

**THE CAUSAL RELATIONSHIP BETWEEN
STOCK MARKETS: A WAVELET
TRANSFORM-BASED APPROACH**

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STOCK MARKETS: A WAVELET
TRANSFORM-BASED APPROACH**

by

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LIST OF ABBREVIATIONS

DWT	Discrete Wavelet Transform
MRA	Multi-resolution Analysis
MODWT	Maximal Overlap Discrete Wavelet Transform
Haar	Haar Wavelet
db	Daubechies Wavelet
sym	Symmlets Wavelet
coif	Coiflets Wavelet
dmey	Discrete Approximation of the Meyer Wavelet
ACF	Autocorrelation Function
AIC	Akaike Information Criteria
SIC	Schwartz Information Criteria
FPE	Final Prediction Error
HQC	Hannan Quinn Information Criteria
AR	Autoregressive Model
VAR	Vector Autoregressive Model
VECM	Vector Error Correction Model
ADF	Augmened Dickey Fuller Test
PP	Phillips-Perron Test

MS-AR Markov-Switching Autoregressive Model

MS-VAR Markov-Switching Vector Autoregressive Model

MS-VECM Markov-Switching Vector Error Correction Model

DWT-VECM Wavelet-Vector Error Correction Model

DWT-MS-VECM Wavelet-Markov-Switching Vector Error Correction Model

HUBUNGAN PENYEBAB ANTARA PASARAN SAHAM :PENDEKATAN WAVELET

ABSTRAK

Dalam tahun kebelakangan ini, harga pasaran saham adalah salah satu daripada petunjuk ekonomi yang paling penting yang mendedahkan status ekonomi sesuatu negara serta menerokai hubungan kalangan negara-negara di dunia. Seperti yang sedia maklum, harga pasaran saham adalah tidak menentu dan mengandungi data hingar yang memberi kesan kepada ketepatan dan kesahihan keputusan sesuatu model. Oleh itu, para penyelidik semasa memberi tumpuan kepada memeriksa kaedah penguraian untuk menyelesaikan masalah data hingar dan menentukan kemeruapan pasaran saham dengan lebih tepat. Terkini, penurasan wavelet telah digunakan sebagai alat yang berkesan untuk mengurangkan hingar dalam siri masa kewangan. Selain itu, penurasan wavelet mempunyai beberapa ciri-ciri yang lebih berbanding penuras yang lain. Maka dari sudut ini, tesis ini mencadangkan teknik yang berbeza untuk menyiasat hubungan antara pasaran saham dengan menggabungkan penurasan wavelet dan model tradisional dalam usaha menyelesaikan masalah kesan hingar dalam data siri masa kewangan, dan mendapatkan keputusan lebih tepat. Tesis ini dibahagikan kepada tiga bahagian. Bahagian pertama memperkenalkan perbezaan antara lima keluarga fungsi berdasarkan kepada dua jenis wavelet (DWT dan MODWT) untuk mendapatkan siri dengan kurang hingar. Selain itu, perbezaan antara DWT dan MODWT dalam hal yang sama. Dalam bahagian ini, keputusan menunjukkan bahawa wujudnya perbezaan antara fungsi bagi menghilangkan hingar dalam siri dan DWT adalah lebih baik

daripada MODWT untuk mendapatkan siri dengan kurang hingar. Bahagian kedua pula, menggunakan teknik baru dengan menggabungkan DWT dan salah satu model linear popular iaitu model vektor pembetulan ralat (VECM) untuk mengkaji hubungan antara pasaran saham negara maju (Amerika Syarikat dan UK) dan pasaran saham negara terpilih di Timur Tengah dan Afrika Utara (MENA). Kemudian, teknik yang dicadangkan dibandingkan dengan model VECM tradisional, dan teknik yang dicadangkan ini telah menunjukkan menjadi alat yang berguna dari segi prestasi serta penyuaian dengan siri pasaran saham kewangan dalam tesis ini. Bahagian akhir menggabungkan DWT dan salah satu model bukan linear, iaitu model pertukaran Markov pintasan heteroskedastic- pembetulan ralat vector (MSIH- VECM) untuk menyiasat hubungan antara pasaran saham negara maju (Amerika Syarikat dan UK) dan pasaran saham terpilih di Timur Tengah dan Afrika Utara (MENA). Kemudian, dibandingkan antara model cadangan dengan model tradisional MSIH- VECM, dan juga model dicadangkan adalah lebih baik dari segi prestasi dan penyuaian dengan siri pasaran saham kewangan daripada model tradisi (MSIH-VECM) dalam tesis ini. Melalui kaedah yang dicadangkan, kedua-dua model menjadi fleksibel dan masalah hingar yang tinggi dalam siri pasaran saham dapat dibendung. Teknik ini telah terbukti menjadi alat yang berguna dari segi prestasi dan penyuaian dengan siri pasaran saham kewangan bagi model linear dan tak linear dalam tesis ini. Lebih-lebih lagi, ia menyediakan maklumat yang berharga mengenai hubungan antara pasaran saham berbanding dengan model tradisional. Oleh itu, teknik yang dicadangkan merupakan sumbangan utama kepada kesusasteraan hubungan pasaran saham. .

