

The co-movement between equity markets of Thailand and
China: A wavelet-based approach



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ความเคลื่อนไหวร่วมระหว่างตลาดหุ้นไทยและจีน โดยการใช้วิธีเวฟเล็ต



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คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย

ปีการศึกษา 2564

ลิขสิทธิ์ของจุฬาลงกรณ์มหาวิทยาลัย

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By Miss Shilei Sun
Field of Study Finance
Thesis Advisor Tanawit Sae-Sue, Ph.D.

Accepted by the FACULTY OF COMMERCE AND ACCOUNTANCY,
Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of
Science

INDEPENDENT STUDY COMMITTEE

..... Chairman
()
..... Advisor
(Tanawit Sae-Sue, Ph.D.)
..... Examiner
(Assistant Professor TANAKORN LIKITAPIWAT,
Ph.D.)
..... Examiner
(Narapong Srivisal, Ph.D.)



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ลายมือชื่อ อ.ที่ปรึกษาหลัก

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This paper applied the MODWT wavelet method to decompose correlations of the stock market of Thailand and China into different time scales and frequencies. The decomposed correlations are then examined and compared between short-term and long-term, and also between different time periods when the interdependence of two markets is expected to change. The result shows that long-term correlation is not significantly higher and sometimes is significantly lower than the short-term, whereas the correlation does significantly increase from 2005 to 2020. Furthermore, the paper investigates the effectiveness of using the correlation in the suitable time scale and frequency in an application of a minimum variance portfolio. By comparing the traditional correlation and correlation obtained from the wavelet method, we found that the minimum variance portfolio from the wavelet method performs better. The result implied that the wavelet method support investors and policymakers to understand the linkage between two markets and make better decisions based on the co-movement of returns.



Field of Study: Finance

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Student's
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Advisor's
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CHAPTER 1: INTRODUCTION

Introduction

Equity market co-movement is an essential topic for international investment diversification, portfolio management, and risk management. For example, asset and time diversification, the primary strategy that multinational equity investors use in the different asset classes required the understanding of market co-movement (Peng, 2015). In risk management, co-movement between markets allows investors to minimize portfolio risk in the most efficient way. Thus, the analysis on distinct equity market correlation will indicate investors about the market return co-movement when making the investment decision.

This paper focuses on the market co-movement between Thailand and China during 2005-2020. We will define two main reasons why the co-movement between the two equity markets becomes increasingly important during this period. First, in the past two decades, China has gradually opened up and integrated with the global financial system. China has launched the Qualified Foreign Institution Investors (QFII) (2002) to strengthen the linkage with the international market; it's the first time that allowed the qualified foreign international financial institution to invest in the China mainland stock market (A shares). In 2007, China published Qualified Domestic Institutional Investors (QDII) to speed up the capital flow; it allowed qualified domestic financial institutions to invest in overseas stock and bond markets. As a result, China's economic development will become more critical for other countries in the world. Second, according to the previous literature, trade and financial integration contribute to the stock market return co-movement between two markets (Beine,

2011). In 2020, China became the 2nd largest trade partner of Thailand (ECONOMICS, 2021). Especially after China entered WTO in 2001, the export of Thailand increased 10x from 2.86 billion USD dollars to 29.5 billion USD dollars in 2020, while the export of China increased 20x from 2.3 billion USD dollars to 50.5 billion USD dollars.

On the other hand, the market co-movement between Thailand and China is expected to consistently change and possibly take a complex form during 2005-2020. Therefore, a standard method to measure the market co-movement may not be accurate. In this case, the wavelet method is used to assist the co-movement analysis. The wavelet decomposition is applied to two stock indexes (SET & CSI300) to transform them into different frequency-domain and time-domain. For example, the movement of the SET index could be decomposed into separate layers: short term (high-frequency), medium-term (medium-frequency), and long term (low-frequency) movements, and further analysis can be conducted separately on these layers.

Some studies show the co-movement between the stock market vary across high and low frequencies and constantly change in time. And wavelet method allowed analysis of the dynamic correlation by different frequencies. Thus, in the context of the increasing trading linkage and economic relationship between Thailand and China, the study of equity market co-movement in time and frequency domain provides the quantitative analysis and reference for different investors in Thailand interested in China. It also has practical significance for risk management, portfolio optimization, and other financial practice.

CHAPTER 2: LITERATURE REVIEW

Literature Review

In international financial markets, three different types of relationship analysis have been discussed: First, some research defined it as linear correlation or interrelation by using the standard method, namely the Pearson's correlation coefficient, how strong the correlation is. Clive W.J Granger (2000); François Longin (1995) and some other research prove the financial contagion or interdependence, like how the crisis happened in the U.S. affects other markets and the change of correlation coefficient before and after the financial crisis (Connolly, 2000; Elisabetta Bertero, 1990). In recent years, some of the market co-movement analysis has been discussed at the varying time (William N. Goetzmann, 2001). Some are focus on analyzing different factors that impact the co-movement, like how increased trade linkage and financial integration impact other equity markets in the world (Beine, 2011).

According to the definition and mathematical proofs from Baur (2004), the co-movement means two stock markets "share the movement" or "moving in the same direction" by applying bivariate (and multivariate) and dynamic analysis to see whether it increased/decreased through time. Based on this definition, this paper will find the co-movement between Thailand and China by transforming time series into the frequency domain and time domain.

A plethora of studies analyzing the market co-movement and integration among the ASEAN stock market Click and Plummer (2005) found the ASEAN 5 market are significant cointegration with each other from 1998 to 2002. They concluded that the benefits of international diversification among these five markets

are reduced but not eliminated by applying the historical correlation analysis and autoregression (VAR) model. Lim (2009) examined the data from 1990 to 2008 and found the market interdependence and integration increased among the ASEAN-5 market after the global financial crisis. Furthermore, they found the U.S. market had a significant impact on the ASEAN 5 stock market. Bakri Abdul Karim (2012) prove that the ASEAN stock markets are integrated during the 1997 and after 2008 financial crisis by using Autoregressive Distributed Lag (ARDL). And it's moving to more integration in this area after the global financial crisis, the diversification benefit of invest across ASEAN markets tend to diminish.

And also, other papers that analyze other stock markets, Singh and Singh (2017) find the existence of time-varying co-movement between BRIC countries (Brazil, Russia, India, and China) and the U.S. stock market. Wang et al. (2011) analyzed Asia, Europe, North America, and the pacific market and find out China has the highest level of dependence. Xinyu (2019) figures out the country in ASEAN 6 that has the strongest correlation with China is Singapore, Thailand, and Malaysia is comparatively weaker but shows a rising tendency. But the research on co-movement that focuses only on Thailand and China is still waiting to analysis.

In terms of data transformation, Albaity and Shanmugam (2012); Forson and Appiah (2020) analyze the co-movement based on the time series GARCH model and VAR to find the dynamic correlation coefficient and define the significant level of co-movement among the market. Given that most stock market time series are non-stationary and the difference between long-term and short-term investors behaviors, compare with the time series model, wavelet transform provides another option when we consider frequency in the analysis.

Kumar Tiwari et al. (2013) use Maximal Overlap Discrete Wavelet Transform (MODWT) find that the Asian equity market is highly integrated at the lower frequency level and comparatively less integrated at the higher frequency level. Jiang, Nie, et al. (2017) find ASEAN market interdependence level is more robust in the short term by using continuous wavelet transform (CWT). Wavelet transforms overcome the limitation of spectral analysis and Fourier analysis. It allowed decomposing the time series into high and low frequency and analyzing the co-movement in these two domains (Aloui & Hkiri, 2014; Benhmad, 2013).

