The share price of TSE-listed companies has steadily reacted positively to the foreign exchange rate return movements in recent years, resulting in a remarkable boom. As a capability, the quantile

Table 3. The Spearman Correlation between TSE Indices and the Global Macroeconomic Variables

	USDRL	OPEC Oil Basket
TEPIX	0.8834(0.0000)*	-0.4900(0.0000)
TSE50	0.9051(0.0000)	-0.5223(0.0000)
IND	0.8875(0.0000)	-0.4881(0.0000)
FLZT	0.8277(0.0000)	-0.2694(0.0000)
CMCL	0.8145(0.0000)	-0.4033(0.0000)
CMNT	0.6232(0.0000)	-0.3457(0.0000)
DRG	0.8902(0.0000)	-0.6734(0.0000)
KHDR	0.7751(0.0000)	-0.6640(0.0000)
BNK	0.6062(0.0000)	-0.5174(0.0000)
FOD	0.8895(0.0000)	-0.6019(0.0000)
NFTI	0.7830(0.0000)	-0.2902(0.0000)

Source: Research finding.
Note: *p-values are shown in parenthesis.

regression methodology can take into account the bottom, middle, and top quantiles of the distribution. Therefore, this section discusses the stock returns in bear-market (bottom quantiles), normal-market (middle quantiles), and bull-market (top quantiles) scenarios. As demonstrated in Figures 4-5, the time series were divided into eight investment windows. Table 4 shows the investment windows corresponding to each wavelet decomposition level. The regression analysis for the bottom, middle, and top quantiles at different time-series wavelet decomposition levels allows for the analysis of the returns based on stock market indices in bear-market, normal-market, and bull-market scenarios in different investment windows.

Table 4. Investment Windows Corresponding to Wavelet Decomposition Levels

Decomposition level	Investment horizon length(days)
D1	2-4
D2	4-8
D3	8-16
D4	16-32
D5	32-64
D6	64-128
D7	128-256
D8	256-512

Source: Research finding.

The Comovement Analysis of the Stock Market Indices

In a short-term window (D1, D2, and D3), the 95% confidence interval of the OLS covers the quantile regression coefficients, particularly for the free-market USD exchange rate return. From a statistical point of view, it is concluded that the quantile regression and OLS regression results are not noticeably different for short-term investment. The effects of changes in the OPEC basket price on the TEPIX remain negligible in the short-term. As evident from Figure 7-(b, c, d, e, f) the impact of the crude oil price movements is negligible in a bear market, and in the 16–64-day interval, the investors need to be cautious of the oil price changes only in the 10% quantile. Furthermore, although the movements of free-market USD exchange rate return do not wield significant influence over the TEPIX in D1 to D4 intervals, the effect is considerable in a long-term window. In the D8 window, representing an investment horizon of 256–512 days (Figure 7-(f)), away from a bear market, the effect of daily free-market USD exchange rate return on the TEPIX increases, with the highest impact of the USD exchange rate return on the TEPIX that appear in the 80% quantile. Meanwhile, on the same investment horizon, the effect of OPEC oil changes on the TEPIX shows a much gentler rising slope than that of the USD exchange rate return with the largest impact corresponding to the 90% quantile.

Except for the D1 decomposition level, that is the short-term, the 2–4-day investment horizon maintains a significant positive correlation with the TSE50 index in all other horizons. In the mid-term horizon, Figure 8-(e, f, g), 16–128 days, the effect of the USD exchange rate return on the TSE50 is rising. Notably, on the D6 level, representing the mid-term 64–128-day investment horizon, the quantile regression produced a strictly increasing curve. According to Figure 8-g, in this investment horizon, the rise of the free-market USD exchange rate return promotes the end of the bear market to enter a bull market. Moreover, in the long-term investment horizon (Figure 8-(h, i)), the rise of the free-market USD exchange rate return has the strongest impact on the TES50. According to Figure 8-(i), in a bull market and the 128–256-day horizon, the investors can expect a 33% positive influence over the TSE50 from the free-market

USD exchange rate return. Yet, in the same horizon, in the worst-case scenario, the positive effect of the USD exchange rate return rising in the 50% quantile on the TES50 reached 25%. Regarding the impact of the OPEC basket movements on the TES50, it is notable that despite mostly-minute fluctuations in most investment horizons, the quantile coefficients curve shows an increase only in the long-term horizon. Particularly on the *D8* level (256–512 days), even though, in a bear market, the crude oil price can have up to 20% negative impact on TES50, which is closer to normal and bull markets, the negative impact of crude oil prices is limited, and the positive effects are promoted with the largest positive effect (nearly 18%) appearing in the 90% quantile.

Figure 9 shows the changes in the slopes of quantile regression coefficients corresponding to IND against the free-market USD exchange rate return and the OPEC basket. In the short-term investment horizon (Figure 9-(b, c, d)), the 95% confidence interval of the quantile regression contains OLS regression coefficients. Furthermore, over the same horizon, the impact of changes in the free-market USD exchange rate return is negligible on IND. Entering the mid-term horizon promotes the effect of free-market USD exchange rate return on IND. Because the increasing slope of quantile coefficients in 16–32 and 64–128-day investment horizons are the clear indications for the greater impact of the free-market USD exchange rate return on IND as the bear market shifts toward the bull market (Figure 9-(e, f, g)). In the mid-term investment horizon, the most considerable effect of the exchange rate return in the 80% quantile is in the *D6* level, where the free-market USD exchange rate return shows up to 27% positive influence over IND. In the long-term investment horizon (Figure 9-(i,j)), rising exchange rate returns are found to undermine the index in a bear market, whereas the quantile coefficients develop a strictly-increasing slope in the long-term when leaving the bear market. The slope of the quantile coefficients of the OPEC basket in the long-term 256–512-day is increasing with the coefficient assuming the smallest negative value (15%) in the extreme bear market (10% quantile). With the index on the rise, the negative impact of the OPEC basket on IND diminishes, and its positive effect heightens to the point where it exceeds 10% in the extreme bull market (90% quantile).

As indicated in Figure 10, the FLZT has much more susceptibility to the USD exchange rate return rather than the OPEC basket price. In the long-term 256–512-day horizon, the effect of the exchange rate return on FLZT is increasing, peaking in the 70% quantile. In a bull market where the rise of the exchange rate return weakens FLZT, indicating that the investors leave the metal market in the long-term, the exchange rate return should keep increasing.

As evident from Figure 11-(g) affected by the rising crude oil prices, CMCL increases in the 256–512-day investment horizon. Similar to other indices studied here, CMCL has larger quantile coefficients for USD exchange rate return movements. For example, in the 64–128-day horizon (Figure 11-(h)), a rise in the foreign exchange rate return has an overwhelmingly positive effect on CMCL, which is maximized by 35% in the 80% quantile (strong bull market).

The quantile regression of CMNT time series against the exchange rate return and crude oil price in Figure 12 shows the most considerable positive effect (nearly 45%) to take place in the 80% quantile in the 128–256-day horizon. Meanwhile, in the same investment horizon and even in the 256–512-day interval, OPEC oil price changes weaken CMNT. As illustrated in Figure 12-(g), the impact reaches -30% in the extreme bull market (90% quantile) in the long-term investment horizon (256–512 days).