THE CAUSAL RELATIONSHIP BETWEEN STOCK MARKETS: A WAVELET TRANSFORM-BASED APPROACH

ABSTRACT

Stock market index has recently become one of the most important economic indicators that reveals the economic status of a country and explores the causal relationship among countries. Stock market indices are typically chaotic and contain noise data, which affect the accuracy and validity of the results of some models. Therefore, this study focuses on decomposition methods to solve the problem on noisy data and to determine stock market volatilities accurately. Recently, wavelet filtering has been applied as an efficient tool for reducing noise in financial time series. Wavelet filtering exhibits several properties that are not found in other filters. Thus, this thesis proposes different techniques to investigate causal relationships among stock markets by combining wavelet filtering and traditional models to solve the noise problem in financial time series data and therefor to obtain accurate results. This thesis is divided into three parts. The first part introduces the difference between five functions based on two types of wavelet, namely, discrete wavelet transform (DWT) and maximal overlap discrete wavelet transform (MODWT). The differences between DWT and MODWT is are discussed. Results reveal that differences between functions in their way reducing noise in series, that DWT is better than MODWT. The second part proposed a new technique by combining DWT and the vector error correction model (VECM) to investigate causal relationships between the stock markets of developed countries (such as the US and

the UK) and the selected stock markets of the Middle East and North Africa (MENA) region. This proposed technique is compared with the traditional VECM, the finding shows that the former is a useful tool to modeling the causal relationship among the stock market ,and fit as shown when applied to the financial stock market series in this thesis. The final part combines DWT and Markov-switching intercept heteroskedastic-VECM (MSIH-VECM), which is a nonlinear model, to investigate causal relationships between the stock markets of developed nations (US and UK) and selected stock markets of the MENA region. The proposed technique is compared with the traditional MSIH-VECM. From the analysis, it shows that the former is better in terms of performance and fit better with the financial stock market series in this thesis than the latter. The proposed technique enables both models to become flexible and prevents the high noise in stock market series. This technique is proven to be a useful tool in terms of performance and fit with the financial stock market series in the linear and nonlinear models. It also provides valuable information on the relationships among the studied stock markets compared with traditional models. The proposed technique is a main contribution to literature of studying causal relationship among stock market.

CHAPTER 1

INTRODUCTION

1.1 Overview

Financial time series is popular in the fields of economics, finance, and statistics, and equity index is one of the important economic indicators. The rise and fall of the economy of a country is based on the fluctuation of its stock market. Local, regional, and global events influence the movements of stock markets in developing or developed countries. The increasing integration of the global economy has led investors and scholars to focus on the causal relationships among stock markets worldwide. This topic has therefore become popular in the field of economics and has been studied by investors and market regulators. Most of the researchers in previous studies investigated causal relationships among stock markets by applying linear models, such as vector autoregression (VAR) or vector error correction model (VECM). However, these models have weaknesses in their ability to capture asymmetries in the series; compared to a non-linear model, such as regime-switching models. The main advantages of Markov-switching (MS) processes, as frequently advocated in the literatures, include their capability to handle several crucial features of a time series (such as non-linear phenomena) and to model temporal asymmetries and the persistence of a macroeconomic time series (Diebold, 1986). These features are crucial in analyzing causal relationships among global stock market returns. The MS autoregressive time series model has become increasingly popular since Hamilton (1989) applied this technique to measure the business cycle in the United States (US). However, given the high noise

level in the financial time series data, the conventional models such as VECM may provide a distorted picture of economic relationships, and reflect the average behavior of economic states rather than their distinctive features. This situation is caused by the effect of the noise data on the financial series (Jammazi and Aloui, 2010). Meanwhile, Aloui and Jammazi (2009), and Hamilton and Susmel (1994) , suggested that regime switching can be detected more appropriately and clearly across time using a low frequency data than using a high frequency data.

In the past 20 years, wavelet filtering has been used in various fields, such as medicine, engineering, and mathematics. Recently, it has been applied in financial and economic fields. A significant development of the current methodology, wavelet filtering decomposes the financial time series data and provides insight into the dynamics of economic and financial time series. According to Gençay et al. (2001) wavelet filtering has several properties not found in other filters. For example, it can capture events in the stock market data and identify these events with specific time horizons and locations in time. It can also be used to reduce the noise and extract the real main components and entire information of the financial time series data. As a result, wavelet filtering is a useful mathematical tool in decomposing the financial time series data. This current study intends to address the inaccuracy of the results caused by the noise in the data and to illustrate the causal relationships between stock markets, using a new technique which are combination DWT and VECM and combination DWT with one non-linear model, such as the MSI heteroskedastic (MSIH-VECM).

