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The Nexus between Stock Market Return and Trading Volume on Vietnam's Stock Market: A Wavelet Approach

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Abstract. This paper uses the wavelet approach to examine the nexus between trading volume and stock market return on Vietnam's stock market. Daily data of VN-Index and trading volume in the Hochiminh City stock exchange (HoSE) are collected. Applying The Granger Causality Test, the results show that lagged return includes the predictive power for the trading volume. The results from wavelet analysis in time-frequency space indicate that the connection between VN-Index return and trading volume exists only at the approximate 128 – 300 days cycles from approximately Mar 2012 to Mar 2014 and Jan 2017 to Jul 2022. Therefore, the wavelet approach is essential to provide a deep insight into the nexus among financial time series. To the authors' best knowledge, volume–return (V-R) analysis using the wavelet was not used in previous literature.

Keywords: trade volume, stock market return, wavelet

1. Introduction

The nexus between stock market return and trading volume has attentive investors and researchers for a long time. There was a large amount of existing literature that studied the co-movement between market return and trading volume from different markets, such as Rashid (2007), Mpofu (2011), Chen et al. (2001), Alkhazali (2014). Most of the previous studies used econometrics techniques in the time domain, such as correlation, regression, or ARCH/GARCH models...

Short- and long-term investors have divergent concerns when investing in stock markets. Short-term investors pay attention to this relationship at higher frequencies, but long-run ones concentrate on it at lower frequencies (Gradojevic, 2013; Nghi & Kieu, 2021). According to Granger & Lin (1995), the relations between economic time series may vary between frequency bands. Therefore, frequency domain analysis is needed and used in a wide range of economic and financial time series in the previous literature such as Yanfeng (2013), Gradojevic (2013), Ozer & Kamisli (2016), Nguyen & Le (2021), Nghi & Kieu (2021). This technique was also applied to examine the impact of trading volume on stock market return (Hang et al., 2021).

However, both time-domain and frequency-domain analysis have drawbacks. The frequency information is lost when analyzing time series using the time-domain approach, whereas frequency-domain techniques exclude the time information. Therefore, wavelet analysis could overcome the above difficulties, which merged the two. Decomposing data in time-frequency space can show the correlation between variables at different frequencies during the period (Rua, 2010). Although widely applied in natural and technological sciences, this approach is used scarcely in economics. Some studies have investigated the relationship between economics or financial time series using wavelets recently, such as Rua & Nunes (2009), Goodell & Goutte (2021), Graham & Nikkinen (2011), Jiang et al. (2017)…. However, to our best knowledge, time-frequency space analysis has not been applied to test the V-R relations in previous literature.

Vietnam's stock market was established in July 2000 and became an essential channel for allocating capital more efficiently, contributing to economic growth. Market capitalization is continuously increasing and attracting more and more investors. Volume and return are momentous indicators of the market. Hence, investigating the V-R relationship is vital for investors and policymakers to have more information to make suitable decisions. Because of this, this article examines the nexus between trading volume and market returns on Hochiminh City Stock Exchange (HoSE), the largest stock exchange in Vietnam. Aside from testing this relation using the traditional method in the time domain, this research enhances the results by applying the wavelet approach, an analysis in time-frequency space, that prescribes more conspicuous information about the return-volume relationship.

2. Literature review

2.1. The V-R nexus

Volume is a momentous indicator affecting stock return (Hang et al., 2021). Market microstructure theory proves that both stock return and volume are involved in the information advent of the market (Wang et al., 2018). Price change and trading volume react from news and shocks in the market and co-move with each other (Rashid, 2007), (Hang et al., 2021). These mirror the investors' expectations when investing in the market.

The sequential information arrival model could explain the causality between trading volume and stock return (Copeland, 1976). This theory noted that the information flow to the participants in the market is noticed asymmetric. Several intermediate equilibrium points are set up before reaching the rearmost market equilibrium. Therefore, lagged volume may comprise helpful information to predict current stock return, and lagged stock return may have valuable information to predict present trading volume (Pisedtasalasai & Gunasekarage, 2007).

When investors have divergent opinions on the market, the stock owners are optimistic about its value. It leads to increase demand and stock price (Miller, 1977). Epps (1975) assumed two groups of investors: "bulls" and "bears." The optimistic "bulls" react only to positive information about their assets, while the "bears" are more pessimistic and respond only to negative news. Hence, the markets consisted only of the "bulls'" demand curve and the "bear" supply curve. He proved that the relative optimism of the "bulls," along with relevant assumptions about investors' utility functions, results in the market demand curve being steeper than the supply curve. Therefore, the effects of increased trading volume on positive price change are more prominent than negative price change (Karpoff, 1987). Karpoff (1987) also reviewed previous empirical and theoretical studies about the price-volume co-movement in financial markets and suggested some reasons to examine this effect.

