IDENTIFICATION AND ANALYSIS OF STOCK MARKET DYNAMICS

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Declaration

I hereby declare that the thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Bai Limiao
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Summary

This thesis investigates stock market dynamics in two sub-horizons: long-run cycles and short-run fluctuations. Stock market presents distinct dynamics at different time horizons. In long-run, it is usually characterized as two sub-stages: expansion and contraction, commonly known as "bull" and "bear" markets, respectively. The continuous transition between stages of expansion and contraction forms some irregularly cyclical patterns. Timing of the peaks and troughs of the market cycles is critically important for shareholders and regulators. Thus, one focus of this thesis is to develop a model to forecast the stock market turning points. In short-run, stock markets always show fast fluctuations that are driven by many influential factors, defined as market forces. Identification of such market forces can significantly improve risk management and equity pricing. Therefore, another focus of this thesis is to identify the market forces and study their time-varying interactions with the stock markets. In particular, the tasks and contributions of this study boil down to the following aspects:

First, based on a system adaptation framework and wavelet multi-resolution analysis, an empirical model is developed to forecast the major turning points of stock markets. This system adaptation framework has its internal model and adaptive filter to capture the slow and fast dynamics of the market, respectively. The residue of the internal model is found to contain rich information about the market cycles. In order to extract and restore its informative frequency components, we use wavelet multi-resolution analysis with time-varying parameters to decompose this internal residue. An empirical index is then proposed based on the recovered signals to forecast the market turning points. This index is successfully applied to US, UK and China markets, where all major turning points are well forecasted.

Second, we investigate the short-run market dynamics under unexpected shocks. In particular, we select the case of 9/11 terrorist attack to examine its transient influences to

the intermarket interactions, focusing on the intermarkets between the US stock markets and other financial markets, including debt, currency, commodity and international stock markets. In this study, a time-varying Granger causality test is employed to reveal their dynamic causal linkage. To the best of our knowledge, this is the first study to reveal the time-varying causality on intermarket dynamics under the shock of terrorist activities. Our results find that 9/11 terrorist attack sharply changed the causal strength or directions between the U.S. stock markets and many other markets. For instance, the UK and Australia stock markets did not have significant Granger causality to the US stock markets before the terrorist attack, but after that, the causality became significant over a short period. Moreover, we find that the forecasting capability of the market forces increased after the terrorist attack. This result indicates that the terrorist attack enhanced the intermarket linkage. In addition, we find that the sentimental indicator played an increasingly important role in leading the stock price movements under this crisis environments. Furthermore, we also employ a DCC-GARCH model to examine dynamic comovement between intermarkets. The results indicate that the contagion phenomena only exist in several of our tested markets instead of all.

Lastly, we investigate the driving forces in the China stock market. As a representative of emerging stock markets, the China stock market is usually characterized as high volatility and low predictability. The driving forces behind such characterized dynamics are still debatable. Moreover, after the financial crisis of 2007-2008, the market environments changed significantly, making its dynamics even more complicated. To identify the market forces and capture their dynamic interaction with stock prices, this study adopts a system adaptation framework to give a comprehensive analysis on the China markets. Unlike some existing studies that report the bidirectional Granger causality between stock prices and interest rates, our results find that the SHIBOR, a new benchmark of market interest rates in China, does not show dynamical causality linkage or long term equilibrium with the stock prices. In addition, the interest rate policy is also found to have weak effects on stock market. Many other financial variables, such as the PE ratio and newly introduced index futures are studied, in which the difference between the spot exchange rate and NDF serves as a good leading indicator. Our results also find that after the financial crisis, the China market is more influenced by a regional developed market, Hong Kong market, rather than the US market.

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Chapter 1

Introduction

1.1 Introduction

Stock markets play important roles in each economy by allocating capital and channeling funds among economic players to promote economic efficiency. An efficient and healthy stock market is commonly considered as a mirror of the national economy. Therefore, the behavior of stock prices, e.g. rise, fall and volatility, always attract attention from both investors and regulators. In academia, identification and forecasting of stock price dynamics have also been critical topics all the time. The current literatures mainly offer two fundamentally contrary opinions concerning the stock price dynamics: random walk and non-random walk.

The random walk hypothesis (RWH) states that changes of stock price follow the same distribution and are independent of each other. The past movements or trends of stock price cannot provide any information to predict its future. As discussed by Malkiel [1], the logic of RWH is that the flow of information is very fast so that all information can be immediately incorporated into stock prices. Therefore, tomorrow's price change will only reflect tomorrow's news that is independent of the price change today. However, the tomorrow's "news", by definition, is unpredictable. Consequently, tomorrow's price change must be unpredictable and random. This idea is consistent with the effective market hypothesis (EMH). According to EMH, all the investors are assumed to be rational and the stock market is extremely efficient in reflecting all available information. Once new information rises in the market, it can spread very quickly and is incorporated into stock prices without any delay. Thus, no stock analysts can play any roles in selecting "undervalue" stocks to achieve returns higher than the average value of randomly selected portfolios. In 1970's, RWH and EMH are widely accepted by financial economists in academia. In addition, some influential articles and books, for examples, "Efficient Capital Market" by Fama [2] and "A Random Walk Down Wall Street" by Malkiel [3] popularized these theories.

On the contrary, another line of researchers believe that the stock prices are non-random walk and can be predicted to some degree. Starting from the link of information efficiency and the hypothesis of random price changes, a number of empirical tests have been conducted to examine the EMH and RWH theories. Many results show that stock returns, in addition to the normal distribution, sometimes follow fat-tailed [4] and negative skewed distribution [5]. Furthermore, some other interesting phenomenons, e.g. mean reversion and seasonality effects, have also been found to exist in the stock price returns [6]. These evidences indicate that the random walk theory is not robust and stock prices can follow some trends. Similar evidences can be found from a famous book, "A Non-Random Walk Down Wall Street" by Lo and Mackinlay [7]. Moreover, many studies from behavioral finance document that the investors tend to be irrational, e.g. overconfident and overreacted, in their ivestment rather than being perfectly rational as assumed by the EMH [8, 9, 10, 11]. Daniel [11] shows that such overconfidence implies long-lag autocorrelations, excess volatility and public-event-based predictability. Thus, in recent years, the mainstream views become that there exist trends in the stock markets and the stock price is at least partially predictable.

The early exploration in identifying and forecasting stock price dynamics can be traced back to the famous Dow Theory, which was developed by Charles Dow in 1890's. The basic idea of the Dow Theory is that the movement of stock market follows three type of trends: upwards, downwards and sideways. These trends, once underway, will tend to continue until some new market signals come to break their momentum and reverse their trends. The Dow Theory became foundations of a group of market analysts who were then called chartists, and are now known as "technical analysts". The idea of Dow Theory is very similar to the theory of stock market cycles in academia [12, 13, 14]. Whereas, both the Dow Theory and stock market cycles theory focus on the stock price dynamics in long-run, but neglect its short-run fluctuations and the corresponding influential factors behind. In practice, the stock market is an extremely complex system that involves many interacting factors, varying from social, political to sentimental aspects. Thus, the movement of stock price is driven by many influential factors, which are defined as market forces [15]. Identification of market forces is crucially important for stock pricing and risk management. In this thesis, our main aim is to study the stock market dynamics in both long-run cycles and short-run fluctuations.

The following of this chapter is organized as below: Sections 1.2 and 1.3 separately discuss stock market dynamics in two sub-horizons: the long-run cycles and short-run fluctuations. Section 1.4 reviews the general methods used in modeling and forecasting stock markets. Section 1.5 reports the research gap identified and aim of this thesis.

1.2 Long-term Cycles

Market cycles are the patterns that the price level of market repeats its upward and downward movements over some specific time scales. In financial markets, financial time series always show such cyclical patterns at all-time scales [16, 17], varying from long term cycles to high frequency fluctuations. However, the term "cycle" does not imply any regularity in timing or durations. According to duration, market cycles can be classified into three categories: primary cycles, intermediate cycles and short-term cycles [18]. The average length of primary cycles is three to seven years, which are driven by both economic environment and the sentiment of investors [19, 20, 21]. Intermediate cycles typically last three to eighteen months, while short-term cycles last six to twelve weeks, which are usually driven by unpredicted news or random events. This kind of short-term fluctuation is inevitable in every financial market. In this thesis, we mainly focuses on forecasting and analysis of primary cycles. Throughout the rest of the thesis, market cycles refer to primary cycles unless otherwise specified.

In terms of the market cycle structure, cycles generally include three phases: uptrend (expansion or bull markets), downtrend (contraction or bear markets), and sideways [22]. As discussed by Gonzalez et al [23], academics commonly agrees that bull markets associated with persistently rising asset prices, increased financial well-beings and strong investor interest. On the contrary, bear markets are generally associated with falling conditions as opposed to the bull markets. Successfully identifying the transition period between two phases is extremely important for market participants and policy makers.

For investors, the timing of bull or bear market can help them in risk managements and trading strategy development. As suggested by Shen [24], investors can earn more profits by following a strategy of market-timing rather than a strategy of buy-and-hold. For regulators, identification of market state is essential in policy making, because the state of stock market can affect the credit supply and stability of real economy. As suggested by Rigobon and Sack [25] and Bohl et al [26], the monetary authorities do react to many stock market activities. Moreover, bull and bear markets always play significant roles in general economic analysis. Stock price is argued to be a leading indicator for macroeconomic conditions because it is, in essence, discounted future dividends [27, 28]. Starting from Mitchell and Burns in 1930s [29], there are numerous literatures documenting evidence that the state of stock market contain predicting information for business cycles [30, 31].

The understanding of stock market cycles change over time. In the early stage, the focus is to examine the existence of cycles and wether the cycles are periodical. In 1960s, Granger et al [12] firstly suggest that the spectral analysis might be useful in analyzing the market time series. The Fourier analysis assumes that irregular patterns of time series can be a sum of many periodic sine waves of different frequencies and amplitudes. Spectral analysis attempts to decompose an observed irregular time series signal into sine waves. In the power spectrum, the dominant frequencies might indicate the existence of market cycles. In the following years, there are various literatures aiming to find evidence of market cycles using the similar power spectrum methods [32, 33, 34], but their results are not conclusive. People then find that the Fourier analysis might be an inappropriate tool in this field because the market cycles are not properly to be periodic. Subsequently, the non-periodic cycles began to attract more attention. According to chaos theory, non-periodic cycles have average durations, but the exact duration of a future cycle is unclear [35].

One important tool of the chaos theory is rescaled range (R/S) analysis that is to measure the strength of trends or “persistence”. It is first proposed by Hurst [36] to investigate how reservoir capacity changes over time. Mandelbrot [37] refined this method and applied it to financial time series that stimulate similar research in financial market cycles during the late 1970s and 1980s [38, 39, 40]. Lo [41] modifies R/S analysis and examines the long-memory dynamics in stock markets. A time series with long memory is characterized by long-range dependence and non-periodic long cycles. Lo [41] suggests that the modified R/S test is not sensitive to non-normality and conditional heteroskedasticity in the financial time series. Moreover, it is also robust to short-term dependence, which allows for a rich pattern of interactions between long and short-term dynamics. Contrary to the previous results, Lo does not find significant evidence for the long-range dependence in his testing samples.

An alternative methodology for duration dependence examination is the hazard models which focus on an end-of-duration occurence [42, 43, 44]. According to the hazard models, the dynamics of duration can be recognized by a conditional probability of duration termination. Therefore, the likelihood of ending the duration depends on the elapsed time length since the start of this duration. Cochran and Defina [42] use parametric hazard models to study whether the US stock market cycles exhibit duration dependence over the period between January 1885 to July 1992. They argue that if such cycles tend to keep a fixed length, the conditional probability that when a cycle will end should be an increasing function of its duration. Therefore, the hazard function should exhibit corresponding positive duration dependence. When the stock market cycles are characterized by such positive duration dependence, the duration of the historical cycles can provide useful information in predicting the future market turning points. Their empirical evidence show that the duration dependence exists in pre-World war II expansions and post-World War II contractions, but does not exist in prewar contractions or postwar expansions. This result suggests that the stock prices have a tendency to maintain fixed lengths of bull or bear markets at specific stages. Moreover, the evidence of fixed cycle lengths rejects the description of stock prices as random walks. Cochran and Defina argues that if the stock prices do follow a random walk, there are no duration dependence.

Realizing the existence of market cycles, people are inspired to explore techniques for market timing. Regarding the identification and forecasting of stock market cycles, the current literatures mainly offer two fundamentally different lines of methods: parametric and non-parametric methods. The parametric methods apply some specific models to study the data generating process of stock prices. Estimating of a parametric model produces inferences on lengths of bear or bull markets. In practice, there is no parametric model that can simulate the stock data generating process. On the contrary, most of the current methods proceed by first fitting a statistical model to the data and then use the estimated model to infer the possible turning dates. The best known parametric model is the Markov switching (MS) model, which is pioneered by Hamilton [45] in predicting the business cycles. Later, it is applied to the stock market turning points forecasting [13, 14, 46]. In these models, the stock behavior is considered as a discrete latent state process that follows a Market chain with two distinct states. Empirical literatures commonly distinguish the two regimes by their different means, variance and normally distributed innovations. To be specific, the bull (bear) market regime associated with positive (negative) average stock returns and low (high) volatilities. Moreover, increasing the number of regimes might allow it to model specific features of stock markets, e.g. crashes [47]. However, one problem of running such a parametric model is the cost of misspecification risk. Changes in the market dynamics can severely influence its performance. For instance, in some conditions, periods with high volatility are alarmed as bearish state, even if they obviously exhibit positive average returns [46, 48].

Instead of fitting some parametric models, the non-parametric methods just look at the original data of stock price series and use a set of rules to identify the featured pattern of cycles. In particular, this procedure attempts to locate the peaks and troughs of cycles by characterizing the dynamics around the local maxima and minima, respectively. Thus, these methods are also called rules-based models. The non-parametric algorithm was first developed by Bry and Boschan [49] in order to automatically detecting the turning points of business cycles. Later, many variants of this algorithm were developed and used for identification and prediction of stock market turning points [50, 51, 52]. In all of these rules, two of them play most important roles. The first one is that an increase of some ratio, e.g. 20% [52], since the last trough signifies a bull market, and that a decrease of 15% over last peak indicates a bear market. The second rule is that a market trend must last at least some periods, e.g. 70 weeks [52]. This rule is to filter the noisy alarms between peaks and troughs. It is essential to note that many technical analysts in trading industry use the similar rules-based methods to identify trading signals. The advantage of rules-based methods is that they are transparent and robust. Although these methods are criticized as being subjective in setting the filtering rules and lack of statistical interface, these characteristics allow them to avoid the risk of misspecification. Their disadvantage is that the first rule always introduce lags in forecasting so that they miss the optimal peaks and troughs [48]. Using the rule-based models, investors would pay up to 20% cost per trend to time the markets. Therefore, these methods are usually criticized as ex-post forecasting.

In recent years, some advanced engineering approaches in signal processing and pattern recognition have been introduced to economic and financial time series analysis, which bring new technology to the non-parametric methods. Known as a "mathematical microscope", the wavelet method is a powerful multi-resolution analysis (MRA) tool in this field. In particular, the wavelet can decompose a signal into multiple time scales, including large-scale approximation and finer scale details. It allows us to retrieve specific components at any frequency bands where market cycle patterns are critically concerned. Compared with Fourier analysis, the wavelet does not require the signal to be periodic or stationary, which makes is more appropriate for the non-periodical cycles analysis. Wavelet analysis has attracted increasing interest in business cycle identification and prediction [53, 54, 55, 56]. The literatures applying wavelet approaches in stock market cycle forecasting are still limited.

In this thesis, one aim is to investigate the long run stock market dynamics and propose a model to forecast the market cycle turning points. In previous work, Zheng and Chen [57] proposed a system adaptation framework to study the stock markets. This system adaptation framework has its internal model and adaptive filter to capture the slow and fast dynamics of the market, respectively. The residue of the internal model is found to contain rich information about the market cycles [57]. In this work, a wavelet MRA is applied to decompose this residue of internal model and retrieve its informative frequency components. Inspired by the non-parametric models, we propose a leading index based on some rules to identify the featured pattern of the market turning points. Compared with the conventional non-parametric methods, our leading index is an ex-ante forecasting indicator rather than ex-post one. This leading index would shed lights on market turning points forecasting and contribute to the non-parametric lines.

1.3 Short-term Fluctuations and Market Forces

Stock price, in short-run, presents fast fluctuations that reflect the dynamic change of supply and demand relationship between sellers and buyers. This price discovery process is generally interpreted as “the search for an equilibrium price” [58] and “the incorporation of the information implicit in investor trading into market prices” [59]. More simply, Baillie et al [60] interpret it as a process of “news being gathered and interpreted”. These interpretations imply that some useful information in the markets serves as dynamic forces to drive the movement of stock prices. Extensive empirical studies have been conducted towards identification of market forces. The current literatures mainly focus on three aspects: macroeconomic variables, intermarket and sentimental factors. The following is a survey and discussion of the market forces in each of these three aspects.

1. Macroeconomic Variables

The early exploration of market forces mainly focuses on macroeconomic variables, e.g. inflation rate and money growth are reported to have a negative impact on stock prices [61, 62, 63]. Later, a famous study of Chen et al [15] uses a multi-factor arbitrage pricing (APT) model to identify five potential variables: expected inflation, unexpected inflation, growth rate of industrial production, a term structure spread and a bond default risk premium. They conclude that the industrial production growth, the default and term premia are significant influential factors, but the effect of inflation is weak. Lamont [64] examines whether a portfolio constructed according to the future path of macroeconomic variables can earn positive abnormal returns. His evidence shows that the portfolios constructed to track the change of industrial production, labor income and consumption can earn positive returns, but the portfolio to track the CPI can not.

Oil price is another important leading indicator to the stock markets. Following by the major oil price shocks in 1970’s a number of literatures document the impact of oil price on real economy and financial markets. Park and Ratti [65] argue that if oil price shocks have effects on the real economy through company and consumer behavior, there should be a significant impact of oil price shocks on stock markets. They find that oil price shocks have significant impacts on real stock returns within the following month for U.S. and 13 European countries druing the period of 1986:1-2005:12. Sadorsky [66] suggests that rises of oil price have significantly negative impacts on the U.S. stock prices and this effect has increased since the mid 1980's. On the contrary, Huang et al [67] do not find evidence to show significant connection between daily price of the U.S. stock returns and oil futures. Ciner [68] concludes that there exists significant interactions between real stock returns and oil price futures, but the relationship is non-linear.

Several classical economic theories suggest that there exists a relation between exchange rates and stock prices. First, "flow-oriented" models of exchange rates argue that currency movements affect international competitiveness and trade balance, thereby influencing real income and output [69]. When a country's currency appreciates, it will decrease her international competitiveness in goods market. Therefore, this has a negative effect on company's future cash flow, and furthermore the corresponding stock prices. Second, "stock-oriented" [70] models of exchange rates, or portfolio-balance models, give the capital account a critical role in determining exchange rate dynamics. These models presume an internationally diversified portfolio and the function of exchange rate to balance the demand and supply of assets. In this way, the rise of domestic stock prices will lead to an appreciation of domestic currency. The channel is that the rise of domestic stock prices will encourage more international investors to buy more domestic stocks and simultaneously selling foreign assets to obtain domestic currency indispensable for buying new domestic stocks. Thus the demand of domestic currency will increase that causes a appreciation of domestic currency.

In addition to these theoretical hypothesis, many empirical literatures document relationships between exchange rates and stock prices, but the results are still inclusive. Solnik [71] conducts an regression analysis on monthly and quarterly data of eight developed countries for the period of 1973-1983. His results show a negative relation between real exchange rates and real domestic stock returns. However, for monthly data over the period of 1979-1983, the results suggest a weak but positive relation. These results indicate that the relationship between exchange rate and stock prices is time-varying. Similarly, Donnelly and Sheehy [72] suggest a significant contemporaneous relationship between the exchange rate and stock prices of large exporter firms in U.K.. Griffin and Stulz [73] suggest that weekly exchange rate shocks have a negligible influence on industry stock return performance for six developed countries. However, Bahmani [74] documents that there exists a bidirectional causality between effective exchange rate of the U.S dollar and S&P 500 index. Wu [75] reports that there exists asymmetric effects of four different exchange rates on Singapore stock prices and these effects are sensitive to economic instability.

2. International Stock Markets

The international financial markets are becoming more and more integrated in the past decades. This integration suggests that there exists substantial degree of interdependence between national stock markets, which can affect expected returns, volatilities and spillovers with some world factors. For instance, an unexpected shock in one market might become important "news" event that can rapidly transmit to the other markets and influence the stock prices [76]. Consequently, the topics of price and volatility spillover are always of great interest in finance literatures.

Hamao et al [77] examine daily opening and closing index prices of three developed stock markets: New Youk, Tokyo and London. Their evidence show that the volatility spillover is observed from New York to Tokyo, New York to London, and London to Tokyo for the pre-October 1987 period. In a later literature, Koutmos and Booth [78] also study the interactions among these three markets to examine the spillover changes before and after the financial crisis of October 1987. They find strong evidence to show that the volatility spillover effects are asymmetric for good news and bad news. The volatility spillovers in a given market is much more significant when the arriving news is bad. In addition, they report that the linkage of these three markets have increased substantially after October 1987, suggesting that the interdependent is time-varying under large crisis. Similarly, Yang et al [79] show that the 1997-1998 Asian financial crisis enhances the cointegration and causal linkage among Asian stock markets.

In recent years, as the development of economic globalization, the integration of international stock markets is suggested to be enhanced. Bekaert et al [80] examine the effect of European Union on equity market integration in Europe. They find that EU membership significantly reduces stock market segmentation between the member countries whether or not these countries have adopted the Euro. Furthermore, Caporale et al [81] show that the introduction of Euro increases the spillovers between central and eastern countries (CEECs) markets and the UK markets. Li and Giles [82] examine the volatility spillover effects between developed stock markets and Asian emerging stock markets over the period of 1993-2012. They find significantly directional shock and volatility spillover from the U.S. stock market to Japan and six Asian emerging markets. It is also found that the spillover effect is strengthened and become bidirectional during the Asian financial crisis. Moreover, the linkage between Japan market and the Asian emerging markets become more significant in the last five years of their testing period.

3. Sentimental Factors

The history of stock market is full of striking events deserving their own names: the Great Crash of 1929, Nifty Fifty bubble of the early 1970's, the Black Monday crash of October 1987, and Dot-com Bubble of late 1990's. All of these events refer to dramatic changes of stock price that are hard to be explained by standard finance models. According to classical finance models, all the investors are rational and the stock price should reflect its true valuations. However, these theories can not fit such dramatic change patterns. The behavioral finance suggests that investors are subject to sentiment. Investor sentiment can be broadly considered as a belief about investment risks and future cash flows that is not justified by the facts at hand. Research has demonstrated that fluctuations of investor sentiment can change stock prices, thus investor sentiment is an important influential factor for stock pricing [83, 84, 85]. Some researchers suggest that shifts of investor sentiment can explain the short-term movement of stock prices better than any other set of fundamental factors [86].

The effect of sentiment varies under different conditions. In long-run, the economic environments, contraction or recession, can have different effects on investor sentiments, and thereby the stock price behavior. Garcia [87] investigates the effect of sentiment on stock prices during the period of 1905-1958. The proxy used for sentiment is the fraction of positive and negative words in two columns of financial news from New York Times. His results suggest that the sentiment index can only predict the stock returns during economic recession periods. In short-run, some unexpected events can also significantly influence the investor sentiment. Kaplanski and Levy [88] investigate the impact of aviation disasters on stock markets. Their evidences show that aviation disasters have significant negative event effect on stock returns. In particular, each aviation disaster can cause a market loss of more than $60 billion, whereas the estimated actual economic loss is no more than $1 billion. Shan and Gong [89] exploit whether Wenchuan Earthquake of China in 2008 influences the stock returns through investor sentiments. They find that during a period of 12 months after the earthquake, stock returns are significantly lower for companies headquartered near the earthquake center than those further away. Moreover, this pattern does not exist before or long after the earthquake, and can not be explained by actual loss or a change of systematic risk. Their results are consistent with the line that investor sentiment affecting stock prices.

A number of empirical index have been developed to measure investor sentiment both in academia and industry, including Put-Call Ratio [90], Barron's Confidence Index [91], and Chicago Board Options Exchange's Market Volatility Index (VIX) [92]. In recent years, the effect of media on investor sentiment become especially attractive to financial market study. By reaching a large population of market participants, mass media can quickly and broadly diffuse news and influence stock pricing [93]. Based on attitude of financial news, Baker et al [94] propose an Equity Market-related Economic Uncertainty (EMEU) index to capture the stock market uncertainty sentiment, which is found to be an excellent predictive indicator. More recently, the fast development of social media and text mining techniques arouses interest from researchers to extract useful information in predicting movement of stock markets. Bollen et al [95] analyze the text content of Twitter to get a positive vs negative mood index. Their results suggest that the index can significantly improve the forecasting performance. Antweiler and Frank [96] investigate the effect of messages on Yahoo Finance and Raging Bull about 45 companies in the DJIA and Dow Jones Internet Index. Their results find that stock messages can help predict market volatility. Da [97] finds that the search frequency in Google (Search Volume Index) is useful in forecasting stock prices in the next two weeks and an eventual price reversal within the year.

Although numerous studies have been conducted towards the market forces, the results are still inclusive. One reason is that the stock markets is a time-varying system associated with fast changing dynamics and environments. The driving forces might change all the time. However, the current macroeconomic analysis only concerns the analysis of static equilibrium. Thus, properties of equilibrium price become the central matter of many questions. These properties are usually studied by simply solving a set of market-clearing price equations, but how exactly this price is achieved is always abstracted. For instance, Cutler et al [98] report that real stock returns are significantly positively correlated with industrial production growth over the period of 1926-1986, but not in the subperiod of 1946-1985. Their evidence does not provide supports to the hypothesis that the long-term interest rates, money supply and inflation can affect stock returns. McQueen and Roley [99] attribute the failure to identify these macroeconomic forces to a shortcoming of the time-invariant models that are generally used in empirical studies. They suggest that the announcement of economic changes can have different implications under different business stage. For instance, an increase in employment is considered as a bullish sign when the economy rebound from recession, but a bearish sign around a peak of business cycle. In their study, the series' effect is assumed to depend on overall economic conditions. Their results find that only two of their eight macroeconomic variables significantly influence the S&P 500 portfolio in a time-invariant model. However, under the time-varying economic regimes, six variables have significant influences in at least one of the regimes. Therefore, a time-varying model might has significant advantages in studying the dynamic market forces, especially under some dynamical conditions. In this thesis, one of our aim is to use a time-varying system adaptation framework to study the market forces under sharply fluctuating environments.

Another problem is that most of the existing studies focus on developed markets but neglecting the emerging markets. Harvey [100] reported that emerging stock markets are independent from international capital markets, and thus their market dynamics and driving forces are quite different from that in the developed markets. As rapid development of the emerging markets, identification of market forces is becoming critically important for policy makers and shareholders. Gay [101] investigates the relationship between two macroeconomic variables, exchange rates and oil prices, and stock index prices in four emerging markets: Brazil, Russia, India and China (BRIC). Their results show that either the exchange rates or oil prices has no significant with the stock prices in all of these markets. He suggests that the driving in emerging markets might come from other macroeconomic variables or international markets, which deserve further studies. In this thesis, we select the China market as a representative of the emerging markets to conduct comprehensive study to understand her market driving forces.

1.4 Stock Market Analysis Methods

In financial time series analysis, a number of quantitative techniques have been developed. The traditional econometric methods mainly focus on linear regression analysis, such as autoregressive moving average (ARMA) and vector autoregressive (VAR). In recent years, benefiting from the interdisciplinary development, many techniques from other disciplines, for example, computer science, physics, and system theory, have been applied for market modeling and forecasting.

The conventional econometrics mainly uses linear regression models for empirical analysis because their structure and economic meaning are clear. There are various time series models for different stochastic processes, which can be roughly categorized into two sub-categories: the univariate and multivariate models. The univariate model deals with single observations recorded sequentially over equal time increments. In practice, three basic models are widely used, including the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. The linear combinations of these methods produce the famous autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. The multivariate techniques, e.g. VAR model and autoregressive moving average with exogenous inputs (ARMAX) model, are used to analyze the relationship between various financial variables. The VAR and ARMAX models are generally used for causal analysis between variables. Note that all of these models assume the variance do not change over time, while the time-varying variance (heteroskedasticity) is always of interest to financial time series problems. The autoregressive conditional heteroskedasticity (ARCH) and its family concern the process with time varying variance, which makes them popular in stock returns forecasting and risk analysis [102]. One main disadvantage of these parametric linear models is the subjectivity of choosing parameters that can lead to mis-specification and key feature lost [103, 104].