In the mid-term, DRG receives a considerable impact from the exchange rate return variations. Figure 13-(g) shows that away from a bear market (moving from the 10% to higher quantiles), the negative impact of the exchange rate return changes on DRG diminishes from 15%, transforming into an increasing effect as a shift is made from normal markets. In the extreme bull market (90% quantile), the effect reaches a high of 30%. Figure 13-(i) suggests a similar trend for the effect of the exchange rate return on DRG in the 64–128-day horizon. In this horizon, the increasing effects of the exchange rate return movements on DRG start to decline from 32% in the extreme bear market, reaching a low of 8% in the 50% quantile. The trend then reverses in the onset of the bull market as the influence of the exchange rate return over DRG is promoted, exceeding 35% in the extreme bull market. Similar to Figure 13-(g, i), Figure 13-(j) indicates the symmetric correlation of DRG's effect on the independent exchange rate return, as the effect of the exchange rate return on DRG reaches nearly 40% in the extreme bull market in the long-term 128–256-day investment horizon. Meanwhile, by extending the investment horizon in the drug market to 256–512 days, the exchange rate return movements leave entirely different effects on the market. In this case, the market will see investment leave in the long-term, particularly in a bull market (Figure 13-(h)). Figure 13-(i) illustrates a remarkable observation regarding the impact of crude oil on DRG. Despite the persisting negative correlation of DRG on the crude oil price in most cases, that is 20–80% quantiles (rising oil prices have a constant impact on DRG, and vice versa), the crude oil prices wield a positive effect on DRG in limit states (extreme bull and bear markets). Overall, as illustrated in Figure 13-(h, j), DRG displays symmetric negative and then an increasing negative correlation on the crude oil price in the long-term horizon. In the long-term 256–512 horizon, the negative correlation peaks at 25% in the extreme bear market. Meanwhile, in the 128–256-day horizon, the symmetric correlation of DRG on crude oil shows a 25% negative effect in limit states (extreme bear and bull markets).

An analysis of the automotive stocks against the exchange rate return movements produced remarkable conclusions. According to Figure 14-(c, d, e), KHDR has a constant negative correlation on the exchange rate return fluctuations in the 4–32-day horizon. That is, the rising exchange rate returns prompt a flight of capital from the automotive group, whereas a decrease in the exchange rate return attracts investment to this market. Yet, as evident from Figure 14-(e), the dependence has a small impact as the largest effect (nearly -10%) can be found in the16–32-day investment horizon in a strong bull market (80% quantile). In the mid-term, i.e. 32–64-day investment horizon, the dependence of KHDR on the exchange rate return is symmetric and positive. So that with the largest quantile coefficients appearing in limit states (the top and bottom ends of the series), i.e. at 22%, the extreme bull market shows the strongest, positive, mutual effect with the exchange rate return. On the other hand, in the 64–128-day horizon (Figure 14-(g)), the positive effect of the USD exchange rate return on KHDR reaches nearly 41% in the extreme bear market. In this case, a mutually positive effect appears between KHDR and the USD exchange rate return in the 20% quantile. Therefore, in the two scenarios, rising exchange rate returns prompt investment in automotive stocks at down prices. It should be noted that the situation is different in the 30% quantile, namely the moderate bear market, where the quantile coefficient sets back to around 2%, suggesting a negative correlation between the two variables. Beyond the bear and normal markets, in the onset of the bull market, a positive correlation reappears between KHDR and the exchange rate return, reaching a local maximum of 30% in the bull market limit state. Despite the asymmetric positive correlation between KHDR and the exchange rate return appearing in the long-term 128–256-day investment horizon (Figure 14-(i)), a strong negative correlation is shown in both limit states (10 and 90% quantiles) in the 256–512-day interval (Figure 14-(g)). Therefore, in cases where automotive stocks are extremely bearish or bullish, the shareholders tend to sell stocks and invest in foreign currencies, and vice versa—decreasing exchange rate returns convince more investors to leave the foreign-exchange market and invest in automotive stocks. The effect of crude oil prices on KHDR is symmetric and positive in the 8–16-day horizon (Figure 14-(d)). The effect is maximized in extreme bear and bull markets at 8 and 5%, respectively. As demonstrated in Figure 14-(e), except for the two limit states (10 and 90% quantiles), the price of crude oil displays a constant positive effect. In the extreme bear market, the crude oil prices affect KHDR by nearly -3%, which reaches -10% in the extreme bull market. That is, even though the crude oil movements support investment in automotive stocks in other quantiles, the investment increases significantly in an extremely bullish automotive market when oil prices drop, whereas rising oil prices block investment in the stocks. Meanwhile, by extending the investment window to 32–64 days (Figure 14-(c)), the symmetric positive correlation between KHDR and the crude oil price increases, peaking in the 80% quantile—despite a significantly weaker correlation in limit states (extreme bull and bear markets). In the long-term 128–256-day investment window (Figure 14-(i)), except for in 70 and 80% quantiles, KHDR shows a significant negative correlation with the crude oil prices. As an interpretation of changes in the correlation at play, the capital flow into the automotive stocks can be said to oppose the crude oil price swings, except for the case of the strong bull market. Yet, the positive effect of the crude oil prices on the bull market in the 80% quantile is fragile, and the effect of crude oil prices on KHDR is reversed immediately when the situation improves. On the other hand, Figure 14-(h) shows that in the longer-term 256–512-day investment horizon, the crude oil prices have a stronger impact on KHDR in a bear market than a bull market. Although the effects begin to fade as market conditions improve, the effect of the crude oil prices on KHDR is boosted at the onset of the bull market.

Figure 15-(b, d, e) indicates the negative correlations between BNK and the exchange rate return in 2–4, 8–16, and 16–32-day investment horizons. That is, in the short-term, a higher exchange rate return encourages the investors to leave the market, whereas a drop in the exchange rate return prompts them to invest in the bank stocks. In the mid-term of 32–64 and 64–128-day horizons (Figure 15-(f, h)), a positive symmetric correlation appears between the BNK and the exchange rate return. The extreme bear market shows the correlation at its strongest in the 64–128-day horizon. Yet, in both cases, the correlation's effectiveness deteriorates when a shift is made from a bear market to a bull market before the impact of the exchange-rate on BNK increases again. A similar trend is found with BNK in the long-term of 128–256-day horizon to the mid-term window. The only difference is that, contrary to the previous case, the exchange rate return wields the highest impact on BNK in the extreme bull market. A remarkable observation is to be made in the long-term of 256–512-day horizon. According to Figure 15-(g), the longer is the investment horizon, the more considerable is the negative effect of the exchange rate return on BNK. The overall asymmetric negative correlation between BNK and the exchange rate return is evident on this horizon. What is remarkable here is that, as the market gets more bearish, the negative impact of the exchange rate return on BNK becomes stronger. So that with the exchange rate return on the rise, the capital flight increases from bank stocks in an extreme bear market in the long-term. The crude oil prices have a negative asymmetric impact on BNK in the long-term of 256–512-day horizon (Figure 15-(g)). Yet, unlike the exchange rate return, under similar conditions, the correlation between BNK and crude oil prices promotes in a less bearish market, reaching a high of -20% at the 30% quantile. The negative impact of the crude oil price on BNK reduces as a shift is made from the bear market. However, the negative effect of the crude oil prices on BNK emerges again in the extreme bull market. A similar situation is found in the 128–256-day horizon (Figure 15-(i)). The only difference is that the bear and bull markets show a smaller negative impact on BNK in this investment horizon rather than in the equilibrium conditions.

The correlation between the oil products index and the exchange rate return movements is symmetric and positive in the D5 level (Figure 16-(f)). In longer investment horizons, the correlation between the oil products and the exchange rate return remained positive and significant. Particularly, in the 128–256-day horizon (Figure 16-(i)), the strongest effect (70%) corresponded to the 10% quantile and the smallest impact (40%) to the 30% quantile. The correlation between the oil products index and the crude oil price is significantly positive in all investment horizons, except the 128–256-day interval, which was negative and negligible. According to Figure 16-(f, h), the best time for investment in oil products, based on the crude oil movements, was the mid-term 32–128-day horizon.