Further, Younis et al. (2020) determined the volatility and correlation among India, Pakistan, Malaysia, Singapore, and Indonesia compared with China by using wavelet-based approaches like wavelet power spectrum and wavelet coherence. They divide the frequency into few different scales, where 128-256 is located at low frequency, 256-512, and 512-1024 is named medium frequency and high frequency. And observed a strong co-movement that on the medium frequency and high frequency in most countries, while followed a strong low-frequency co-movement in 1993-94.

Thus, this paper aims to fill the gap in the literature that analyzes the co-movement between Thailand and China by using the wavelet-based approach. Also, this paper will compare the correlation scale between low frequency and high frequency, which might provide potential implications to investors who consider Thailand and China market co-movement that combine both frequency and time domain when building their portfolio. In the end, we will create the portfolio by wavelet method and traditional method and compare their variance measures against

each other. The comparison results may help practitioners decide whether the wavelet method is worthwhile for practical portfolio construction.



CHAPTER 3: DATA

Data Overview

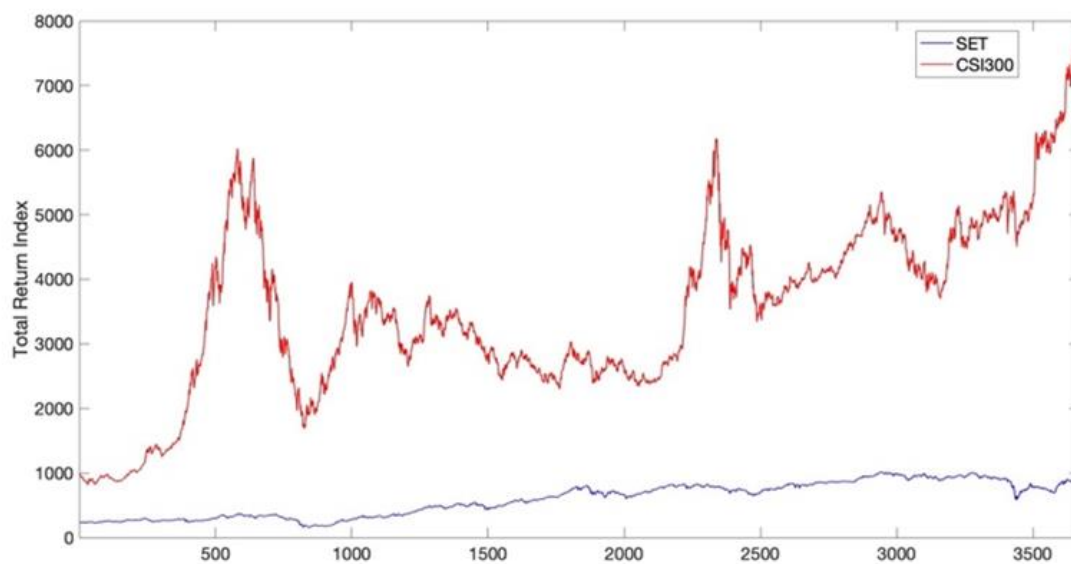
This paper uses Thailand and China equity market total return index data over last 15 years (Refinitiv Thailand Total Return Index & CSI 300 Total Return Index), in particular, the data is collected from Refinitiv database from April 8th, 2005, to March 23rd, 2021. Furthermore, to compute the market return from the total return index, this paper will apply the continuously compounded returns (r_t) defined as follows:

$$r_{it} = 100 \times \ln \left(\frac{P_{it}}{P_{it-1}} \right)$$

Where r_{it} means the ln return of index i at time t , and P_{it} represents the index i at time t . There are total of 3668 continuous compounded returns observations after observations from invalid trading date (no trading or not trade in the same day) are removed.

Figure 1 is total return Index of two market, where CSI 300 has higher fluctuation than SET. The CSI300 reaches the highest point at 6028.42 on October 16th, 2007, whereas SET has a stable performance around 365.65.

Figure 1 illustrates Total Return Index of CSI300 and SET



Data Description

According to the descriptive statistics in Table 1 of these two markets, the mean return for SET and CSI300 are positive, and CSI300 has a higher volatility as measured by standard deviation 1.77. The negative skewness is showing with a kurtosis higher than 3, implying a non-normal distribution for both return series.

Table 1: Descriptive Statistic Data

Index	Mean	Median	Min	Max	Std. Dev.	Skewness	Kurtosis
SET	0.0369	0.0665	-16.8539	11.1435	1.3442	-1.3274	17.8594
CSI 300	0.0511	0.1107	-9.6950	8.9518	1.7695	-0.5055	3.8812

Notes: Std. Dev. represents Standard Deviation

Figure 2 illustrates SET Compounded Return Time Series

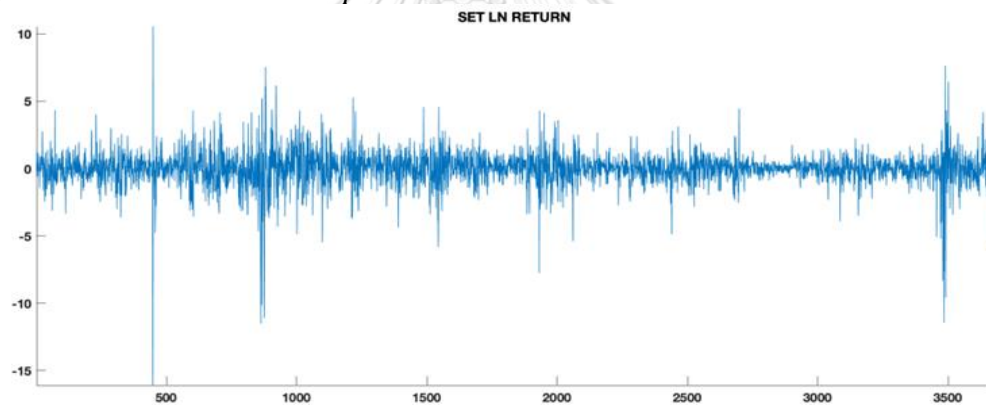
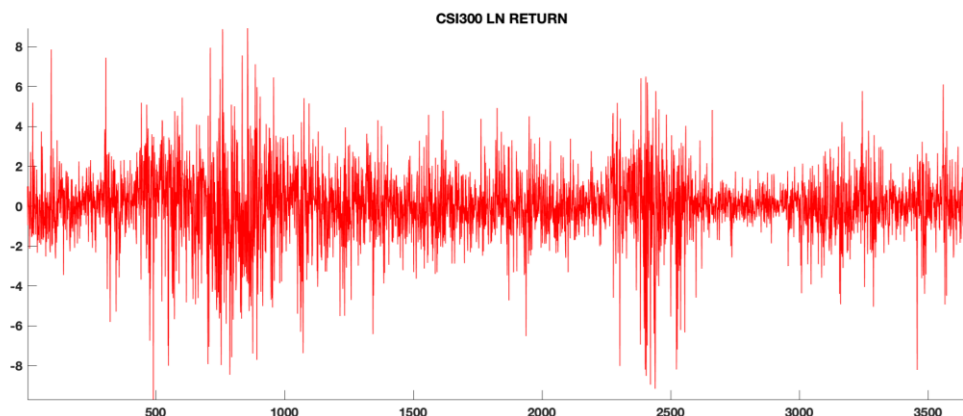