Another line of financial market forecasting methods is artificial intelligence (AI), which is represented by artificial neural networks (ANNs) and support vector machine (SVM). The financial market, by its nature, is complex (non-linear) and volatile. The AI methods can simulate the complicate non-linear relationships between the input and output of the system, thus they are believed to be promising in stock market forecasting.

ANNs are one group of the mostly studied AI methods and some of their broad features make them work well in this field. The first one is that these models can provide a set of inputs, which enable them to find rules relating the historical states of a system to its future activity. Second, being a data-driven model and nonparametric, they imposes fewer prior assumptions on the underlying process, which makes them less susceptible for mis-specification problems than most parametric methods. In addition, the adaptive nature of ANNs enables them to remain accurate and robust in the non-stationary environments [105]. A large number of studies have demonstrated that the ANNs are powerful tools in forecasting stock market [106, 107, 108]. However, the ANNs have some inherent disadvantages. The first one is the overfitting problem, which means when the ANNs fit the data too well the generalization might be lost. Moreover, the solution might be naive when the model training is difficult for some highly noisy and non-stationary financial data [109]. In addition, when the dimension of input data is high, the ANNs might have limitations in learning their patterns [110].

In the past decade, SVM has been successfully used in predicting financial time series due to its excellent generalization performance. The SVM implements structural risk minimization principle to minimize generalization error, which is better than the empirical risk minimization principle of ANNs. The solution of SVM can achieve global optimum rather than the tends of falling into local optimum of ANNs. SVM has been introduced to the financial market studies, including the prediction of future contacts [111], stock price index [112, 113], and market trends [114]. These studies generally report that SVM methods outperformed ANNs, ARIMA and ARCH models. A drawback of the SVM approach is that such non-parametric methods lack understanding of the underlying dynamics governing the price evolution. For instance, it can not model the dynamic process that how the new information is incorporated into the stock prices by the interaction between buyers and sellers [115]. This situation leads people to seek better or alternative methods.

The new interdisciplinary subject of system economics provides a promising solution. Systems theory is an interdisciplinary field of sciences, which abstracts the organization of phenomena with the goal of elucidating principles. It can be applied to many types of systems in nature and society. The early application of system theory in economics produced the agent-based computational economics (ACE), which studies the agents' behavior and interaction based on a set of incentive and information rules. The ACE has been widely used in many branches in economics, especially in modeling problems of the artificial stock market, like asset pricing [116], market prediction [117], and financial crisis [118]. The ACE can also help to understand the market microstructure. Poggio et al [119] propose a double auction market model to examine market dynamics and properties, such as price discovery efficiency, wealth distribution, trading volume, and bid/ask spreads. The system dynamics methods emphasis on information feedback and icon-based modeling with a clear abstraction of the interactions. Gerencsér and Mátyás [120] model the stock exchanges as a nonlinear closed-loop system. The belief and behavior of the heterogeneous agents are the dynamic factors. It provides a new perspective to study the nonlinear structure feature of the market and its interaction with agents.

System theory provides many advanced approaches to model the time-varying behavior of a complex system. Zheng and Chen [57, 121] propose a system adaptation framework to model and forecast the stock markets. This framework is composed with an internal model and an adaptive filter, which correspondingly investigate the slow and fast dynamics of the stock markets. The market influential factors serves as inputs of the adaptive filter, thus their time-varying interactions with the stock markets can be well captured. The testing results show that the forecasting performance of this model is much better than the conventional methods. Moreover, based on the system adaptation framework, a time-varying Granger causality test method is proposed [122]. The advantage of this method is that it allow us to capture the dynamic causal linkage between economic variables. As discussed by Orrell and McSharry [123], the system economics not only provide useful tools to predict markets, but more importantly it allows us to use such prediction methods to better understand the system's behavior, and find a way to improve the economy's health.

1.5 Motivation and Aim of this Thesis

Although numerous studies have been conducted towards the stock market dynamics, the results are still inclusive. Benefiting from the development of interdisciplinary subject, many new technologies have been adopted to shed light on the stock market dynamics.

The main aim of this thesis is to study the stock market dynamics in two sub-horizons: long-run cycles and short-run fluctuations. In particular, our concentration focus on three aspects as below:

1. **Forecasting the turning points of stock market cycles**

   The current non-parametric methods in identifying and forecasting the market turning points are mainly based on specific rules. One of the main rules is that when the stock price increases by some ratio, e.g. 20%, from the last trough, it signifies a bull market [52]. Similarly, a decrease of 15% over last peak indicates a bear market. This rule definitely introduces a time lag in forecasting so that it misses the optimal peaks and troughs [48]. Consequently, using such a rule-based model, investors would pay up to 20% cost for each trend to time the turning points. Therefore, this method is usually criticized as ex-post forecasting.

   In this thesis, we aim to develop an ex-ante model to forecast the market turning points. Based on a system adaptation framework, Zheng and Chen [57, 121] apply a Fourier analysis to investigate its internal residue and developed an empirical index for turning points forecasting. The results indicate that the internal residue contain rich signals in forecasting market turning points. However, one problem is that the Fourier analysis might be inappropriate for stock analysis because the stock prices are generally characterized as non-periodical signals. In this work, a wavelet MRA is adopted to decompose the internal residue of this system adaptation framework and retrieve informative signals. Based on the retrieved signals, a leading index is proposed to forecast the market turning points. Compared with the conventional non-parametric methods, our leading index is an ex-ante indicator rather than ex-post one. This work would contribute to the line of non-parametric methods and shed lights on market turning points forecasting.

2. Exploring the fast dynamics of intermarkets-under 9/11 terrorist attack

As discussed previously, the stock market forces might change under different economic environments. Some unexpected shocks can significantly change the market environments, and thereby the market forces. The conventional economic analysis focuses on analysis of equilibrium between market forces and stock price movements but neglect their dynamic interaction process. McQueen and Roley [99] argue that the shortcoming of these equilibrium analysis models is their time-invariant parameters, which does not allow them to capture the time-varying dynamics. Therefore, these methods will fail when the market environments suddenly change. Evidence suggests that the terrorist attack can lead to a turbulent market environment and change the market forces [124, 125, 126]. Identification of time-varying market forces under such turbulent environments can significantly improve risk management and equity pricing.

Our aim of this thesis is to investigate the transient reaction between the U.S. stock market and its driving forces under 9/11 terrorist attack. In this study, we apply a time-varying Granger causality approach to identify the dynamic market forces and examine their transient interaction with the U.S. stock markets. In particular, we mainly focus on the intermarket forces, e.g. bond, exchange and commodity markets. Furthermore, the international stock markets and sentimental factors are also investigated. Our results will reveal the transient price and information spillover effects between different markets. Moreover, we also carry an empirical study to examine the comovement of intermarkets and investigate the contagion phenomenon.

3. Identifying driving forces in emerging markets: A case study of China markets

The driving forces in developed markets have been extensively studied in numerous literatures. However, literatures investigating the driving forces in emerging markets are still very limited. Harvey [100] reports that emerging stock markets are independent from international capital markets, and their market dynamics are quite different from that in the developed markets. In recent years, the development of the emerging markets is extremely fast. Thus, identification of market forces is becoming critically important for market participants and regulators.

The third aim of this thesis is to conduct a comprehensive study towards the driving forces on the China stock markets, which are representatives of the emerging markets. According to market capitalization, Shanghai Stock Exchanges became the world's 6th largest stock market at 2.3 trillion USD as of December 2011. Whereas, it is still under tight capital account controls exercised by the authorities and not entirely open to foreign investors. As an emerging market, it is usually characterized as immature in rules, less efficient and having high volatilities [127, 128]. Moreover, the driving forces behind these characterized dynamics are still not clear. In this study, the time-varying Granger causality is applied to reveal the dynamic relationship between selected indicators and the stock prices. In addition, we employ a cointegration analysis to investigate their long-run equilibrium. Last, an event study is also carried to investigate whether the interest rate policy can impact the stock markets.

The rest of the thesis is organized as following: Chapter 2 introduces the system adaptation framework and a time-varying Granger causality test approach that are used in this thesis. Chapter 3 reports the market turning points forecasting model and some empirical results. Chapter 4 presents the transient intermarket reaction under 9/11 terrorist attack. Chapter 5 is particularly to study the driving forces of China stock markets. Finally, Chapter 6 concludes the remarks of this thesis and suggests some future directions.

Chapter 2

Stock Market Modeling with System Adaptation Framework

2.1 Introduction

The stock market is a complex system involving many interacting factors, e.g. economic, political and sentimental factors. The system theory is becoming attractive in modeling the dynamic behavior of such complex stock market systems. According to system theory, a stock market can be considered as a plant linking outside information flow with stock price movement. Thus, modeling such a system can be simplified as a dynamic identification of input and output signals. The process of identifying a system model consists of finding mathematical functions that connect these signals. In this chapter, we discuss a system adaptation framework approach in modeling and forecasting the stock markets. This method will be used in the following chapters.

2.2 Design of System Adaptation Framework

One critical function of a financial market is to provide price discovery. Its basic mechanism is to incorporate external information into asset prices through the dynamic interaction between sellers and buyers. Inspired by this basic function, Zheng and Chen [57] developed a system adaptation framework to model and forecast the dynamic behavior of financial markets, see Figure 2.1. In this model, the real financial market is treated as an unknown plant S and its dynamic behavior is mathematically described by the identification model $\widehat{S}$, as shown in Figure 2.1. The market in this model is considered to have slow and fast dynamics. The slow dynamics process is to capture the market trends, which is modeled by an internal model I. While the fast dynamics process is to capture the influences of market driving forces, which is modeled by an adaptive filter A. The input r consists of external market forces and the output $\widehat{p}$ is the estimated stock price. The actual stock price p is the output of the real financial market S.

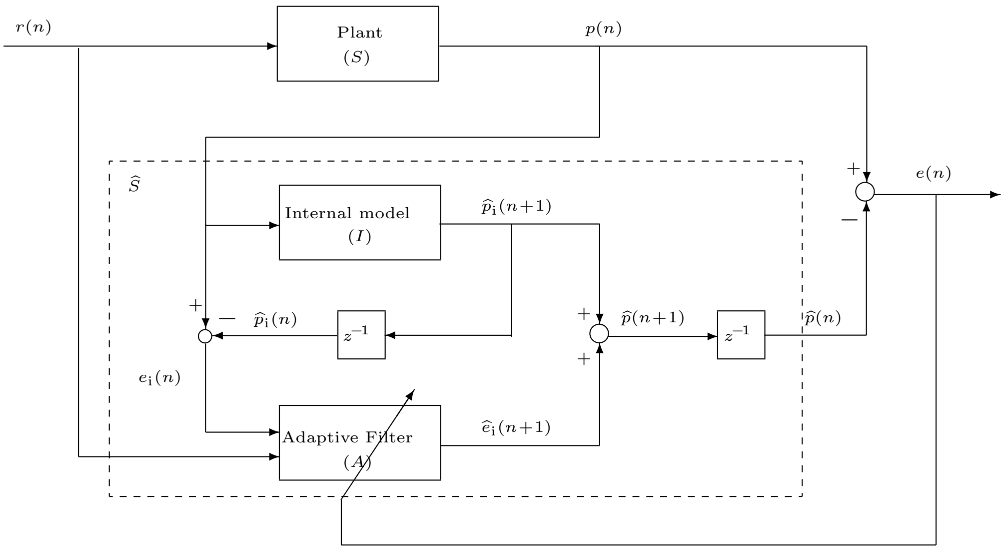

Figure 2.1: Block diagram of the system adaptation framework

To capture the slow dynamic properties, the internal model works as a price trend generator. It produces an estimated price series, which have the same trends as the actual prices. The internal model firstly apply an exponential moving average (EMA) model to preprocess the historical price series. Subsequently, an output-error (OE) model is introduced to estimate the price movements. The difference between the actual price $p(n)$ and estimated price $\widehat{p}_{\mathrm{i}}(n)$ is defined as internal residue $e_{\mathrm{i}}(n)$

$$e_{\mathrm{i}}(n) = p(n) - \widehat{p}_{\mathrm{i}}(n). \tag{2.1}$$

In the price discovery process, one assumption is that all the influential information that is related to the asset can be incorporated into the asset prices. Thus the external information serves as market forces and drive the movements of asset prices. Considering the dynamic characteristics of the information it is essential to introduce a time-varying model to capture its influences. In this model, an adaptive filter A is introduced to capture the influences of the dynamic information flow. This adaptive filter uses the major market influential factors to account for the internal residue. It generates an one-step-ahead estimated series: $\widehat{e}_{\mathrm{i}}$. Working as a cycle generator, the estimated error e is fed back to tune the model parameters. This time-varying feature of the adaptive filter allows us to capture the fast dynamics of the market. In this model, a Kalman filtering technique is used to implement the recursive forecasting by updating its estimated hyperparameters. Below is the design of its internal model I and adaptive filter A.

Throughout this thesis, the notation $\mathbb{R}$ and $\mathbb{Z}$ denote the set of real numbers and integers, respectively. $\mathcal{L}^2(\mathbb{R})$ denotes the vector space of measurable, square-integrable one-dimensional function.

2.3 Internal Model Design

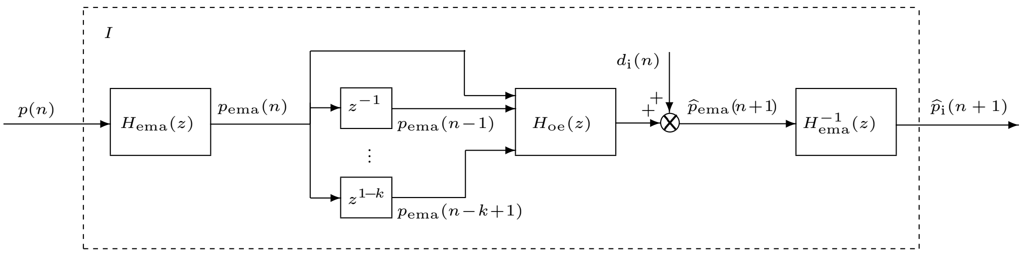

Figure 2.2: The internal model of the system adaptation framework

The internal model consists of three parts, see Figure 2.2 for its structure. First, the historical prices are smoothed by an exponential moving average (EMA) model

$$p_{ema} = \frac{2}{N+1}p(n) + (1 - \frac{2}{N+1})p_{ema}(n-1) \tag{2.2}$$

where N is the moving average period; p is the actual stock prices; p_{ema} is the EMA price which is the output of the EMA model. According to Equation 2.2, the transfer function from actual price p to the EMA price p_{ema} can be denoted as follows

$$H_{ema}(z) = \frac{P_{ema}(z)}{P(z)} = \frac{\frac{2}{N+1}}{1-(1-\frac{2}{N+1})z^{-1}} \tag{2.3}$$

In this thesis, we apply the classical 12 days for all the EMA models, thus we have

$N = 12$. The second part is an OE model with multi-inputs and single-output (MISO). Its input $u_{\text{oe}}(n)$ includes both current and $k-1$ previous samples of the EMA prices, which is denoted by

$$u_{\text{oe}}(n) = \begin{bmatrix} u_{\text{oe},1}(n) \\ u_{\text{oe},2}(n) \\ \vdots \\ u_{\text{oe},k}(n) \end{bmatrix} = \begin{bmatrix} p_{\text{ema}}(n) \\ p_{\text{ema}}(n-1) \\ \vdots \\ p_{\text{ema}}(n-k+1) \end{bmatrix}. \tag{2.4}$$

Hence, the transfer function of this MISO OE model is

$$H_{\text{oe}}(z) = \begin{bmatrix} H_{\text{oe},1}(z) & H_{\text{oe},2}(z) & \cdots H_{\text{oe},k}(z) \end{bmatrix}, \tag{2.5}$$

where for $j = 1, 2, \cdots, k$, $H_{\text{oe},j}(z)$ is the transfer function for the j-th channel of the OE model. The function of $H_{\text{oe},j}(z)$ is defined by

$$H_{\text{oe},j}(z) = \frac{C_j(z)}{F_j(z)}, \tag{2.6}$$

where

$$C_j(z) = c_{j,1} + c_{j,2}z^{-1} + \cdots + c_{j,n_c}z^{-n_c+1}, \tag{2.7}$$

and

$$F_j(z) = 1 + f_{j,1}z^{-1} + \cdots + f_{j,n_f}z^{-n_f}. \tag{2.8}$$

This system is considered to have a disturbance, $d_i(n)$, which is assumed to be white noise. Thus the estimation of the EMA price can be denoted by

$$z\widehat{P}_{ema}(z) = H_{oe}(z)U_{oe}(z) + D_i(z) \tag{2.9}$$

where $z\widehat{P}_{ema}(z)$ and $U_{oe}(z)$ are the Z-transform of $\widehat{p}_{ema}(n+1)$ and $u_{oe}(n)$, respectively. The final step is to transform the EMA price price $\widehat{p}_{\text{ema}}(n+1)$ back to $\widehat{p}_{\text{i}}(n+1)$.

The parameter estimation of the OE model uses the prediction error method reported by Ljung [129]. We denote the estimation error of our OE model as follow

$$e_{oe}(n) = p_{ema}(n) - \widehat{p}_{ema}(n). \tag{2.10}$$

We have

$$e_{oe}(n) = p_{ema}(n) - H_{oe}(z)u_{oe}(n-1) \tag{2.11}$$

Define the parameter vector as θ, we have

$$\theta = [\theta_1 \ \theta_2 \ \dots \ \theta_k], \tag{2.12}$$

where

$$\theta_j = [f_{j,1} \ f_{j,2} \ \dots \ f_{j,n_f} \ c_{j,1} \ c_{j,2} \ \dots \ c_{j,n_b}] \tag{2.13}$$

Thus, e_{oe} can be rewritten as

$$e_{oe}(n) = p_{ema}(n) - \phi(\theta, u_{oe}(n-1)), \tag{2.14}$$

where $\phi(\theta, u_{oe}(n-1))$ is the function of θ and $u_{oe}(n-1)$. The parameter vector θ is estimated by minimizing the cost function as below

$$V_k(\theta) = \sum_{n=1}^{K} e_{oe}^2(n) = \sum_{n=1}^{K} \left[p_{ema}(n) - \phi(\theta, u_{oe}(n-1))\right]^2, \tag{2.15}$$

where K is the sample size. We can find that, $V_K(\theta)$ is nonlinear with respect to θ. The iterative Newto-Raphson method is used to minimize the cost function of $V_K(\theta)$. The estimation process is as below

$$\widehat{\theta}_K^{i+1} = \widehat{\theta}_K^{i} + \mu_K \left[\frac{\partial^2 V_K(\widehat{\theta}_K^{i})}{\partial \theta^2}\right]^{-1} + \frac{\partial V_K(\widehat{\theta}_K^{i})}{\partial \theta} \tag{2.16}$$

where μ_k is the step size and $\partial^2 V_K(\widehat{\theta}_K^{i})/\partial\theta^2$ is a Hessian matrix giving the search direction. The detail of this prediction error algorithm can be found in [129]

2.4 Adaptive Filter Design

As discussed previously, the adaptive filter is to capture the dynamic influences of exogenous market forces. In the system adaptation framework, the adaptive filter uses a time-varying state space model with exogenous variables as bellow

$$Y(z) = \left[\frac{B_1(z,n)}{A(z,n)} \; \frac{B_2(z,n)}{A(z,n)} \; \dots \; \frac{B_m(z,n)}{A(z,n)}\right] U(z) + \xi(z), \tag{2.17}$$

where $U(z)$ and $Y(z)$ are the input and output of the system; $\xi(z)$ is the noise; and

$$B_j(z,n) = b_{j,0}(n) + b_{j,1}(n)z^{-1} + \cdots + b_{j,n_j}(n)z^{-n_j} \tag{2.18}$$

$$A(z,n) = 1 + a_1(n)z^{-1} + \cdots + a_{n_a}(n)z^{-n_a} \tag{2.19}$$

Thus the relationship between the exogenous variables r, and output $\widehat{e}_i(n+1)$ can be expressed by the following time-varying model

$$\begin{aligned}\widehat{e}_i(n+1) = &-\sum_{j=1}^{n_a} a_j(n)e_i(n-j+1) + \sum_{j=0}^{n_1} b_{1,j}(n)r_1(n-\delta_1-j) + \\ &\cdots + \sum_{j=0}^{n_m} b_{m,j}r_m(n-\delta_m-j) + \sum_{j=1}^{n_a} a_j(n)\xi(n-j) + \xi(n),\end{aligned} \tag{2.20}$$

where the exogenous variables r are the inputs of the adaptive filter; δ is the lag length of the corresponding input; ξ is the Gaussian noise; $a_i(n)$ and $b_j(n)$ are time-varying coefficients and statistically independent. The time-varying characteristics allows the model to capture the fast dynamics of the interaction between the inputs and outputs. Furthermore, it is assume that the time-varying coefficients following a general stochastic process as follows

$$x(n) = x(n-1) + \eta_x(n) \tag{2.21}$$

where x is the time-varying coefficient; η_x is a Gaussian noise with $N(0, Q_x)$.

The adaptive filter model in Equation 2.20 can be converted into a state space form using some well-established approaches. This system adaptation framework adopts a classical Kalman filter. Constructing vectors of $X(n)$ and $H(n)$ as below

$$X(n) = [a_1(n) \; a_2(n) \; \dots \; a_{n_a}(n) \; b_{1,n_1}(n) \; \dots \; b_{m,0}(n) \; \dots \; b_{m,n_m}(0)]^T \tag{2.22}$$

$$\begin{aligned}H(n) = &[-e_i(n) \; -e_i(n-1) \; \dots \; -e_i(n-n_a+1) \; r_1(n-\delta_1) \; \dots \; r_1(n-\delta_1-n_1) \\ &\dots \; r_m(n-\delta_m) \; \dots \; r_m(n-\delta_m-n_m)],\end{aligned} \tag{2.23}$$

Hence, we can get the state space model

$$X(n) = X(n-1) + \eta(n), \qquad \eta(n) \sim N(0, Q) \tag{2.24}$$

$$\widehat{e_i}(n+1) = H(n)X(n) + \mu(n), \qquad \mu(n) \sim N(0, \sigma^2) \tag{2.25}$$

where Q is a diagonal matrix and its diagonal elements are the variance of the corresponding input noise; and $\mu(n)$ is denoted as below

$$\mu(n) = \sum_{j=1}^{n_a} a_j(n)\xi(n-1) + \xi(n). \tag{2.26}$$

To estimate $X(n)$, the aim is to minimize the identification error $e(n) = e_i(n) - \widehat{e_i}(n)$.

Considering that the regressors contain the lagged terms of the output, which might correlate with $\xi(n)$, an instrumental variable $u(n)$ in introduced to eliminate the possible estimation bias:

$$\begin{aligned} u(n) = &- \sum_{j=1}^{n_a} \widehat{a}_j(n-1)u(n-j) + \sum_{j=0}^{n_1} \widehat{b}_{1,j}(n-1)r_1(n-\delta_1-j-1) + \\ &\cdots + \sum_{j=0}^{n_m} \widehat{b}_{m,j}(n-1)r_m(n-\delta_m-j-1). \end{aligned} \tag{2.27}$$

This instrumental variable is correlated with the regressor vector but uncorrelated with the noise $\xi(n)$. Thus the instrumental vector $\widehat{H}$ can be constructed as follows

$$\begin{aligned} \widehat{H}(n) =& [-u(n) - u(n-1) \ \ldots \ -u(n-n_a+1) \ r_1(n-\delta_1) \ \ldots \ r_1(n-\delta_1-n_1) \\ & \ldots \ r_m(n-\delta_m) \ \ldots \ r_m(n-\delta_m-n_m)], \end{aligned} \tag{2.28}$$

and we have the estimated $\widehat{X}(n)$

$$\widehat{X}(n) = [\widehat{a}_1(n) \ \widehat{a}_2 \ \ldots \ \widehat{a}_{n_a}(n) \ \widehat{b}_{1,0}(n) \ \ldots \ \widehat{b}_{1,n_1}(n) \ \widehat{b}_{m,0}(n) \ \ldots \ \widehat{b}_{m,n_m}]^T, \tag{2.29}$$

From Equation 2.24, we know that the unknown parameters, or hyperparameters, in the covariance matrix Q determine the variations of all the state variables. It is essential to first optimize the hyperparameters, thereafter, the Kalman filter algorithm can be recursively performed for the prediction and estimation. In this approach, the maximum likelihood method is used to estimate the hyperparameters. In this method, the noise variance ratio (NVR) matrix Q_r and $\widehat{P}$ are introduced as below

$$Q_r = \frac{Q}{\sigma^2} \tag{2.30}$$

and

$$\widehat{P} = \frac{P}{\sigma^2} \tag{2.31}$$

where P is a prediction error covariance matrix associated with the estimated state vector $\widehat{X}$. In the following, the notation $(n|n-1)$ is used to denote that the estimation of parameters in step n is conditional on the information up to the step $n-1$. Thus we have

$$\begin{aligned}\widehat{P}(n|n-1) =& \frac{P(n|n-1)}{\sigma^2} \\ & \frac{1}{\sigma^2} E\left[(\widehat{X}(n) - \widehat{X}(n|n-1))(\widehat{X}(n) - \widehat{X}(n|n-1))^T\right]\end{aligned} \tag{2.32}$$

Based on a series of data $e_i(1), e_i(2), \ldots, \varepsilon_i(\tau)$, the Log-likelihood function of $e_i(\tau + 1), e_i(\tau+2), \ldots, e_i(K)$ can be calculated through the prediction error decomposition as follows

$$\begin{aligned}& LogL\left(e_i(\tau+1), \ldots, e_i(K) | e_i(1), \ldots, e_i(\tau)\right) \\ &= \frac{-(K-\tau)}{2} log 2\pi - \frac{1}{2} \sum_{n=\tau+1}^{K} log|var(e(n))| - \frac{1}{2} \sum_{n=\tau+1}^{K} \frac{e^2(n)}{var(e(n))},\end{aligned} \tag{2.33}$$

where $e(n) = e_i(n) - H(n-1)\widehat{X}(n-1|n-2)$ is the corresponding prediction error with its variance $var(e(n))$ as follows

$$var(e(n)) = \sigma^2 \left[1 + \widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)\right]. \tag{2.34}$$

Thus the following Log-likelihood function need to be maximized

$$\begin{aligned}logL(\cdot) =& \frac{-(K-\tau)}{2} log 2\pi - \frac{K-\tau}{2} log\sigma^2 - \frac{1}{2} \sum_{n=\tau+1}^{K} log\left[1 + \widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)\right] \\ & - \frac{1}{2\sigma^2} \sum_{n=\tau+1}^{K} \frac{e^2(n)}{1 + \widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)}.\end{aligned} \tag{2.35}$$

The estimation of σ^2, i.e. $\widehat{\sigma}^2$, can be estimated by partially differentiating Equation

2.35, as below

$$\widehat{\sigma}^2 = \frac{1}{K-\tau} \sum_{n=\tau+1}^{K} \frac{e^2(n)}{1+\widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)}. \tag{2.36}$$

Substituting Equation 2.36 into Equation 2.35 and removing the constant term, we can get the compact form as follows

$$\begin{aligned} log\widehat{L}(\cdot) = & \sum_{n=\tau+1}^{K} log\left[1+\widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)\right] \\ & + (K-\tau)log\left[\frac{1}{K-\tau}\sum_{n=\tau+1}^{K}\frac{e^2(n)}{1+\widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)}\right]. \end{aligned} \tag{2.37}$$

The hyperparameters are estimated by minimizing Equation 2.37. With the estimated hyperparameters, the Kalman filter is applied for the further estimation and prediction. In this recursive process, the identification error $e(n)$ is fed back to tune the parameters. The following are the recusive algorithm Prediction:

$$\widehat{X}(n|n-1) = \widehat{X}(n-1|n-1) \tag{2.38}$$

and

$$\widehat{P}(n|n-1) = \widehat{P}(n-1|n-1) + Q_r \tag{2.39}$$

Updating:

$$\widehat{X}(n|n) = \widehat{X}(n|n-1) + \widehat{P}(n|n-1)\widehat{H}^T(n)\left[1+\widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)\right]^{-1} e(n) \tag{2.40}$$

and

$$\widehat{P}(n|n) = \widehat{P}(n|n-1) - \widehat{P}(n|n-1)\widehat{H}^T(n)\left[1+\widehat{H}(n)\widehat{P}(n|n-1)\widehat{H}^T(n)\right]^{-1}\widehat{H}(n)\widehat{P}(n|n-1). \tag{2.41}$$

2.5 Time-varying Granger Causality Test

In this system adaptation framework, one important problem is to select the market forces as its inputs. Zheng and Chen [122] propose a time-varying Granger causality test approach to identify such market forces. This method can adaptively calculates the causality strength at each time step. The causality strength is compared with a corresponding threshold at each time step to determine whether the causality is significant.