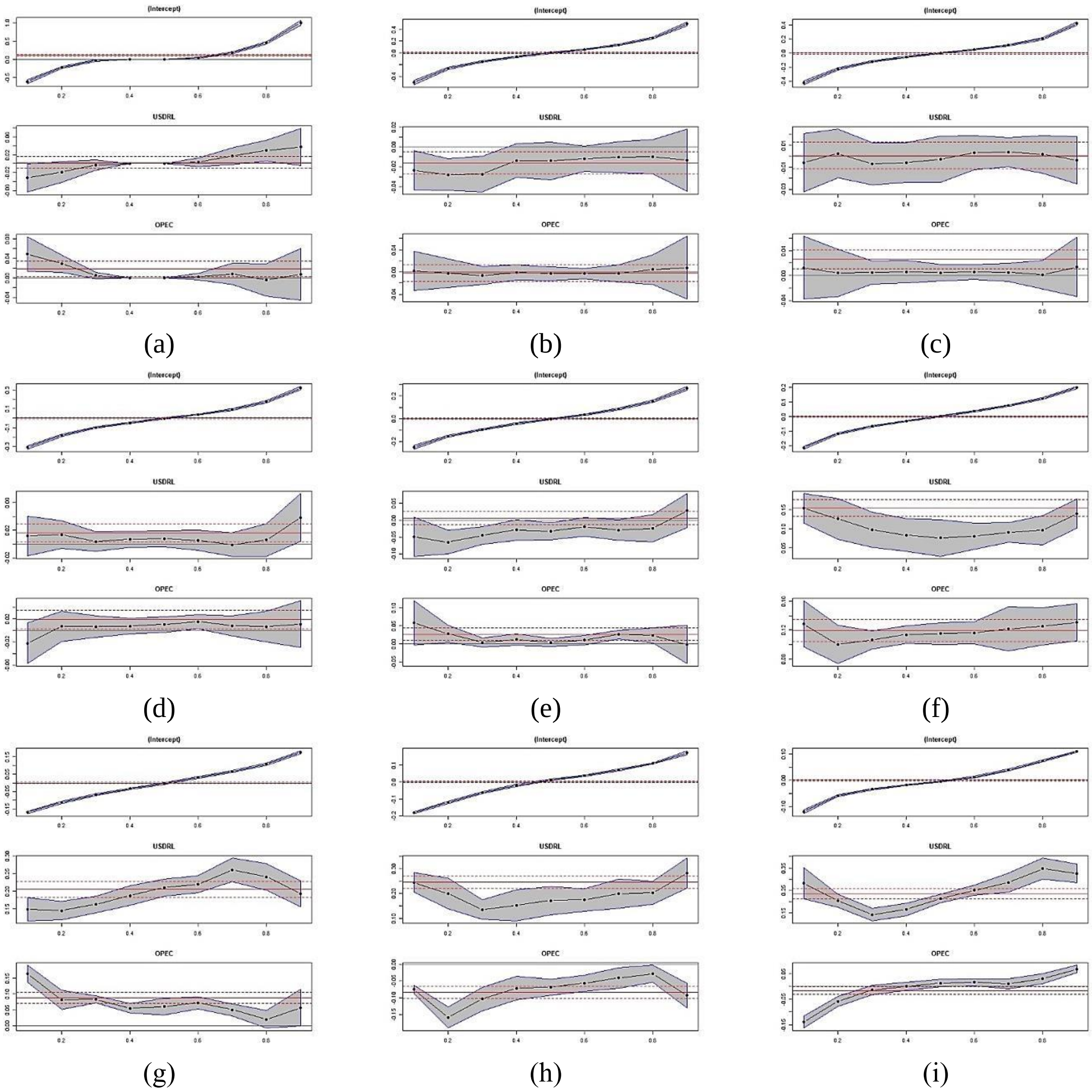


Figure 7. The quantile regression of the TEPIX index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the TEPIX return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment horizons. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.
Source: Research finding.

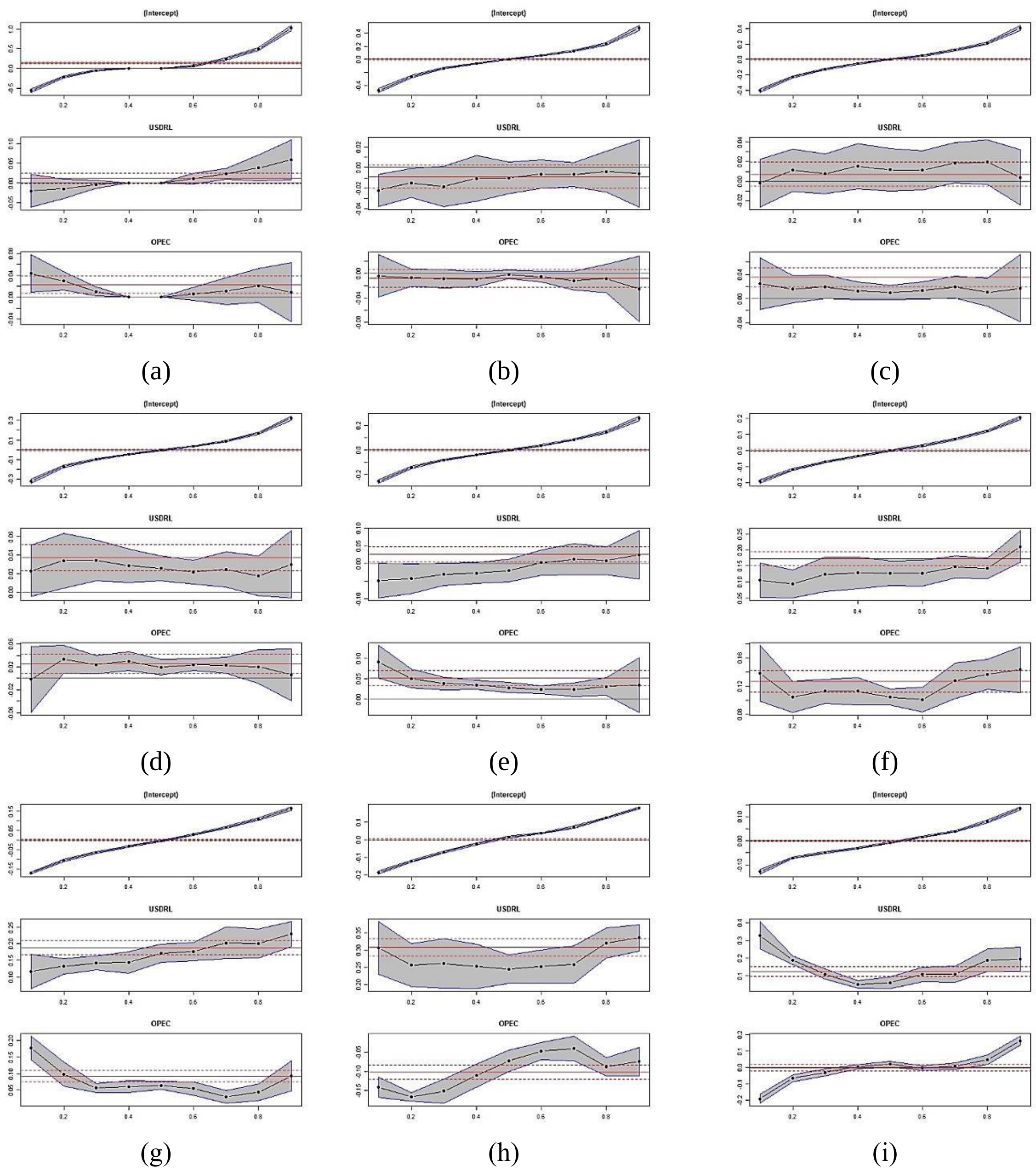
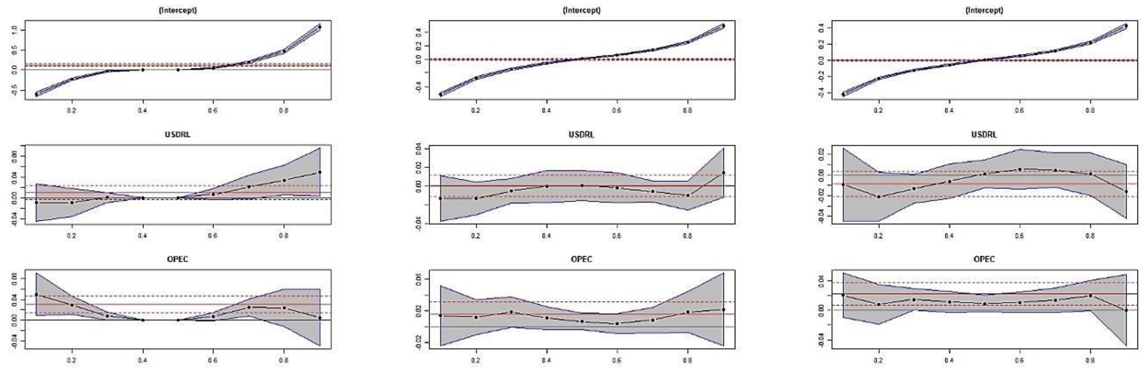
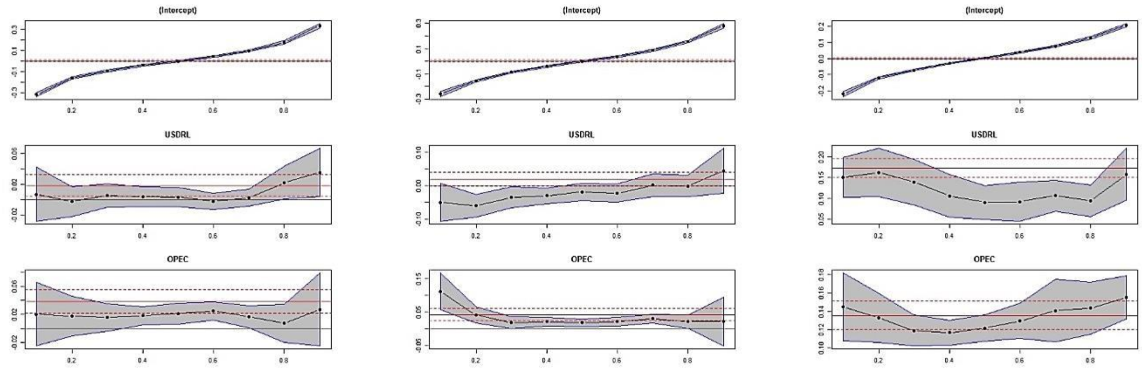