Figure 3 illustrates CSI 300 Compounded Return Time Series



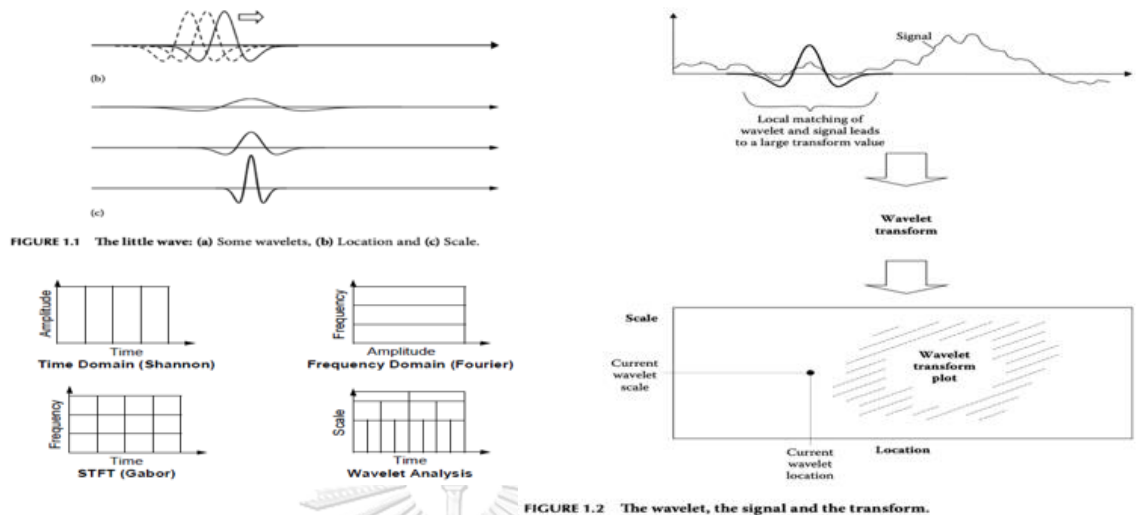
CHAPTER 4: METHODOLOGY

Methodology Overview

The *wavelet transform (W.T.)* is mainly used to analyze noisy, non-stationary, and transient signals, making it broadly used to investigate physical phenomena, climate analysis, and financial indices analysis (Addison., 2017). By applying the wavelet transform to the price or return data of stocks, we believe that it will help filter out the short-term noise and provide meaningful information regarding the correlation and volatility of the stock markets in the long term.

Wavelet Transform is a localized wavelike function $\psi(t)$ and distinctly different from the traditional Short Time Fourier Transform (STFT) and other methods (Figure 4). Its ability to transform and examine the signal simultaneously in both time and frequency makes the signal information in a more useful form. A wavelet can be moved to different locations on the signal, and it can be squeezed or stretch like Figure 1.1 (b) (c). When the wavelet and the shape of the signal local match at a specific scale and location like Figure 1.2, it will lead to a large transform value. But if it does not match well, then a low transform value is obtained. The transformed value will be located in the two-dimensional plane, which is captured at various locations of signal and multiple scales of wavelet.

Figure 4 illustrates Traditional Short Time Fourier Transform (STFT) and other methods¹



To be specific, the variety of location presents the varying of time in this paper (time domain), while the different wavelet scale shows the different frequency of stock indices. Generally, this two-dimension plane can be filling up in two ways: in a smooth continuous transform process called *continuous wavelet transform* (CWT) or in discrete steps called *discrete wavelet transform* (DWT). According to a book that was written by (Addison., 2017), the normalized wavelet function is written as:

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

One of wavelets that has been widely applied is called Morlet's wavelet, which has also been used in Aloui and Hkiri (2014) and Jiang, Nie, et al. (2017). This Morlet's wavelet is defined as:

$$\psi^M(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t} e^{-t^2/2}$$

¹ Addison, P. (2017). The illustrated wavelet transform handbook (2nd ed., pp. 2-3). CRC Press.

Here the ω_0 is the central frequency of the wavelet function, and according to Addison. (2017) the value of ω_0 will provide a balance between time and frequency localization. Following Aloui and Hkiri (2014); Jiang, Nie, et al. (2017); Younis et al. (2020), the *continuous wavelet transform (CWT)* is given by :

$$F(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-\tau}{s}\right) dt$$

Specifically, $F(\tau, s)$ represents wavelet coefficients, which can be found by a specific wavelet $\psi(t)$ projecting on the selected time series. In other words, all the windows that are used to capturing the signal are the dilated (or compressed) and shifted versions of the mother wavelet $\psi(t)$. The wavelet is translated across signal using τ like a window function and scaled by dividing by s . So $\left(\frac{t-\tau}{s}\right)$ is stretch and compress the wavelet, which a significant value of s corresponds to lower wavelet frequencies. So, when the wavelet matches the frequency of the wavelet and matches part of the signal with a very similar frequency, we get high output $F(\tau, s)$. Approximation coefficients are wavelet coefficients but represent the low frequency of the signal. Detail coefficient represents the high-frequency components of the signal.

Discrete Wavelet Transform (DWT)

Rather than the continuous integrals required for the continuous wavelet transform (CWT), it is possible to completely reconstruct the original signal by using infinite summations of discrete wavelet transform (DWT). Since DWT is useful for data de-noising and decomposing, CWT is suitable for data extraction and self-similarity detection. This paper will apply DWT for correlation analysis considering

non-stationary and noisy financial data. Based on Mallat (2008) the discrete wavelet transform (DWT) is given by:

$$DWT(a, b) = \frac{1}{\sqrt{b}} \sum_{m=0}^{p-1} f[t_m] \psi\left(\frac{t_m - a}{b}\right)$$

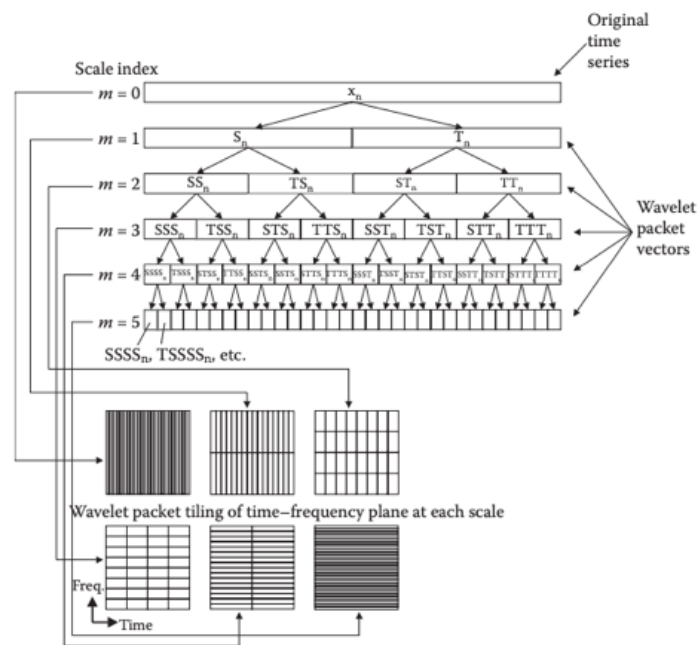
$$a = \tau \text{ in CWT} = k2^{-j}$$

$$b = s \text{ in CWT} = 2^{-j}$$

j is scale index, k is wavelet transformed signal index

Calculating wavelet coefficients at every possible scale produces a lot of data. Therefore, we use (a, b) to replace (τ, s) to be discrete, and the wavelet won't generate massive amounts of data. (a, b) are based on the power of two (Dyadic), the relationship between frequency and wavelet scale show as the equation. DWT make frequency analysis becomes much more efficient and accurate. Then we will apply the generalizations of the DWT, which can adapt the signal and allow for more flexibility in the partitioning of the time-frequency plane: the wavelet packet transform (W.P.). In the W.P. signal decomposition, the coefficient will be further decomposed by each scale (Addison., 2017) in Figure 5.