In terms of predictability, the general idea of Granger causality can be expressed as improving the prediction. If an input signal r Granger causes the output e_{i}, the past information of both r and e_{i} should improve the prediction of e_{i} in comparison with the past information of e_{i} alone. In this approach, the input and output series r and e_i are respectively characterized by the following univariate AR and bivariate AR models:

$$r(n) = \sum_{i=1}^{q_r} \alpha_{1,i}(n) r(n-i) + \vartheta_1(n), \quad \sum\nolimits_{11}(n) = var(\vartheta_1(n)), \tag{2.42}$$

$$e_i(n) = \sum_{i=1}^{q_e} \beta_{1,i}(n) e_i(n-i) + \nu_1(n), \quad \sum\nolimits_{21}(n) = var(\nu_1(n)), \tag{2.43}$$

and

$$r(n) = \sum_{i=1}^{q_r} \alpha_{2,i}(n) r(n-i) + \sum_{i=1}^{q_e} \beta_{3,i}(n) e_i(n-i) + \vartheta_2(n), \quad \sum\nolimits_{12}(n) = var(\vartheta_2(n)), \tag{2.44}$$

$$e_i(n) = \sum_{i=1}^{q_e} \beta_{2,i}(n) e_i(n-i) + \sum_{i=1}^{q_r} \alpha_{3,i}(n) r(n-i) + \nu_2(n), \quad \sum\nolimits_{22}(n) = var(\nu_2(n)), \tag{2.45}$$

The time-varying causality strength from r to e_i and from e_i to r are respectively defined as

$$F_{r\to e_i}(n) = ln \frac{\sum_{21}(n)}{\sum_{22}(n)} \tag{2.46}$$

and

$$F_{e_i\to r}(n) = ln \frac{\sum_{11}(n)}{\sum_{12}(n)} \tag{2.47}$$

If $F_{r\to e_i}(n) > F_{e_i\to r}(n)$, it indicates that r Granger causes e_i at time n, and vice versa. In general, an appropriate threshold is needed to determine the significance of a causality effect. If an input variable r Granger causes e_i, we randomize the order of e_i such that the causality relationship might be eliminated or changed. But this randomize procedure do not change the distribution of e_i. This is the mechanism of surrogate data approach. The shuffling procedure is repeated for many times, N_s, to produce meaningful results. After all these processes, we calculate the threshold for each time point, represented by $\kappa\%$. The occurring probability for any value above this threshold is lese than $1-\kappa\%$. It is believed the be a statistically significant Granger causality relationship when the causality strength exceeds this threshold. It is noticed that, literatures generally set $\kappa\% = 95\%$ [122].

Chapter 3

Stock Market Turning Points Forecasting Using Wavelet Analysis

3.1 Introduction

In long-run, stock markets usually present distinct trends, including expansion and contraction, commonly known as "bull" and "bear" markets, respectively. The continuous transition between the distinct trends of expansion and contraction forms some cyclical patterns. It is worthy to note that such long-run cycles are irregular in durance and patterns, for instance, some market cycles also include obvious sideways trends. Timing of the transition period between trends is critically important for shareholders and regulators. In this chapter, we propose an ax-ante model to forecast the market turning points.

As discussed in Chapter 1, the current method of forecasting of the market turning points mainly include parametric and non-parametric approaches. The parametric methods have the risk of misspecification and are less robust than non-parametric approaches [46, 48]. However, the nonparametric methods mainly use some specific rules to identify and forecast the turning points. One of the main rules is that when the stock price increases by some ratio, e.g. 20%, from the last trough, it signifies a bull market [52, 51]. Similarly, a decrease of 15% over last peak indicates a bear market. This rule definitely introduces a time lag in forecasting so that it misses the optimal peaks and troughs [48]. Consequently, using such a rule-based model, investors would pay up to 20% cost for each trend to time the turning points. Therefore, this method is usually criticized as ex-post forecasting. It is worthy to note that many technical analysis are using the similar rules in identifying trading signals, for instance, the moving average convergence/divergence (MACD), which is also a inherently lagging indicator [130, 131].

In recent years, many advanced methodologies in engineering are borrowed to develop new leading indicators for market cycles timing. Known as a "mathematical microscope", the wavelet method is a powerful time-frequency analysis tool in this field. By using wavelet multi-resolution analysis (MRA), a signal can be split into multiple time scales, including large-scale approximation and finer-scale details. It allows us to focus on specific time scales where cycle patterns are critically concerned, and it does not introduce any lags. The development of this method has attracted extensive attention from economic researchers [132, 133]. By using wavelet to investigate the high-frequency data of the Nikkei stock index, Capobianco [134] revealed the hidden periodic components. Yamada and Honda [56] applied the MRA of the discrete wavelet transform (DWT) to Japanese stock prices to retrieve the middle-frequency signals, which were found to contain predictive information of Japanese business turning points.

The maximal overlap discrete wavelet transform (MODWT) is a non-decimated form of the DWT, which applies high and low pass filters to decompose a signal [135]. One of its main advantages is the translation invariance, meaning that a shift in the signal does not change the wavelet and scaling coefficients. Therefore, it is not sensitive to the starting point of a signal. Xue et al. [136] applied the MODWT to extract the multi-frequency components from the intraday equity prices, in which the jump dynamics of equity prices were found to be sensitive to the data sampling frequency. Their results revealed that the high frequency bands contain more jump points than that in the low frequency bands. Based on a MRA of the MODWT, Gençay et al. [137] proposed a method to extract the intraday seasonality which was simple to calculate and free of model selection parameters. Similarly, the MODWT is employed in analyzing the business cycle and growth cycle, see [138, 139]. The multi-scaling extraction of wavelet has also been applied to the volatility analysis, risk hedging and portfolio allocation [140, 141]. In recent years, although wavelet methods have been widely used in financial time series analysis, the literature in forecasting market turning points still lacks.

In this chapter, we propose a model to forecast the market turning points using wavelet analysis. The model is based on our previous developed system adaptation framework [122, 57], as discussed in Chapter 2. Our study found that the residue of its internal model contains predictive signals on the market cycles [57, 142]. Recall that the internal model I is to capture the slow dynamics of the stock markets, and the internal residue, defined by Equation 2.1, is the difference between the actual price $p(n)$ and estimated price $\widehat{p}_{\mathrm{i}}(n)$. In this chapter, we first apply the internal model to the stock prices to generate a signal-rich residue series. The wavelet MRA with time-varying parameters is then applied to decompose the internal residue and retrieve concerned signals, based on which an empirical index for forecasting market turning points is proposed.

The rest of this chapter is organized as bellow. Section 2 gives our turning points forecasting methods with an introduction of wavelet analysis. Section 3 presents the empirical results from US, UK, and China stock markets. Section 4 concludes this chapter.

3.2 Turning Point Forecasting: A Frequency Domain Approach

In engineering, frequency domain approaches are frequently used in signal analysis to find out significant features that cannot be presented in the time domain. The signals in the time domain show how signals evolve over time, while in frequency domain it shows the power spectrum at each frequency band. One advantage of analyzing time series in the frequency domain is that it allows us to remove the noisy signals at special frequencies and recombine the remaining components in order to recover the original signals. In this study, we need to extract the middle-frequency components of the internal residue to forecast turning points.

3.2.1 Wavelet Analysis

Fourier transform is a typical method to convert signals from time domain to frequency domain. There are some previous works using Fourier methods to study the market turning periods [57, 121]. However, Fourier transform assumes the signal is periodic. It might not be applicable to some non-stationary signals, e.g., the financial time series. Rather than the trigonometric functions in Fourier, wavelets define a finite domain which makes it well localized with respect to both time and frequency. This characteristics allows it to be well used in the study of non-stationary signals. The MRA of the DWT splits a signal into a coarse approximation (large time scale) and a group of finer details (small time scales) [143]. The coarse approximation indicates the trend information of signal, and its finer scales show details of all the other information.

The DWT has two basic types of functions: $\Phi(t)$ and $\Psi(t)$, also known as father wavelet and mother wavelet, respectively. The parents functions can be dilated and translated to get a set of wavelets. In this study, we use the common dyadic DWT, according to which, the scaling function $\Phi_{j,n}(t)$ and wavelet function $\Psi_{j,n}(t)$ can be obtained by

$$\Phi_{j,n}(t) = \frac{1}{\sqrt{2^j}} \Phi\Big(\frac{t - 2^j n}{2^j}\Big), \tag{3.1}$$

and

$$\Psi_{j,n}(t) = \frac{1}{\sqrt{2^j}} \Psi\Big(\frac{t - 2^j n}{2^j}\Big), \tag{3.2}$$

where $j, n \in \mathbb{Z}$, j is the dilation parameter and n is the translation parameter. $\Phi_{j,n}$ represents the signal approximation or low frequencies of the data, while $\Psi_{j,n}$ captures the other high frequencies. Hence, for a signal with finite energy $f(t) \in \mathcal{L}^2(\mathbb{R})$, its DWT is

$$f(t) = \sum_{n=-\infty}^{\infty} a_{J,n}(t)\Phi_{J,n}(t) + \sum_{j=-\infty}^{J} \sum_{n=-\infty}^{\infty} d_{j,n}(t)\Psi_{j,n}(t), \tag{3.3}$$

where J is the maximum decomposition level; $a_{J,n}(t) = \langle \Phi_{J,n}(t), f(t)\rangle$ and $d_{j,n}(t) = \langle \Psi_{j,n}(t), f(t)\rangle$, which can be computed by Mallat's pyramid algorithm [143]. In order to capture the fast changing dynamics of signal, parameters in our MRA are set to be time dependent. Let

$$A_J(t) = \sum_{n=-\infty}^{\infty} a_{J,n}(t)\Phi_{J,n}(t), \tag{3.4}$$

and

$$D_j(t) = \sum_{n=-\infty}^{\infty} d_{j,n}(t)\Psi_{j,n}(t), \tag{3.5}$$

where the sequence of $A_J(t)$ represents the J-th level wavelet smooth and $D_j(t)$ represents the j-th level wavelet details, see Fig. 3.1 for its mechanism. Since we use the daily data, A_J theoretically captures the nonlinear trend with periodicity greater than 2^{J+1} days and D_j captures the signal details with periodicity between 2^j and 2^{j+1} days.

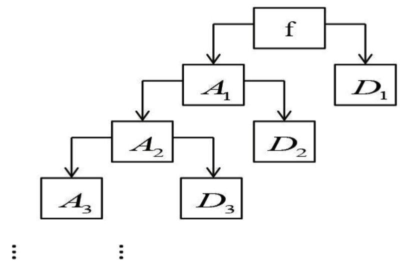

Figure 3.1: Wavelet decomposition mechanism

As introduced above, this study focuses on market cycles with average periodicity around three to seven years, which theoretically corresponds to the frequencies between D_{10} (2.8 years) and D_{12} (11.2 years). It has been proved that using higher frequency data would better capture signal volatility. Our empirical studies found that the informative frequencies lie in the bands between D_7 (0.35 years) and D_{12}, which are referred to as middle-frequency components. Moreover, each market has its own dynamic features, so that the specific frequency bands for different markets should be selected respectively.

There are various discrete wavelets available for the MRA, e.g., the wavelets family of Daubechies, Harr, coiflets and symlets. The selection of wavelets depends on the signal properties and the problem nature. With the advantage of compact support and orthogonality, the Daubechies wavelets are widely used in the analysis of problems with local high gradient [144]. Considering that the internal residue has nonstationary and drastic fluctuations during some periods, the Daubechies wavelets are employed in this study.

Figure 3.2 shows an example of multi-resolution decomposition of the internal residue. The internal residue of the Dow Jones Industrial Index Average (DJIA) is decomposed by wavelet of Daubechies 12 (db12) at level $J = 12$. In this figure, the trend term A_{12} and all the other frequencies from D_{12} to D_1 are precisely decomposed. The middle-frequency signals, $m(n)$, are retrieved by

$$m(n) = D_{11}(n) + D_{10}(n) + D_9(n) + D_8(n), \tag{3.6}$$

see Figure 3.3.

The MODWT is a non-orthogonal variant of the DWT. Compared with the DWT,

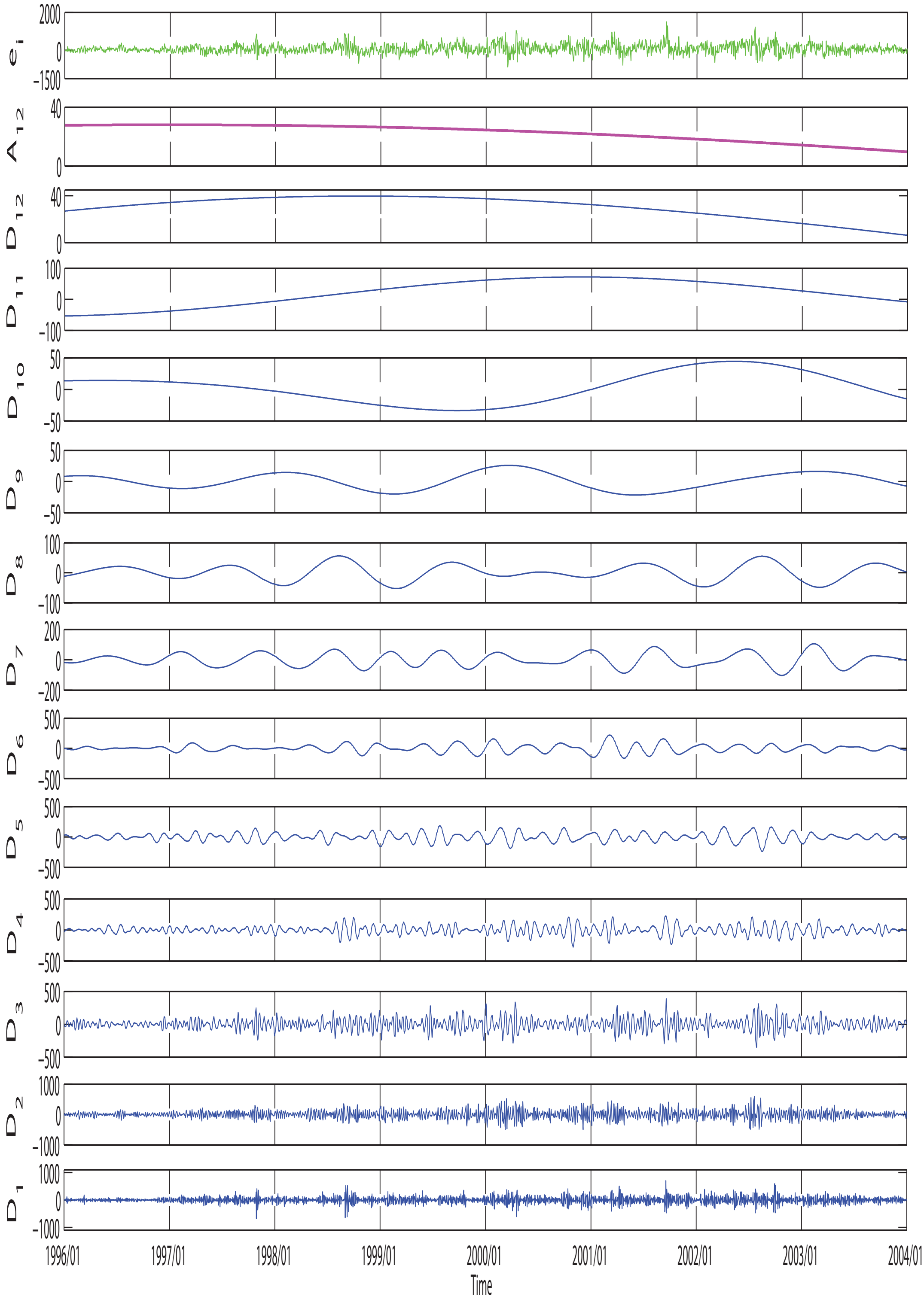

Figure 3.2: Decomposition of internal residue of the DJIA with the DWT

the MODWT is a highly redundant and nonorthogonal transform [135]. It retains downsampled values at each level of the decomposition rather than decimating the coefficients as the DWT. Therefore, the number of wavelet and scaling coefficients at each level remains to be the original sample size. For this reason, the MODWT is also called time-invariant DWT. The MODWT is also employed in this work to have a comparison with the DWT in terms of predicting turning signals.

3.2.2 Market Turning Index

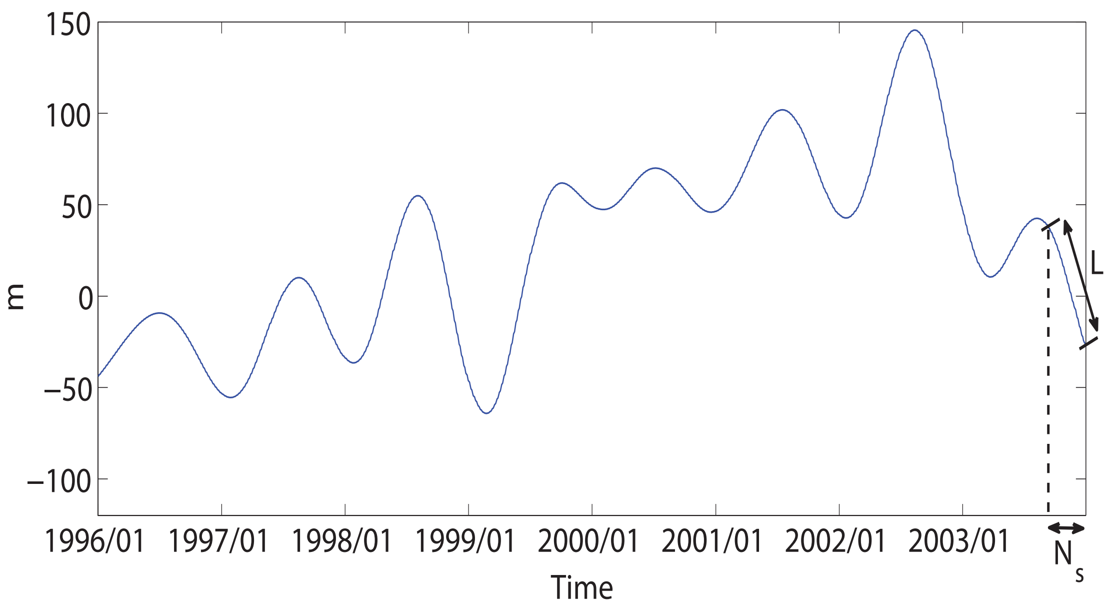

Figure 3.3: One snapshot of the retrieved middle-frequency signal m with the DWT

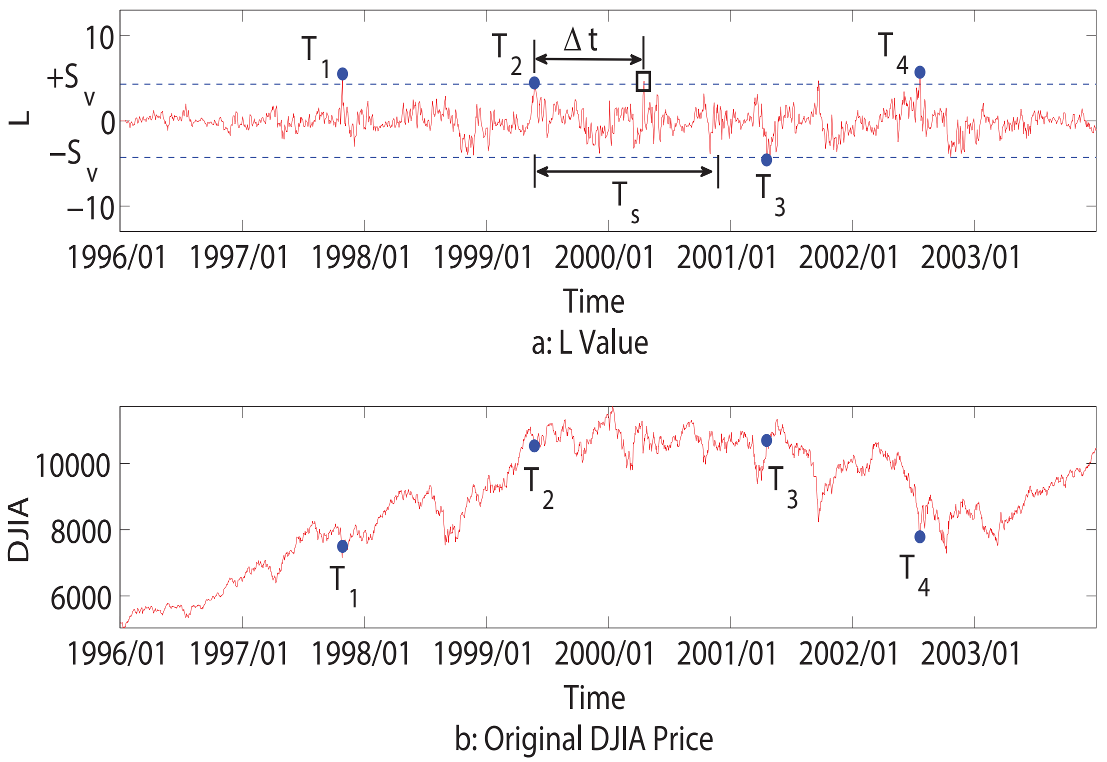

Figure 3.4: Turning point identification rules

To find out the turning information from the retrieved signals, an index which is capable of capturing the dynamical changes in the signals is needed. Our empirical testing found that when the market steps into the turning period between two primary trends, the internal residues usually show some patterns in the middle-frequency components. The slope L of retrieved signals in the past N_s days, see Figure 3.3, working well as an measurement to capture such kinds of oscillations. The intense fluctuation of L indicates a turning point for primary market cycles, i.e., once L is large enough to exceed some threshold, the corresponding time is identified as a market turning point.

Based on the index L, two rules are proposed to identify the major turning points, which are illustrated in Figure 3.4. The forecasted turning points are denoted by T_k, $k = 0, 1, 2, \cdots, n$.

> *Rule I.* A threshold value, S_{v}, is defined to identify a new turning point. If the slope $L > +S_{\mathrm{v}}$ or $L < -S_{\mathrm{v}}$ it is marked as a candidate of the next turning point, $\hat{\mathbf{T}}_{k+1}$, $k = 0, 1, 2, \cdots, n$.
>
> *Rule II.* A time slot threshold, T_{s}, measuring in days, is defined to filter the redundant turning points after a confirmed one. Since our interested market cycles are around three to seven years, once a new turning point is found, the next turning point is not likely to appear in the near future. The time length between a candidate turning point and the last confirmed turning point is defined as Δt:
>
> $$\Delta t = \hat{\mathbf{T}}_{k+1} - T_k. \tag{3.7}$$
>
> If $\Delta t > T_{\mathrm{s}}$, the candidate $\hat{\mathbf{T}}_{k+1}$ is confirmed as a new turning point T_{k+1}, otherwise it is removed as a redundant one.

For the initial condition, we set the starting date of the testing period to be a default turning point T_0. One example for these two rules is shown in Figure 3.4, in which the DWT is used for MRA. The parameters are set as: $N_s = 10$, $S_v = 4.3$ and $T_s = 360$. Figure 3.4.a is the internal residue and Figure 3.4.b shows the original DJIA price with the forecasted turning points correspondingly marked by blue points. In this study, the initial point T_0 is not presented in the results unless otherwise specified. As demonstrated in Figure 3.4.a, the point in the rectangular box satisfies the condition of

Rule I ($L < -S_\mathrm{v}$) and it is marked as a turning point candidate, but it is obvious that $\Delta t < T_\mathrm{s}$ which does not satisfy *Rule II.* Thus it is considered as a redundant point.

3.3 Results

We select three stock market index to do empirical testing, including DJIA, Financial Times Stock Exchange (FTSE) 100, and Shanghai Stock Exchange Composite Index (SSE). Among the three index, two are from developed markets, which correspondingly represents US and Europe market, and one from China that represents emerging market.