When investors have mixed beliefs about stock and face the penury of that stock, the stock price reverberates the opinion of the optimistic investors driving the price to rise (Mpofu, 2011; Hang et al., 2021). The more difference in investors' viewpoints, the more trading volume. Therefore, a large trading volume may increase the stock return. Trading volume reflects essential information about speculative activities on the stock exchange (Blume et al., 1994). Hence, trading volume is critical to predicting the stock exchange price. This hypothesis was also confirmed by Gervais et al. (2001).

Moreover, trading volume is one of the measurements of liquidity that can affect stock price change (Brennan et al., 1998; Liu, 2006; Wang et al., 2018). It also depicts investors' learning curve that drives overconfidence, then impacts future stock prices (Gervais & Odean, 2001; Statman et al., 2006).

Mubarik & Javid (2009) investigated the nexus among stock return, volume, and volatility in the stock market of Pakistan from July 1998 to October 2008.

Using ARCH/GARCH models and the Granger causality test, the authors indicated the significant interaction between trading volume and stock return. Toe & Ouedraogo (2022) studied the V-R connection between trading volume and return on the major African stock markets. Using daily data from eleven African Stock Exchanges from September 24, 2010, to September 24, 2020, the Granger Causality Test indicated that volume wasn’t affected by the returns, while the return was caused by volume in some countries’ Stock Markets. Wang et al. (2018) investigated the dynamic V-R relation from both U.S. and international markets from out–of–sample return forecasting. The authors collected data from the U.S. and global markets. The results reported that the high return followed the increased volume in the U.S. market, especially in the pre-2000 phase. The study also included evidence of the relationship between trading volumes and stock price changes from other markets.

Bajzik (2021) summarized previous literature on the relationship between stock return and trade volume using meta-analysis. The paper showed that these relations might vary in different stocks or countries. For example, trading volumes forecasted the stock prices in the developed markets worse than in the emerging ones. Therefore, continuing to study the trade volume - stock return links are needed.

2.2. Frequency-domain Analysis, Wavelet approach, and their Applications in Economics

Most of the previous studies used econometrics tools in the time domain that cannot analyze the interaction between two variables at different frequencies. Thus, the frequency-domain techniques were proposed and applied.

The frequency approach can test the relations between economic time series at different cycles based on Fourier transformation. Yanfeng (2013) examined the interaction between oil prices and Japan’s economy in the frequency domain. From a frequency domain aspect, the linkages between the Turkish financial markets were also tested (Ozer & Kamisli, 2016). Gradojevic (2013) investigated the frequency causality among the growth rate on the stock exchange indices in Serbia, Hungary, Croatia, Slovenia and Germany. Similarly, the frequency causality approach put forward by Breitung & Candelon (2006) was applied to examine the return and volatility spillovers from the US and Japanese stock markets to Vietnam’s stock market (Nguyen & Le, 2021; Nghi & Kieu, 2021). Recently, Hang et al. (2021) investigated the frequency-dependent effects of volume on the growth rate of the Vietnamese stock market. All the above research indicated that the co-movements of economics time series varied at frequency bands.

However, all the above literature used only time-domain/frequency-domain approaches that cause frequency/time information to be missing. Wavelet, a technique that analyzes data in time-frequency space, could be used to overcome these drawbacks. Although widely applied in natural and technical sciences, this approach has recently been used in the economics literature. Rua & Nunes (2009) examined the relationship among returns of the leading developed economies, namely Japan, Germany, the UK and the US, between January 1973 and December 2007. Graham & Nikkinen (2011) investigated the co-movement of Finnish stock markets and world markets, proxied by six MSCI country indices, six MSCI regional indices, and the MSCI World index, from January 1, 1999, up to October 15, 2009. Jiang et al. (2017) studied the interaction of ASEAN stock markets from September 1, 2009, to December 1, 2016. Jiang & Yoon (2020) analyzed the relations among six stock markets and oil. Recently, Goodell & Goutte (2021) examined the impact of the COVID-19 pandemic on the prices of Bitcoin from December 2019 to April 2020. The above studies could analyze the relationships among economics time series at different frequencies during the period by using the wavelet approach.