Figure 5 illustrates Schematic diagram of wavelet packet decomposition.²



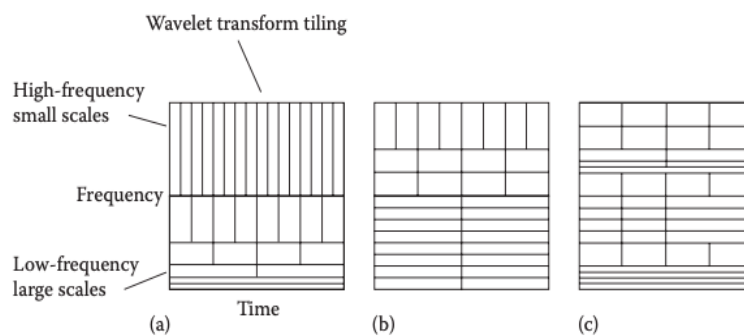
Furthermore, the modified version of DWT, called maximal overlap discrete wavelet transform (MODWT), can also be applied in this analysis. It helps obtain a multi-scale decomposition of return series. At the same time, it has few advantages compared with standard DWT (Hermansah et al., 2019).

1. MODWT is suitable for any sample size, while DWT's sample size can only be written as 2^N (N is positive integers).
2. MODWT can down-sampling (reduce data size to half), so compare with DWT in each level of decomposition, there is a wavelet and smooth coefficient as much as the length of data.
3. Shifting in MODWT will not change the value of the wavelet coefficient.
4. MODWT can increase the information at the low-frequency level.

² Addison, P. (2017). *The illustrated wavelet transform handbook* (2nd ed., pp. 184). CRC Press.

In the end, the wavelet transform will decompose the signal into both the Time-Frequency domain (Figure 6). Base on all discussions and papers mentioned above, the wavelet-based approach is an appropriate method to analyze the stock market co-movement over time.

Figure 6 illustrates Schematic diagrams of allowable wavelet packet tiling of the time-frequency plane.³



Notes: The right-hand tiling is that used in the wavelet transform algorithm and corresponds to the components contained in the bold boxes shown in Figure 5.

To reconstruct the original time series, multiresolution analysis (MAR) will be applied to shows the market movement on a different scale. This MODWT and MAR in Matlab is given by:

```
levelForReconstruction = [true, true, true, true, true, true]; % Logical array
```

for selecting reconstruction elements

```
wt = modwt(CSI_logReturn, 'sym4', 7); % Perform the decomposition using
```

modwt (LA8)

```
mra = modwtmra(wt, 'sym4'); % Construct MRA matrix using modwtmra
```

```
CSI_logReturn1 = sum(mra(levelForReconstruction,:),1); % Sum along
```

selected multiresolution signals

³ Addison, P. (2017). *The illustrated wavelet transform handbook* (2nd ed., pp. 185). CRC Press.

Hypothesis Development

Real-world data, signal or stock market index is comprised of noise and abrupt changes in its movement. These abrupt changes often carry information, and we want to keep the information in the signal while removing the extra noise. Three steps will be applied in this stage to extract the information by the wavelet transform method.

1. Perform a multi-level wavelet decomposition.
2. Analyze the details and identify a thresholding technique.
3. Filter out the detail coefficient and reconstruct data.

We perform a multi-level wavelet decomposition to obtain the approximation and detail coefficients, for which the discrete transform will split up the signal into an approximation level (low-pass sub-band) and a detail level (high pass sub-band).

- a. Using MATLAB function – Wavedec – to do decomposition.

```
dwtmode('per','nodisplay');
```

```
wname = 'sym';
```

```
leve = 7;
```

```
[C,L] = wavedec(f,level,wname);
```

- b. Applying- Detcoef function to extract the coefficients and plot the coefficients for each level.

```
plotDetCoefhelper(f,c,l)
```

- c. Choose SureShrink (or rigrsure) with the soft thresholding technique. The process of thresholding the coefficients and reconstructing the signal can use a signal function:

```
fd = wden(f,'rigrsure','s','sln', level,wname);
```

where “f” = noisy signal;

“rigrsure” = thresholding technique

“s” = soft thresholding

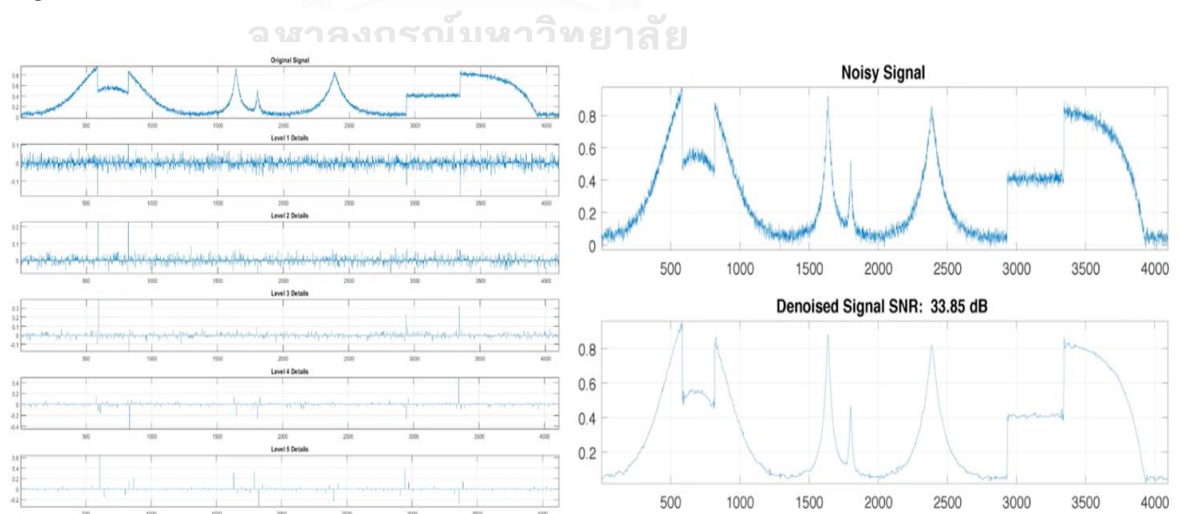
“sln” = rescale threshold by using a single estimate of noise

“Level” = the wavelet decomposition level

“wname”=types of wavelets.

As an example, the figure below 7 shows the original signal along with the details plotted for level 1 through 5. Noticed that the activity in the details reduces drastically as the scale or level increases. Therefore, we can obtain the information by comparing both the time and frequency domain with the multi-level denoised signal.

Figure 7 illustrates the original signal along with the details plotted for level 1 through 5.⁴



⁴ Devleker, K. (2016). Understanding Wavelets, Part 3: An Example Application of the Discrete Wavelet Transform. Youtube. Retrieved 14 July 2022, from <https://www.youtube.com/watch?v=-OhibnAXBEM>.

This time and time-scale have been used by a vast body of papers like Addison. (2017); Aloui and Hkiri (2014); Compo (1998); Jiang, Nie, et al. (2017); Tiwari et al. (2016); Younis et al. (2020). Loh (2013) used wavelet coherence analysis and discovered the strong correlation between most Asia-pacific markets and the European/U.S. markets in the long term. On top of that, Tiwari et al. (2016) analyzed the rolling correlation, contagion and the level of co-movement between the stock market of the U.K./Germany and the PIIGS (Portugal, Ireland, Italy, Greece and Spain) from 2003 to 2013. The wavelet analysis found a high correlation in the short run only present during financial distress episodes. In the long run, it presents for the entire horizon. Moreover, Kiviaho et al. (2014) explained that co-movement differs between short term and long term. It found a stronger co-movement in the long-term between European frontier markets and the U.S/UK/Germany/France markets. The domestic monetary policy is the most influential factor for the short term. In contrast, global monetary policy and domestic exchange rate movement are identified as the most prominent factors for the long term. Back to our research, Thailand and China execute different monetary policy in the country, and the connect of stock market investment is not as strong as other countries. Thus, we assume that short term surprise does not have a big impact on two markets co-movement. Therefore, the first hypothesis of this paper will focus on observing the co-movement in different time scales and figure out how co-movement performed in different time scales.