3.3.1 US Market

For the US market, we focus on the DJIA and the testing period is from year 1996 to 2013. The daily closing prices from year 1991 to 1995 are used to train the OE model through MATLAB System Identification Toolbox. The identified OE model is

$$H(z) = \begin{bmatrix} \frac{2.614z^{-1}-9.925z^{-2}-2.945z^{-3}+8.961z^{-4}}{1+0.9776z^{-1}+0.00428z^{-2}} \\ \\ \frac{10.81z^{-1}-5.121z^{-2}+2.79z^{-3}-2.534z^{-4}}{1+0.1485z^{-1}+0.3395z^{-2}} \\ \\ \frac{-2.859z^{-1}+0.2158z^{-2}+1.733z^{-3}-0.3547z^{-4}}{1+0.06269z^{-1}-0.5227z^{-2}} \end{bmatrix}^\mathrm{T}. \tag{3.8}$$

Figure 3.5.b shows the internal residue. The DWT is used to extract the middle frequency components, where Daubechies 12 (db12) wavelet is selected to decompose the internal residue at level $J = 12$. The middle-frequency bands are selected between D_8 and D_{11}:

$$m(n) = D_{11}(n) + D_{10}(n) + D_9(n) + D_8(n). \tag{3.9}$$

The other parameters are set as

$$N_\mathrm{s} = 10,\ S_\mathrm{v} = 4.3,\ T_\mathrm{s} = 360. \tag{3.10}$$

Figure 3.5 presents the forecasting results with the DWT: Figure 3.5.a shows the original index prices, in which the forecasted turning points, T_k, $k = 1, 2, \cdots, n$, are labeled by blue markers respectively; Figure 3.5.b is the internal residue; Figure 3.5.c

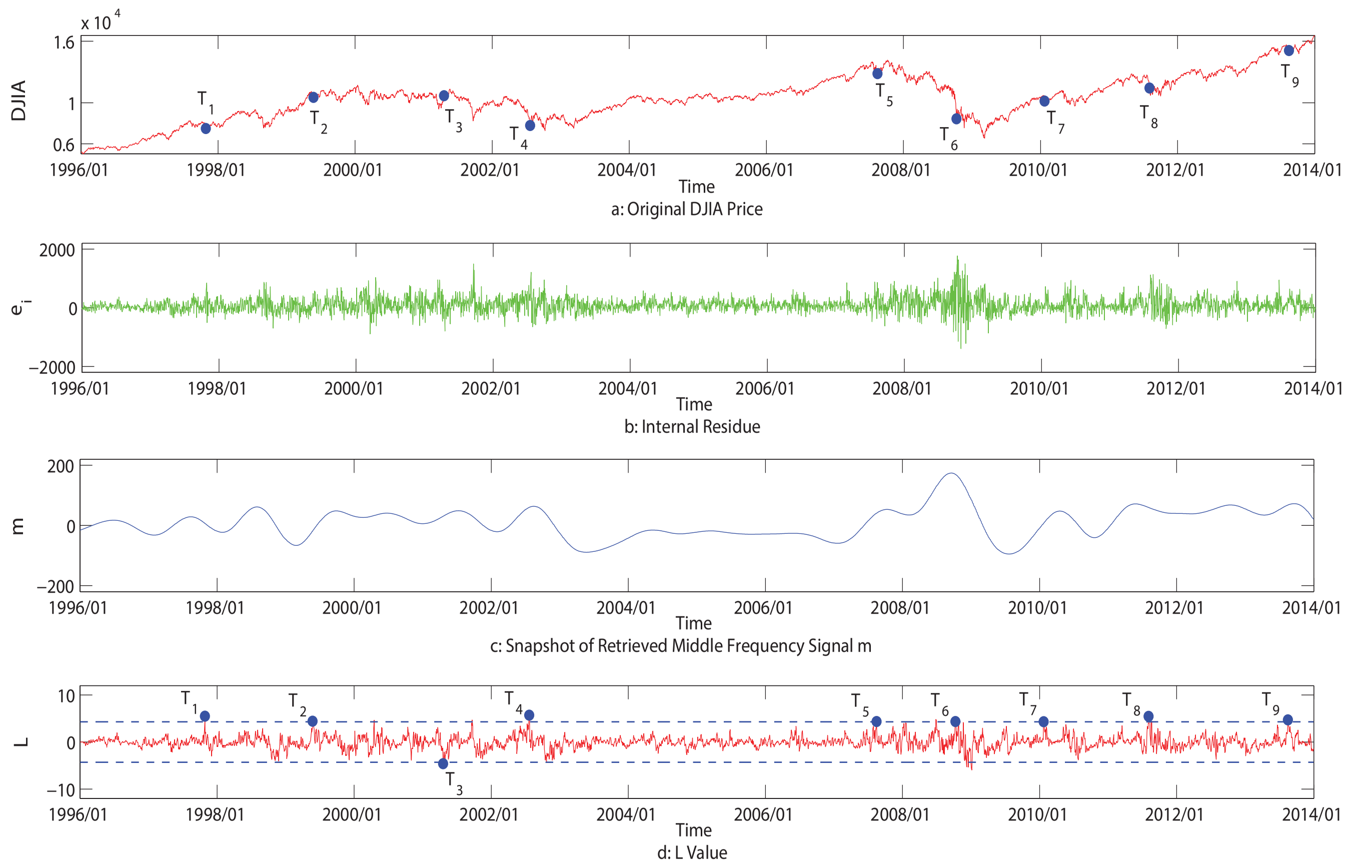

Figure 3.5: Turning points forecasting of the DJIA with the DWT

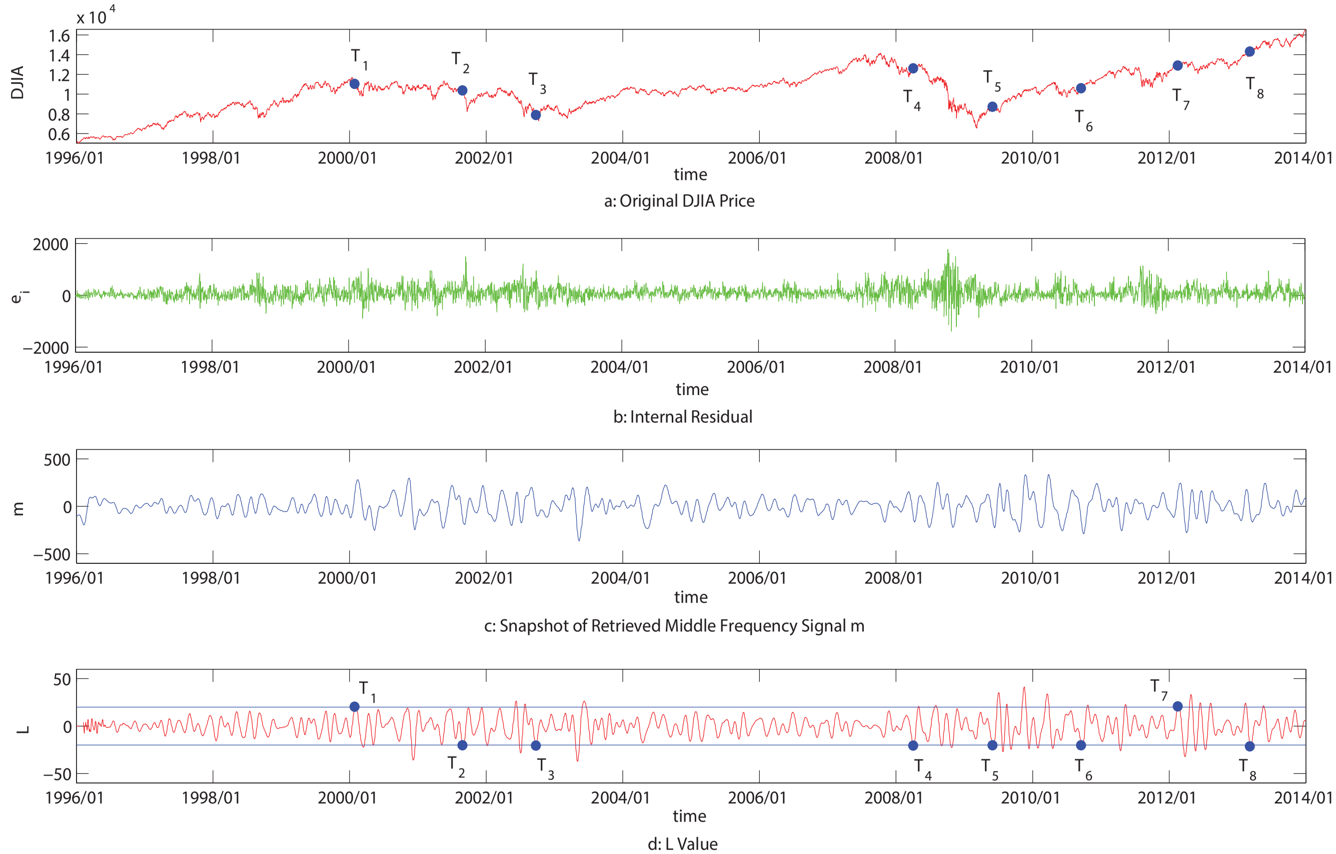

Figure 3.6: Turning points forecasting of the DJIA with the MODWT

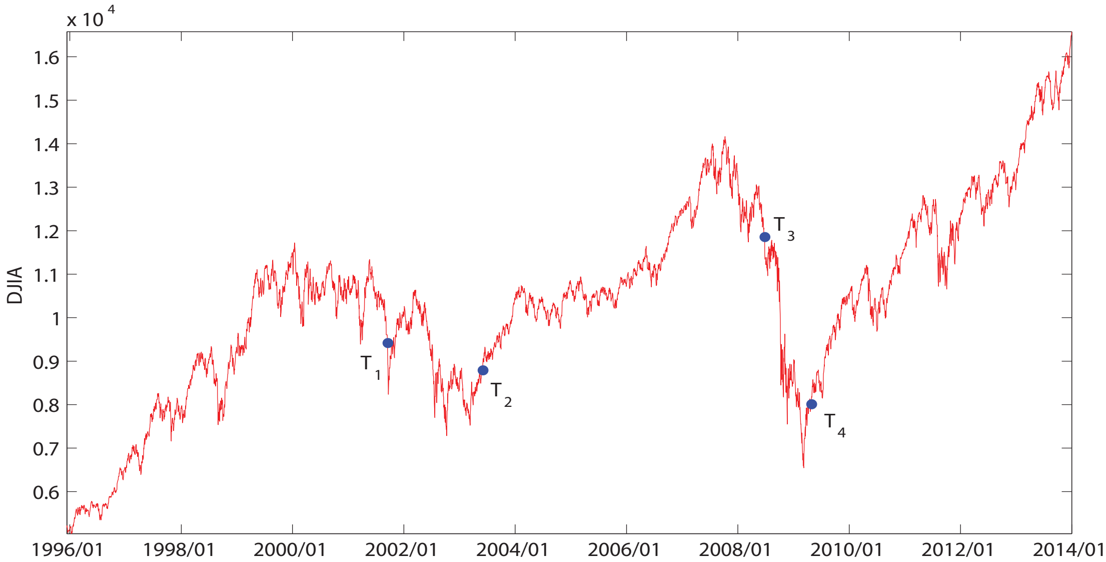

Figure 3.7: Turning points forecasting of the DJIA with the non-parametric methods

shows a snapshot of the retrieved middle-frequency signals at the end of the testing period; Figure 3.5.d presents the value of slope L in each step, in which the blue points are the forecasted turning points.

From the results, we can find that nine turning points are forecasted during this period. The first forecasted turning point is in October, 1997, when the market was in a short tranquil period. Two months later, the market began to rise sharply due to the dot-com boom. Therefore, point T_1 gives excellent forecasting for this rapid growth. The second forecasted turning point, T_2, alarms that the market is going to end the rising trend. As expected, after T_2, the market switched to an one-year's tranquil period. Before the end of this tranquil period, our model gives another turning signal at T_3. It correctly signifies the starting of a bear market, which lasted for one year because of the burst of the dot-com bubble. After that, our model provides a successful forecasting for the bottom of this bear market at T_4. It is obvious that, after T_4 the market went through a short fluctuation period, and then entered into a rally period.

The US stock market was heavily hit by the latest sub-prime financial crisis. The market reached its peak in October 2007, and then started to crash quickly. Our model gives an alarm signal T_5 in August 2007 that was two months before this crash. The next forecasted point T_6 suggests the ending of the crash, which has been proved to be accurate. Stimulated by the Federal Reserve's quantitative easing programs, the market began to rebound after a short period of fluctuation. During the recovering period, our model gives several turning alarms from T_7 to T_9. Although they are not the major turning points, there are still significant fluctuations around these points.

The MODWT is also used to study the dynamics of the proposed index. The internal residue is also decomposed at level $J = 12$ by db12. The empirical results find that the MODWT needs higher frequency bands to capture the turning signals than the DWT. The middle frequency bands are thus selected from D_5 to D_7:

$$m(n) = D_7(n) + D_6(n) + D_5(n). \tag{3.11}$$

The other parameters are set as

$$N_{\mathrm{s}} = 12,\ S_{\mathrm{v}} = 20,\ T_{\mathrm{s}} = 380. \tag{3.12}$$

Figure 3.6 shows the results forecasted by the MODWT. From Figure 3.6.d, we can find that the change of the slope is continuous and smooth. However, compared with the DWT, the MODWT does not provide additional information in this case. The MODWT forecasts one less turning points than the DWT, and the forecasted turning points of T_1 to T_5 are not as precise as the DWT. The MODWT also generates noisy points at T_6, T_7 and T_8.

To compare the forecasting performance of this method, we also use classical non-parametric methods to identify the turning points. The rules we use is that when the stock price increases by 15%, from the last trough, it signifies a bull market. Similarly, a decrease of 15% over last peak indicates a bear market. To filter the noisy alarms, the second rule we use is that a trend must last at least 300 days. Figure 3.7 reports the forecasted turning dates of this non-parametric index. The non-parametric method only gives four turning points. The first one corresponds to the peak in May 2001, however, this turning alarm appear in September 2001. It is late for nearly four months. Our DWT method gives this alarm in April 2001, which was one month before the peak. Similarly, the following three alarmed turning points are also later than the true turning dates. Thus our index performs better than the traditional non-parametric method for the DJIA.

3.3.2 UK Market

London stock exchange (LSE) is the only stock exchange in the UK and also the largest one in Europe. In LSE, the most widely used index is FTSE 100, which is a blue-chip index of 100 largest companies on its list. In the past decades, it experienced several primary cycles. In this section, we use FTSE 100 to test our model's performance.

Daily closing prices are used in this model. The training period is selected as from January 1991 to January 2001. The forecasting period is from February 2001 to December 2013, and the corresponding OE model is obtained as Equation 3.13:

$$H(z) = \begin{bmatrix} \frac{-1.906z^{-1}-2.196z^{-2}+0.1489z^{-3}+0.5238z^{-4}}{1+0.8047z^{-1}} \\ \\ \frac{-0.1284z^{-1}+3.468z^{-2}+1.158z^{-3}-0.7299z^{-4}}{1+0.1306z^{-1}} \\ \\ \frac{2.605z^{-1}-4.287z^{-2}+0.4033z^{-3}+1.269z^{-4}}{1-0.9788z^{-1}} \end{bmatrix}^{\mathrm{T}}. \tag{3.13}$$

The wavelet we use is Daubechies 8 (db8) wavelet at level $J = 12$. The middle-frequency components are retrieved as

$$m(n) = D_{11}(n) + D_{10}(n) + D_9(n) + D_8(n). \tag{3.14}$$

The other parameters are selected as

$$N_{\mathrm{s}} = 10,\ S_{\mathrm{v}} = 1.81,\ T_{\mathrm{s}} = 680. \tag{3.15}$$

Figure 3.8 shows the forecasting results with the DWT. It is interesting to find that since 2000, FTSE 100 has experienced two primary cycles with three major turning periods. The first one is in March, 2003, when FTSE 100 hit its low-point of 3287. Our model gives an alarm signal T_1 for this turning point two month ago. The external factors that triggered the bear market of 2002-2003 mainly come from the economic depression of US and EU, which are major trading partners of UK. During this period, the burst of the dot-com bubble and 9/11 terrorist attacks significantly hit their economy, which reduced the foreign investment in the UK. In addition, the fear of terrorism threat and the intense emotion brought by Iraq war severely reduced investors' confidence in the

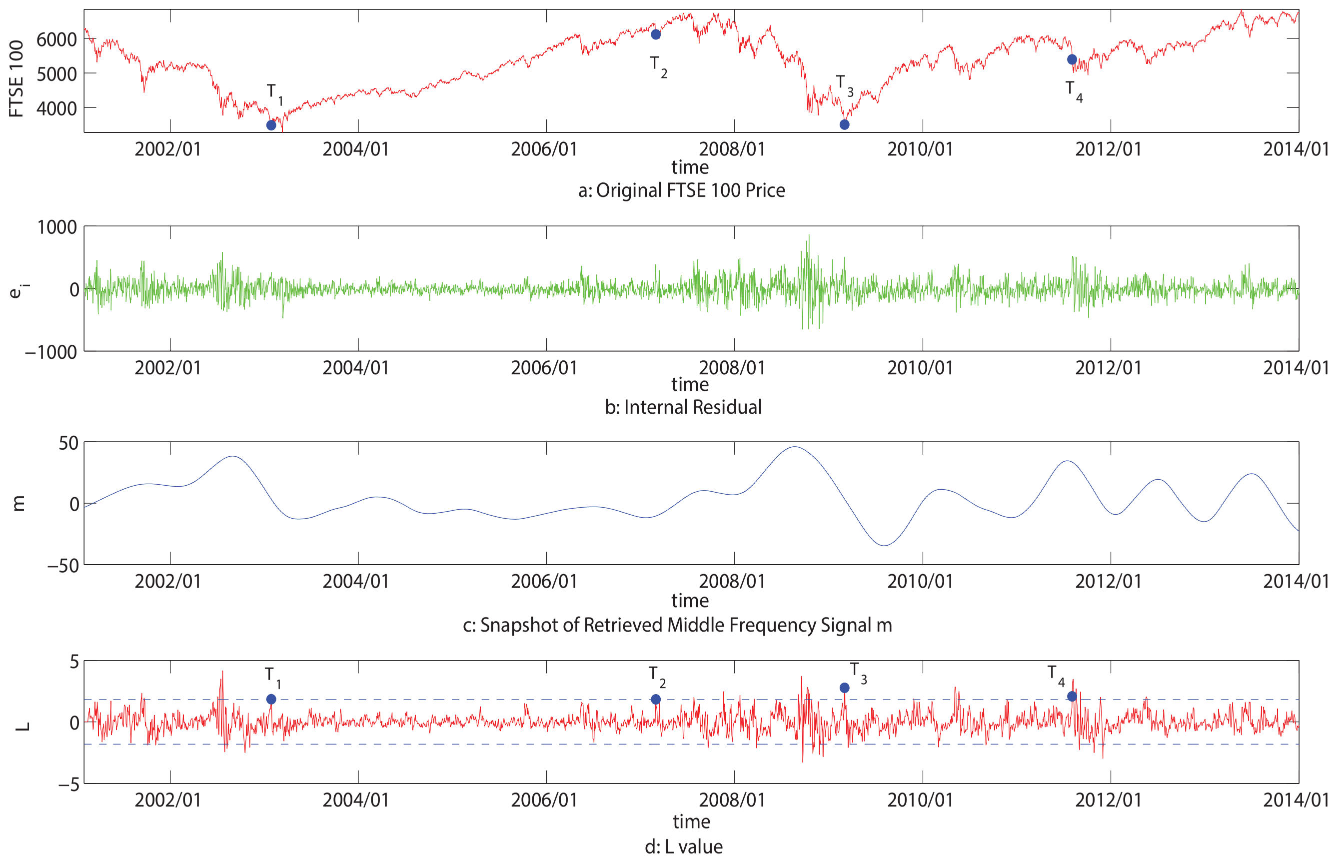

Figure 3.8: Turning points forecasting of the FTSE 100 with the DWT

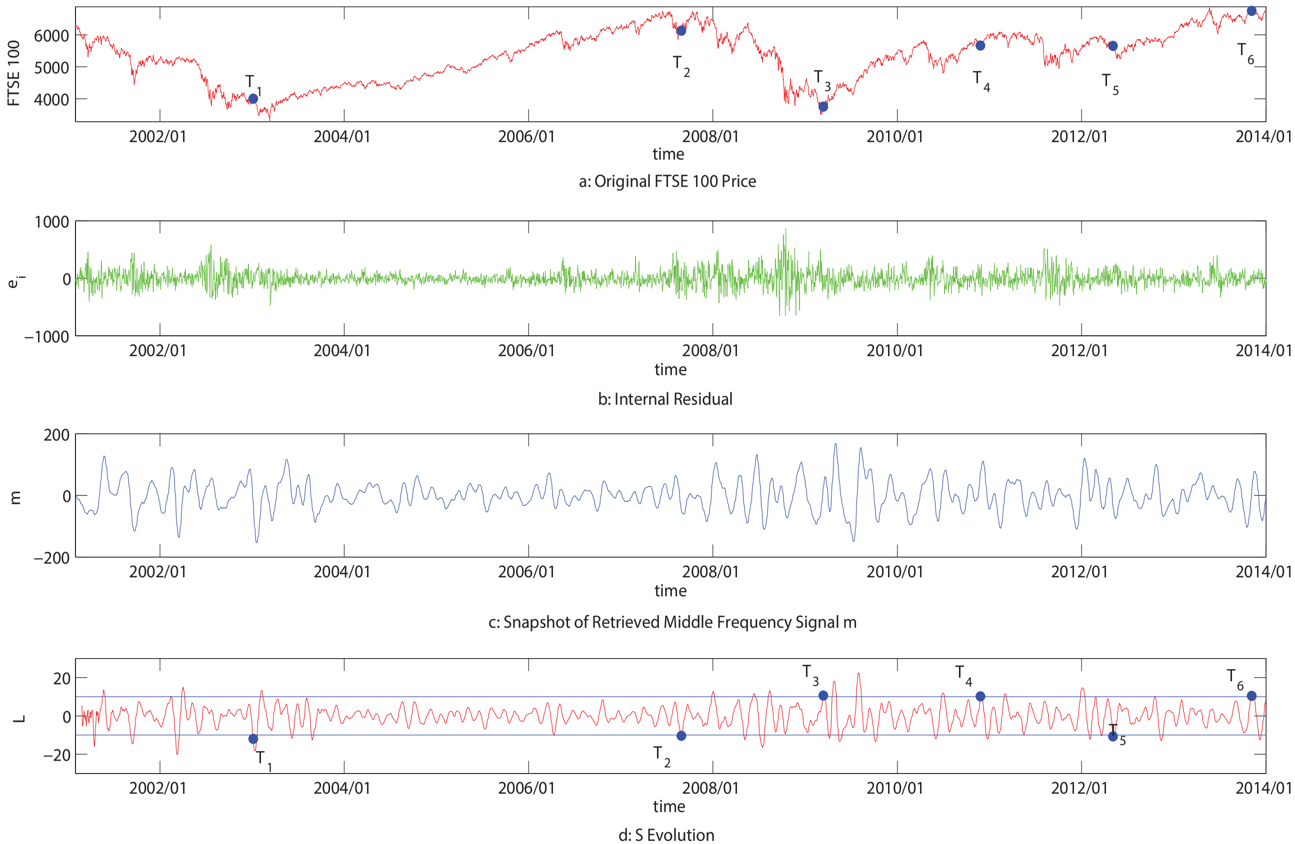

Figure 3.9: Turning points forecasting of the FTSE 100 with the MODWT

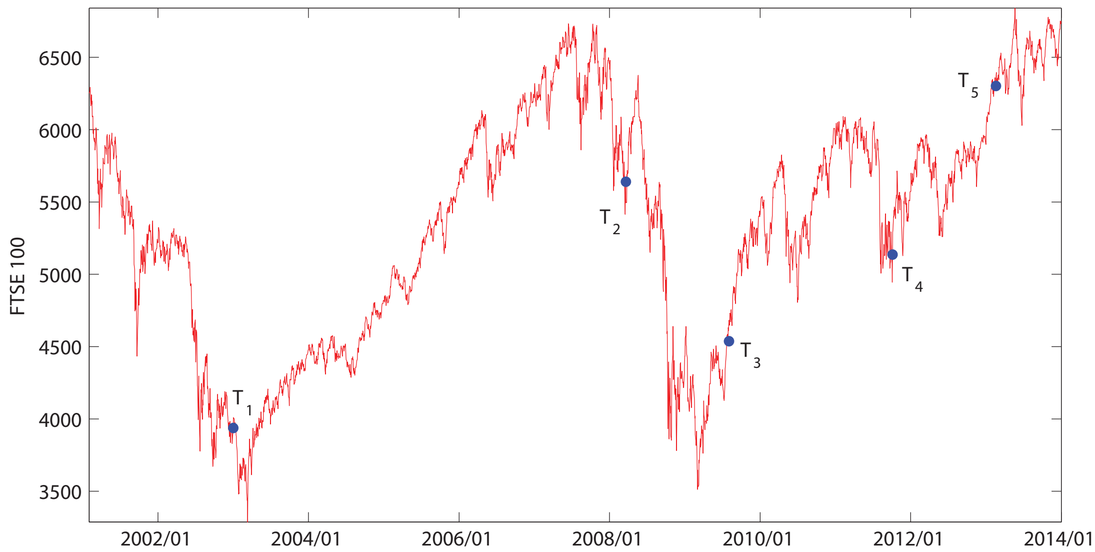

Figure 3.10: Turning points forecasting of the FTSE 100 with the non-parametric methods

future, which results in the slumped investment and economic growth. There was an overall decline from real estate, manufacturing and service industry until the market reached its record low of this century.

The latest financial crisis of 2007-2008 significantly hits London stock market. When the market reached its peaks in July 2007 it began to sharply fluctuate and then suddenly crashed. This turning point is forecasted by our model at T_2, March 2007. After this turning period, the market declined more than one year until reached its six-year low in March 03, 2009. Our model successfully forecasts this turning point, see T_3 in figure 3.8. Compared to the peak of 2007, FTSE 100 lost almost half of its value. The US subprime mortgage crisis and shrink of foreign investments are the major external factors that account for this economic downturn. Financial sectors, which accounted for 9.4% of UK GDP in 2006, sustained huge losses in the crisis. Another dominant industry, the real estate, also experienced large decline of price and sales volume that significantly influenced the economy. After hitting its bottom, the market had its rally until now. During this rebound, there are some intense fluctuations where our model also gives some corresponding signals. In early August, 2011, the market experienced a sharp and continuous decline, lasting two weeks. Detecting this signal, our system gives a turning point alarm at T_4, but it was proved this fluctuation did not change the primary trend.

The MODWT is also applied to the FTSE 100. The db8 wavelet is used to decompose the internal residue at level $J = 11$. The middle-frequency components are selected as

$$m(n) = D_7(n) + D_6(n) + D_5(n). \tag{3.16}$$

The other parameters are selected as

$$N_{\mathrm{s}} = 10,\ S_{\mathrm{v}} = 10,\ T_{\mathrm{s}} = 520. \tag{3.17}$$

Figure 3.9 presents the forecasting results of the MODWT. There are six turning points forecasted during the testing period. The timing of T_1 and T_3 are similar to the results of the DWT. The turning signal T_2 is later than the corresponding one from the DWT, but it still locates in the turning period. After 2009, the MODWT generates more noisy alarm signals than the DWT.

Figure 3.10 reports the forecasted turning dates of the non-parametric method. The rules we use include that a bull market is identified when the stock price increases by 15% from the last trough, and a a bear market is identified when the stock price decreases by 15% over last peak. The filter window length is 500 days. We can find that there are five turning points forecasted. The first one is earlier than the true turning point. However, T_2 and T_3 are later than the true turning points. Moreover, T_4 and T_5 are two noisy alarms.

3.3.3 China Market

The stock trading in the emerging markets is very active in recent years. The emerging markets have some unique features distinguishing from developed markets. Their volatilities are much higher than that in the developed markets [145], which are characterized by high risk and high return. One possible reason is that these markets are very sensitive to political events, and they always overreact to some new policies. It makes the cycle forecasting in such emerging markets more important but more challenging [146].