1.2 Problem Statement

Causal relationships among stock markets has been studied before by using standard models such as VAR, VECM models. However, the problem with these models is that they are sensitive to the noise in the series. This will obtain inaccurate information about causal relationships among stock markets. Due to the noise in the financial time series can lead to the biased estimation of parameters, erroneous or invalid inferences, and poor volatility forecasts (Jammazi and Aloui, 2010). There are some filters used to reduce the noise in series, such as wavelet transform and Fourier transform. The mathematical properties of the matrices involved in computing these transforms are similar as well. The major difference between Fourier transform and wavelet transform is that, wavelet functions are localized in time domain meanwhile Fourier functions (sine and cosine) are not. "This localization feature, along with wavelet localization of frequency, makes many functions and operators using wavelet sparse when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as data compression, detecting features images, and removing noise from time series" Graps (1995). This thesis chooses wavelet filtering to reduce the noise in stock market data. There are two different types of wavelet filtering such as DWT and maximal overlap discrete wavelet transform MODWT. Both types provide different results to obtain less noise data. This difference has been investigated by previous studies, however, most of these studies are not focusing on financial time series data.

1.3 Objectives

The main objectives of this thesis are as follows:

1. To determine a suitable function based on DWT and MODWT (Haar, db2, sym4, coif2, and dmey) is better in reducing noise in stock market series at level and return series.
2. To determine the best filter between DWT and MODWT in reducing the noise data at level and in return series.
3. To use a new technique based on the combination of the wavelet transform and VECM in describing causal relationships between stock markets of developed countries (US and UK) and selected stock markets of the Middle East and North Africa (MENA) region.
4. To use a combination of DWT and MS-VECM as a new technique to assess causal relationships between stock markets of developed countries(US and UK) and selected stock markets of the Middle East and North Africa region.

1.4 Scope of the Study

This thesis focuses on solving the problem of noise data in the stock market series using wavelet filtering. The causal relationship between the stock markets of developed countries and those of the MENA region is also be investigated.

1.5 Significance of the Study

Causal relationships among stock markets is important and must be studied by investors and market regulators. Stock market prices are typically chaotic; hence, capturing the dominant properties of their fluctuations is difficult. Given the effects of the noise data on the traditional models, reducing the noise and its effects on the stock

market series is necessary. This study intends to address this problem by employing a new technique based on the combination of wavelet transforms, which is an efficient tool of reducing noise in the series without appreciable degradation (Nguyen and Nabney, 2010) and (Jammazi, 2012), and some traditional models. Through the proposed technique, the models become flexible, and the high noise problem in the stock market series is solved. This technique has been proven to be useful in terms of performance and fit well with the financial stock market series. Previous studies have indicated that different wavelet functions perform differently in terms of efficiency and accuracy in other fields. However, this study examines the differences in the ability to reduce noise in financial data based on five function in DWT and MODWT. This study proves that the decomposition of the stock market series by DWT is better than that by MODWT for both original and return data in obtaining data with less noise. These results contribute to the body of knowledge on wavelet filtering in terms of filtering financial time series.

1.6 Limitation of the Study

This thesis is limited to reducing the noise data in the stock market index by wavelet filtering and focuses on the causal relationships among stock markets of developed countries (US, UK) and selected countries of the MENA region based on VECM and MS-VECM. The US and UK stock markets are used in this study because they are among the largest stock markets in the world, and they have a vital role in their economies (Marashdeh, 2005). For example, the National Association of Securities Dealers Automated Quotation (NASDAQ-100) includes 100 stocks from the largest American and international non-financial companies; based on the strict listing crite-

ria of the market capitalization for NASDAQ, excellent liquidity is observed between stocks (Ergun and Nor, 2010). Standard & Poor's 500 (S&P500) is an American stock market index based on the market capitalizations of 500 large companies with common stocks listed in New York. It is also one of the most commonly followed equity indices. Many consider it as one of the best representations of the US stock market and a bellwether for the US economy. Other markets also include Dow Jones. The price-weighted average for Dow Jones is calculated from the stocks of 30 of the largest and most widely held public companies in the US and is the most widely quoted market indicator in the world (Shoven and Sialm, 2000). The MENA region is also used in this study because it is rarely studied despite its high returns and rapid growth in the past years. A number of countries from this region have even registered outstanding performance in recent years (Cheng et al., 2010). For example, the market capitalization in the Gulf Cooperation Council (GCC), which includes the markets of Qatar, Oman, Bahrain, Kuwait, United Arab Emirates, and Saudi Arabia, was about US 132 billion US dollars at the end of 2000 and increased to about 534 billion US dollars at the end of 2004 (Hammoudeh and Li, 2008). Similarly, the Saudi Arabian stock exchange had a market capitalization larger than that of South Korea in the period from 2004 to 2005 (Cheng et al., 2010).