Hypothesis 1: the long-term time scale (lower frequency) has a stronger co-movement when compared with the short-term time scale (higher frequency)

We believe the co-movement between Thailand and China varies under the different market condition in the past two decades due to many factors that impact the

two markets' interrelationships, and we expect it to be apparent in the correlation. Nevertheless, we believe that the main factors that contribute to the changing co-movement between Thailand and China are the strengthening of trade linkage and the financial liberalization in China.

The increasing trade linkage and financial liberalization have reinforced the interdependence level of cross-country stock markets on the fundamental economic side. For example, Beine (2011) investigated 25 developing countries over 15 years, find trade linkage has a positive impact on the stock market correlation. Paramati et al. (2016) gives firm support that trade intensity drives the stock market interdependence significantly in the short and long run. Lahrech and Sylwester (2013) find the trade agreement NAFTA increased equity market linkages between the U.S. & Mexican and Canadian & Mexican. For this research, it appears that the trade linkage between Thailand and China had been gradually strengthened in the past two decades. More specifically, China entered WTO in 2001 and, from then up until recently, China ranked as the 2nd trade partner of Thailand in 2020. According to previous studies, we would expect a positive impact on the two markets' correlation along the increased of trade intensity. Thus, the second hypothesis is developed based on the impact of economic globalization and financial liberalization.

Hypothesis 2: In the past two decades, the co-movement in the second decade (2014-2021) is higher than in the first decade (2005-2013).

On the financial market side, the analysis of the correlation cross-countries helps to understand the financial shocks spillover. It's essential for fund risk management and central bank policymaker to make the decision based on the

international financial context. There are few essential stock market crises that happened during this period. For instance, the China market panic in 2007-2008 which caused by financial austerity policies plus the impact from international crisis, and stock market crash in 2015. Past literature has shown that in times of crisis, the correlation of stock returns moves higher short-term. Supporting this idea, Jiang, Yu, et al. (2017) found that the financial crisis has strengthened the interdependent relationship of the world's six major stock markets, and Paramati et al. (2016) prove the global financial crisis has had a significant influence on the stock market of Australia and Asia.

Furthermore, the paper by Loh (2013) used wavelet coherence analysis and conducted the co-movement cross time scale. The paper has found a wide variation of changing co-movements during various financial crises. Nevertheless, the co-movement dynamics differ significantly during the two financial crisis periods – the European debt crisis and U.S. sub-prime crisis. In other words, it could be the result of different natures of the crisis. Therefore, the 3rd hypothesis will test the impact of the financial crises in China (2007 and 2015), whether it increased or decreased the stock market correlation between Thailand and China.

Hypothesis 3: All the co-movement (long term, short term and others) after the market crisis in the year 2007/2015 will be significantly higher than it before the crisis.

Studying the correlation between Thailand and China is essential for the risk assessment of an investment portfolio. The portfolio theory of Markowitz (1952) emphasized the essentiality of investment diversification to avoid the loss associated

with a single asset class. The benefit from diversification is becoming higher when the correlation between two stock market returns is low. In other words, the increased co-movement between different market returns will decrease the international diversification of portfolios.

To build an optimal investment portfolio between Thailand and China, the feature of time-varying and timescale (frequency) varying should be taken into account to provide a more accurate correlation analysis. For instance, the participants in the stock market that have different investment horizontal can divide the correlation into multiple time scales. Such as the large investment banks that trading in several minutes/hours/ days are more interested in short-term market movement. On the other hand, for commercial banks and insurance companies, these participants may be more concerned with the medium-term performance in several weeks/months. Others like pension funds typically have a long-term investment horizontal of several years.

Following the idea of using the accurate correlation in the suitable time scale would benefit the investors, this research would like to investigate simple portfolio strategies that implement the correlation between Thailand and China stock indices. For simplicity, a standard minimum variance portfolio is constructed based on two different correlations: a traditional correlation and the wavelet transformed correlation. The wavelet transformed correlation, particularly with MODWT is used to denoise the data prior to deriving the correlation coefficients, is believed to generate a more optimal portfolio.

In order to investigate the portfolio strategy, this paper will calculate the minimum variance hedge ratios separately based on the traditional correlations and

the wavelet correlations, then apply these ratios to build two different portfolios. The formula for the hedge ratio is shown below:

$$h = \rho \frac{\sigma_{CSI}}{\sigma_{SET}}$$

The hedge ratio h represents the amount invested in SET index for one Chinese Yuan invested in CSI index. (ρ) is the correlation of 2 asset, and (σ_{CSI}) (σ_{SET}) are the volatility of CSI and SET, respectively.

Base on the method used by (Berger & Fieberg, 2016) we apply the rolling time window and use the minimum variance portfolio in the past (the # n trading day) as the future (the $n+1$ trading days) asset allocation weight. For example,

- 1st-time window: trading day 1- day 120, length 120 days, forecast the allocation on day 121.
- 2nd-time window: trading day 2- day 121, length 500 days, forecast the allocation on day 122, etc.

The returns of the two constructed portfolios will then be tested and compared for their actual variances. Thus, the last hypothesis of correlation under wavelet will be:

Hypothesis 4: Under the minimum variance hedge ratio, the MODWT will formulate an investment portfolio better than the traditional minimum variance portfolio.

CHAPTER 5: RESULTS

Results

As we first use Wavelet Multi-Resolution Analysis in MATLAB to decompose the original time series of stock returns into seven different time scales based on Maximal Overlap Discrete Wavelet Transform (MODWT) the wavelet filter Daubechies least asymmetric (LA) is applied in the decomposition with the samples of 3668 observations ($N=3668$). The resulting decomposition of returns in all seven details and one approximation component is shown in figure below 8 & 9. And the corresponding time dynamics of each level is given in Table 2.

Figure 8 illustrates MODWT multiresolution analysis for Stock Exchange Thailand Total Return Index

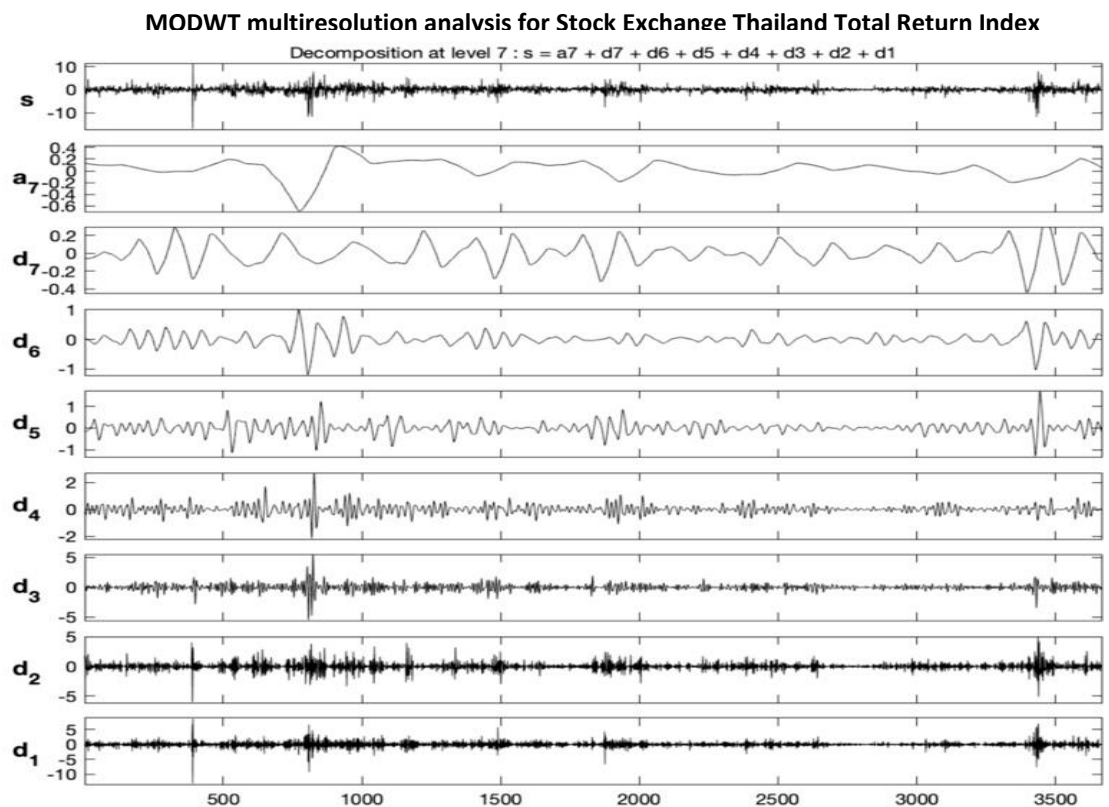


Figure 9 illustrates MODWT multiresolution analysis for CSI 300 Total Return Index