As a typical emerging market, the China market is studied in this session. The data we use is the daily closing prices of the SSE. The training period is selected as from year 1999 to 2004. The forecasting period is from year 2005 to 2013, and the corresponding

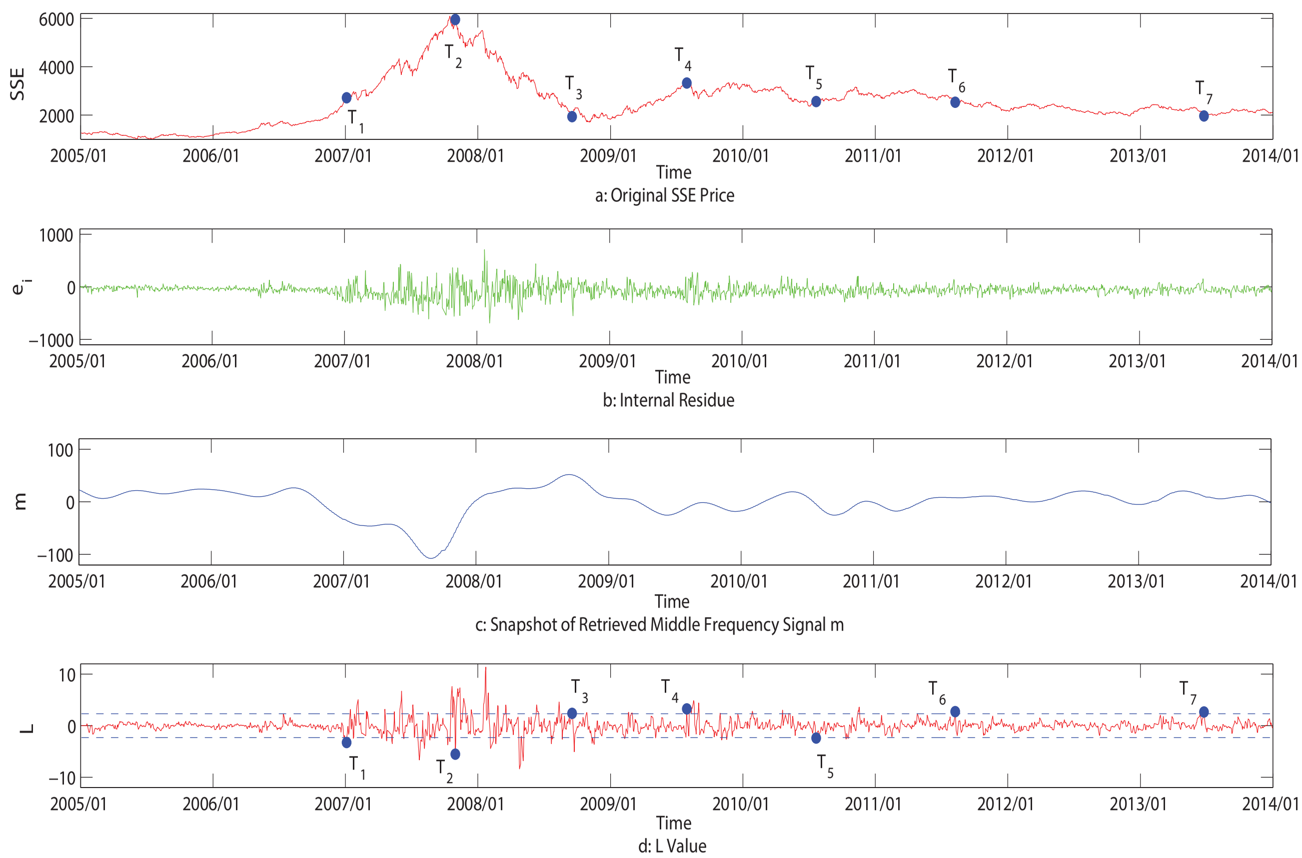

Figure 3.11: Turning points forecasting of the SSE with the DWT

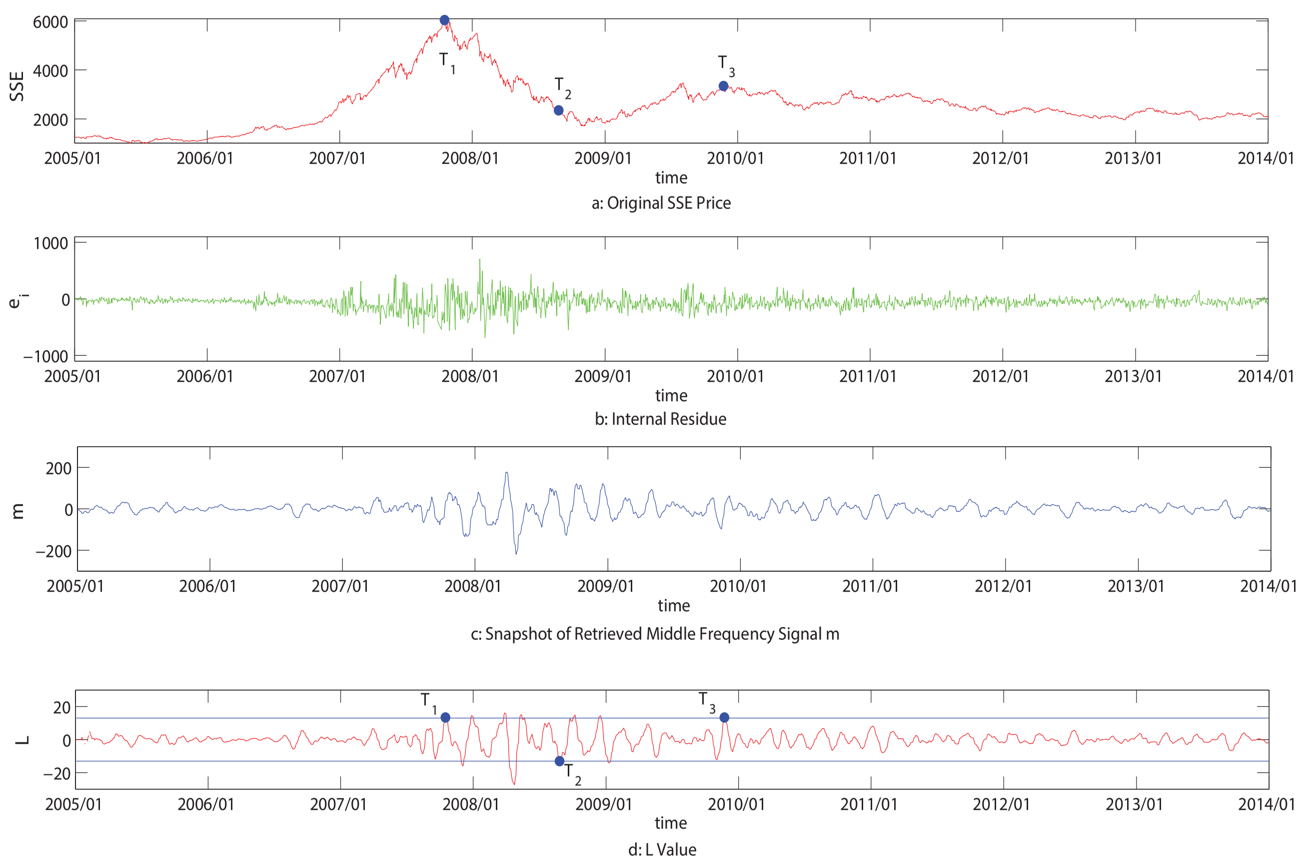

Figure 3.12: Turning points forecasting of the SSE with the MODWT

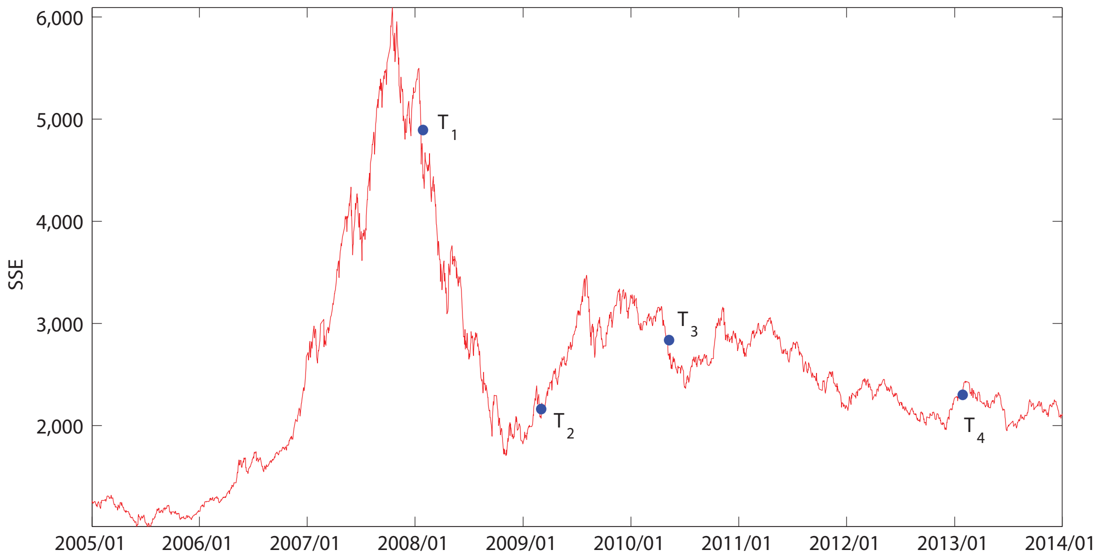

Figure 3.13: Turning points forecasting of the SSE with the non-parametric methods

OE model is as bellow

$$H(z) = \begin{bmatrix} \frac{2.504z^{-1}-1.086z^{-2}-0.03676z^{-3}}{1-0.1794z^{-1}+0.002452z^{-2}} \\ \\ \frac{-0.8056z^{-1}+1.445z^{-2}-0.8015z^{-3}}{1-1.793z^{-1}+0.995z^{-2}} \\ \\ \frac{0.08992z^{-1}-0.1419z^{-2}+0.05945z^{-3}}{1-1.681z^{-1}+0.7428z^{-2}} \end{bmatrix}^{\mathrm{T}}. \tag{3.18}$$

The DWT is used to forecast the turning points. The wavelet we use is Daubechies 9 (db9) wavelet at level $J = 12$. The middle-frequency components are restored as

$$m(n) = D_{10}(n) + D_9(n) + D_8(n) + D_7(n). \tag{3.19}$$

The other parameters are selected as

$$N_{\mathrm{s}} = 10,\ S_{\mathrm{v}} = 2.3,\ T_{\mathrm{s}} = 300. \tag{3.20}$$

The results are presented in Figure 3.11. T_1 forecasted the beginning of a rising market. Although this is not the optimal starting point, it is a good forecasting for the long time economic activities, henceforwards the market stepped into a rapidly growing period. During this period, the China market adjusted its policy to be more open to the international investors, i.e., the non-tradable share reform in 2006. This rising market reached its peak in October 2007. This turning point is precisely forecasted by our model at T_2. After this peak, the China market began to crash. In the following one year it quickly declined until the end of 2008. It is clear that T_3 very successfully forecasted the bottom of this declined trend. This crash was caused by many reasons, including reform of exchange rate, US financial crises and recession in the global economy. The next forecasted point, T_4, signifies the peak of the following recovery market very well. After this peak, the market entered into a tranquil period until present. T_5 and T_7 capture two stepwise decline in 2010 and 2013, which are results of the continuous recession of global economy.

The MODWT is also applied to the China market. The wavelet is selected as Daubechies 4 (db4) wavelet at level $J = 11$. The middle-frequency signals are reconstructed as

$$m(n) = D_7(n) + D_6(n) + D_5(n). \tag{3.21}$$

The other parameters are used as

$$N_\mathrm{s} = 12,\ S_\mathrm{v} = 13,\ T_\mathrm{s} = 300. \tag{3.22}$$

Figure 3.12 presents the forecasting results by using the MODWT. Only three turning points are forecasted in the whole testing period. T_1 gives an alarm of the coming downturn caused by the 2007-2008 financial crisis. The point T_2 indicates an alarm for the bottom of the declining trend, which is around one month earlier than the result of the DWT. T_3 indicates the end of the following rebounding trend, which is a little later than the timing of the DWT. Compared with the results from the DWT, the MODWT results miss the starting point of the bull market between 2006 and 2007, and do not give any alarm after 2010.

Figure 3.13 reports the forecasted turning dates of China markets using the non-parametric methods. The rules we use include that a bull market is identified when the stock price increases by 15% from the last trough, and a a bear market is identified when stock price decreases by 15% over last peak. The filter window length is 400 days. Four turning points have been identified during the testing period. The T_1, T_2 and T_3 miss the optimal turning dates, which are considered as ex-post forecasting. Moreover, T_4 gives an noisy alarm.

3.3.4 Analysis of Results

The results with the DWT for the US, UK and China markets demonstrate that our model is capable of capturing all the major turning points during the testing periods. As each market has its specific dynamics, the model parameters should be specified accordingly. However, the same feature is that the middle-frequency components of internal residues in all markets can capture their primary market cycles. This model performs best for the FTSE 100 among the three markets. The UK economy is highly influenced by external environment, making its market dynamics highly consistent with US and EU markets. When its external environments critically changes, the market responses to it by giving some oscillating signals that are precisely captured by our model. Compared with the classical non-parametric methods, the turning points forecasted by DWT are earlier than the true turning dates, which are more valuable to investors. While the turning dates identified by the traditional non-parametric methods generally miss the optimal turning dates.

Considering the time-invariant feature of the MODWT, it is a powerful tool in analyzing financial time series. However, it misses some turning points in the China and US markets and generates more noisy alarms in the UK market. In addition, in the US market, most of the forecasted turning points by the MODWT are later than those forecasted by the DWT. The MODWT has its advantages over the DWT in signal decomposition, but it does not provide additional information to the cases in this study. The DWT performs better in our framework in terms of capturing the oscillation signal during the turning period.

Comparing the US with China markets from 2005 to 2013 with the DWT, it is found that more turning points are forecasted in the China market than the US market. The reason may lie in the differences between the dynamical properties of the two markets in nature, e.g., essential differences in market size, structure and functionality, which make the fluctuation of the China stock market more dramatic than the US market.

US has a typical market-based financial system with large size of direct financing and well-developed capital markets, while the financial system in China is bank-based with underdeveloped capital markets as well as relatively isolated and small stock market. Currently, the stock market capitalization in China is still less than one quarter of that in US. Therefore, the China stock market is easily affected by external environments.

In a mature stock market like US, institutional investors usually dominate the trading activities. However, in the China stock market, individual investors account for more than 85% of all trading volume. The majority of this group of investors is lack of basic knowledge about financial investment, portfolio management and risk control, which makes them prone to speculative short-term trading. This kind of trading behavior inevitably results in dramatic fluctuations. In terms of market functionality, unlike the US market, not many listed companies in China stock exchange have significant influence and value. In this way, it cannot maintain a stable and efficient stock market. Additionally, due to the defective regulations in the option trading, short-selling mechanism and exit mechanism, the China stock market is relatively easy to be manipulated. All of these factors intensify the fluctuation in the China stock market.

3.4 Conclusion

Based on the system adaptation framework we previously proposed [122, 57], its internal model is used in this study to capture the dynamical properties of stock markets and generate a signal-rich residue for turning points forecasting. The MRA of the DWT and MODWT are used to decompose the internal residue and further extract its middle-frequency signals. By analyzing the slope of retrieved signals, a turning points forecasting index is proposed.

Compared the results of the DWT with the MODWT, it is found that the DWT works better for this indicator. The testing results of US, UK and China markets demonstrate that nearly all the major turning points in the testing periods can be well forecasted by our index with the DWT, even including some smooth transition timings. In some other early works, the emerging markets are always considered to be more volatile and hard to forecast [146], e.g., China market which is highly driven by policy. Our model finds that the middle-frequency signals can also give remarkable forecasting information at such emerging markets. One reason might be that, the high-frequency data in these markets are more noisy than that in the mature markets. However, such kinds of noises can be effectively filtered by the wavelet methods.

We should notice that this method is not limited to stock markets. It can be widely used to study other economic time series or other financial markets, e.g., markets of future, commodity and other derivative instruments. Based on this framework, related studies could be extended further, such as constructing other forecasting index and doing the forecasting in different frequency bands. In addition, the MODWT still deserves more study in detecting the oscillation of financial time series, which may shed some light in market turning points forecasting.

Chapter 4

Transient Reaction of Intermarket Relationship under 9/11 Terrorist Attack

4.1 Introduction

Stock markets, in short-run, present fast fluctuations that reflects the dynamic interactions between dring forces and market movements. When the market experiences some unexpected shocks, this interaction might dramatically changes. In this chapter, we will study the transient reaction of intermarkets under the 9/11 terrorist attack. The United States experienced devastating terrorist attacks on September 11, 2001. In addition to the political and social impacts, it also significantly influenced the U.S. economics. One of the serious effects was that it created drastic turbulence and uncertainty to the stock markets, which forced investors to leave the market and resulted in a sharp drop of the equity prices. After 9/11, the US stock markets closed in the following four trading days. The Dow Jones Industrial Average (DJIA) dropped by 7.13% on September 17th when the US stock market reopened, and in the following one week it dropped by 14.26%. The 9/11 terrorist attack also significantly influenced foreign stock markets. The European markets decided to keep open after 9/11 that made them subjected to the consequence of the uncertainty. The stock market of UK, Germany, France, Netherland and Switzerland experienced significant negative shocks as well as the Hong Kong and Japan markets. In addition to the stock markets, the other financial markets of commodity, debt and derivatives were also significantly shocked. From this disaster we can find that the increasing integration the world financial markets demonstrated highly consistent reaction pattern after 9/11. However, one critical question arises: What is the dynamic interactions, e.g. comovement and lead-lag relationships, among these financial markets?

The aim of this study is to analyze the dynamic interrelations between US stock markets and other financial markets around the period of 9/11. Our study mainly focuses on two questions. The first one is that whether the terrorist attack change the US stock market forces. The market influential factors are considered as market forces. Study of market forces can help the investors to identify the determinants of price transmission between cross markets. Moreover, it can also the underlying information diffusion mechanism. Thus the knowledge of market forces and their dynamic fluctuations is of great interest to the policy markers and shareholders. The terrorist attack significantly shocked the market conditions that might change the lead-lag relationship between financial markets. The second question we are concerning is the comovement between US stock markets and other related financial markets. The dynamic co-movement during the post period of terrorist attack is critically important for the risk managers in accessing the effect of their portfolio diversification strategy.

The reaction of the financial markets to the terrorist attack presents several characteristics. First, the initial market impact is likely to be overreaction. The financial markets generally show sharp decrease or increase patterns [147, 148]. After that, the investors become more rational to look at the medium-term economic influence. Second, the terrorist shock to the financial market is generally absorbed in a short period. Thus its micro impact is more serious than the macro impact [149, 150, 151]. Considering these features, this study mainly focus on the transient market reactions after the 9/11 attack.

There are increasing literatures documenting the influence of terrorism on financial markets. One line of papers focus on identifying the abnormal returns, which mainly use event study methods. Chen et al [151] use event study to access the effects of terrorism on global capital markets. It is found that the US capital markets become more resilient than in the past and recover sooner from terrorist attack than the markets of other countries. Kollias et al [152] apply event study and GARCH models to investigate two terrorist incidents' impacts on stock markets, i.e. the bomb attacks of 11th March 2004 in Madrid and 7th July 2005 in London. In many aspects, these two terrorist bomb attacks are regarded as the European equivalents of 9/11. Their results suggest that there are significant negative abnormal returns across most sectors in the Spanish markets but not so in the case of London markets. In addition, London markets rebound much quicker than Spanish markets. The similar studies regarding the negative effects of terrorism on the financial markets can be found from [153, 154, 155, 156].

Second, the volatility and price spillover is also one of the most critical problems in the financial markets under terrorism activities. Many approaches have been adopted in accessing the spillover effect, among which the Granger causality [157, 158] might be the most commonly accepted methodology in addressing the concepts of spillover. This causal test emphasizes the impacts of past shocks in one market on the current volatility or price movement in another. Based on Granger causality mechanism, a conventional approach for spillover study is the vector autoregression model. Many studies show that the existence and direction of causality can dramatically change during the crisis period [124, 125, 126]. One problem of the Granger causality approach is that it can only gives a static view between two series but fails to capture the time-varying changes of the causality. In order to study the dynamic change of the causality we need to divide the series into several sub-periods and separately test each individual causal relationships. To access the effects of 9/11 on the Granger causality between the US and other 25 foreign stock markets, Hon et al [159] separate the corresponding stock prices into two sub-periods: one year before September 11th, 2011, and one year after that. Their results indicates that there is significant Granger causality from US economy to all the foreign economy after 9/11. However, only one foreign stock market, Germany markets, show Granger causality to the US markets. Similarly, in accessing how the 2007-2009 financial crisis influences the Granger causality among international stock markets, Cheung [160] separates the corresponding series into two sub-periods: one is before the financial crisis and another one is during the crisis.

There are some critical disadvantages to separate the time series. First, if the change of Granger causality lasts for only a short period, the separating strategy can not capture such changes. Another problem is that it can not show the dynamic process. After the terrorist attack, the fluctuation of Granger causality might be vary dramatic.

This transient change of price spillover is critically important for the risk management. Unfortunately, the static view can not capture the time-varying characteristics of this fluctuation. In this study, we apply a time-varying Granger causality test to examine this transient reaction of intermarkets.

The third line of literatures focusing on the equity price contagion and co-movement among international stock markets. Forbes et al [161] define the contagion from one market to another as a significant increase of cross-market correlations after a crisis. There are many literatures documents that the international stock market correlations rise under volatile environments [162, 163, 164]. Unlike the previous literatures testing the correlations, Hon et al [159] focus on the intrinsic heteroskedasticity when testing the contagion of 9/11 terrorist attack. Their results indicate that the international stock markets, especially the Europe markets, respond closely to the US stock market shocks in the following month after 9/11. Regarding to the study of contagion, most of the current literatures focus on the contagion among international stock markets but neglect the co-movement between stock markets and other financial markets, e.g. debt and commodity markets, which is examined in our study.

The rest of this chapter is organized as below. Section 2 reports the data. Section 3 introduces the methods and presents the results. Section 4 discusses the results and concludes this chapter.

4.2 Intermarket Indicator Selection

In this study, we use daily data for empirical analysis. The US stock index is selected to be DJIA and we select twelve other economic variables. The selection of financial variables are as bellow.

1. Debt Market Indicator

In this study, we use the BofA Merrill Lynch US high Yield Master II bond index (BOND) as the debt market indicator. This index tracks the performance of US dollar denominated below investment grade rated corporate debt, which is publicly issued in the US domestic market. It is a commonly used benchmark index for high yield corporate bonds.

2. Foreign Exchange Market Indicator

To access the interaction between foreign exchange markets with stock markets, we use a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners (USD/major), including Euro Area, Canada, Japan, Mexico, China, United Kindom, etc. The detail of the index can be found from Federal Reserve Bank of the US [1].

3. Oil Market Indicator

The oil market indicator we use is Cushing West Texax Intermediate (WTI) spot price. WTI is considered as a "sweet" crude as it has low sulfur concentration that is easily to be refined. WTI is generally used as a benchmark in oil pricing because it owns most customers, transparency and liquidity.

4. Gold Market Indicator

London Gold Fixing Price (GFP) is a benchmark in the international gold market. The price auction takes place twice daily at 10:30 AM and 15:00 PM with price set in US dollars per fine troy ounce. In this study, we apply the GFP at 10:30 as the gold price indicator.

5. Sentimental Indicator

Besides the direct loss in terms of human life and destruction of property, the 9/11 terrorist attack had wide-ranging indirect impacts on social and economic aspects. It is believed such attacks adversely influence the investor confidence, and thereby as well as on outlook of financial markets and economic conditions [165, 166]. In this study, we use an Equity Market-related Economic Uncertainty (EMEU) index [94] to measure the market sentiment. The EMEU is a news-based measure of equity market uncertainty. It is constructed through an analysis of news articles containing terms related to equity market uncertainty. The newspapers are selected from the database of Access World News, which collects thousands of newspapers from across the globe. The newspaper used by EMEU is restricted to that in United States. Thus it can accurately reflect the sentiments in US equity markets.

[1] https://research.stlouisfed.org/fred2/series/DTWEXM

6. International Stock Market Indicator

We select seven representative stock market indices from worldwide to serve as the international stock market indicator, including Financial Times Stock Exchange 100 Index (FTSE 100), Deutscher Aktienindex (DAX), Hong Kong Hang Seng Index (HSI), Shanghai Stock Exchange Composite Index (SSECI), Australian S&P/ASX 200 index (SPASX), Bovespa Index (Ibovespa) of Brazil Stock Market and S&P/TSX composite index (SPTSX) of Toronto Stock Exchange.

The data of BOND, USD/major, WTI, EMEU and DJIA are obtained from Federal Reserve Bank of ST. Louis. All the other data are from Yahoo Finance.

4.3 Methods and Results

As discussed previously, the interaction among financial markets is a dynamic process. In this study, we employ two dynamic approaches to test the time-varying interactions between financial markets. First, we apply a time-varying Granger causality to test the lead-lag relationships between DJIA and the selected variables. Moreover, this test allows us to identify the changes of market forces and improve the forecasting accuracy. Second, we use a DCC-GARCH model to examine the dynamic comovement among markets. This comovement test can show the contagion phenomena under terrorist attack.

4.3.1 Time-varying Granger Causality Test

Considering the dynamic characteristics of stock markets, we adopt the system adaptation framework based time-varying Granger causality approach, as discussed in Chapter 2. This method allow us to adaptively calculate the bidirectional Granger causal strength at each time step. Thus it will gives an transient view of the intermarket reaction around the terrorist event.

Since our concern is the transient reaction of the financial markets to the 9/11 terrorist attack, the testing period will focus on 100 trading days around the terrorist attack. It includes 50 trading days before 9/11 and 50 trading days after that. In what follows we report the time-varying Granger causality test results. For the system adaptation framework, the first step is to estimate its internal OE model. The estimated

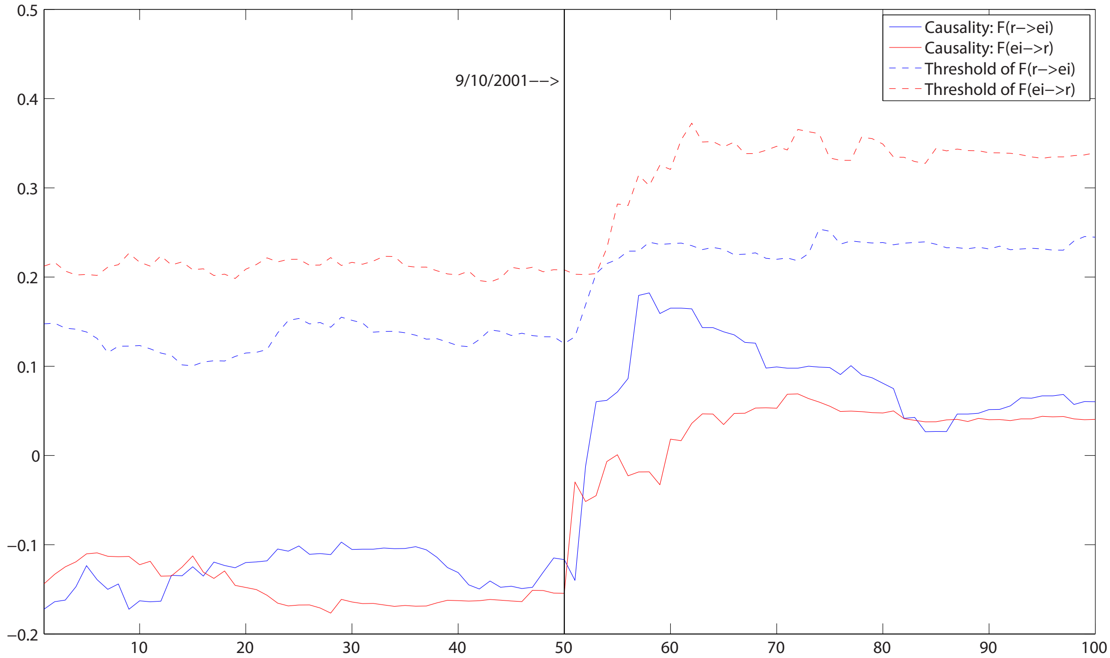

Figure 4.1: Time-varying Granger causality between the internal residue and BOND

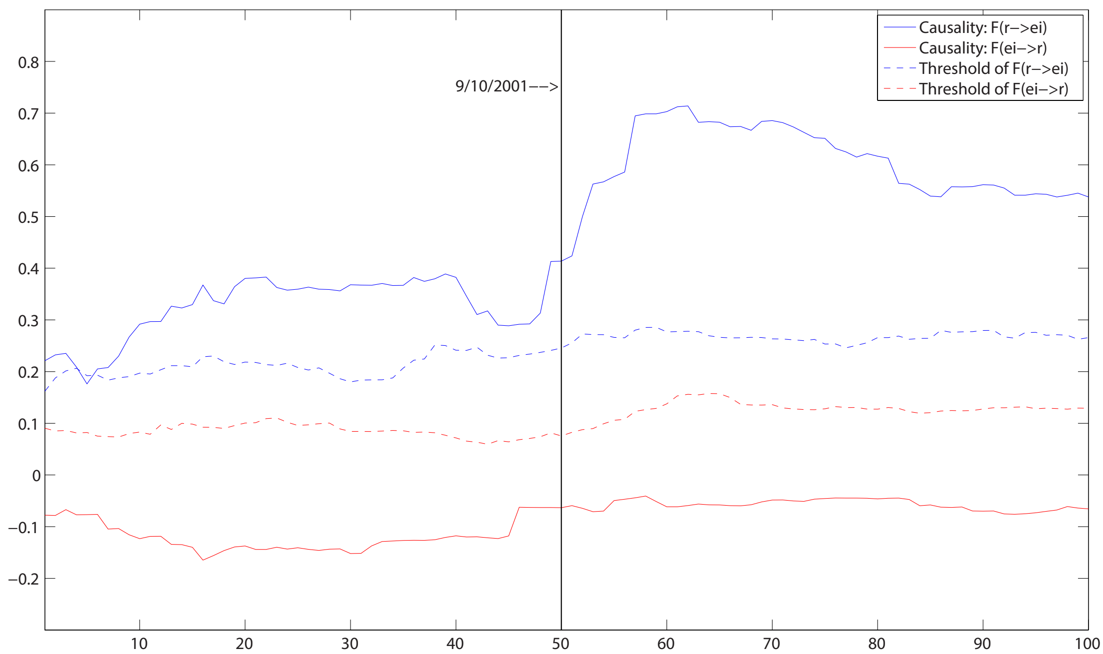

Figure 4.2: Time-varying Granger causality between the internal residue and USD/major