1.7 Outlines

This thesis is organized as follows: Chapter 1 introduces the research and provides an overview of the objectives, and problems that motivate this study. The chapter also presents the scope and contributions of this study, as well as its significance. Chapter 2 reviews and discusses previous works related to wavelet transform and some linear

and non-linear models used in modeling the financial time series data. This chapter discusses the difference between the present study and the previous studies. Chapter 3 presents a more detailed review of wavelet transform and some linear and non-linear models. This chapter also discusses several selected methods used in this study. Chapter 4 discusses and compares five functions based on DWT and MODWT: Haar, db2, dmey, sym4, and coif2. The performances of DWT and MODWT in obtaining less noisy data in both stationary and non-stationary financial data sets are also compared. Chapter 5 proposes a novel technique of investigating the causal relationship between the developed stock market indices of the US and the UK and the ten stock market indices of the MENA countries. This technique involves combining wavelet filtering and VECM, and the results prove that the proposed technique (DWT-VECM) is better than the traditional model (VECM) in terms of performance and fitting the financial stock market series. It also provides real information on the causal relationships among stock markets. Chapter 6 introduces the new technique based on the combination of wavelet filtering and MS-VECM. This technique is used to examine the causal relationship between the developed stock market indices of the US and the UK and the four stock market indices of the MENA countries. The results show that the proposed model is more useful than MS-VECM in terms of performance and fitting the financial stock market series. Finally, Chapter 7 presents the conclusions of the study and suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents important concepts by critically discussing in broad terms the definition of financial time series data and how researchers have tried to solve the noise problem in the series. This chapter also reveals some studies that investigate the causal relationship among stock markets using linear and non-linear models and how wavelet transform is applied in this field. The financial time series data are provided in Section 2.2. The different filters for reducing the noise in the financial time series data are discussed in Section 2.3. Previous studies that provide information on the difference among the wavelet functions are presented in Section 2.4. Previous studies that show the causal relationship among global stock markets are revealed in Section 2.5. The application of wavelet transform in the stock market field, which is related to this study, is presented in Section 2.6. The difference between the current study and the previous studies is explained in Section 2.7. Finally, a summary of this chapter is presented in Section 2.8.

2.2 Financial Time Series Data

In general, a time series is simply a sequence of numbers collected at regular intervals over a period. Financial time series data processing is concerned with the theory and practice of processing asset price over time, such as currency, commodity data, and stock market data (Tsay, 2005). According to the Brooks (2008) financial data are

almost always not normally distributed and are also often considered very noisy, which means that separating underlying trends or patterns from random and uninteresting features is more difficult. The next section explains the process of removing the noise from the data using time series filtering.

2.3 Time Series Filtering

Researchers have recently focused on examining the methods of reducing the noise from financial time series data and on obtaining relevant information to overwhelm the noise. Several filtering methods for financial time series are explained by Gençay et al. (2001):

1. Infinite impulse response filter. This linear filter is a special case of constant coefficient linear difference equation, and the impulse response of the filter is not finite. The impulse response in this filter is dependent on the stability of the difference equation (Gençay et al., 2001).
2. Non-causal finite impulse response *FIR* filter. The future, current, and past values of the input in this filter are required to obtain the filter output. This filter is less attractive in practice because some data points at the beginning and at the end of the output are missing. Non-causal *FIR* is known as a simple centered moving average in economics and finance.
3. Causal finite impulse response *FIR* filter. The current and past values of the input in this filter are required to obtain the filter output. Therefore, it is a non-causal filter. This filter is more common in practice because some data points at only the beginning of the output are missing. Causal *FIR* is known as an

exponentially weighted moving average in economics and finance.

4. Fourier transform. This method is used to filter the financial time series signal. The Fourier basic functions (i.e., sines and cosines) are appealing when working with stationary time series. Fourier transform summarizes information on the data as a function of frequency and therefore does not preserve information in time.
5. Wavelet transform. This method is used to filter the non-stationary time series data and utilizes a basic function that is stretched and shifted to capture features that are local in time and frequency. Gençay et al. (2001) showed that wavelet transform is a convenient method of denoising, identifying structural breaks, separating observed data into timescales, and comparing multiple time series.

Thus, this thesis provides further information on the importance of using wavelet transform in financial time series research. Different types of wavelet transform exist, and each type of wavelet consists of different families. The difference among the wavelet families can be used to obtain the smoothest series. The next section discusses the difference among some functions used in this thesis.

2.4 Comparison of Wavelet Families

Previous studies that provide knowledge on the efficiency and accuracy of some wavelet functions in capturing the behavior of data in different fields are reviewed in this section. Mahmoud et al. (2007) compared the Haar and Daubechies of DWT using the field programmable gate array technology and the bit error point of view between the reconstructed output and input audio signals on simulated data. The simulation results

show that the Daubechies wavelet is more efficient for audio applications than the Haar wavelet.