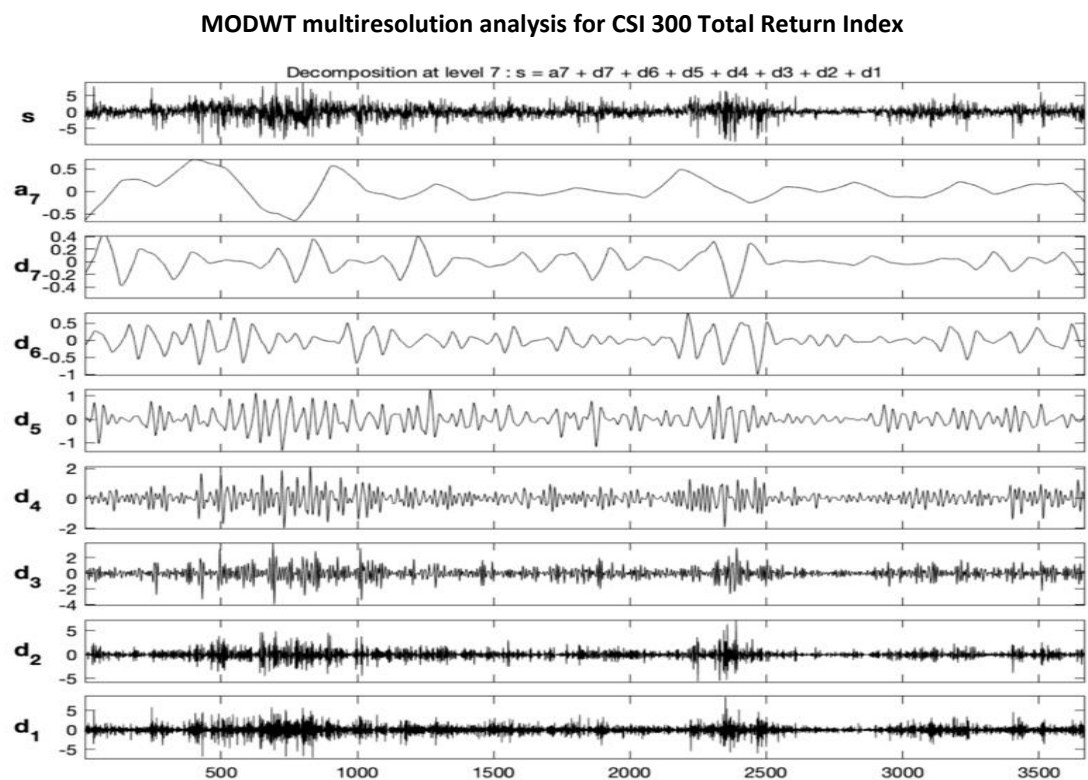


Table 2: Time Interpretation for different levels (frequencies)

	Periods (days)	Scale (weeks)	
Level 1 – d1	2-4 days	< 0.8	Intraweek
Level 2 – d2	4-8 days	0.8-1.6	Weekly
Level 3 – d3	8-16 days	1.6-3.2	Fortnightly
Level 4 – d4	16-32 days	3.2-6.4	Monthly
Level 5 – d5	32-62 days	6.4-12.4	Monthly to Quarterly
Level 6 – d6	62-133 days	12.4-26.6	Quarterly to Biannual
Level 7 – d7	133-265 days	26.6-53	Annually
Approx. – a7	265 – inf.	53 <	

We take five trading days as one week, 20 days as one month. Thus, d1 show the trading periods of 2 - 4 days, d2 is 4 - 8 days which represents weekly, d4 represents monthly while d7 is annually. The approximation level a7 means the long-term data that over one year of trading days. The relative energy for each level is shown in Table 3, where d1 takes the highest portion for both markets. It can be viewed as the short term (2 – 4 days) volatility is having the highest impact on the original return time series.

Table 3: Wavelet Relative Energy for SET & CSI300 Return Series

	d1	d2	d3	d4	d5	d6	d7	a7
SET	50.84%	22.01%	14.16%	5.68%	3.17%	2.11%	0.78%	1.26%
CSI300	48.62%	25.17%	12.89%	5.83%	3.16%	1.79%	0.65%	1.89%

We suspect this is the result of individual investors being the main players in both stock markets, thus markets are easily impacted by short term market volatility or surprises. Moreover, the relative energy decreased along the increase in trading days (scales). This shows the middle to long-term investing strategy are not affect by surprise that much, and also has a comparably low frequency in trading. To summarize, the market volatility is mainly affected by short term investors, and this impact is decreases along the increase in trading days. This result is supported by Wang (2017) and DAJCMAN (2012), whose work has also found the high short-term impact in China and the US markets. And here is the data description in Table 4 after the decomposition of return series for each level.

*Table 4: Data description of SET wavelet statistic and CSI wavelet statistic***Panel A: SET_wavelet_statistic**

statistic	d1	d2	d3	d4	d5	d6	d7	a7
mean	-0.000109	0.000267	-0.000120	-0.000283	-0.000210	-0.000459	-0.000329	0.038188
median	-0.006117	-0.004939	0.010276	0.003239	0.004065	0.000628	-0.002988	0.057281
min	-13.093187	-6.012783	-5.465130	-2.166958	-1.288613	-1.187762	-0.437992	-0.682322
max	8.616997	4.929762	5.439832	2.683522	1.688519	0.996458	0.423691	0.424391
std	0.950163	0.632450	0.521399	0.309398	0.243890	0.199890	0.119955	0.148492
skewness	-0.687661	0.100624	-0.333240	0.462992	0.120540	-0.519657	-0.088354	-1.515863
kurtosis	20.738158	9.352014	16.831881	7.650023	6.076841	6.671462	0.934024	5.586855

Panel B: CSI_wavelet_statistic

statistic	d1	d2	d3	d4	d5	d6	d7	a7
mean	-0.000096	0.000003	0.000275	0.000296	0.000319	0.001468	0.002446	0.046340
median	0.003004	-0.006295	0.006822	0.005953	-0.002268	0.004991	0.003296	0.022893
min	-7.221340	-5.586982	-3.935591	-1.964728	-1.338025	-0.996610	-0.561250	-0.646676
max	8.524369	7.141951	3.821462	2.098357	1.258453	0.792331	0.487790	0.705754
std	1.245363	0.884197	0.624226	0.419032	0.323203	0.234060	0.135687	0.246349
skewness	-0.076164	0.182795	-0.106709	-0.045608	-0.038925	-0.277893	-0.169280	0.160011
kurtosis	3.929417	6.781014	4.077355	2.308696	1.181835	1.241921	2.095258	0.942337

Hypothesis Test 1

We obtained 3668 observations from the wavelet method in each level (d1 to a7), whose data description is shown as Table #. Then we use the result calculate the correlations between CSI300 and SET in each level by pairing the obtained observations in the same level before using the traditional way of computing the correlation. The result will be a total of 8 correlations from short-term (d1) up to long-term (d7, a7). The t-stat is computed by the Fisher Z Transformation, whose formula is shown below:

$$Z = \frac{1}{2} \ln \frac{1 + \widetilde{\rho}_{xy}(\lambda_j)}{1 - \widetilde{\rho}_{xy}(\lambda_j)}$$

$\widetilde{\rho}_{xy}(\lambda_j)$ is the wavelet correlation for level j, and the t-stat is constructed as follow:

$$t = \frac{Z_2 - Z_1}{\sqrt{\frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}}}$$

where Z_1, Z_2 means the d1, d7 wavelet correlation after Fisher Z transformation; n_1, n_2 are the number of observations.