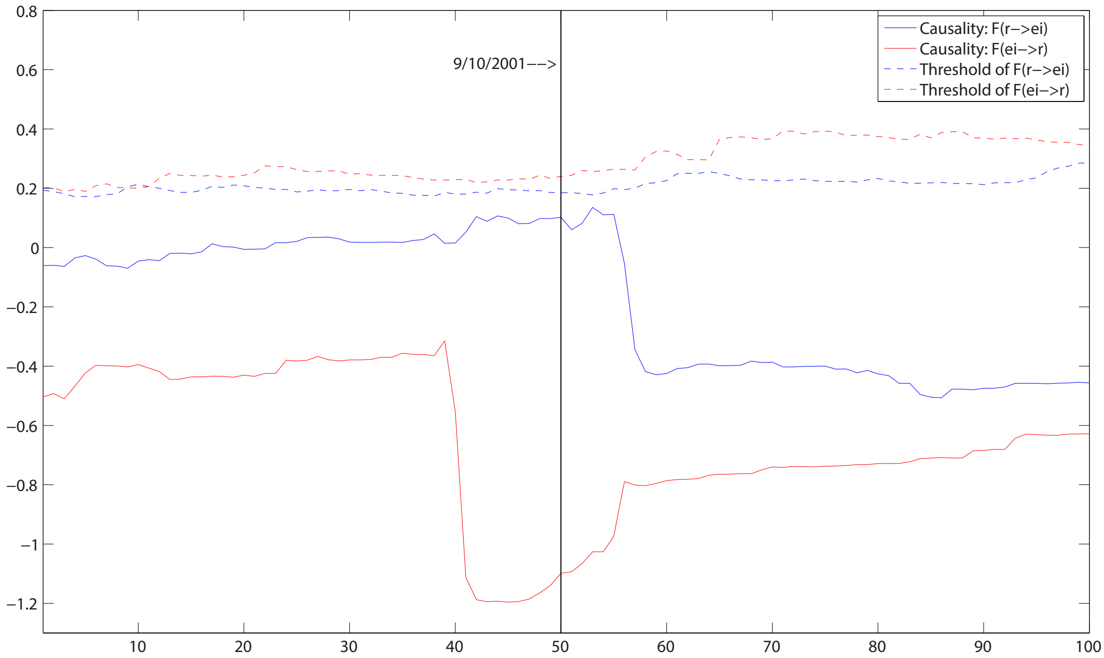

Figure 4.3: Time-varying Granger causality between the internal residue and WTI

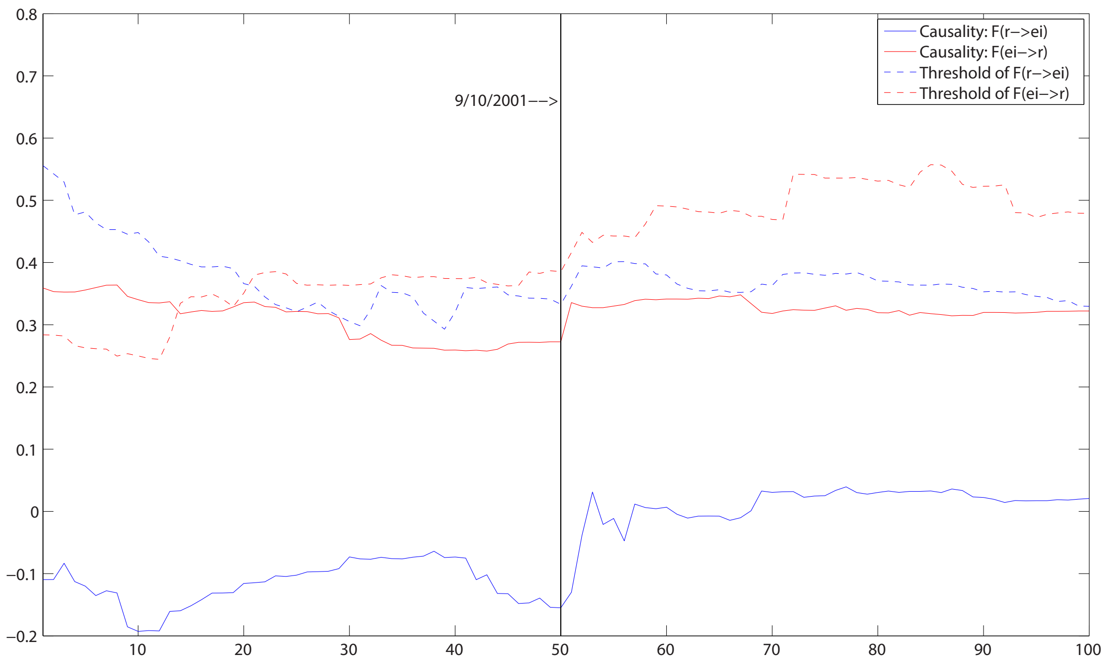

Figure 4.4: Time-varying Granger causality between the internal residue and GFP

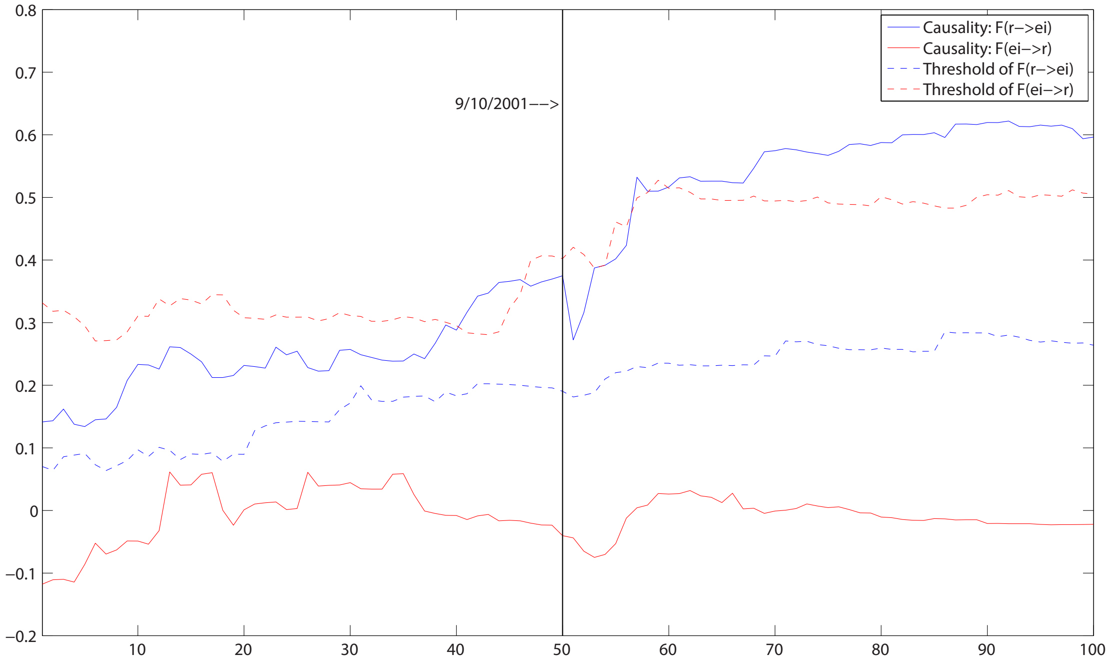

Figure 4.5: Time-varying Granger causality between the internal residue and EMEU

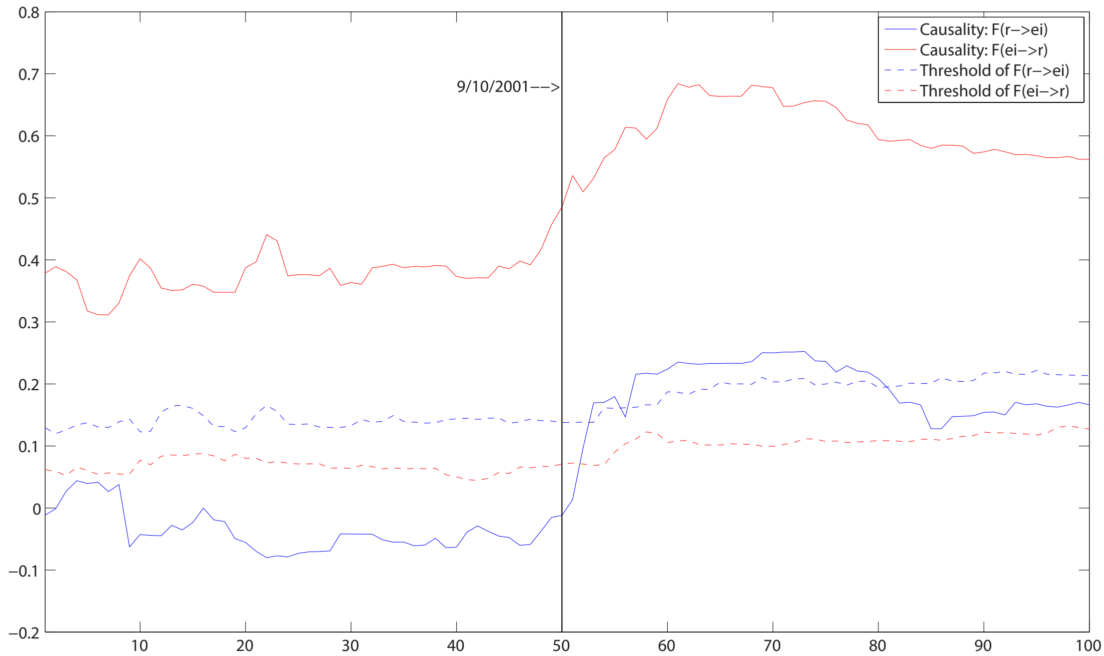

Figure 4.6: Time-varying Granger causality between the internal residue and FTSE 100

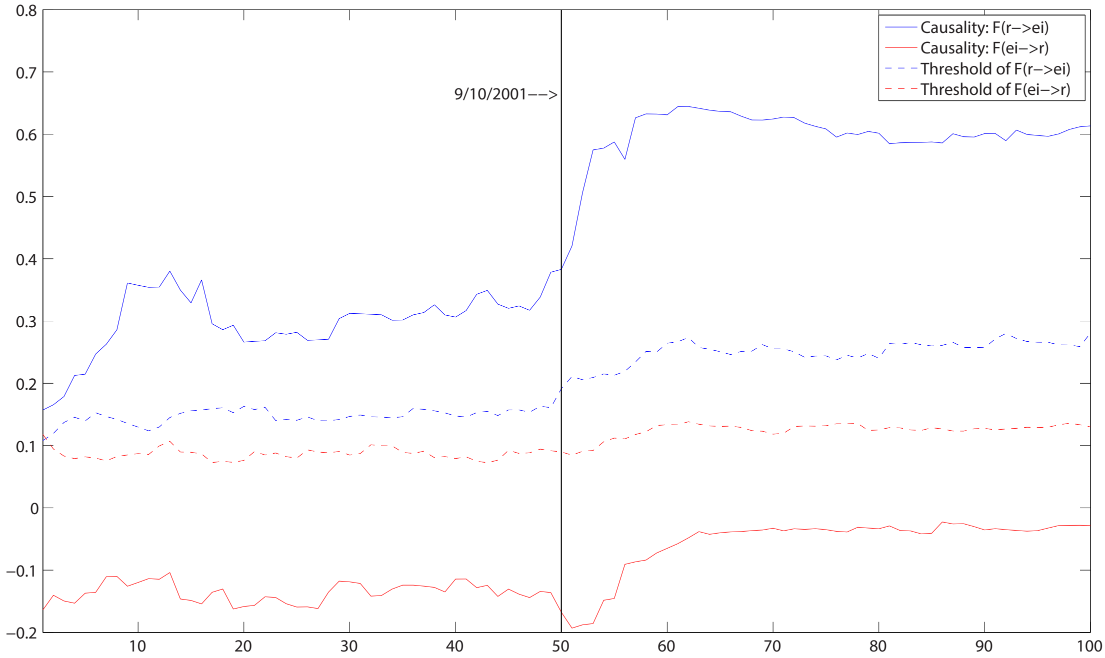

Figure 4.7: Time-varying Granger causality between the internal residue and DAX

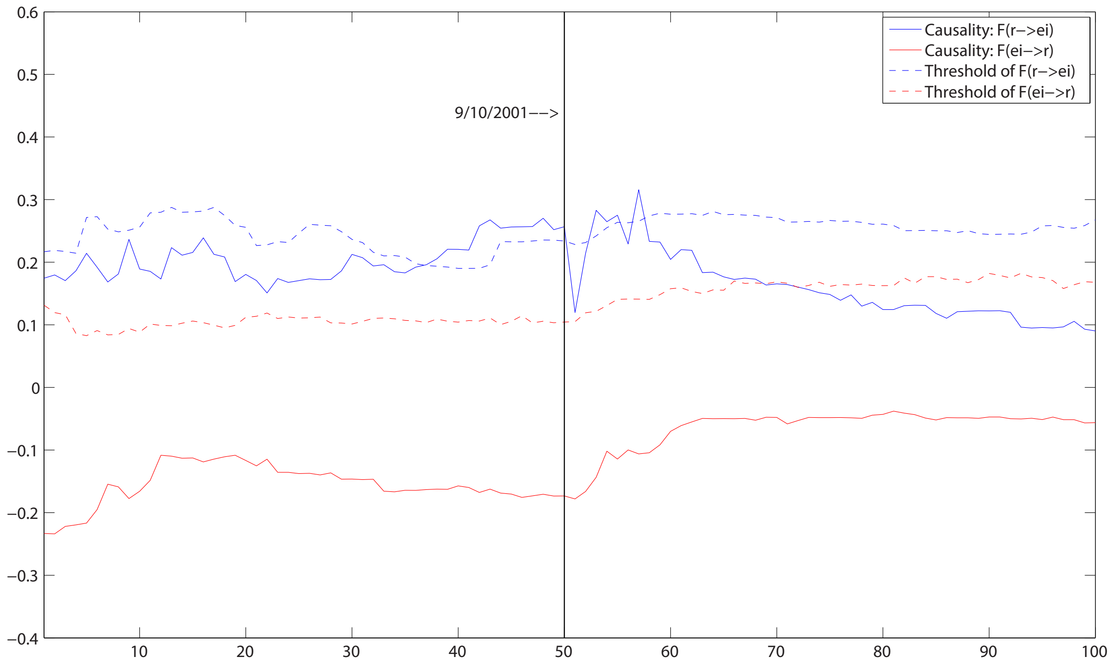

Figure 4.8: Time-varying Granger causality between the internal residue and SPTSX

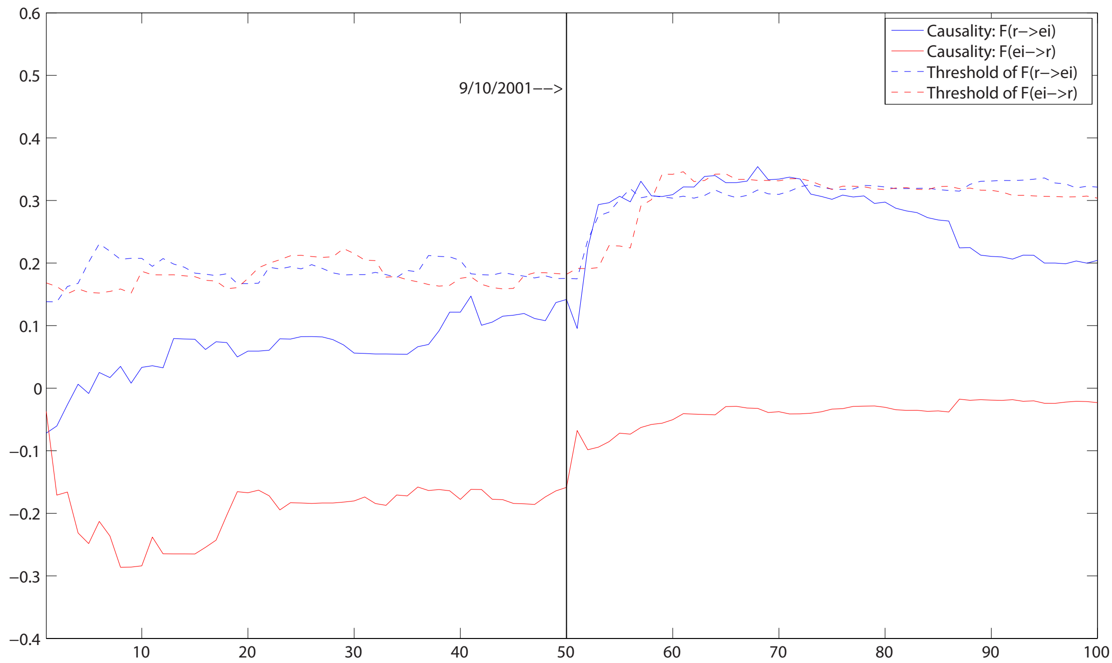

Figure 4.9: Time-varying Granger causality between the internal residue and SPASX

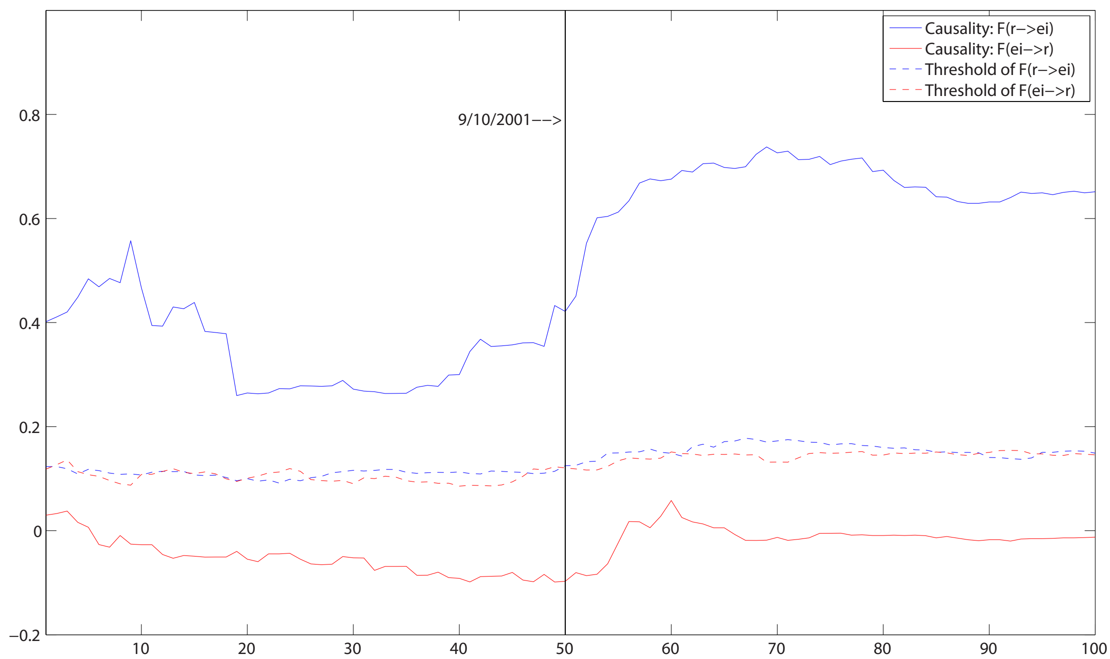

Figure 4.10: Time-varying Granger causality between the internal residue and HSI

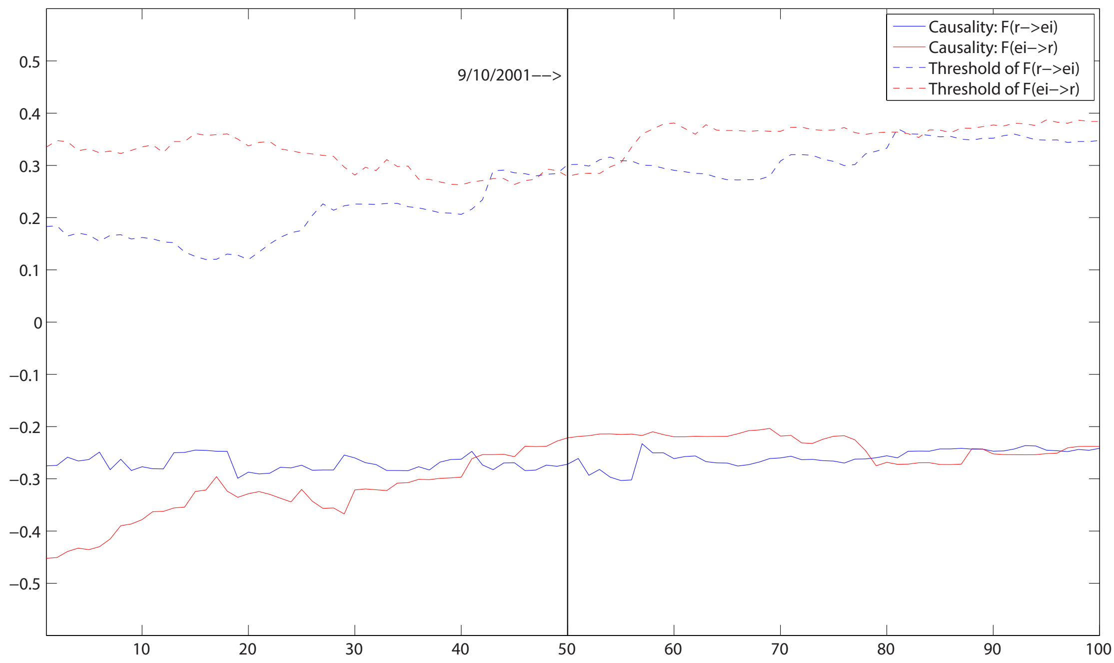

Figure 4.11: Time-varying Granger causality between the internal residue and SSECI

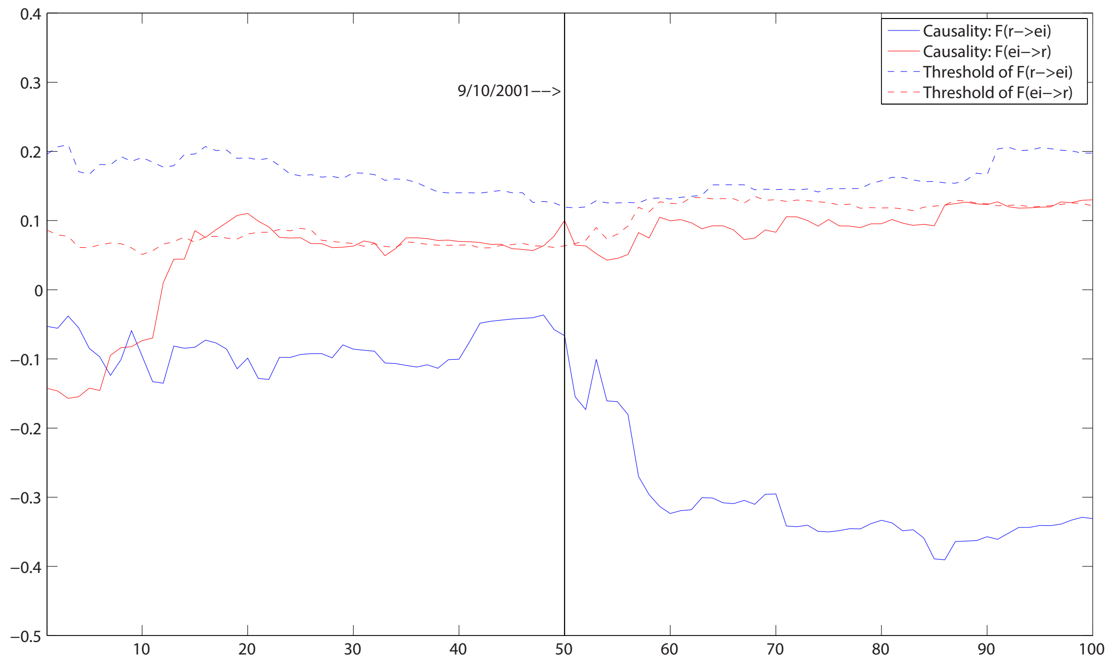

Figure 4.12: Time-varying Granger causality between the internal residue and Ibovespa

OE model is given as below:

$$H(z) = \begin{bmatrix} \frac{-0.1467z^{-1}-0.1398z^{-2}}{1-0.7951z^{-1}} \\ \\ \frac{-0.6976z^{-1}+0.5885z^{-2}}{1-0.814z^{-1}} \\ \\ \frac{2.576z^{-1}-1.025z^{-2}}{1-0.0013z^{-1}} \end{bmatrix}^{\mathrm{T}}. \tag{4.1}$$

Figure 4.1 to Figure 4.12 report the time-varying Granger causality test results between internal residue e_i and the selected indicators r. For each figure, we can observe the bidirectional Granger causality strength and corresponding thresholds. The solid blue lines are the Granger causality strength from the indicators r to the internal residue e_i and the dash lines are the corresponding thresholds. Similarly, the solid red lines are the Granger causality from internal residue to indicators and the dashed red lines are the thresholds respectively. When the causal strength exceeds its corresponding thresholds it indicates the causal relationship is statistically significant.

Among the results, Figure 4.1 to Figure 4.4 present the Granger causality test results between the internal residue and four indicators from debt, foreign exchange and commodity markets. From these figures, we find that only the USD/major exchange rate indicator Granger causes the internal residue over the entire testing period, see Figure 4.2. Moreover, it is interesting to find that this causal strength significantly increased after 9/11. From Figure 4.1 and Figure 4.3, we can find that BOND and WTI do not show any causal linkage with the internal residue during the testing period. As shown in Figure 4.4, the Granger causality from gold price to internal residue is not significant over the testing period. However, the internal residue show weak Granger causality to the gold price at the early stage. Figure 4.5 presents the Granger causality test results between the equity uncertainty indicator and internal residue. The equity uncertainty indicator has unidirectional Granger causality to the internal residue over the testing period. After 9/11, this Granger causality strength experienced a short fluctuation and afterwards significantly increased.

Figure 4.6 to Figure 4.12 report the Granger causality strength between international stock markets and internal residue. The 9/11 terrorist attack has significant impacts to the Granger causality strength between the US and some international stock markets, i.e.

UK, German, Hong Kong and Australia. On the other hand, its effects to the Granger causality between the US and other international stock markets, i.e. China, Brazil and Canada markets, is very weak. From Figure 4.6, we can find that the internal residue show significant Granger causality to the UK stock market over the whole sampling period. However, the Granger causality from UK market to the internal residue is only significant after 9/11, which last around 20 trading days. Moreover, it is worthy to note that both DAX and HSI show unidirectional Granger causality to the internal residue during the whole testing period, see Figure 4.7 and Figure 4.10, and their causal strength significantly increased after 9/11. The Granger causality between Australia market and internal residue is not significant before 9/11, as shown in Figure 4.9. However, after that the Australia market show weak unidirectional causality to the internal residue, which last around 20 trading days. This situation is similar to the interactions between UK market and internal residue.

The Granger causality from Canada market to internal residue is weakly significant before 9/11 but after that it has a fluctuation and subsequently become not significant any more, see Figure 4.8. In addition, our tests also include two emerging markets, the China and Brazil stock markets. As shown in Figure 4.11 , the index of SSECI from China stock market does not present any causal linkage to the internal residue. Although the internal residue has weak Granger causality to Brazil market before 9/11, afterwards it become not significant, see Figure 4.12. These results indicate that the causal linkage or price spillover between the US and these emerging stock markets are very weak during the testing period.

4.3.2 Forecasting Capability of Market Leading Indicators

Our time-varying causality test indicates that there are four variables leading the US stock market during the whole testing period, including USD/major currency, EMEU, DAX and HSI. In the following, these leading indicators are used as inputs of our system adaptation framework to examine their forecasting capability. The testing includes two subperiods: 50 trading days before 9/11 and 50 trading days after that. For each subperiod, the lag length of internal residue in our adaptive filter is selected to be 4, and the lag length of each external input is selected to be 10. In this test, we use an out-of-sample forecasting. The model estimation period is from January 1st, 2000 to

May 10th, 2001. Table 4.1 reports the forecasting performance of the selected indicators by using root-mean-square error (RMSE) and mean absolute error (MAE). In Table 4.1, we compare the forecasting performance of the selected indicators with no inputs. It is clear that the selected indicators significantly improve the forecasting performance of our system adaptation framework: in subperiod S1, the RMSE and MAE are respectively improved by 58.3% and 60.9%; in subperiod S2, the RMSE and MAE are improved by 65.8% and 66.9%.

Under the condition of no inputs, we compare the RMSE and MAE before 9/11 with that after 9/11. It is obvious that both the RMSE and MAE significantly increased after the terrorist attack. The larger forecasting errors indicate that the terrorist attack increased market volatilities. Moreover, the forecasting capability of the selected indicators increased after the terrorist attack. In subperiod S1, the selected indicators can explain 58.3% of RMSE, but this ratio increased to 65.8% in subperiod S2. Similarly, the MAE increased from 60.9% in S1 to 66.9% in S2. These results are consistent with the time-varying Granger causality test, in which the causal strength increased after 9/11. This finding implies that the terrorist attack increased the spillover effect from our selected indicator to internal residue.

Furthermore, we compare the forecasting performance of our system adaptation framework with a conventional ARMAX model, see Table 4.2. The lag length of the ARMAX model are set the similar to our system adaptation framework, i.e., 4 for AR and MA terms and 10 for all the exogenous inputs. As shown in Table 4.2, compared with the ARMAX model, the RMSE and MAE are correspondingly improved by 33.9% and 40.4% in our system adaptation framework in subperiod S1. Moreover, in subperiod S2, the performances are even better than S1: the RMSE and MAE are improved by 52.5% and 46.9% respectively. This better performance implies that the time-varying model has significant advantages to the static model when the financial markets are under extreme fluctuations.