However, to our best knowledge, the wavelet approach was not previously applied to examine the V-R co-movement. Therefore, this paper aims to fulfill this research gap by investigating this relationship in time-frequency space from the Vietnamese stock market.

3. Data and Research Method

3.1. Data

Data on the daily market index (VN-Index) and trading volume were collected from Hochiminh City Stock Exchange (HoSE), the largest stock exchange in Vietnam, from Jan 04, 2011, to Aug 01, 2022, including 2886 observations. The growth rate (return) of VN-Index and trading volume were calculated as the log first difference of time series as below:

$$r_t = ln\frac{P_t}{P_{t-1}}$$

where $ln(x)$ is the natural logarithm of x, P_t and P_{t-1} are the market index or volume at time t and $t-1$.

3.2. Research Method

3.2.1. Granger Causality Test

Granger (1969) pointed out an approach named the Granger Causality Test to examine whether one time series has the power to predict another and vice versa. This method is based on VAR (Vector Autoregression) model as below (Gujarati, 2004)

$$y_t = \gamma_0 + \gamma_1 y_{t-1} + \cdots + \gamma_l y_{t-l} + \delta_1 x_{t-1} + \cdots + \delta_l x_{t-l} + \varepsilon_t;$$
$$x_t = \gamma_0 + \gamma_1 x_{t-1} + \cdots + \gamma_l x_{t-l} + \delta_1 y_{t-1} + \cdots + \delta_l y_{t-l} + u_t,$$

then, test the null hypothesis:

$$\delta_1 = \delta_2 = \cdots = \delta_l = 0$$

for each equation. The null hypotheses are "x does not Granger-cause y" in the 1st regression and "y does not Granger-cause x in the following regression".

The V-R relations can be analyzed using the Granger Causality Test for these time series in HoSE.

3.2.2. Wavelet Analysis

Frequency analysis, based on the Fourier transform, decomposes time series to the sum of infinite sine and cosine series. This technique analyzes frequency information but causes missing time information in the dataset. The wavelet approach uses both time information and frequency information.

Let $x(t)$ and $y(t)$ are time series. The continuous wavelet transform (CWT) of $x(t)$ and $y(t)$ concerning ψ(t) is calculated by the following convolution:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\psi_{\tau,s}^*(t)dt = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t)\ \psi^*\left(\frac{t-\tau}{s}\right)$$

where * denotes the complex conjugate and $\psi_{\tau,s}(t)$ are wavelets (daughter wavelets), calculated from mother wavelet $\psi(t)$ as below

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

where τ is the time (translation) parameter and s is the scale (dilation) parameter related to the frequency (Jiang et al., 2017), (Rua, 2010), (Rua & Nunes, 2009).

To be a mother wavelet, $\psi(t)$ must fulfill several criteria (Rua & Nunes, 2009), (Rua, 2010). The most widely used mother wavelet is the Morlet wavelet defined in (Rua & Nunes, 2009), (Fugal, 2009), (Torrence & Compo, 1998).

The original series $x(t)$ can be recovered from time-frequency space by Inverse wavelet transform, which is defined as:

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \psi_{\tau,s}(t) W_x(\tau, s) \frac{d\tau ds}{s^2}$$

The cross-wavelet spectrum $W_{xy}(\tau, s)$ is defined to measure the covariance between two series in the frequency-time domain. Assume that $W_x(\tau, s)$ and $W_y(\tau, s)$ is the wavelet transform of two original time series $x(t)$, $y(t)$, the cross-wavelet spectrum is calculated $W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s)$. Because the mother wavelet is generally complex, the cross-wavelet spectrum is also a complex number that includes real and imaginary parts (Rua, 2010). Cross wavelet power is calculated as $|W_{xy}(\tau, s)|$ and argument $\arg(W_{xy}(\tau, s))$ is the phase difference between $x(t)$ and $y(t)$ in frequency-time space.

The wavelet squared coherency is calculated as the absolute value squared of the smoothed cross-wavelet spectrum, normalized by the smoothed wavelet power spectra (Torrence & Webster, 1999)

$$R^2(\tau, s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau, s)\right)\right|^2}{S(s^{-1}|W_x(\tau, s)|^2)S\left(s^{-1}|W_y(\tau, s)|^2\right)}$$

Where $S(.)$ denotes smoothing in both scale and time. The smoothing operator is presented in Grinsted et al. (2004)

Like the squared correlation coefficient, the wavelet squared coherency changes from 0 to 1, with a high value indicating a significant nexus and vice versa. Therefore, the wavelet squared coherency graph possibly shows the areas in the frequency-time space that exists the relationship between series with time and frequency-varying features.