Hypothesis 1: the long-term time scale (lower frequency) has a stronger co-movement when compared with the short-term time scale (higher frequency)

Thus, can be written as:

$$H_0: \widetilde{\rho}_{xy}(\lambda_i) \leq \widetilde{\rho}_{xy}(\lambda_{d1})$$

$$H_1: \widetilde{\rho}_{xy}(\lambda_i) > \widetilde{\rho}_{xy}(\lambda_{d1})$$

where i is either d2, d3, d4, d5, d6, d7, and a7.

The result of correlation including the t-stat is shown in Table below 5. The wavelet correlation increases at d4 and a7 quite significantly when compare with d1, but decreases at d2, d3, d5, and d6.

Table 5: Test of Hypothesis 1 Results

Test of Hypothesis 1								
	corr_d1	corr_d2	corr_d3	corr_d4	corr_d5	corr_d6	corr_d7	corr_a7
2005-2021	0.2755	0.2116	0.2371	0.3249	0.1753	0.0705	0.2364	0.4604
Observations	3668	3668	3668	3668	3668	3668	3668	3668
z1	0.2828							
z2	0.2828	0.2148	0.2417	0.3371	0.1771	0.0706	0.2409	0.4978
t-stat of z2-z1	0.0000	-2.9101	-1.7588	2.3274	-4.5230	-9.0820	-1.7912	9.2033

The t-stat result as (-1.79) at d7 which is lower than (-1.96) at 95% confidence. Thus, the Hypothesis 1 is rejected, the correlation of two markets does not increase from short-term (d1) to any specific long-term (d5, d6, and d7) for the past 16 years. But in the approximation level a7, the t-stat is significant at both 95% and 99% confidence interval. In other words, if we expand the period of trading days over one year, there are high probability to observe an increased correlation at the long-term scale.

Although the result is not as we previously expected the low correlation between the two markets in long-term does not surprise us that much, because there is also evidence that documented a typically low correlation between Thailand and China. Abdul Karim and Shabri Abd. Majid (2010) mentioned that China appears to be the most isolated market showing consistently low correlation with the other

markets, such as Malaysia, USA, Singapore, Thailand, and Japan. And in general, two markets with low correlation would typically be influenced by short-term shocks.

Therefore, we did not find enough statistical evidence that the long-term scale shows a stronger co-movement than short term scale (d1 intraweek).

Hypothesis Test 2

Hypothesis 2: In the past two decades, the co-movement in the second half (2014-2021) is higher than in the first half (2005-2013).

$$H_0: \widetilde{\rho}_{xy}(Y_{2014-2021}) \leq \widetilde{\rho}_{xy}(Y_{2005-2013})$$

$$H_1: \widetilde{\rho}_{xy}(Y_{2014-2021}) > \widetilde{\rho}_{xy}(Y_{2005-2013})$$

By following the same method, we calculate the wavelet correlation for two periods: from 2005 to 2013, and from 2014 to 2021. The reason for dividing the period this way is because the Shanghai-Hong Kong Stock Connect, Shenzhen-Hong Kong Stock Connect, and Shanghai-Shenzhen Stock Connect policies were launched between 2014 to 2019, which help connect two Chinese mainland stock exchange markets with HK stock market. The unlock of capital flows from these three markets massively increased the liquidity of international capital inflow in China and helped capital outflow to other markets worldwide, which it has expected to have an impact on the China and Thailand stock market.

As table 6 shows, Z1, Z2 are the correlations for these two periods after Fisher Z transformation. There are 2004 observations from '11-Apr-2005' to '27-Dec-2013', and 1664 observation from '02-Jan-2014' to '23-Mar-2021' due to the ineffective data has been removed. According to the result, the null hypothesis is rejected at d2, d4, d5,

and d6 at 95% confidence level, whereas the change is not statistically significant in d1 and d7. Thus, based on the majority of the result, the second half of sample period shows an increase in correlation level as we initially conjectured.

Table 6: Test of Hypothesis 2 Results

Test of Hypothesis 2								
	corr_d1	corr_d2	corr_d3	corr_d4	corr_d5	corr_d6	corr_d7	corr_a7
2005-2013	0.2724	0.1903	0.2532	0.3095	0.1543	-0.0292	0.2395	0.5200
observations	2004	2004	2004	2004	2004	2004	2004	2004
2014-2021	0.2830	0.2526	0.2026	0.3770	0.2222	0.2199	0.2354	0.2078
observations	1664	1664	1664	1664	1664	1664	1664	1664
z1	0.2794	0.1926	0.2589	0.3199	0.1556	-0.0292	0.2442	0.5763
z2	0.2909	0.2582	0.2055	0.3965	0.2260	0.2235	0.2399	0.2109
t stat	0.4928	2.8095	-2.2866	3.2789	3.0133	10.8166	-0.1851	-15.6420

Hypothesis Test 3

Hypothesis 3: All the co-movements (long term, short term, and others) after the market crisis in the year 2007/2015 will be significantly higher than before the crisis.

Since we want to study how stock market co-movement impacted by stock market downturn, the global financial crisis in 2008 and Chinese stock market crash in 2015 are chosen to analysis. According to Lizhan and Huailin (2021); Tsai (2015) this paper also divided crisis into three intervals, which is pre-crisis period, crisis period, and post-crisis period. Which leading to the result of this hypothesis can be explained into two perspectives:

1. Compare correlation t-stat for pre-crisis & during crisis
2. Compare correlation t-stat for pre-crisis & post crisis

And since Xing (2018) had only define 2015 market crash into pre-crash & market downturn these two periods, to consistent the calculation/analysis logic, this paper will add post-crash period and apply the same end date to make it unified with the global one (Table 7).

Table 7: Crisis/Market Downturn Period

Crisis/Market Downturn Period				
by international crisis analysis	2008 subprime crisis analysis			
		Start	End	Observations
	Pre-crisis	25-Jul-05	28-Dec-07	565
	Crisis	2-Jan-08	30-Jun-09	347
	Post-crisis	1-Jul-09	26-Aug-19	2333
by local market crash	2015 market crash			
		Start	End	Observations
	Pre-crash	12-Jun-14	11-Jun-15	231
	Crash	12-Jun-15	25-Feb-16	162
	Post-crash	26-Feb-16	26-Aug-19	810

Thus, we analysis correlation for different period based on d1-d7 level, and separately calculate the t-stat that between pre-crisis & crisis, and pre-crisis & post-crisis. It's clear to see the impact of international crisis and local market crash on those two markets by observing the movement of correlation. However, d1, d2, d3 supposed to be considered as the most important levels since it's taken 87.01% & 86.68% of wavelet relative energy for SET & CSI300 Return Series. Referring to Table 3 in page 24, it represents the most important portion of market volatility and clearly explained the market movement under the surprises.