4.3.3 Dynamic Comovement

We use conditional correlations to measure the comovement of intermarkets. In this study, a DCC-GARCH model is used to test the pairwise dynamic conditional correlations between returns of DJIA and the selected indicators. Assume that the studied

Table 4.1: Forecasting capability of the selected market forces

Model inputs	Subperiod S1 50 trading days before 9/11		Subperiod S2 50 trading days after 9/11	
	RMSE	MAE	RMSE	MAE
No inputs	202.7	165.0	275.3	210.6
USD/major HSI DAX EMEU	84.6	64.5	94.1	69.7
Improvement	58.3%	60.9%	65.8%	66.9%

Table 4.2: Forecasting performance of the system adaptation framework

Model	Subperiod S1 50 trading days before 9/11		Subperiod S2 50 trading days after 9/11	
	RMSE	MAE	RMSE	MAE
ARMAX	128.0	108.2	197.6	131.3
System adaptation framework	84.6	64.5	94.1	69.7
Improvement	33.9%	40.4%	52.5%	46.9%

k time series are multivariate normally distributed with zero mean and conditional variance-covariance matrix H_t, the multivariable DCC-GARCH model can be presented as below:

$$\begin{cases} r_t = \mu_t + \xi_t, \qquad \xi_t|\Omega_{t-1} \sim N(0, H_t) \\ H_t = D_t R_t D_t \end{cases} \tag{4.2}$$

In which, r_t is the $(k\times 1)$ vector of the studied time series; ξ_t is a $(k\times 1)$ vector of zero mean innovations conditional on the available information Ω_{t-1}; $\mu_{i,t} = \delta_{i,0} + \delta_{i,1} r_{i,t-1}$ for the time series i; D_t is a $(k \times k)$ diagonal matrix and its main diagonal elements are the conditional standard deviations of the studied variables, which is defined as below:

$$D_t = diag(h_{11,t}^{\frac{1}{2}} \dots h_{kk,t}^{\frac{1}{2}}) \tag{4.3}$$

where $h_{ii,t}$ is estimated from the univariate GARCH(p, q) model in the following manner

$$h_{ii,t} = \omega_{i,t} + \sum_{j=1}^{p} \alpha_i \xi_{i,t-j}^2 + \sum_{j=1}^{q} \beta_i h_{ii,t-j}, \forall i = 1, 2...k \tag{4.4}$$

In equation 4.2, R_t is the $(k \times k)$ conditional correlations matrix and defined as follows

$$R_t = Q_t^* Q_t Q_t^* \tag{4.5}$$

where Q_t is the conditional variance-covariance matrix of residuals with the following DCC(m,n) structure

$$Q_t = (1 - \sum_{i=1}^{m} a_i - \sum_{j=1}^{n} b_j)\bar{Q} + \sum_{i=1}^{m} a_i(\nu_{t-1}\nu'_{t-1}) + \sum_{j=1}^{n} b_j Q_{t-1} \tag{4.6}$$

where ν_t is standardized residue, $\nu_{i,t} = \xi_{i,t}/(h_{ii,t})^{1/2}$; $\bar{Q}$ is the $(k \times k)$ unconditional variance of matrix of ν_t , $\bar{Q} = E[\nu_{t-1}\nu'_{t-1}]$; Q^*_t is a $(k \times k)$ diagonal matrix containing the square root of the diagonal elements of Q_t, $Q^*_t = diag\{\sqrt{q_{ii,t}}\}$. a_i and b_j are non-negative scalar parameters satisfying $a_i + b_j < 1$.

The conditional correlation coefficient ρ_{ij} between two interested series i and j is as follows

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{4.7}$$

The estimation of DCC-GARCH model include two steps. In the first step, an univariate GARCH model is estimated for the individual time series. In the second step, the standardized residuals obtained from the first step are used to calculate the conditional correlation estimator. The log-likelihood of the observations of ξ_t is given by

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t R_t D_t| + \xi'_t D_t^{-1} R_t^{-1} D_t^{-1} \xi_t) \tag{4.8}$$

where T is the number of observations and n is the number of the variables in the equation system. Since we have $\nu_t = \xi_t/\sqrt{h_t} = D_t^{-1}$, the log-likelihood function can be rewritten as below

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \nu'_t R_t^{-1} \nu_t) \tag{4.9}$$

As suggested by [167], the estimation of GARCH models is highly to be biased when the sample size is not large enough. Thus in this study, the testing period is extended to be from September 2000 to September 2002. In this study we use a DCC(2,2)-GARCH(1,1) model and the identified parameters are reported by Table 4.3. Figure 4.13 to Figure 4.24 present the DCC between the daily returns of DJIA and the selected variables, and Table 4.4 are the corresponding statistics of these DCC results.

Figure 4.13 to Figure 4.16 report the DCC testing results between DJIA and other

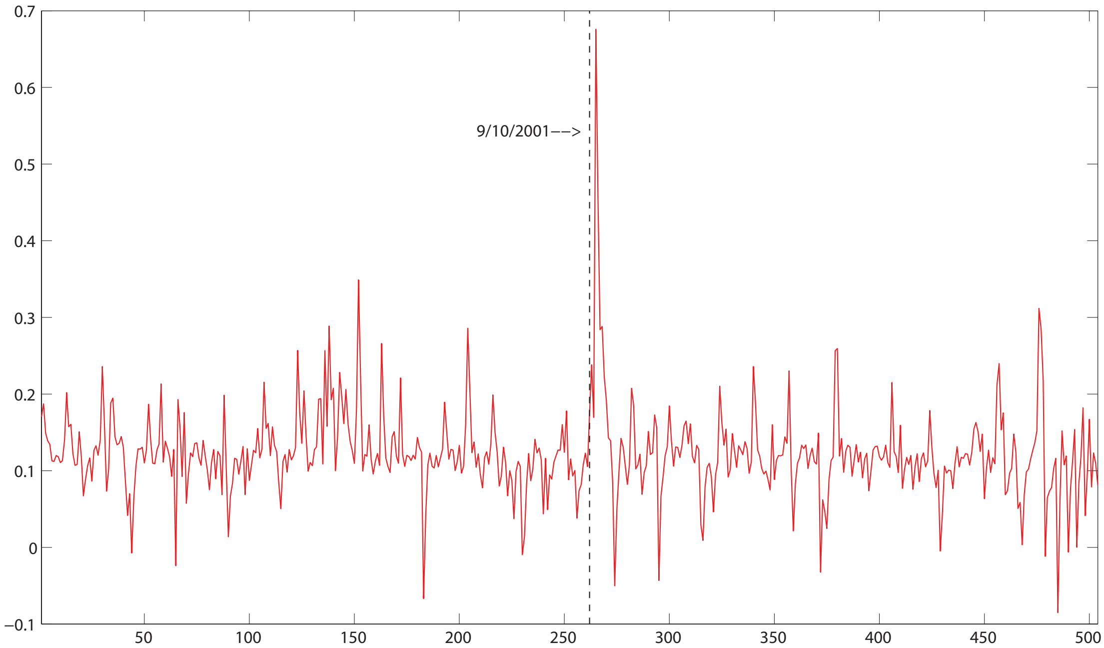

Figure 4.13: Dynamic conditional correlations between returns of DJIA and BOND

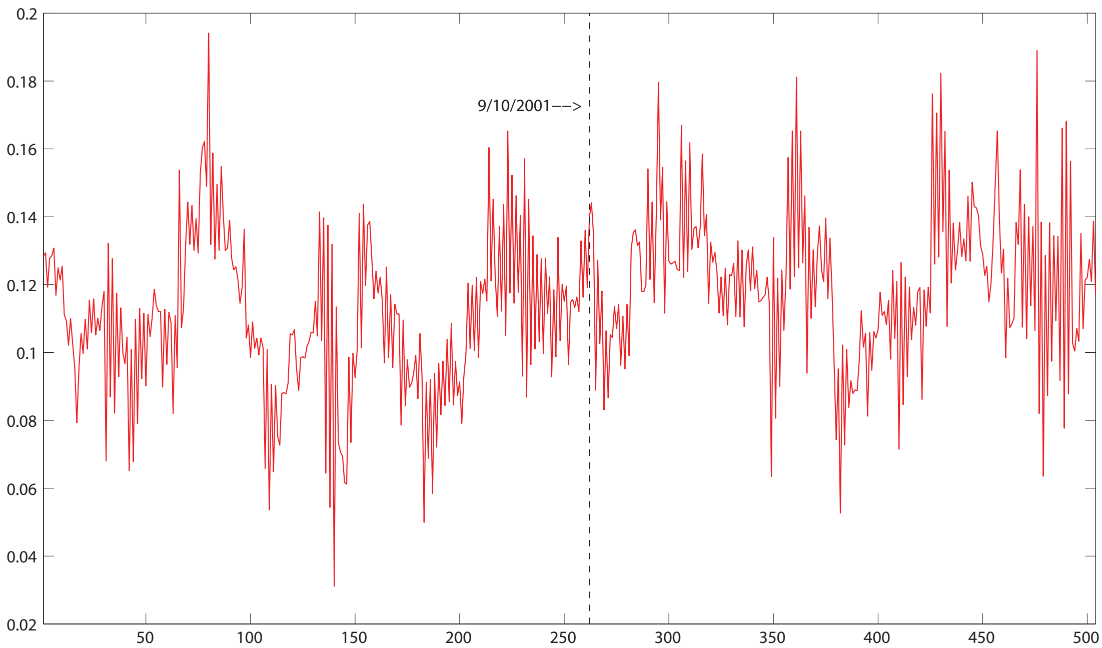

Figure 4.14: Dynamic conditional correlations between returns of DJIA and USD/major

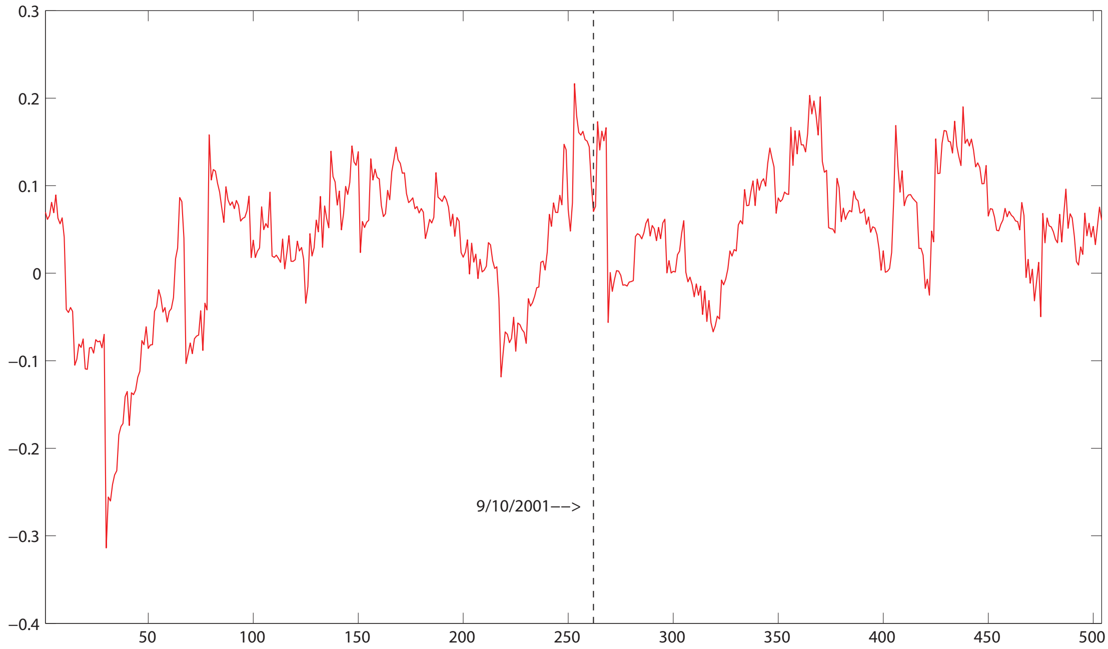

Figure 4.15: Dynamic conditional correlations between returns of DJIA and WTI

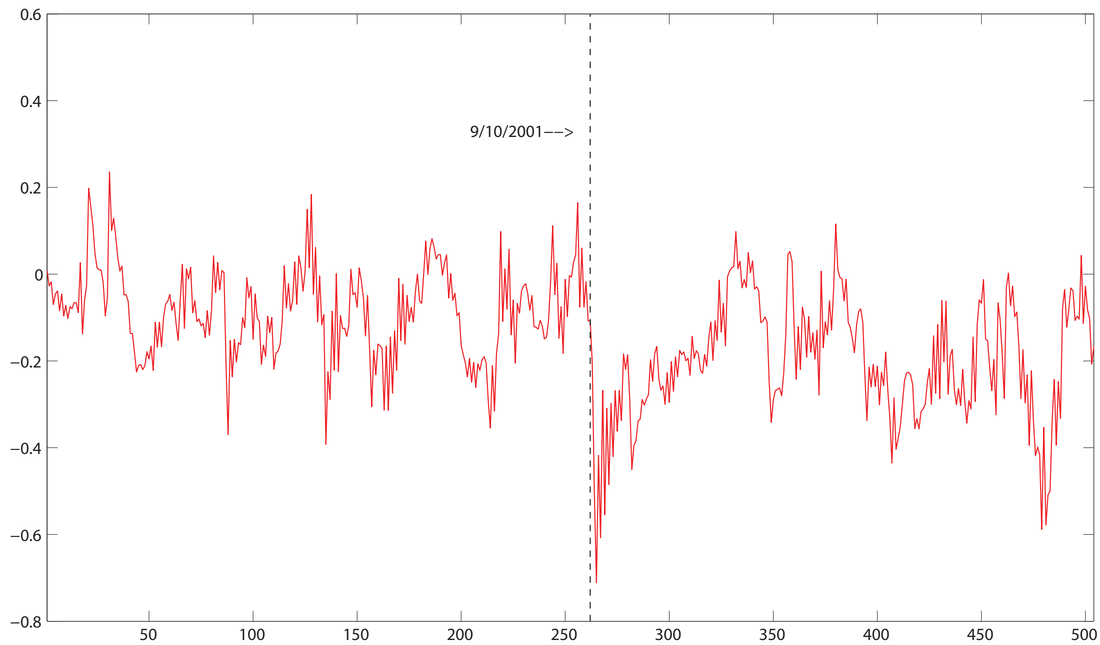

Figure 4.16: Dynamic conditional correlations between returns of DJIA and GFP

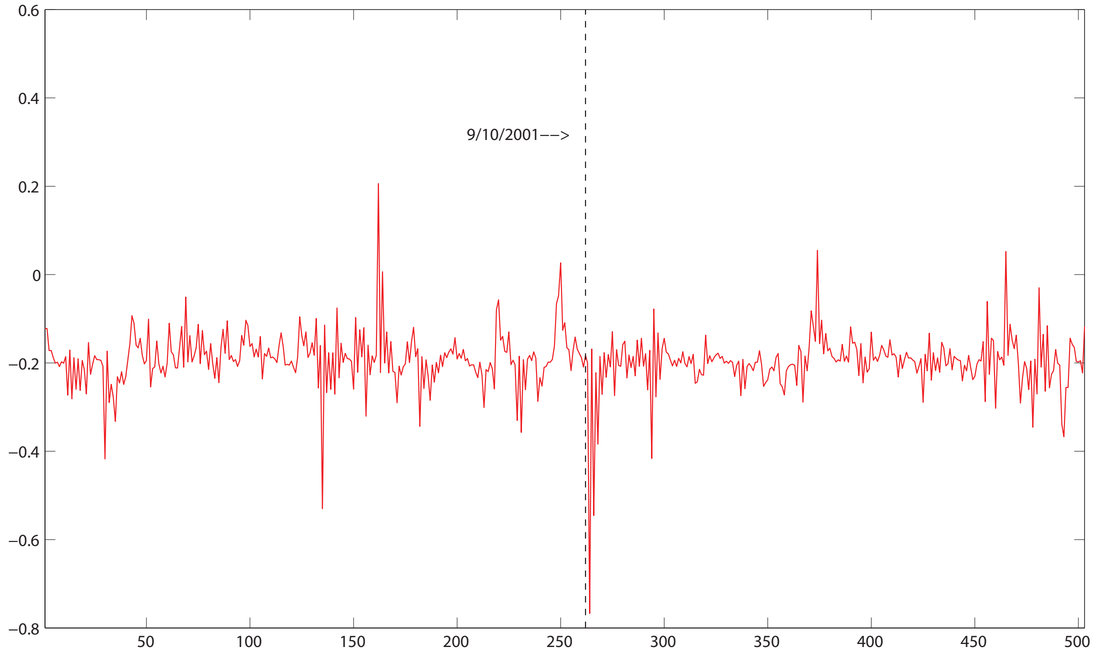

Figure 4.17: Dynamic conditional correlations between returns of DJIA and EMEU

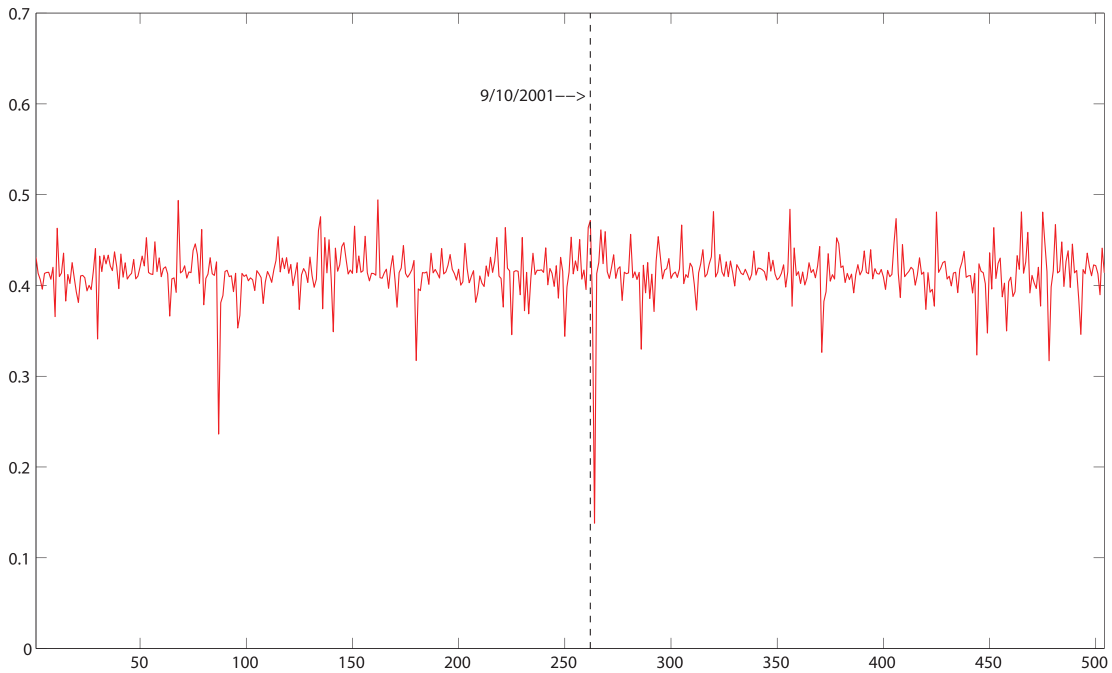

Figure 4.18: Dynamic conditional correlations between returns of DJIA and FTSE 100