Figure 8 : The quantile regression of the TSE50 index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the TSE50 return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; the solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

Source: Research finding.



(a) (b) (c)



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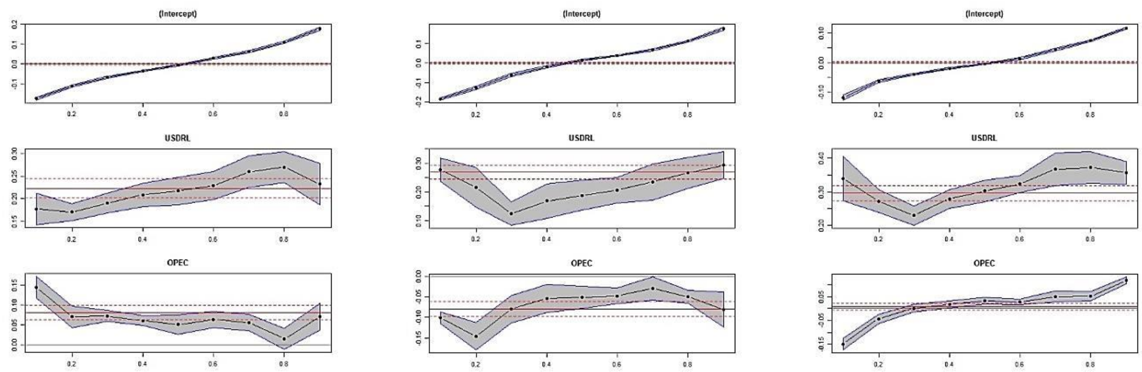


(g) (h) (i)

Figure 9. The quantile regression of the IND index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the IND return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; the solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.
Source: Research finding.

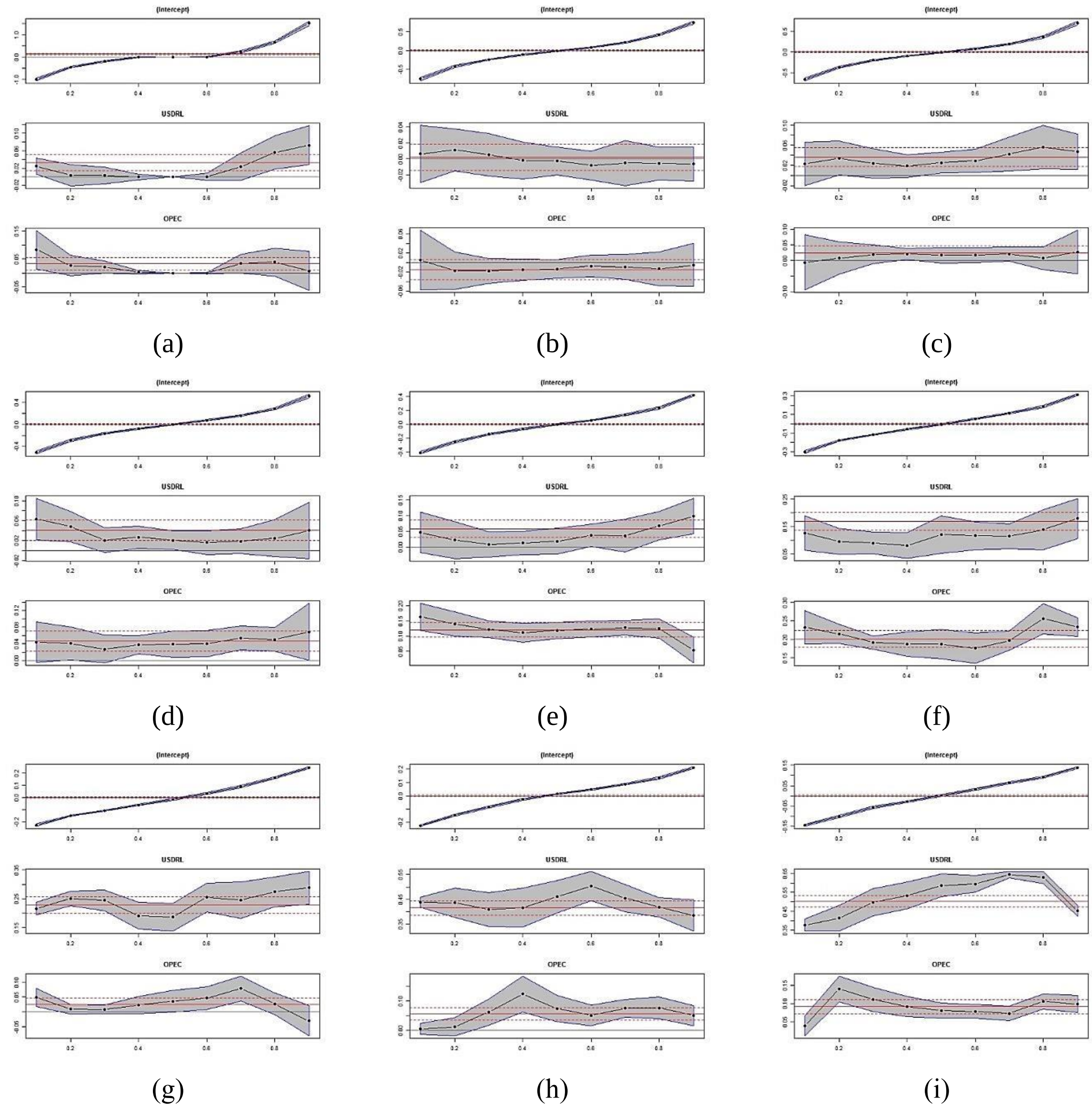
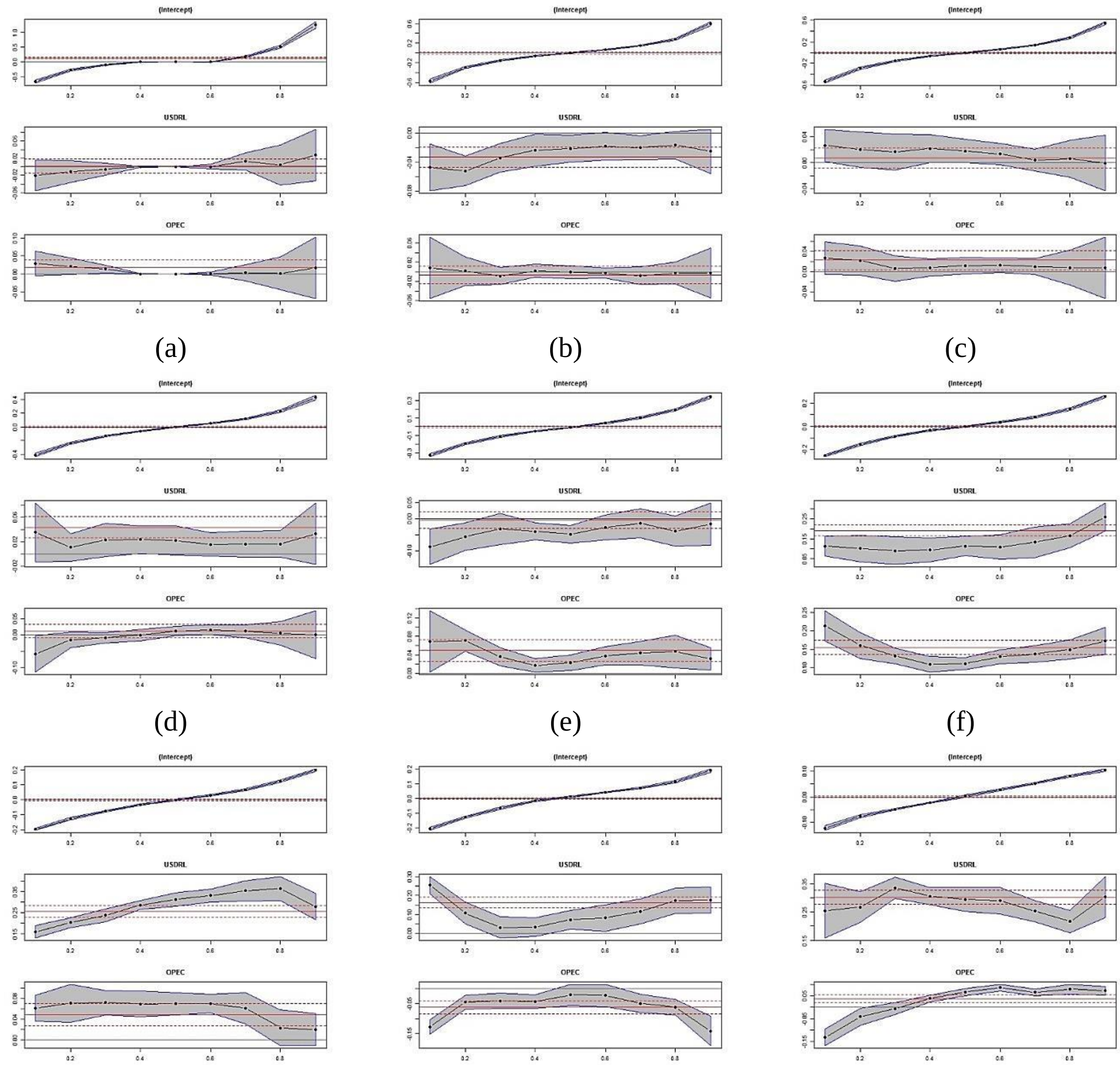