Bolzan et al. (2009) explored the performance of two wavelet functions Haar and Daubechies in extracting the coherent structures from solar wind velocity time series. They found that both wavelet functions can extract coherent structures. However, the Daubechies wavelet function extracts more coherent structures than the Haar wavelet. Stojescu et al. (2010) evaluated the WiMAX traffic prediction accuracy using five different types of MODWT functions. Based on autoregressive integrated moving average, artificial neural network, and random walk methods, the results indicate that Daubechies and reverse biorthogonal produce the smallest errors using some statistical measures of error.

The performance of wavelet transform by Haar and Daubechies in speech denoising data was examined by Chavan et al. (2010). They found that the Daubechies is suitable for speech denoising and that the Haar is unsuitable for these data because it is not as smooth as the Daubechies and has limitations when applied to non-stationary signals. Singh and Sharma (2011) compared three different wavelet families for image compression based on peak signal-to-noise ratio. They concluded that the biorthogonal wavelet is effective for low pixel-size images. However, coiflets is better suited for high pixel-size images. Both biorthogonal and Daubechies provide better results for medium-size images.

Electroencephalogram (EEG) signals were examined using different types of wavelet functions to determine the most suitable wavelet family for analyzing non-stationary bio-signals (Gandhi et al., 2011). Based on the probabilistic neural network and support vector machine classifier, the authors showed that the coiflets is the most suitable

candidate among the wavelet families.

Tumari et al. (2013) recognized the best and suitable wavelet family for analyzing cognitive memory using the EEG signal. The Neurofax EEG 9200 was used to record the acquisition of cognitive memory at channel Fz. The raw EEG signals were analyzed using the Daubechies, symmlets, and coiflets of wavelet transform. The selection between these families depends on their mean square error (MSE). The results indicated that the Daubechies wavelet at a level of decomposition of 4 (db4) was the most suitable wavelet for pre-processing the raw EEG signal of cognitive memory.

As shown in the abovementioned sections, most of the previous studies that compare wavelet families do not focus on financial time series data. Only a few studies focus on this field, as discussed in Section 2.6. According to Li et al. (2014) , denoising using wavelet transform is one of the most important research topics in engineering, and this topic has not received much attention in economics and finance. No consensus also exists on the suitability of the parameters to be used in the wavelet-based denoising process with a particular data set to reduce the biases introduced and further stabilize the estimation results, such as those in financial models.

Given that the seminal work by the present thesis also includes modeling the relationship among selected stock markets, the next section discusses some literature on modeling stock markets.

2.5 Modeling Financial Time Series Data

At present, the increasing economic integration of the global economy has become a popular research topic. It has therefore triggered researchers to focus on the issue of modeling financial time series data to display good and important information to in-

vestors about the causal relationship among the stock market indices around the world. Researchers have previously explored the causal relationship between developed and developing stock markets using different models. Some of these models are discussed below.

2.5.1 Modeling Financial Time Series Data Using Linear Models

Numerous studies have used popular linear models, such as VAR, VECM, and GARCH. For example, Ratanapakorn and Sharma (2002) used the daily data of the European, Asian, Latin American, Eastern European, and Middle Eastern regions to study the long- and short-term relationships among the stock markets during the pre-Asian and Asian crisis periods. Their study was based on co-integration tests, VEC, and VAR models. No long-term relationship existed among the stock markets before the pre-Asian crisis. However, they observed one significant co-integration among the countries during this crisis.

Neaime (2002) examined the causal relationship between the selected MENA stock market and the US and UK stock markets during the '90s using a co-integration approach. The results showed that Turkey, Egypt, Morocco, and Jordan are integrated with the financial markets in the rest of the world. The author noted that shocks to the US and UK stock markets are diffused to the MENA region, but not to the GCC stock market.

Berument and Ince (2005) investigated the causal relationship between the US (S&P500) and Turkey (ISE100) from 1987 to 2004 using daily data based on the VAR model. The results showed that the US stock market is not affected by the Turkish stock market, but the Turkish stock market is affected by the US stock market.

Bley and Chen (2006) explored the dynamics and contemporaneous interaction of the GCC markets and the developed equity markets, such as the US and the UK, using daily data based on the VAR model. A Granger causality test revealed the low correlation between the GCC and developed markets.

Bley (2007) examined the dynamic behavior of 14 MENA stock markets and investigated the influence of the US, UK, and Indian stock market movements on their MENA counterparts. The data range was 1/2000 to 12/2004. The results showed that these markets have become more integrated over time and more sensitive to intra-regional shocks than to inter-regional shocks. The results also indicated that MENA markets are segmented from large Western stock markets. However, the influence of the US and UK stock markets on their MENA counterparts is quite weak.