4. Results

4.1. Descriptive Statistics

Figure 1 and figure 2 represent the market index and volume in the Hochiminh stock exchange (HoSE) from Jan 04, 2011, to Aug 01, 2022. The graph shows that VN- Index has an upward trend in the period Jan 2011- April 2018 and Mar 2020 – Mar 2022 and a downward trend in the remaining period. Trading volume in Figure 2 also shows the rising trend from Jan 2011 to April 2018 and from Mar 2020 to Dec 2021. These indicate the similarity of the time series. The VN-Index return and trading volume time series are calculated by log differences.

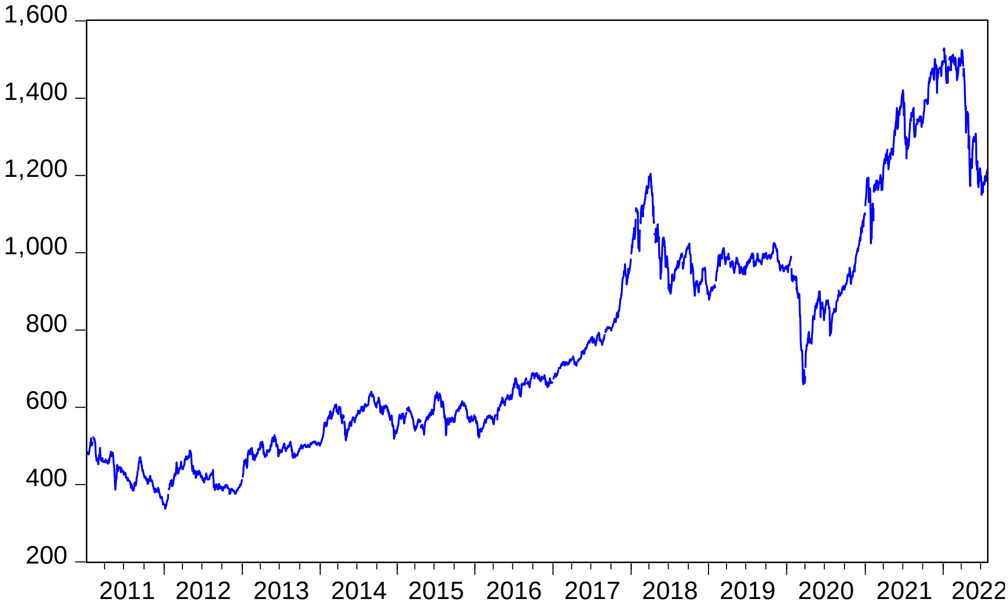

Fig. 1: VN-Index from Jan 04, 2011, to Aug 01, 2022

Source: Authors' calculation

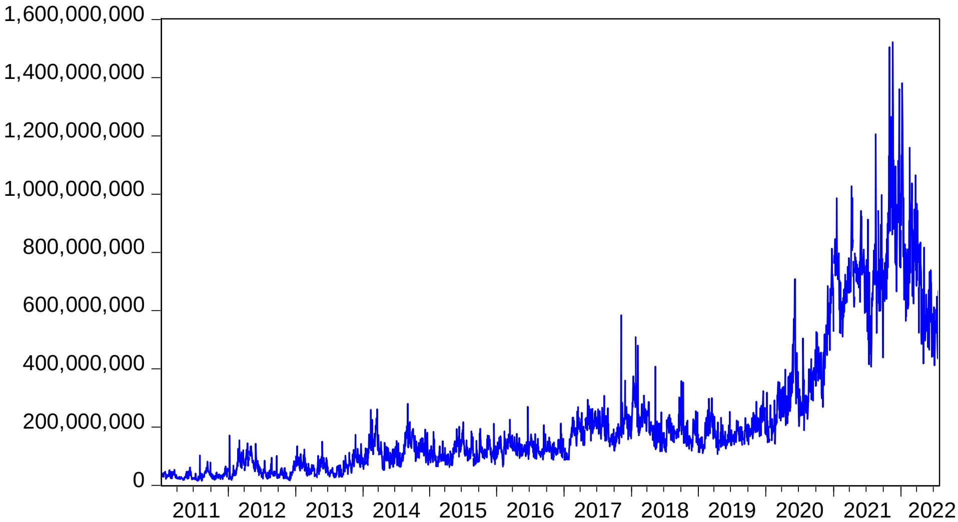

Fig. 2: Trading volume from Jan 04, 2011, to Aug 01, 2022

Source: Authors' calculation

Table 1: Descriptive Statistics of VN-Index and trading volume returns in HoSE

	VN-Index	Volume
Mean	0.031797	0.110075
Median	0.104604	0.266584
Standard deviation	1.164088	24.28992
Skewness	-0.808178	0.043221
Kurtosis	6.703005	6.799567

Source: Authors' calculation.