Figure 10. The quantile regression of the FLZT index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the FLZT return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

Source: Research finding.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 11. The quantile regression of the CMCL index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the CMCL return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

Source: Research finding.

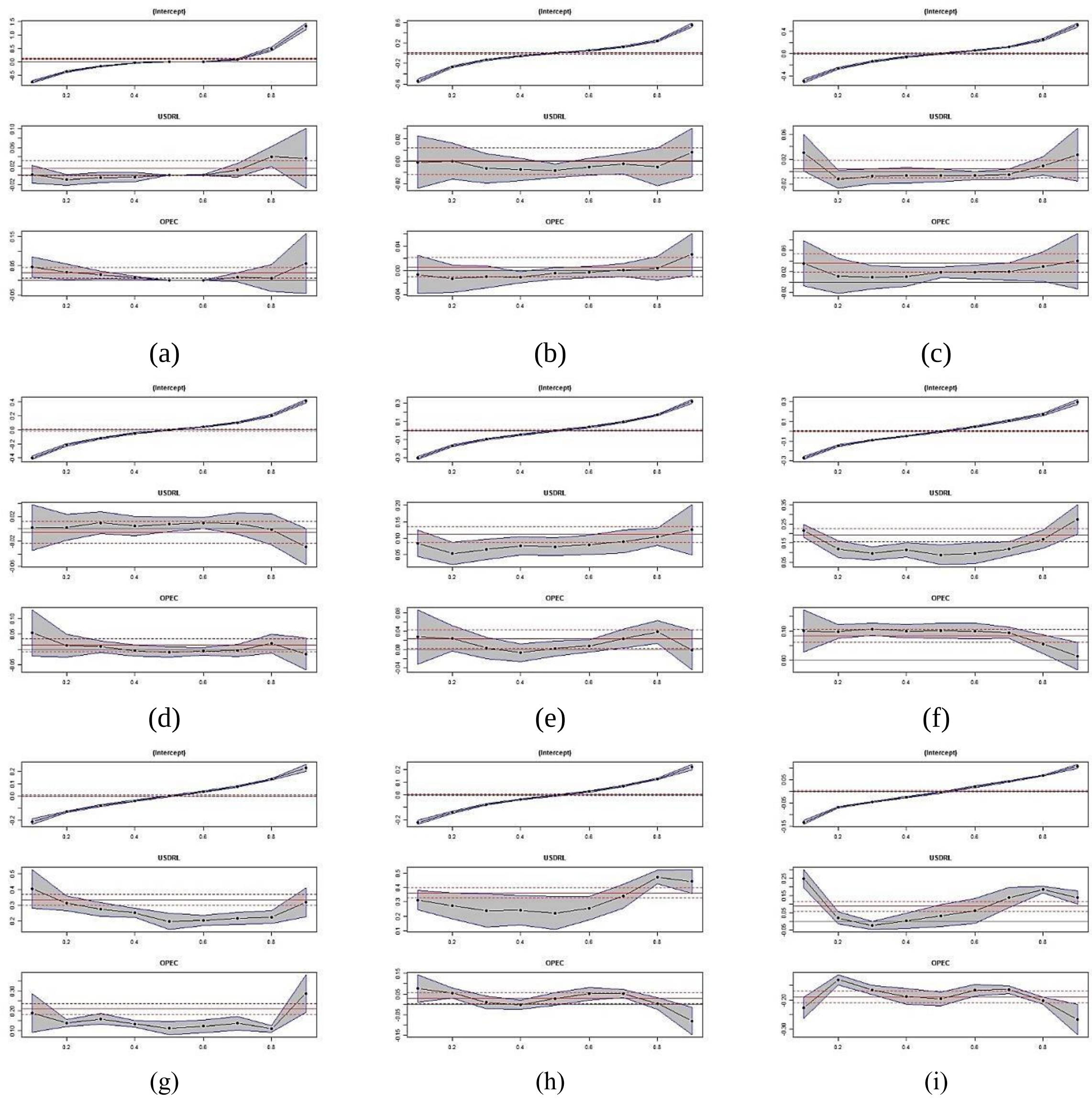


Figure 12. The quantile regression of the CMNT index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the CMNT return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

Source: Research finding.