Yu and Hassan (2008) used daily data from 1999 to 2005 to investigate the linkages and spillover effects among the eight stock markets in the MENA region and the major stock indices of the US, UK, and France based on co-integration tests and VEC and GARCH models. The study showed that a long-term relationship exists between some of the stock markets of the MENA region and those of the US, whereas on a short-term basis the US stock market has a strong Granger causality with most of the stock markets of the non-GCC countries.

Ergun and Nor (2009) investigated the co-movement and linkages among Indonesia, Malaysia, Pakistan, and Turkey using multivariate co-integration test, VECM, and Granger causality test for daily stock market indices from January 2000 to October 2008. The study found that stock market linkages exist among these stock markets.

Beirne et al. (2010) investigated the global and regional effects and used tri-variate VAR-GARCH in the mean model on 41 emerging market economies (EMEs) in Asia,

Latin America, Europe, and seven countries in the MENA region. They found that spillovers from the regional and global markets are present in the vast majority of EMEs. Spillovers in mean return dominate emerging Asian and Latin American markets. However, spillovers in variance dominate in emerging Europe. The relative effect of global and regional spillovers also varies; that is, global spillovers dominate in Asia, and regional spillovers are prominent in Latin America and the Middle East.

Ergun and Nor (2010) examined the dynamic relationship and volatility spillover between the stock markets in Turkey and the US. The study used bivariate co-integration, ECM, CGARCH, and threshold co-integration for daily stock market indices spanning from 1988 to 2008. The empirical results indicated the existence of dynamic linkages between the Istanbul and NASDAQ stock markets after the Custom Union Agreement between Turkey and the European Union was signed, as well as the occurrence of significant volatility spillovers from NASDAQ to the Istanbul stock market.

Paskelian et al. (2013) examined the characteristics and behavior of selected stock market equity indices of the MENA region and explored the co-integrating behavior of nine MENA stock markets (i.e., Egypt, Israel, Jordan, Kuwait, Malta, Oman, Qatar, Saudi Arabia, and Tunisia) with the S&P500 stock market using Granger causality tests based on the VECM. The study used weekly closing price data from January 2000 to February 2012. The results revealed that granger causality exists among several of the MENA stock markets. However, the granger causality estimation results between the equity returns in each of the nine MENA countries and the US S&P 500 stock price index indicated significantly weak exogeneity from the return of the US S&P 500 to all the MENA stock markets.

2.5.2 Modeling Financial Time Series Data Using Markov-Switching Models

Ismail and Isa (2008) used monthly data (i.e., 1990 to 2004) to investigate the causal relationship among the returns of three markets of the Southeast Asian region Malaysia, Singapore, and Thailand based on the co-integration test, VAR, and MS-VAR models. The study revealed that no long-term causal relationship exists between the stock markets of the ASEAN region, whereas the MS-VAR exhibited co-movements among the three returning stock markets in the short term. They also found that the performance and fitting data of the MS-VAR model are much better than those of the VAR model.

Fan et al. (2009) used the weekly closing price of the stock market indices of the US, UK, Japan, Hong Kong, and mainland China to study the long- and short-term causal relationships between the Chinese stock market and international main stock markets from June 5, 1992, to December 26, 2008. Their study was based on co-integration test and VEC and MS-VEC models. They found that a long-term causal relationship has existed between the Chinese stock market and international main stock markets since 1999. In terms of short-term causal relationships, they observed that the international main stock markets directly or indirectly affects the Chinese stock market. A comparison of the VEC and MS-VEC models shows that the MS-VEC has less Akaike information criteria (AIC), Hannan Quinn information criteria (HQC), and Schwartz information criteria (SIC) than the VEC. Therefore, the MS-VEC model performs better than the VEC model in providing effective information on the relationships among these stock markets.

Cheng et al. (2010) used the capital asset pricing model (CAPM), the static international CAPM, the constant-parameter intertemporal CAPM, and the MS intertemporal CAPM to examine the degree of integration between nine stock markets of the MENA

countries (i.e., Bahrain, Kuwait, Oman, Saudi Arabia, Egypt, Israel, Jordan, Morocco, and Turkey) and the stock market of the US. The findings revealed that the stock markets of Turkey and Israel are most strongly integrated with the stock market of the US and that substantial time variation exists in the weights on local and global pricing of risks for all these markets.

Qiao et al. (2011) investigated the causal relationships among the stock markets of the US, Australia, and New Zealand via the MS-VAR and VAR models using weekly stock market returns. The results revealed that the MS-VAR is more appropriate than the linear VAR in modeling the causal relationship among these stock markets. The correlations among the three markets are significantly higher in the bear regime than in the bull regime. The responses of these markets to shocks in other stock markets are stronger in the bear regime.