Table 1 shows that the VN-Index and trading volume growth rates are positive and consistent with the reality of the recovery phase after the global economic crisis of 2008. The negative skewness of the VN-Index indicates that this asymmetric distribution skews to the left. In contrast, the positive skewness of trading volume indicates the right skew distributions. The kurtosis of both series is larger than three, showing a narrowed distribution compared with the Gaussian distribution.

4.2. Granger Causality Test

The returns are tested for the stationary using Augmented Dickey-Fuller (ADF) Test. Table 2 reports that both series are stationary at 1% significance level. Therefore, the V-R nexus can be investigated by Granger Causality Test.

Table 2: ADF Test for trading volume and VN-index returns

	VN-Index	Volume
Hypothesis H_0	The series are nonstationary	
t-Statistic	-34.30241	-33.93173
Conclusion	Rejected at the 1% significance level	Rejected at the 1% significance level

Source: Authors' calculation

Using Akaike Information Criterion (AIC), VAR(13) is chosen as the best model. The results for the Granger Causality Test with 13 lag orders are outlined in in Table 3. They show that the hypothesis VN-Index return does not Granger-cause trading volume at HOSE is rejected at a 1% significance level. Therefore, the market index is one of the determinants that can forecast the trading volume in HoSE. However, the hypothesis that trading volume does not Granger-cause VN-Index return is not rejected at the 10% significance level, implying that the effect of trading volume on the market index is not evident. Therefore, the market index conveys valuable information to predict the trading volume in HoSE.

Table 3: Granger causality test between trading volume and VN-index returns

	Causality test with Granger	
Hypothesis H_0	VN-Index return does not affect to volume.	Volume does not affect to VN-Index return
F-Statistics	8.97945	0.49309
Conclusion	Rejected at the 1% significance level.	Do not reject at the 10% significance level.

Source: Authors' calculation

The results are in line with the findings from Hiemstra & Jones (1994), Chen et al. (2001), Lee & Rui (2002), Ciner (2002), Mahajan & Singh (2009), Pisedtasalasai & Gunasekarage (2007)… This causality could be explained by the sequential information arrival model (Copeland, 1976), increasing our knowledge regarding the V-R relationship, particularly in HoSE. The V-R nexus is significant to investors from an investment viewpoint because volume mirrors market expectations. Its ties with the return will provide considerable implications for trading, forecasting, speculation, and hedging activities.

4.3. Wavelet Analysis

The Granger causality test has a drawback: it can't analyze short-term and long-term relationships separately (Ozer & Kamisli, 2016; Nghi & Kieu, 2021). Another disadvantage of this technique is the missing time information, i.e., the effects between time series at a particular time can't be confirmed. The wavelet approach can overcome these difficulties. Therefore, it should be used to obtain a deep insight into the nexus between VN-Index return and volume growth rate.

Figure 3 presents the wavelet coherence of VN-Index return and volume growth rate in HoSE. A contour plot shows the wavelet squared coherency in the three dimensions figure. The time is presented by the horizontal axis, the frequency is referred to by the vertical axis, and the wavelet-squared coherency is indicated by the greyscale. The color indicates the magnitude of correlation on the right of the figure. The greyscale increases from blue to yellow according to the rise of the measured value. Arrows show the phase differences between VN-Index return and volume. For example, → and ← indicate that trading volume growth rate and VN-Index return are in phase (positive correlation) and out of phase (negative correlation). Moreover, ↗ and ↙ report that trading volume growth rate is lagging the VN-Index return, while ↖ and ↘ show that the trading volume is leading the VN-Index return (Goodell & Goutte, 2021). Therefore, graph analysis can help us examine the relationship between the series with both frequency and time information.