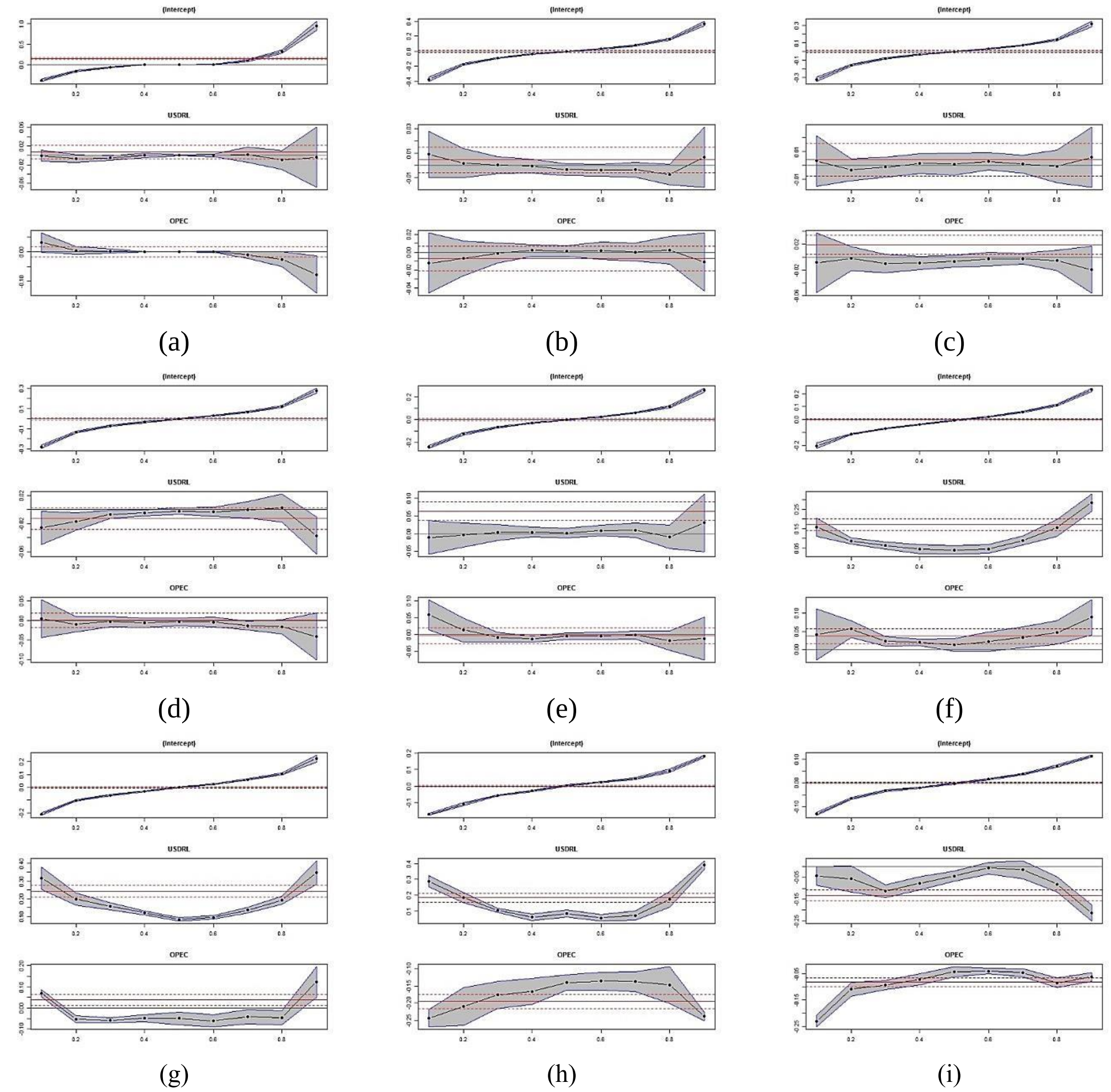


Figure 13. The quantile regression of the DRG index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the DRG return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

Source: Research finding.

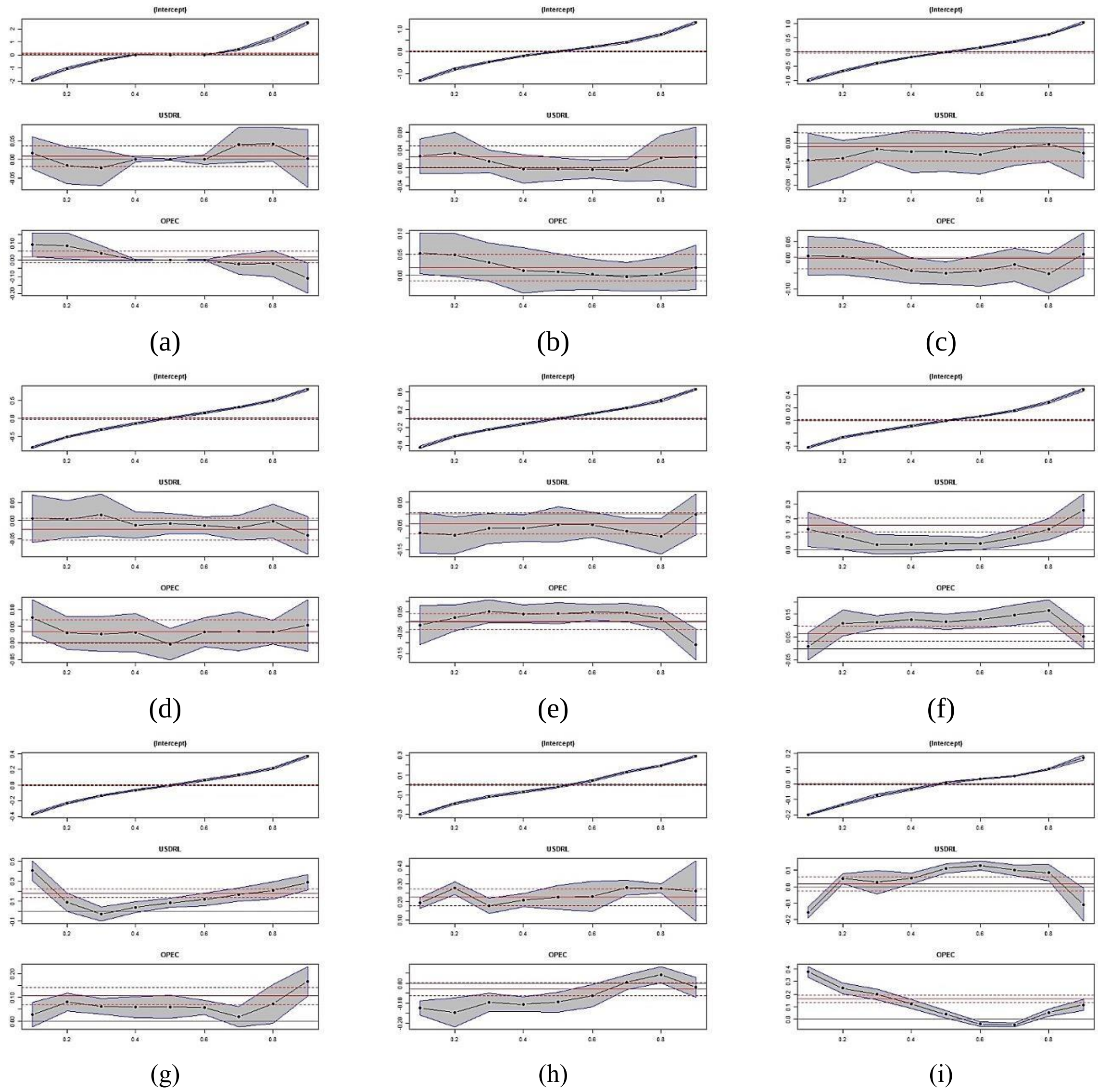


Figure 14. The quantile regression of the KHDR index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the KHDR return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