Tan (2012) used the MS-VAR model to examine the causal relationship of stock market returns between the international stock markets (specifically, US, UK, Singapore, and China) and the stock market of the Philippines from 2000 until 2010. Weekly stock market returns were used for this study. The findings revealed that the Philippine stock market is most correlated with the stock markets of Hong Kong and Singapore rather than with the stock markets of the US and the UK in both regimes. These results indicated that a stronger causal relationship exists between economies in the same region. As shown in the above mentioned sections, a few studies have investigated the causal relationship between the stock markets of developed countries and the MENA region

2.6 Related Studies

This section presents some of the relevant applications of wavelet transform in financial time series data, which are related to this work. In the area of comparing wavelets, Razak et al. (2010) compared four wavelets functions of DWT and MODWT-Haar, Daubechies, symmlets, and coiflets-by applying them to Malaysian stock prices. The results revealed that the Daubechies and symmlets are the best functions with DWT, whereas the Daubechies is better than symmlets with MODWT. With regard to modeling financial time series data, most of the studies in Sections (2.5.1) and (2.5.2) investigate the causal relationship of stock returns by applying the simple correlation and multivariate analysis techniques, such as co-integration tests, VAR and GARCH models, and MS models, which are used and are effective in studying the causal relationship among stock markets. However, given the high noise level in financial time series, conventional models may result in a distorted picture of economic relationships, which in turn tends to reflect the average behavior over economic states rather than their distinctive features (Jammazi and Aloui, 2010). Based on Magdon-Ismail et al. (1998), the information processing of financial data, the extraction of relevant information from overwhelming noise, and the learning system used to fit the noisy data in financial data, noisier data lead to worse tests, and the data become less pronounced. This result is caused by the effect of the noise data on the financial series. Therefore, wavelet transform is an efficient tool of reducing noise in the series without appreciable degradation Nguyen and Nabney (2010) and Jammazi (2012). It is a powerful mathematical tool for signal processing because of its ability to reduce the noise in financial time series and decompose macroeconomic time series into their timescale components. Several applications of wavelet analysis have recently been used in eco-

nomics and finance, particularly in investigating the relationship and international co-movement. Dajcman et al. (2012) applied the MODWT, correlation estimator, and a running correlation technique to examine the dynamics of the stock market return co-movement between individual Central and Eastern European (CEE) countries (i.e., Slovenia, the Czech Republic, and Hungary) and developed European stock markets (Austria, France, Germany, and the UK) from 1997 to 2010. The results revealed that the developed stock markets are more interdependent during the observed period than the CEE stock markets. Moreover, return co-movements between the former and the latter stock markets vary over time scales and time. At all scales and for the whole observed period, the Slovenian stock market was found to be less interconnected to the developed European stock market than the Hungarian and Czech stock markets.

Lee (2002) used the Haar function of DWT and regression to investigate international stock market spillover effects. The technique was applied to the daily returns of the stock markets of the US, Germany, and Japan and to two emerging stock markets of the MENA region (i.e., Egypt and Turkey). The results showed that spillover effects occur from major developed stock markets to emerging markets in the MENA region, but not vice versa.

Gallegati (2005) used multi-scale correlations on a scale by scale basis by applying the symmlities⁸ function of MODWT to analyze stock market return co-movements among five stock markets of the MENA region: Jordan, Morocco, Israel, Egypt, and Turkey. The results suggested that over the period 1997-2005 MENA stock markets were neither regionally nor internationally integrated, with a partial exception represented by Israel and Turkey.

Rua and Nunes (2009) used monthly stock market prices and ten economic sectors

for major developed economies-Germany, Japan, UK, and US to assess co-movements among these stock markets and among the sectors using applied wavelet squared coherency. This study notably found that the strength of international stock return co-movements depends on frequency. In general, they found that co-movement among markets was stronger at lower frequencies, and the strength of the co-movement in the time frequency space varies across countries and sectors.

Graham et al. (2012) applied the coherency of continuous wavelet analysis to examine the co-movement of the US stock index and of 22 emerging stock market returns (i.e., Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey). They reported that the strength of co-movements differed from country to country. For example, the co-movements between US and Brazil and between Mexico and Korea are high, whereas the co-movement among US, Egypt, and Morocco is low.

Jammazi (2012) used monthly stock market prices and two crude oil data (WTI and Brent) of five developed countries (i.e., US, UK, Germany, Japan, and Canada) to quantify the magnitude and time-varying nature of volatility spillovers from the crude oil market to equity markets (DJIA, FTSE100, Dax30, NIKKEI225, and TSX) by applying wavelet filtering, Haar wavelet decomposition method, and noise elements in the series. In addition, the trivariate BEKK MS GARCH model was adopted to analyze the effect of the smooth part on the degree of stock market instability as a second step. The results show that the Haar wavelet decomposition method was important in improving the accuracy of the smooth signal in detecting key real crude oil volatility features. Moreover, apart from the UK and Japanese cases, the responses of the stock

market to an oil shock depends on the geographic area of the main source of supply, that is, whether the source is from the North Sea or from North America.