Based on the Table 8, the correlations are all increased from pre-crisis to during crisis & pre-crisis to post crisis in the 2008 & 2015. The t-stat is significant increased at 95% level in d1& d2 level in 2008 global crisis, strongly supporting the hypothesis 3 for both pre vs during and pre vs post crisis period in these two levels. And for 2015 local market crash, the hypothesis 3 is supported by the result in all 3 levels for pre vs during crisis period; and is supported at d1, d2 for pre- vs post-crisis period as the t-stats pass the threshold at 95% confidence level.

However, when compare with the significant correlation increased in d1 & d2, it just results in a slightly increased at d3 level (8 - 16days) for global crisis in 2008, and pre-crisis & post-crisis for local-market crash in 2005. This could be caused by the big difference wavelet relative energy of d1, d2, and d3; the higher energy the significant increasement in correlations, refer to Table 3.

Table 8: *Statistic-Global Financial Crisis*

Statistic-Global Financial Crisis	d1	d2	d3	d4	d5	d6	d7	a7
correlation from 25-Jul-2005 to 28-Dec-2007	0.11532758	0.01797357	0.160133635	0.17190839	-0.05735	-0.3361078	-0.2175837	-0.098927
correlation from 02-Jan-2008 to 30-Jun-2009	0.37467317	0.23974039	0.269976933	0.4600831	-0.1181749	0.19127036	0.03619593	0.87017461
correlation from 01-Jul-2009 to 26-Aug-2019	0.2831464	0.23924128	0.231667082	0.24537634	0.28389123	0.23085332	0.41299132	0.17750234
t-stat pre +during 1	4.06103321	3.30899322	1.684493922	4.72975797	-0.895699	7.937172	3.75901227	20.9336331
t-stat pre+post 1	3.72924487	4.80887229	1.58370672	1.63536949	7.43315794	12.4435983	14.0510374	5.92942485
Statistic-Local Market Crash (CN)	d1	d2	d3	d4	d5	d6	d7	a7
correlation from 12-Jun-2014 to 11-Jun-2015	-0.0409164	-0.0214584	-0.01478542	0.05392718	-0.192929	-0.5579145	0.40217153	0.17345741
correlation from 12-Jun-2015 to 25-Feb-2016	0.39177427	0.41406913	0.381949679	0.40662166	-0.6560846	0.56851001	-0.2596032	-0.3925713
correlation from 26-Feb-2016 to 26-Aug-2019	0.28508701	0.26965312	0.095412891	0.48266489	0.52260721	0.35493927	0.06486373	0.64735599
t-stat pre+during 2	4.402131	4.47124187	4.037185008	3.65440367	-5.715479	12.3413047	-6.6967818	-5.7109794
t-stat pre+post 2	4.4546716	3.97209903	1.472989566	6.29871365	10.335776	13.3431482	-4.8163807	7.93889229

Hypothesis Test 4

Hypothesis 4: Under the minimum variance hedge ratio, the MODWT will formulate an investment portfolio better than the traditional minimum variance portfolio.

Optimal variance hedge ratio is one of the strategies to minimize variance of investment portfolio that include 2 assets. We apply it in this paper to formulate portfolios from two different schemes: traditional and MODWT. The portfolio returns are then computed and compared by variance to see which one achieves the lowest value.

Firstly, we use 1-Jan-07 as the start day and 6 months (around 110-120days) as rolling window to compute quarterly log return, volatilities (σ_{CSI} and σ_{SET}), and the correlation of two markets. Then the portfolios are formed according to the hedge ratio h . By using two different time series of correlations, one obtained from the traditional method and the other from the wavelet method, as an input in the hedge ratio, multiple portfolios will be formed. The portfolio return on the subsequent period is then calculated based on the equation

$$P(R_{t+1}) = CSI(R_{t+1}) - h_t \times SET(R_{t+1})$$

Representing the return as if portfolio is buy-and-hold until the next quarter. Because we have 8 wavelet correlations at different time scales and one traditional correlation, we have a total of 9 minimum variance portfolios being formed.

The result of actual variances computed from the return series of minimum variance portfolio is shown in Table 9. Unfortunately, we can only observe the -

variance of $d1$ is lower than the portfolio that build under traditional method. It means that the wavelet method does not have a significant advantage in terms of portfolio variance minimization.



Table 9: The return series of minimum variance portfolio

Portfolio	P(Rt)_Ori	P(Rt)_d1	P(Rt)_d2	P(Rt)_d3	P(Rt)_d4	P(Rt)_d5	P(Rt)_d6	P(Rt)_d7	P(Rt)_a7
Mean	0.03223749	0.03127446	0.03465977	0.03809183	0.02157972	0.04860153	0.04036591	0.07752132	0.05019092
Standard Error	0.03025061	0.02942351	0.03127696	0.03191434	0.03532832	0.03058341	0.03940639	0.0382067	0.03525145
Median	0.01865561	0.02115825	0.03783234	0.01418266	0.01442633	0.02937833	0.01570791	0.02614081	0.0173906
Standard Deviation	0.22637481	0.22018535	0.23405533	0.23882508	0.26437292	0.22886532	0.29489042	0.28591276	0.26379769
Sample Variance	0.0512500	0.0476300	0.0538200	0.0560400	0.0686500	0.0514900	0.0854400	0.0803900	0.0683900
Kurtosis	1.18602049	1.12570915	1.10487949	1.49540922	3.17613637	0.72682969	2.57673313	2.57044158	3.74362093
Skewness	0.58142754	0.57785695	0.3623455	0.47458859	0.12114351	0.55690551	0.65847103	1.23400005	1.27542264
Range	1.17396611	1.12351607	1.17438668	1.27487655	1.72613233	1.13339581	1.76701013	1.62636069	1.56699271
Minimum	-0.5230863	-0.5174866	-0.5475575	-0.5397387	-0.8786432	-0.4787841	-0.6765387	-0.5154827	-0.4568502
Maximum	0.6508798	0.60602948	0.62682918	0.73513785	0.84748911	0.65461173	1.09047147	1.11087798	1.11014252
Sum	1.80529934	1.75136983	1.94094687	2.13314251	1.2084644	2.72168559	2.26049091	4.34119366	2.81069162
Count	56	56	56	56	56	56	56	56	56
Confidence Level (95.0%)	0.06062357	0.05896602	0.06268043	0.06395777	0.07079953	0.06129053	0.07897217	0.07656794	0.07064548

Conclusion

To summarize, the wavelet method has a competitive advantage in correlation decomposition and provides better insight into market movements under various time scales. The gradually increased correlation proved that the intensity of trade linkage and other economic activity between Thailand & China has an impact on the market correlation. Also, by decomposing the signal (market return) into different levels (time-period) while a market crisis, we observe an increase of correlation that happened during & post-crisis in all levels; and resulted in a significant increase at 95% confidence at d1-d3 (daily to monthly).

However, this method also has some limitations when applied to the stock market of China and Thailand. It did not show any summative relationship between short-term & long-term correlation. We cannot make an instructive conclusion regarding correlation under different time scales. Likewise, with that comes failure to only formulate one optimal portfolio which has lower variance when compared with the traditional method.

Even though wavelet does not have the advantage in terms of constructed minimum variance portfolio, it helps a lot if considered when analyzing market movement under various time scales. Thus, the wavelet method is still valuable to investors when creating investment strategy; and always provides insights for policymakers while analyzing the overall market movement and risk management.

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จุฬาลงกรณ์มหาวิทยาลัย
CHULALONGKORN UNIVERSITY

VITA

NAME	Shilei Sun
DATE OF BIRTH	24 January 1994
PLACE OF BIRTH	Chengdu, China
INSTITUTIONS ATTENDED	Stamford International University
HOME ADDRESS	Soi 37/1 Chan Rd, Bangkok, Thailand



จุฬาลงกรณ์มหาวิทยาลัย
CHULALONGKORN UNIVERSITY