Figure 3 indicates a significant V-R correlation at the approximate 128 – 300 days cycles from the period of observations 300 - 800 (corresponding to the approximate Mar 2012 to Mar 2014) and 1500 - 2890 (corresponding to the approximate Jan 2017 to Jul 2022). The arrows report that the VN-Index return leads trading volume, similar to the time domain Granger Causality Test. Thus, trading volume is driven by the market index in the long run, implying that investors and policymakers should use the market index to forecast the trading volume in HoSE in the long term (128 – 300 days cycles)

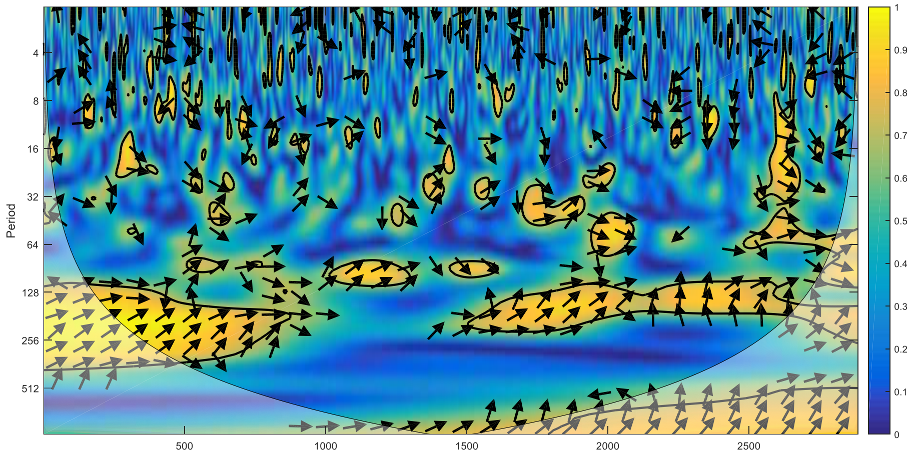

Fig. 3: Wavelet coherence of VN-Index return and trading volume growth rate
Source: Authors' calculation

The results reveal that trading volume is affected by the market index in the long run. In our opinion, much information arrived at the Vietnamese stock market during the research period, including official news and rumors. Then it was difficult for this information to reflect the volume and return correctly. Thus, the V-R relationship was not confirmed in the short run. In the long term, the news approved by the authorities would reflect stock returns, then affect investors' decisions and trading volume. Therefore, return leaded volume in the long term.

Trading volume is affected by the market index in the long term. Then, the long-run investors (cycles from 128 to 300 days) should use the market index to forecast the trading volume in HoSE, but it is optional for the short-run ones. Policymakers should also take heed of the long-run effects of market price on trading volume to have a suitable policy.

In summary, although traditional Granger Causality shows the effect of VN-Index return on trading volume, the wavelet emphasizes that this relationship exists only at specific periods and frequency bands. Therefore, this article provides evidence that the V-R nexus differs across frequency and time bands. These imply that investors should make divergent decisions according to investment frequencies and the decision-making time points. Thus, wavelet analysis should be applied to understand the V-R relations deeply.

5. Conclusions

This article tests the V-R relationship from Jan 04, 2011, to Aug 01, 2022, in HoSE. Using Granger Causality Test (Granger, 1969), the results show that VN-Index return Granger causes the trading volume growth rate at a 1% significance level. Therefore, investors and policymakers could predict the trading volume based on market return. The findings enhance our understanding of the V-R causality, particularly in HoSE, providing more necessary information to investors and policymakers.

Moreover, the wavelet analysis results show that the trading volume–market index relation on HoSE exists only at specific periods and frequency bands. More specifically, there is a significant effect of VN-Index return on trading volume at the approximate 128 – 300 days cycles from Mar 2012 to Mar 2014 and from Jan 2017 to Jul 2022, implying investors and policymakers should use market growth rate to forecast trading volume only in above periods and spectrum bands. Therefore, the findings confirm the hypothesis that the causality between time series may vary, belonging to frequency (Granger & Lin, 1995), and prove that it also depends on time. Therefore, the analysis in time-frequency space is required to understand the nexus between the two series deeply.

This research has two significant contributions. First, this paper delivers evidence of a momentous effect of VN-Index return on trading volume growth rate in HoSE that increases the knowledge regarding the price-volume relation in stock markets. Secondly, it shows that this relationship varies at different cycles and periods. To the authors' best knowledge, this nonlinear V-R nexus is not previously represented in the literature. Therefore, the wavelet approach should be used to investigate the V-R relations. Its results include time and frequency information that assists both short- and long-run investors have more knowledge to invest at the right time.

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