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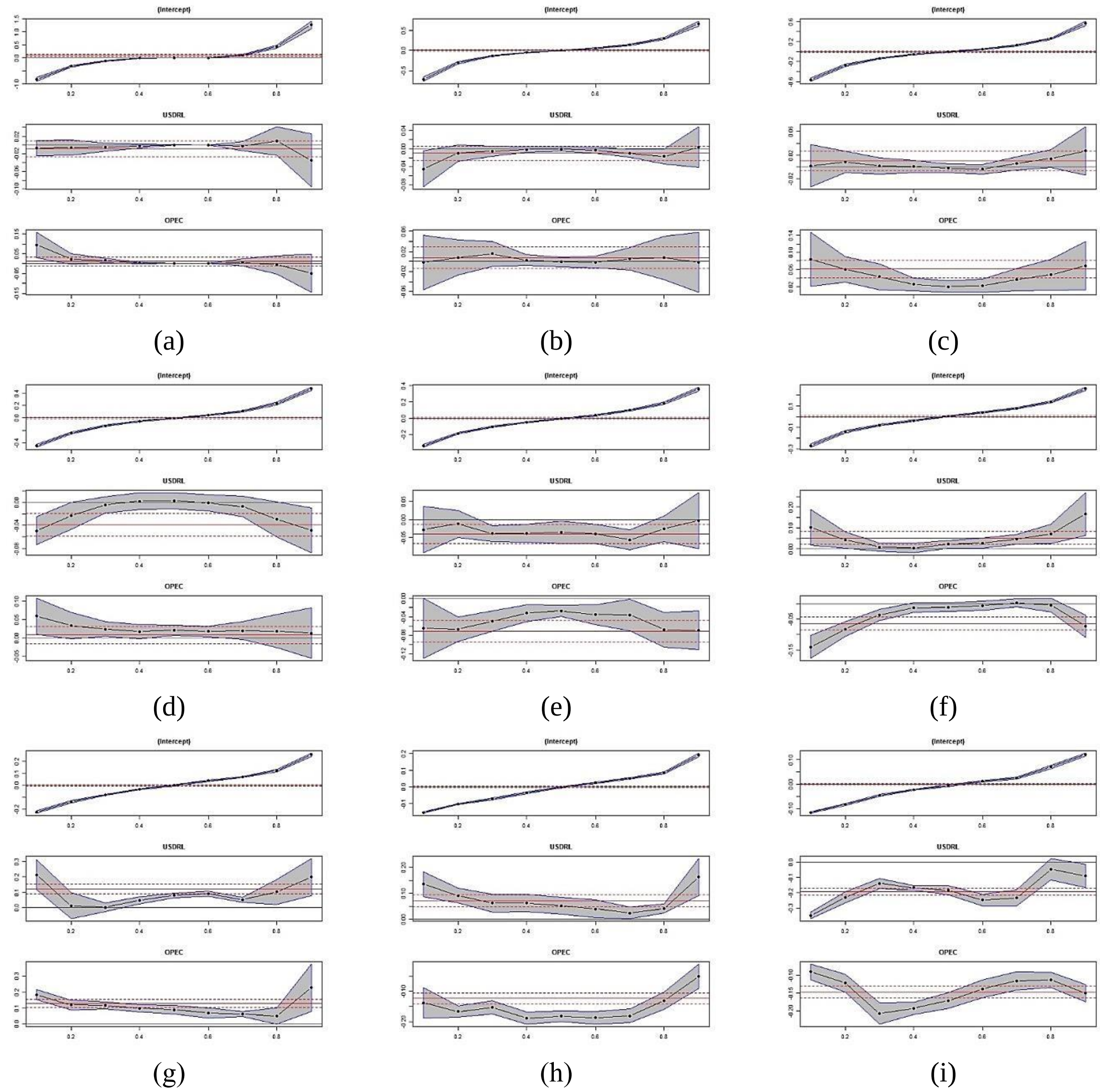

Figure 15. The quantile regression of the BNK index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the BNK return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.

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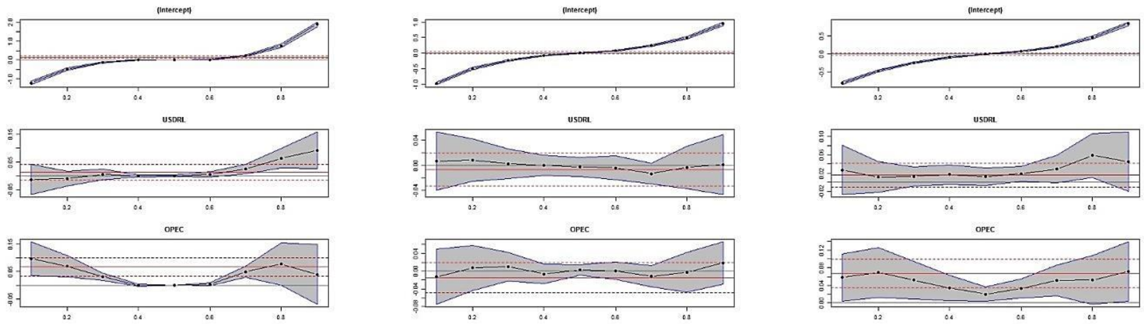

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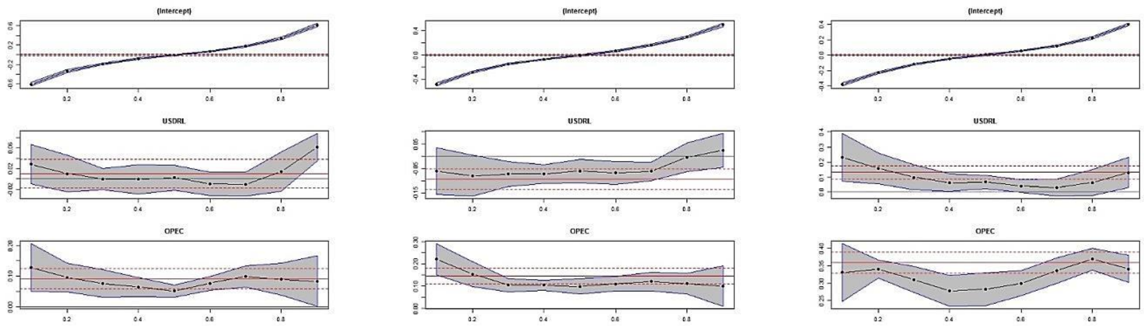

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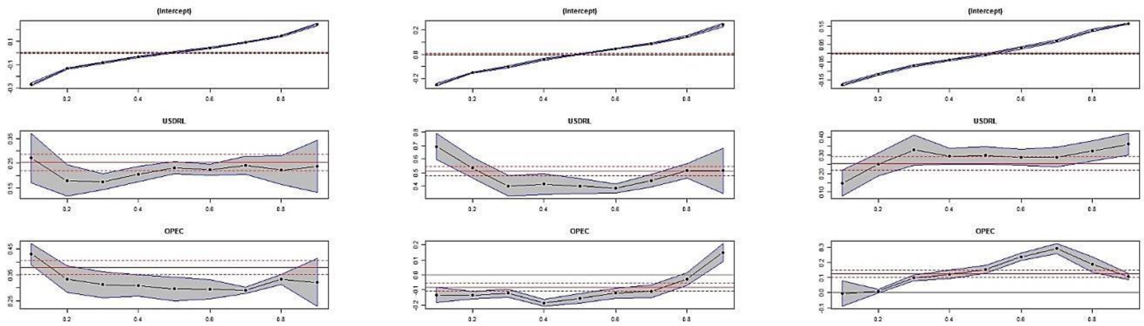

(g) (h) (i)

Figure 16. The quantile regression of the NFTI index signal and its wavelet decomposition at different bands at 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 quantiles. (a) quantile regression of the NFTI return signal; (b)-(i) quantile regression for the wavelet decomposition at D1 to D8; different levels represent different investment windows. 0.1, 0.2, and 0.3 quantiles represent bear markets, whereas 0.4, 0.5, and 0.6 quantiles represent normal markets, and 0.7, 0.8, and 0.9 quantiles represent bull markets. The solid red line represents OLS regression, and the dotted red lines around it mark the 95% confidence interval. The solid black dots on the quantile regression curve show 10–90% quantiles. The gray area stretching on the sides of the quantile curve represents the 95% confidence interval of the quantile regression.
Source: Research finding.

Conclusion

A hybrid quantile regression–wavelet approach was adopted to comprehensively analyze the impact of the fluctuations of the USD and OPEC oil price on Tehran Stock Exchange’s key indices. The most notable feature of this study is that the proposed model was simulated in different investment horizons, considering the bearish, normal, and bullish market.