Graham et al. (2013) examined the co-movement of selected MENA region stock markets with respect to the US stock market, as well as the regional co-movement among these markets, from June 2002 to June 2010. The authors applied wavelet squared coherency with simulated confidence bounds to explore short- and long-term stock market co-movements, and detect changes in market relationships over time. The evidence suggested a modest degree of co-movement of stock returns between S&P 500 and MENA stock markets at higher frequencies. The results also showed a relatively high degree of co-movements among stock markets in the MENA region at lower frequencies across the entire sample, and these dependencies increased toward the end of the sample period.

2.7 Critical Review

Based on the comparison of the wavelet families in Section 2.4, studies in various areas using wavelet methods indicate that various wavelet families perform differently in terms of efficiency and accuracy in other fields. However, denoising data and efficiency using wavelet tools remain insufficiently explored in financial time series data. Additionally, the difference between DWT and MODWT in this area to obtain less noisy series is poorly studied. These reasons motivate the study of different less noises among the five wavelet functions of DWT and MODWT -Haar, Daubechies, Symlet, Coiflet, and Meyer wavelets-for original and return time series. In addition, the difference between DWT and MODWT is detected in terms of the usefulness in decomposing financial time series and noise elements in such series. Regarding the modeling

of financial time series data and investigation of the causal relationship among global stock markets in Section 2.5, the difference between previous studies and the current study is that the latter employs a new technique based on the combination of discrete wavelet transform and the linear model in Chapter 5 called VECM and another nonlinear model in Chapter 6 called (MSIH)-VECM. The novel insight in characterizing the causal relationship between stock markets of developed countries and selected stock markets of the MENA region is the application of discrete wavelet transform as an efficient tool of reducing noise in a series. The main and complete information on the actual signal that labels the smooth low-frequency part of the original series is then extracted. Subsequently, the causal relationship among stock markets is estimated using the two aforementioned linear and nonlinear models. Through the proposed technique, the model becomes flexible and the high noise problem in a stock market series is solved. This technique has been proven as a useful tool in terms of performance and fit with a financial stock market series. These techniques are in line with the study of Jammazi (2012), who nevertheless used Haar with the MS GARCH model in stock market prices and the two crude oil data of the five developed countries.

Table 2.1: Summary previous studies related to the current study

Author and year	Case study	Method	Issues
Razak et al. (2010)	Malaysian stock market	DWT and MODWT	compared four wavelets functions of DWT and MODWT
Dajcman et al. (2012)	Stock markets of (CEE) countries and developed countries	MODWT	dynamics of the stock market return co-movement
Lee (2002)	US,Germany,Japan,Egypt,Turkey stock market	Haar of DWT and regression	spillover effects among stock markets
Gallegati (2005)	stock markets of the MENA countries	Sym of MODWT	analyze stock market return co-movements
Rua and Nunes (2009)	stock market prices and economic sectors	wavelet squared coherency	assess co-movements among stock markets and among the sectors
Graham et al. (2013)	US stock index and of 22 emerging stock market	wavelet squared coherency	Examine the co-movement among the stock markets
Jammazi (2012)	stock market prices and crude oil data	Haar wavelet and BEKK MS GARCH	Examine the volatility spillovers from the crude oil market to equity markets
Graham et al. (2013)	stock markets of the US and MENA countries	wavelet squared coherency	examined the co-movement of MENA and US stock markets

2.8 Summary

This chapter comprehensively discusses the importance of studying the causal relationship among stock markets, modeling these kinds of financial time series, and the effect of noise on such data. The ways in which previous studies have managed this problem are also discussed. The importance of using wavelet transform to solve this problem to reduce data noise is compared with that of using other filters.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter provides an overview of the methods used to achieve the aims of the research. A unit root test is performed to examine the stationarity of financial time series data in stock markets. Five functions, namely, Haar, Daubechies2, Symmlets4, Coiflets2, and Discrete approximation of Meyer wavelets, are used to decompose the financial time series data of stock markets, based on two types of wavelet transforms: DWT and MODWT. The autocorrelation function (ACF) is the method applied to analyze functions or series of values. Thus, ACF is used to compare these functions in both DWT and MODWT and also in DWT and MODWT in terms of obtaining less noisy series. The long-term causal relationship is tested through a co-integration test, whereas the short-term causal relationship is examined using two proposed models: wavelet with VECM and wavelet with MS-VECM. Finally, Akaike information criteria (AIC), Schwartz information criteria (SIC) are used to compare the proposed models compared with traditional models, such as VECM and MS-VECM.

3.2 What Is a Wavelet ?

The term "wavelet," which goes back to Morlet and Grossmann in the early 1980s, means a small wave. From a mathematical point of view, wavelets are functions that disperse data into distinct frequency components, which means each part can be studied individually to investigate a data series in depth. Wavelets are suitable to analyze