The TEPIX time series rate displayed a significant relationship with the USD exchange rate return. In the short-term, rising exchange rate returns have a negligible effect on the average stock market returns. Yet, the effect increases in longer investment horizons and higher exchange rate returns promote a market boom. It should be noted that the investors need to balance investment in the stock market by investing in the foreign exchange market in the long-term window. At the same time, the TEPIX displayed a weak correlation with the OPEC basket price, as the long-term impact of oil price movements was negligible compared to that of the exchange rate return in the same window, particularly during a market boom. The results collected from other stock market indices support the analysis of overall market conditions. TES50 and IND, like other major stock market indices, also indicate a strong correlation between the exchange rate return and long-term stock market developments. Meanwhile, the price of oil exhibited a mostly positive and asymmetric correlation with the two important indices in the mid- to long-term. An interesting observation was made in the 70%, 80%, and 90% quantiles of the wavelet decomposition of the stock return signal. It was found that in most cases and particularly in the 128–256-day investment horizon, at the onset of the bull market between the 70% and 80% quantiles, the market becomes more bullish with the exchange rate return on the rise, making a shift from a strong bull market (80% quantile) to an extreme bull market (90% quantile). This outcome led to the expectation that rising exchange rate returns in the 4–9-month horizon encouraged the shareholders to invest more in the stock market. Meanwhile, under similar conditions, increasing oil prices prompted an exodus from the capital market, except for bank and oil product stocks.

In the end, drawing on the findings of this study, the authors will incorporate other variables—including high-profile crypto-currencies such as Bitcoin, price of industrial metals on the global market, exchange rate return for other major currencies including the EUR, Chinese Yuan, and UAE Dirham, and major indices such as VIX and the gold index price—in future studies to evaluate the comovement of Tehran Stock Exchange with major global indices. Relying on quantile regression and using neural networks such as the generative adversarial networks in future works can open to new opportunities for players to predict the trends in the capital market.

References

[1] Aguiar-Conraria, L., Azevedo, N., & Soares, M. J. (2008). Using Wavelets to Decompose the Time–Frequency Effects of Monetary Policy. *Physica A: Statistical Mechanics and Its Applications*, *387*(12), 2863–2878.

[2] Baur, D. G. (2013). The Structure and Degree of Dependence: A Quantile Regression Approach. *Journal of Banking & Finance*, *37*(3), 786–798.

[3] Caporale, G. M., Hunter, J., & Menla Ali, F. (2014). On the Linkages between Stock Prices and Exchange Rates: Evidence from the Banking Crisis of 2007–2010. *International Review of Financial Analysis*, *33*, 87–103.

[4] Chen, S., & Chen, T. (2012). Untangling the Non- linear Causal Nexus between Exchange Rates and Stock Prices: New Evidence from the OECD Countries. *Journal of Economic Studies*, *39*(2), 231–259.

[5] Chiang, T. C., & Chen, X. (2016). Stock Returns and Economic Fundamentals in an Emerging Market: An Empirical Investigation of Domestic and Global Market Forces. *International Review of Economics & Finance*, *43*, 107–120.

[6] Chkili, W., & Nguyen, D. K. (2014). Exchange Rate Movements and Stock Market Returns in a Regime-Switching Environment: Evidence for BRICS Countries. *Research in International Business and Finance, 31*, 46-56.

[7] Chuang, C. -C., Kuan, C. -M., & Lin, H. -Y. (2009). Causality in Quantiles and Dynamic Sock Return–Volume Relations. *Journal of Banking & Finance*, *33*(7), 1351–1360.

[8] Fattahi, S., Soheili, K., & Dehghan Jabarabady, S. (2017). Examination of Contagion in Financial Markets in Iran Using a Combination of Ornstein Uhlenbeck Process and Continuous Wavelet Transform. *Journal of Econometric Modelling*, *2*(4), 33–54.

[9] Gençay, R., Selçuk, F., & Whitcher, B. (2002). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics*. Amsterdam: Elsevier.

[10] Hammoudeh, S., & Li, H. (2008). Sudden Changes in Volatility in Emerging Markets: The Case of Gulf Arab Stock Markets. *International Review of Financial Analysis*, *17*(1), 47–63.

[11] Hatemi-J, A. (2003). A New Method to Choose Optimal Lag Order in Stable and Unstable VAR Models. *Applied Economics Letters*, *10*(3), 135–137.

[12] Jiang, Z., & Yoon, S. -M. (2020). Dynamic Co-movement between Oil and Stock Markets in Oil-Importing and Oil-Exporting Countries: Two Types of Wavelet Analysis. *Energy Economics*, Retrieved from
https://www.sciencedirect.com/science/article/pii/S0140988320301754

[13] Koenker, R. W., & D'Orey, V. (1987). Algorithm AS 229: Computing Regression Quantiles. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, *36*(3), 383-393.

[14] Lee, B. S., & Li, M. -Y. L. (2012). Diversification and Risk-adjusted Performance: A Quantile Regression Approach. *Journal of Banking & Finance*, *36*(7), 2157-2173.

[15] Lin, C. H. (2012). The Comovement between Exchange Rates and Stock Prices in the Asian Emerging Markets. *International Review of Economics & Finance*, *22*(1), 161-172.

[16] Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do Global Factors Impact BRICS Stock Markets? A Quantile Regression Approach. *Emerging Markets Review*, *19*, 1-17.

[17] Nademi, Y., & Khochiany, R. (2017). Comovement of Stock Market, Foreign Exchange and Gold in Iran: An Analysis of Econophysics. *Scientific Journal Management System*, *8*(31), 149-166.

[18] Ndako, U. B. (2013). Dynamics of Stock Prices and Exchange Rates Relationship: Evidence From Five Sub-Saharan African Financial Markets. *Journal of African Business*, *14*(1), 47-57.

[19] Pan, M. S., Fok, C. W., & Liu, Y. (2007). Dynamic Linkages between Exchange Rates and Stock Prices: Evidence from East Asian Markets. *International Review of Economics*, *16*(4), 503-520.

[20] Rostami, M., Kalantari Bonjar, M., & Noori Jafarabad, D. (2016). Evaluation of the Efficiency of the Motion of the Industry Indexes in Tehran Stock Exchange with a Market Yield of Oil, Gold, Dollar and Euro Using Wavelet Analysis. *Journal of Investment Knowledge*, *5*(17), 227-251.

[21] Roueff, F., & von Sachs, R. (2011). Locally Stationary Long Memory Estimation. *Stochastic Processes and Their Applications*, *121*(4), 813-844.

[22] Sui, L., & Sun, L. (2016). Spillover Effects between Exchange Rates and Stock Prices:Evidence from BRICS around the Recent Global Financial Crisis. *Research in International Business and Finance*, *36*, 459-471.

[23] Sun, W., Rachev, S., Fabozzi, F. J., & Kalev, P. S. (2008). A New Approach to Modeling Co-movement of International Equity Markets: Evidence of Unconditional Copula-Based Simulation of Tail Dependence. *Empirical Economics*, *36*(1), 201-229.

[24] Tang, X., & Yao, X. (2018). Do Financial Structures Affect Exchange Rate and Stock Price Interaction? Evidence from Emerging Markets. *Emerging Markets Review*, *34*, 64-76.

[25] Xiao, J., Zhou, M., Wen, F., & Wen, F. (2018). Asymmetric Impacts of Oil Price Uncertainty on Chinese Stock Returns under Different Market Conditions: Evidence from Oil Volatility Index. *Energy Economics*, *74*, 777-786.

[26] Yang, S.-P. (2017). Exchange Rate Dynamics and Stock Prices in Small Open Economies: Evidence from Asia-Pacific Countries. *Pacific-Basin Finance Journal*, *46*, 337-354.

[27] Zhu, H., Liu, D., Zhang, S., Zhu, Y., Teng, L., & Teng, S. (2016). Solving the Many to Many Assignment Problem by Improving the Kuhn–Munkres Algorithm with Backtracking. *Theoretical Computer Science*, *618*, 30-41.

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