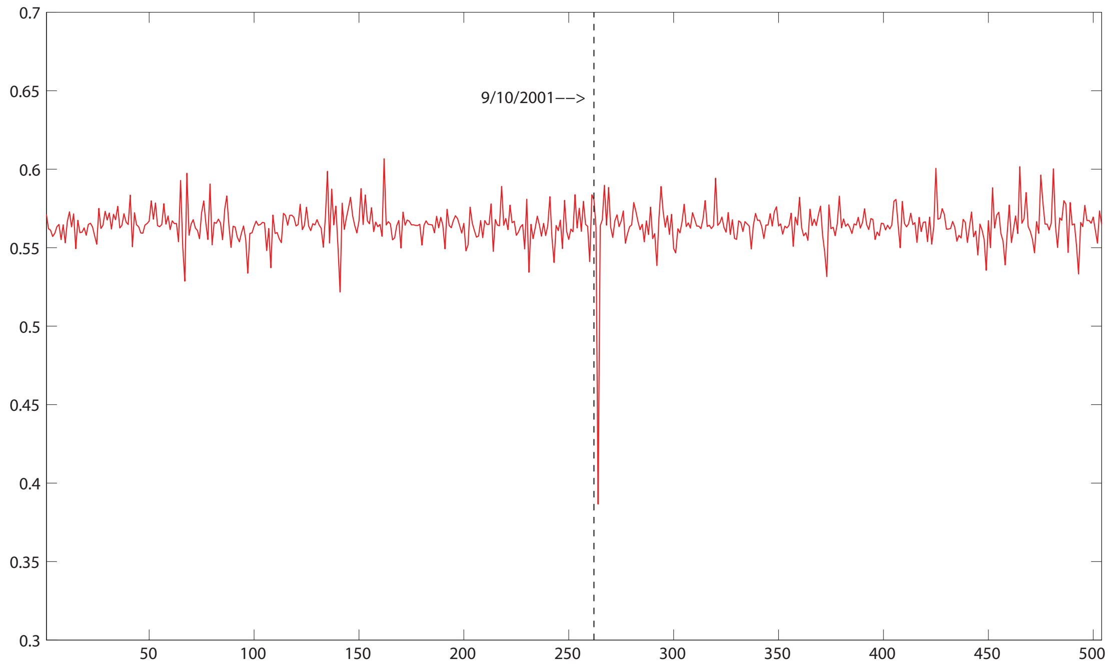

Figure 4.19: Dynamic conditional correlations between returns of DJIA and DAX

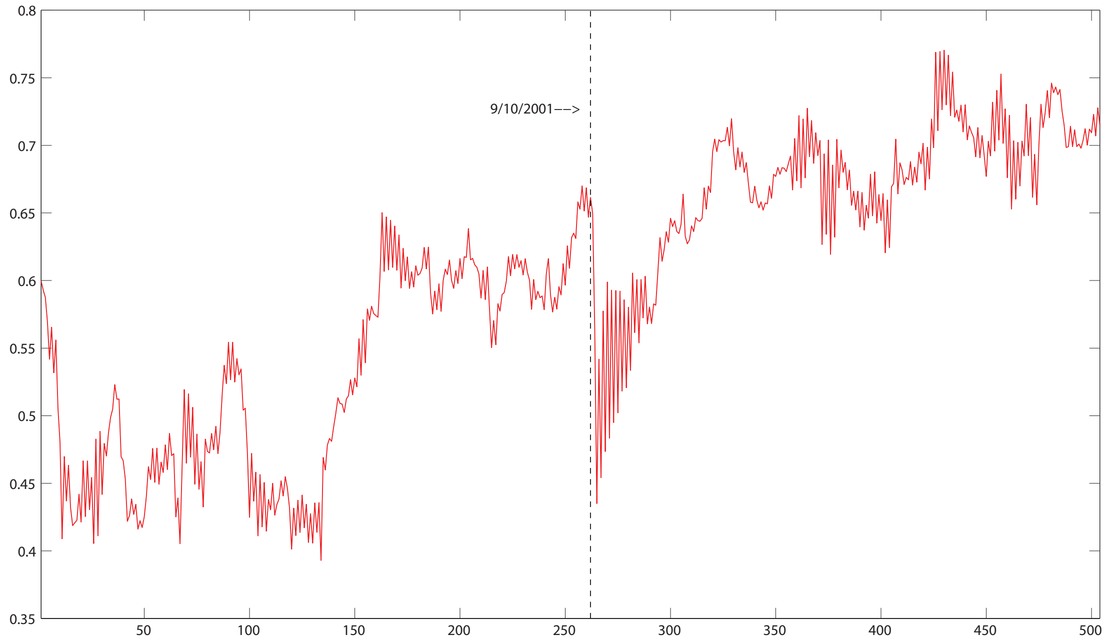

Figure 4.20: Dynamic conditional correlations between returns of DJIA and SPTSX

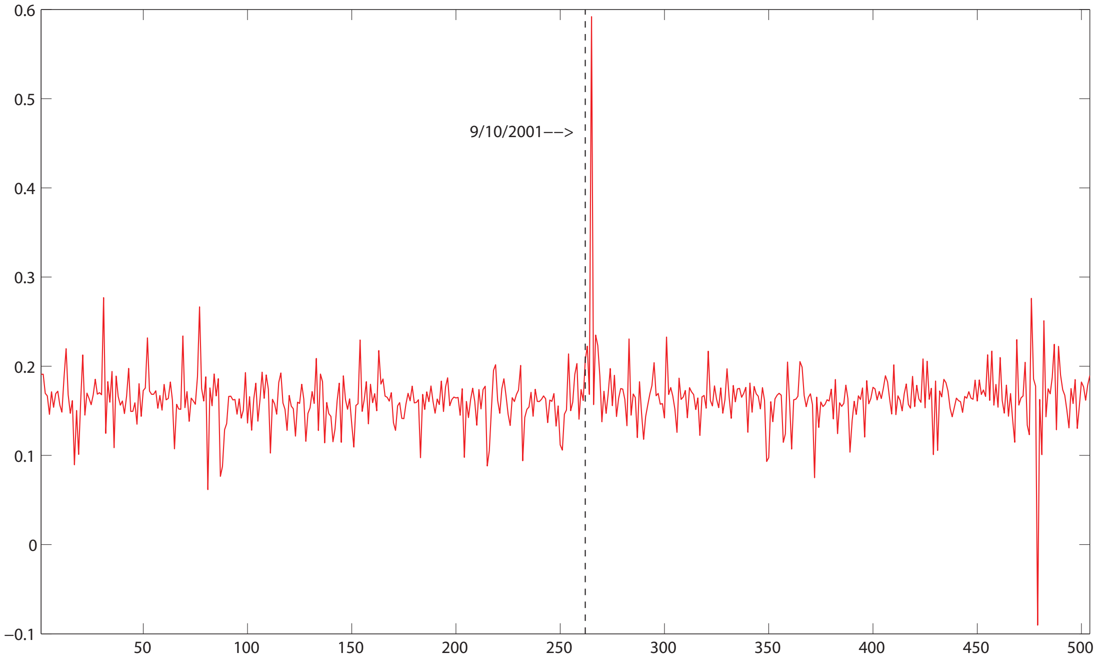

Figure 4.21: Dynamic conditional correlations between returns of DJIA and SPASX

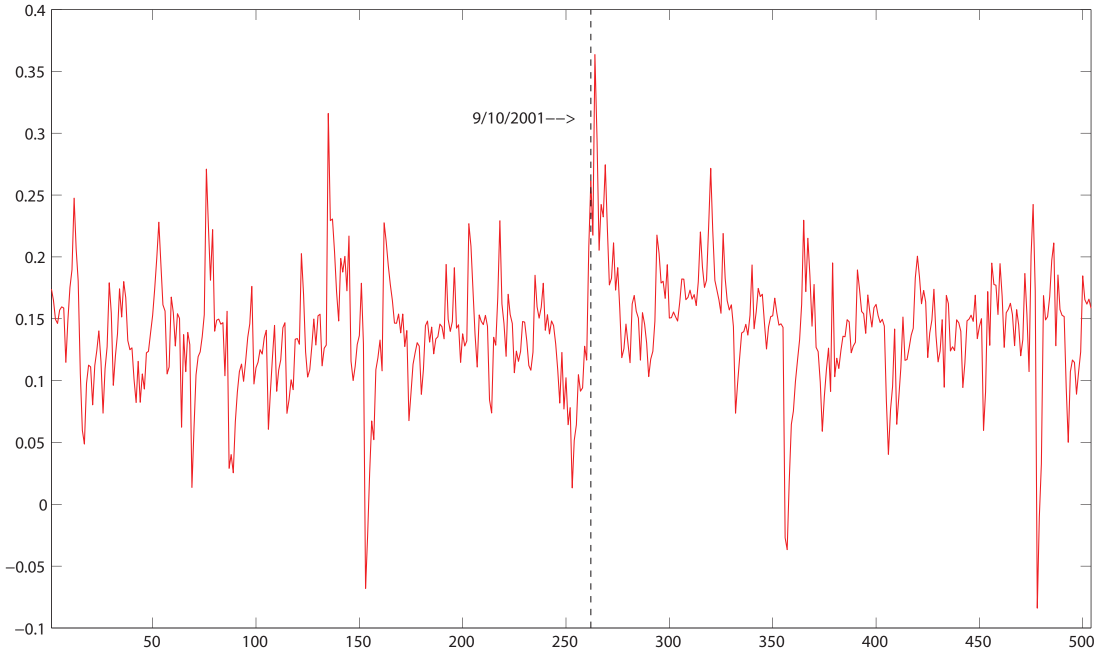

Figure 4.22: Dynamic conditional correlations between returns of DJIA and HSI

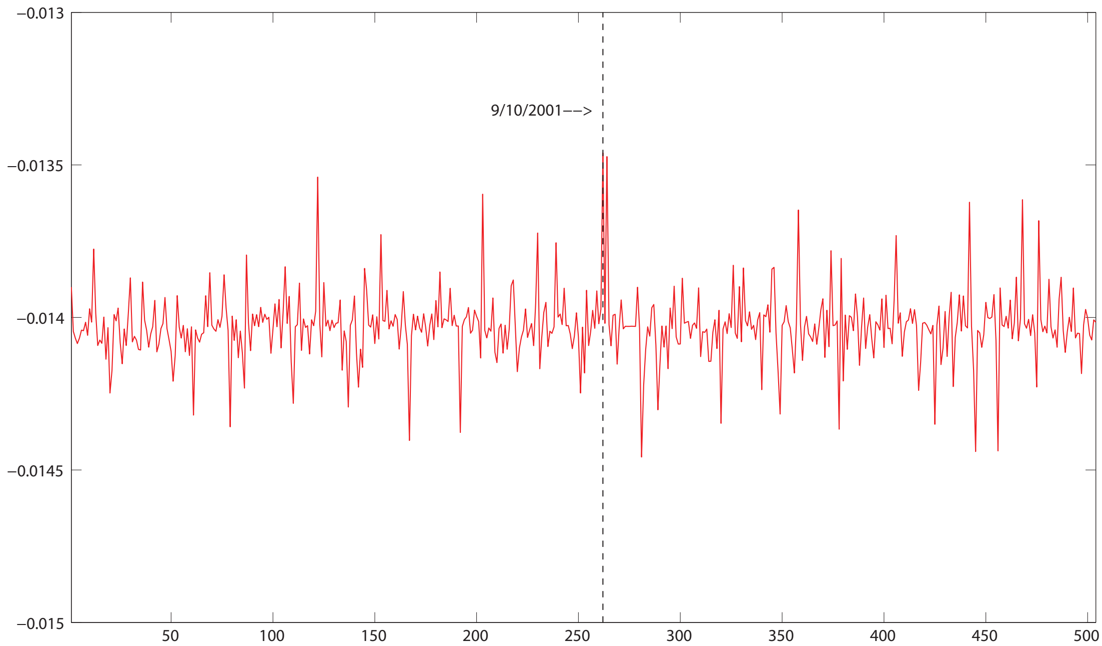

Figure 4.23: Dynamic conditional correlations between returns of DJIA and SSECI

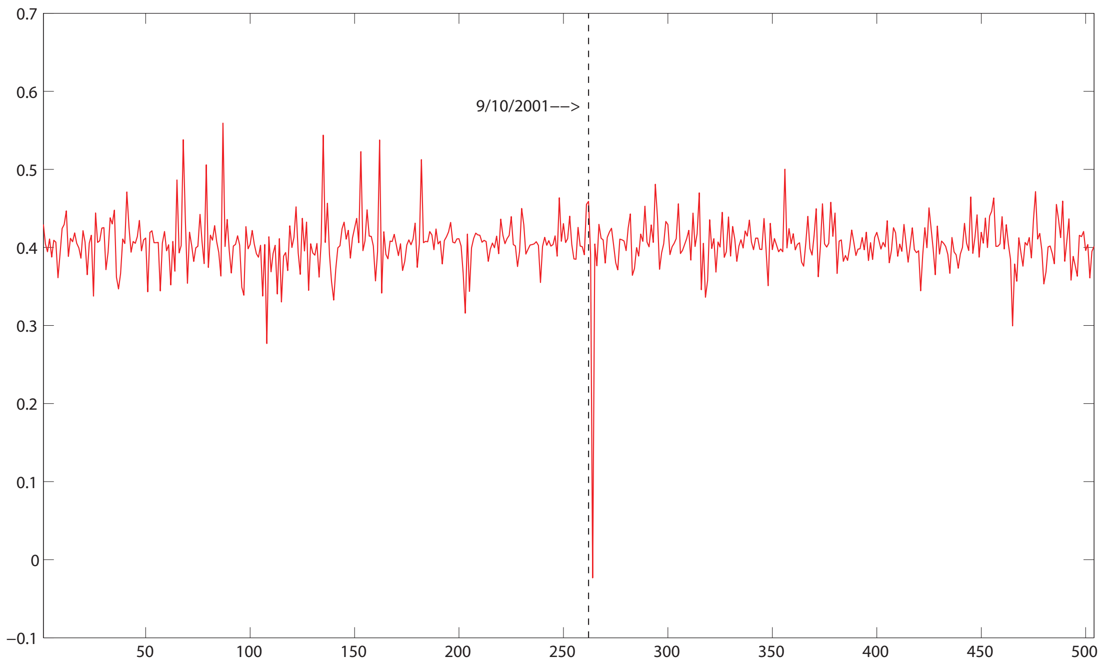

Figure 4.24: Dynamic conditional correlations between returns of DJIA and Ibovespa

Table 4.3: Parameters of the DCC-GARCH test between DJIA and the selected variables

Variables	DCC-GARCH Model Parameters						
	ω	α_1	β_1	a_1	a_2	b_1	b_2
DJIA	1758.8	0.0931	0.8091	-	-	-	-
Bond	0	0.5846	0.4136	0	0.0556	0.3597	0
USD/Major	0.0119	0.0325	0.8968	0	0.0150	0.0793	0.7287
WTI	0.0240	0.0953	0.8634	0.0324	0	0.6308	0.2685
Gold	0.5670	0.0784	0.8180	0.0393	0.0935	0	0.6539
EquityUn	398.5534	0.1182	0.8818	0	0.0641	0	0.3204
FTSE 100	152.6473	0.1277	0.8441	0.0296	0	0	0
DAX	330.8094	0.0830	0.8783	0.0156	0	0	0
S&P/ASX 200	47.7241	0.0617	0.8550	0	0.0324	0	0.1072
S&P/TSX	875.5053	0.2155	0.7592	0.0104	0.0287	0.0658	0.8950
Ibovespa	7020.3	0.0170	0.8835	0.0417	0	0	0
HSI	447.7942	0.0757	0.9119	0.0374	0.0275	0	0.3402
SSECI	94.0374	0.3524	0.5389	0.0001	0	0	0

Table 4.4: Statistics of the DCC results

Variables	Summary Statistics				
	Mean	Median	Maximum	Minimum	Std. Dev.
Bond	0.1227	0.1185	0.6758	−0.0852	0.0583
USD/Major	0.1151	0.1150	0.1941	0.0311	0.235
WTI	0.0398	0.0533	0.2165	−0.3138	0.0788
Gold	−0.1404	−0.1237	0.2556	−0.7110	0.1339
EquityUn	−0.1942	−0.1933	0.2060	−0.7671	0.0652
FTSE 100	0.4136	0.4139	0.4943	0.1381	0.0274
DAX	0.5644	0.5644	0.6067	0.3867	0.0129
S&P/ASX 200	0.1632	0.1630	0.5920	−0.0903	0.0349
S&P/TSX	0.5951	0.6092	0.7704	0.3929	0.0986
Ibovespa	0.4046	0.4047	0.5593	−0.0233	0.0357
HSI	0.1406	0.1437	0.3581	−0.0758	0.0489
SSECI	−0.0140	−0.0140	−0.0135	−0.0145	0.0001

financial markets. From Figure 4.13, we can find that BOND has a relatively stable positive conditional correlations with the DJIA. Before the terrorist attack, it generally fluctuates around the average value of 0.12. However, after 9/11 the conditional correlations sharply rose in the following several days, and nearly reached the global peak 0.7. The average value of the DCC between USD/major and DJIA is about 0.11, and its fluctuations show some cycle patterns, see Figure 4.14. After 9/11, this DCC had a sharp decrease but the amplitude was not very large. The two commodity market indicators, WTI and GFP, present different DCC patterns with DJIA. As shown in Figure 4.15, the DCC between WTI and DJIA was positively correlated before 9/11, but after that it had a small increase with short fluctuations. Subsequently, the DCC experienced a sudden drop and became negative. Compared with WTI, the DCC between gold markets and DJIA had a larger and faster response to the terrorist attack. From Figure 4.16, we can see that their DCC value had a rapid decrease after 9/11 and reached the global low of -0.71. In the following three months, it gradually rebounded to the level of pre-crisis. Therefore, the impact of 9/11 terrorist attack on the comovement between gold and stock markets was relatively stronger and the rebounding time was also longer. Figure 4.17 presents the DCC results between EMEU and DJIA. As expected, these two variables were negatively correlated with each other in most of the testing period. Following the terrorist attack, the DCC sharply declined to the global low -0.77 and then experienced a quick rebound, which lasted around one week.

Figure 4.18 to Figure 4.24 report the DCC between US and international stock markets. In the seven results, most of the correlations experienced drastic fluctuations immediately after the terrorist attack. However, the fluctuating directions and patterns are not unique. The results from two markets of European countries, UK and German, show similar results, see Figure 4.18 and Figure 4.19. Both of them are positively correlated with the US stock market, and their correlations are relatively stable during the testing period. Furthermore, the terrorist attack had significantly negative shock to their correlations with the US markets. This negative reaction is very fast, but subsequently the impact quickly disappear. Therefore, our results did not find the contagion effect between the US and these two stock markets. In addition, it is interesting to find that the DCC test from Brazil stock markets show the similar feature to that of UK and German markets, see Figure 4.24.

The DCC between Canada and US stock markets also plummeted dramatically after the terrorist attack, and afterwards it gradually increased to the level before the crisis, as shown in Figure 4.20. It is worthy to point out that the recovering process took around three months, which is the longest among the seven international stock markets tested. It indicates that the terrorist attack might change the long-term relationship between the US and Canada stock markets. The DCC reaction from Australia and Hong Kong markets present significant contagion pattern: the correlation rose dramatically after 9/11, see Figure 4.21 and Figure 4.22. Following the contagion, the DCC between the US and Australia markets quickly return to the pre-crisis level. However, it took around two weeks for the Hong Kong market to remove the impact of this shock. It is interesting to find that the correlation between the US and China stock markets is very weak during the whole testing period, as shown in Figure 4.23. Moreover, the China market did not show significant fluctuations during the crisis. One reason might be that the China stock market was developing and isolated from the international markets in early 2000.

4.4 Discussions and Conclusions

This study empirically examines the dynamic interactions between the US stock market and other financial markets, including debt, foreign exchange, commodity and international stock markets. Moreover, one sentimental factor, the equity market uncertainty indicator is also studied. We apply a time-varying Granger causality approach to investigate the transient reaction of lead-lag relationship among markets. To the best of our knowledge, this is the first study to reveal the time-varying Granger causality of inter-markets under terrorist attack. There are some important finding from our time-varying Granger causality test results that are worthy to note. First, the causal relationship have different reactions to the terrorist attack. However, in general, the Granger causality strength experienced fast changes after 9/11. Furthermore, some causality directions even changed, e.g. the results from FTSE 100, as shown in Figure 4.6. Second, the explanatory capability of the US stock market forces significantly increased after 9/11. Our study identified four variables that can serves as driving forces of DJIA during the whole testing period, including USD/major, EMEU, DAX and HSI. After 9/11, all of their causal strength to DJIA significantly increased. It indicates that the terrorist attack increased the spillover effect from these variables to the US stock markets. This dynamic change of spillover can help the shareholders and policy marker to track the price and information diffusion among markets. Moreover, the identified stock market forces can be used to forecast the stock prices. As shown in Table 4.1, the identified forces significantly improve the forecasting performance of the system adaptation framework.

In addition to causal relationship, the dynamic correlation around 9/11 is another interest of this study. We apply a DCC-GARCH model to test the correlation fluctuation between the US stock markets and other financial markets. There are some interesting findings from this time-varying correlation testing. First, there were only two markets that shown the contagion phenomena, i.e. the Hong Kong and Australia markets. For the other markets, following the terrorist attack is a sudden fall of the correlation rather than increase. Second, our results find that the terrorist attack generally shocked comovement of financial markets, but the lasting periods of this shock are quite different from each other. In some markets, it took around three month to return to the precrisis level, e.g. the GOLD and SPTSX. However, for the others, e.g. FTSE 100 and DAX, the fluctuation only lasted for a very short period. One reason might be that the co-movements between these markets and the US stock markets are commonly steady except at the terrorist attack period. Take the DAX for example, its DCC normally runs around 0.56 with very small fluctuations except the crisis period, see Figure 4.19. Although the terrorist attack sharply shocked the comovements, it did not influence this steady long-run relationship. After the fast fluctuations, their comovements can quickly return to the normal level.

In this study, we employ two dynamic approaches to analyze the intermarket relationships between US stock markets and eleven other financial markets as well as one news based economic uncertainty indicator. It is worthy to highlight some of our finding from these intermarekt analysis. First, regarding the relationship between the high yield master bond with the stock markets, our results indicate that there exists weakly positive correlation between them, but no significant causal linkage It is easy to understand this positive correlation because the high yield mast bond index tracks the performance of US corporate bonds, which should be positively correlated with the corporate stock prices. However, our finding of no causal linkage between the corporate bonds and stock price is different from the finding of Norden et al [168], in which they use US and Europe firm level bond and stock data between 2000-2002 to investigate the existence of lead-lag relationship. Their results indicate that many firm's stock return can lead the spread change of corresponding bonds. Second, our DCC-GARCH tests reveal that there exists significant contagion between the high yield bond and stock markets. Following the terrorist attack, the correlations sharply rises to global peak. Thus a portfolio of corporate bonds and stocks might increase the risk.

Second, the evidence from foreign exchange markets show that the USD/major had unidirectional Granger causality to the US stock markets. Moreover, the terrorist attack enhance this causal linkage. The unidirectional causal relationship is in favor of the traditional transmission theory. This theory argues that the currency fluctuation will influence the exports, and therefore the corporate profits and stock price will be impacted ultimately. However, many practical factors might influence this theory, e.g. government intervention and imperfect markets. This is why the empirical literatures always get controversial results under different situations. To the best of our knowledge, we have not noticed any other literature documenting the dynamic interactions between currency and stock markets under terrorist attack. One most related paper might be from [126], in which the lead-lag relationship between stock prices and exchange rates is studied using the Asiaflu crisis data. It is found that different countries show different lead-lag patterns under the crisis. Our study might shed light in the dynamic lead-lag study in the terrorist crisis period.

Third, investor sentiment plays a increasing role in stock price dynamics. Investor sentiment, defined broadly, is a belief about the future cash flow and potential risks that is not justified by the true fact at hand [169]. After 9/11, the disasters were continually reported by massive newspapers and televisions. Thus the fear and uncertainty environments negatively influenced the sentiment of investors. Since the indicator EMEU is derived from the influential newspapers in equity markets, it serves well as an indirect indicator of the investor sentiment. The 9/11 terrorist attack increased the causal strength from EMEU to stock markets, as shown in Figure 4.5. This result also indicates that the media reports are important sources influencing the market sentiments and ultimately the stock prices.

This work first applies the system adaptation framework based time-varying Granger causality approach to the study of intermarket reactions under terrorist attack. Although we have got many interesting results it is essential to point out that there are still many work left to do in this field. One direction is to study the interaction among more markets. Since this work mainly consider the relationship between DJIA and several other financial variables, many other economic or financial variables still deserve more study, e.g. the treasury bonds and some financial derivatives. Second, an examination of price and volatility spillover at sector or firm levels can give more details of the dynamic market reactions. Furthermore, it is worthy to note that this dynamic method can be widely used to study some other unexpected shocks, e.g. natural disasters.

Chapter 5

Identification of China Stock Market Forces

5.1 Introduction

Identification of stock market forces is of crucial importance not only in forecasting equity returns, but also in understanding the linkage between stock markets and real economy. The driving forces in developed markets have been extensively studied in numerous literatures. However, there is a lack of literatures investigating the driving forces in emerging markets. Harvey [100] reports that emerging stock markets are independent from international capital markets, and thus their market dynamics and driving forces are quite different from that in the developed markets. As rapid development of the emerging markets, identification of market forces is becoming critically important for policy makers and shareholders.

This study aims to identify the driving forces in the China stock markets, focusing on Shanghai Stock Exchanges (SSE). As a representation of the emerging markets, the development of China stock markets is very fast in recent years. According to market capitalization, SSE became the world's 6th largest stock market at 2.3 trillion USD as of December 2011. However, it is still not entirely open to foreign investors because of the tight capital account controls exercised by the authorities. As an emerging market, it is usually characterized as immature in rules, less efficient and having high volatilities [127, 128]. In addition, there are some evidences indicating that predictability of the China stock markets is much weaker than that in developed markets [170, 171]. The reason behind these characteristics of high volatility, low efficiency and weak predictability is still unclear. After the financial crisis of 2007-2008, the authorities of China try to improve the market efficiency and take many actions, i.e., enhancement of exchange rates reform, increase of money supply and introduction of stock index futures. The new financial environments significantly change the stock market dynamics. However, literatures revealing the China market dynamics, especially under the environments after this financial crisis, are still very limited.

There are several literatures investigating the driving forces in the China stock markets, among which the interest rates and exchange rates are commonly studied factors. Using government bond as interest rate proxy, Delek and Elcin [172] analyze its Granger causal linkage with stock returns in four emerging markets. Their results find that, in the China markets, two and five year maturity bonds Granger cause the stock index price. On the other hand, the stock index presents a Granger causality to 3-month, 6-month, and 4-year government bonds. Liu and Keshab [173] report that there exists a long-term cointegration between the interest rates and stock prices. The relationship between five year interest rates and stock prices is negative and highly significant. Zhao [174] studies the dynamic relationship between exchange rates and stock prices in China markets between 1991 and 2009. The results suggest that there is no stable long-term equilibrium between the real effective exchange rates of RMB and stock prices.

Another line of literatures focus on the interactions between the China and foreign stock markets. Comovement of stocks in multi-countries is important characteristics in the international equity markets. Some studies attribute the comovement phenomena to economic fundamentals and information flow [175, 176], while others argue that it is the contagion effect rather than fundamental factors [177, 178]. People are increasingly interested in the lead-lag relationship or causal linkage between emerging and developed markets. Qiao et al. [179] study the bilateral relationship between the China and Hong Kong stock markets. It is found that their interaction is fractionally co-integrated, and A-share of the SSE market is the most influential one. Li [180] uses multi-variable asymmetric GARCH model to examine the transmission of returns and volatilities across the China markets and some other developed markets. His work does not find any direct evidence to show significant linkage between the China and US stock markets. However, their results report the existence of unidirectional volatility spillovers from Hong Kong to the China markets. It indicates that the China stock markets tend to be more linked to reginal developed markets rather than the US markets.

One motivation of this study is to give a comprehensive study of both macroeconomic and microeconomic factors that influence the movements of the China stock price. Most of the current studies focus on the macroeconomic variables but neglect the effect of microeconomic factors, such as price-to-earning (PE) ratios and price-to-book (PB) ratios. These indicators are commonly used for stock valuation. In developed countries, the relationship between stock price and microeconomic factors has been extensively documented. Campbell and Shiller [181, 182] study the PE and dividend-price ratios and reveal the significance of their predictability for stock returns. Bhargava [183] investigates the Granger causality between PE ratios and corresponding stock prices for Morgan Stanley Capital International (MSCI) indices. The results indicate that PE ratios may not have great impacts to the stock prices as expected. To the best of our knowledge, we have not noticed any literatures investigating the lead-lag relationship between PE ratio and corresponding stock price in the China markets. Therefore, one aim of this study is to examine the effects of microeconomic factors on the stock prices.

The second motivation is to study the interactions between Shanghai Stock Exchange composite index (SSECI) and China Shanghai Shenzhen 300 (CSI 300) index futures. The underlying asset of the CSI 300 index futures contract is CSI 300 index, which is a capitalization-weighted stock market index composed with 300 largest A-Shares listed on the SSE and Shenzhen Stock Exchange. The CSI 300 index futures was first launched on April 16, 2010 on the China Financial Futures Exchange. Although with a short history, it grows to be the world's fifth largest index futures market in 2013 according to trading volume. Many of the existing literatures of developed markets suggest that the stock index futures leads the underlying stock index prices [184, 185, 186, 187]. The reasons are explained as that the stock index futures markets have many advantage over the spot markets, including lower transaction costs, higher degree leverage and absence of short selling constraints [188, 189]. These advantages encourage traders, especially informed traders to trade in the stock index futures markets. As a result, the price discovery in stock index futures markets is faster than that in the underlying spot markets. In the China market, Yang et al. [190] report that the spot prices lead the index futures prices and tend to play a dominant role. On the contrary, Hou's [191] evidences find that the

CSI 300 index futures plays a dominant role in price discovery. As far as we know, there is still no literature investigating the interactions between CSI 300 index futures and SSECI. Thus another aim of this study is to examine the relationship between them.

The third motivation is to reveal both the dynamic short-term Granger causality and long-term equilibrium between the economic variables and stock prices. The relationship between stock markets and economic factors usually exhibits two features: common long-term trends and time-dependent lead-lag relationship [192, 193, 194]. On the China stock market, Li et al. [195] suggest that there exists some structural breaks between economic variables and stock prices during July 2001 to December 2010. Their result reports that the interest rates and stock prices have bidirectional long-run Granger causality to each other during the period of 2007/08-2008/11 and 2009/01-2010/12. However, for the period of 2001/07-2005/10 the stock prices have unidirectional Granger causality to interest rates. Although Li's work [195] has shown the existence of structural breaks in Granger causality but cannot capture its dynamic patterns. Considering the dynamic characteristics of stock markets, this study adopts a time-varying Granger causality approach based on our previously developed system adaptation framework [122, 57]. One advantage of this system adaptation framework is its structure, with which the dynamic impact of market forces can be well captured. Based on this system adaptation framework, our time-varying Granger causality can adaptively calculate the bidirectional Granger causal strength at each time step. In addition to the short-term dynamics, we apply a cointegration analysis to investigate the long-term equilibrium between stock market and external forces. Furthermore, considering the critical role of interest rate policy, we also conduct an event study to investigate its effect on stock prices.

The following of this chapter is organized as below. Section 2 introduces the data. Section 3 reports the methods and results. Section 4 discusses the results and concludes this chapter.

5.2 Market Forces Selection

In this study, we use daily data for empirical analysis. Considering that the data for index future is available from April 16th, 2010, the study period is selected from July 2010 to September 2014. The data of non-deliverable forward (NDF) rate is obtained from Bloomberg and all the other data are obtained from Census and Economic Information Center (CEIC). Daily closing prices of SSECI are used as the SSE price index. We select seven economic variables from five categories: interest rate, exchange rate, international stock market indicator, stock index futures, and microeconomic indicator. The selection of each variable is as below.

1. Interest Rate Indicator

The Shanghai Interbank Offered Rate (SHIBOR) is an average interest rate at which banks offer to lend unsecured funds between prime banks in the China interbank markets. It is becoming a benchmark of market interest rates in the China credit market. In this study, we use the SHIBOR overnight rates as the interest rate indicator for time-varying Granger causality and cointegration tests.

2. Exchange Rate Indicator

In recent years, China has reformed currency policies from fixed exchange rate to flexible exchange rate regime. Furthermore, China pegs currency to a basket of foreign currencies rather than strictly pegging to US dollar. These policies significantly change the CNY/USD currency markets. After that the Chinese Yuan began appreciated against US dollar. In 2009, US started quantitative easing monetary policy, which intensified the appreciation of Chinese Yuan.

In this study, we use two variables as exchange rate indicator: CNY/USD exchange rate (EX), and the difference between CNY/USD spot rate and its NDF rate, defined as below:

$$DNDF(t) = C_N(t) - C(t), \tag{5.1}$$

where $C(t)$ is CNY/USD exchange rate at time t and $C_N(t)$ is NDF rate of CNY/USD at time t.

3. Market Microeconomic Indicator

The price-to-earning (PE) ratio is defined as market price per share divided by annual earnings per share. It is a combination of the company's stock price and profitability. This study uses the daily average PE ratio of SSE markets as microeconomic indicator.

4. Stock Index Futures Indicator

Stock index futures is a future contract on the value of a particular stock index. It is used for hedging and making profits. China starts its first index futures, CSI 300 index futures, since 16 April, 2010. Its underlying asset is CSI 300 index that consists of 300 A-share stocks listed on the SSE or Shenzhen Stock Exchanges. The daily closing prices of one-week CSI 300 index futures (FUTURE) are used as the stock index futures indicator.

5. International Stock Markets Indicator

Two stock indices from developed markets are selected as the international stock market indicator, including Standard & Poor's 500 (SP500) and Hang Seng China enterprises index, HSI H-share index (HSIH), which is the major index that tracks the performance of China enterprises listed in Hong Kong.

5.3 Methods and Results

5.3.1 Identification of Dynamic Short-term Market Forces

As discussed previously, the interaction among financial markets is a dynamic process. The causal relationships and information spillover between economic variables and stock prices can change over time. One reason is that the economic and financial environments usually vary with time. Most studies on Granger causality between the economic variables and stock markets have been performed using the static approach, which can only show the average effect but cannot capture the dynamic patterns of Granger causality. To identify the dynamics of market forces this study applies the time-varying Granger causality method discussed in Chapter 2.

In what follows we report the time-varying Granger causality test results. For easy reference, we recall the study period is from July 2010 to September 2014. For the system adaptation framework, the first step is to estimate its internal OE model. The

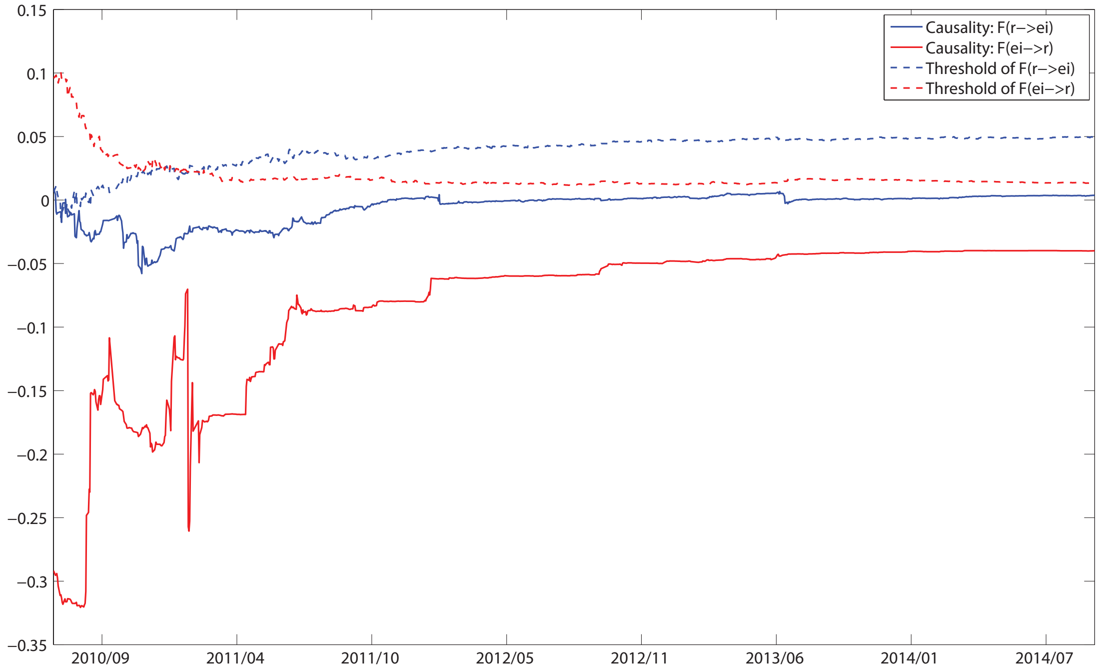

Figure 5.1: Time-varying Granger causality between the internal residue and SHIBOR

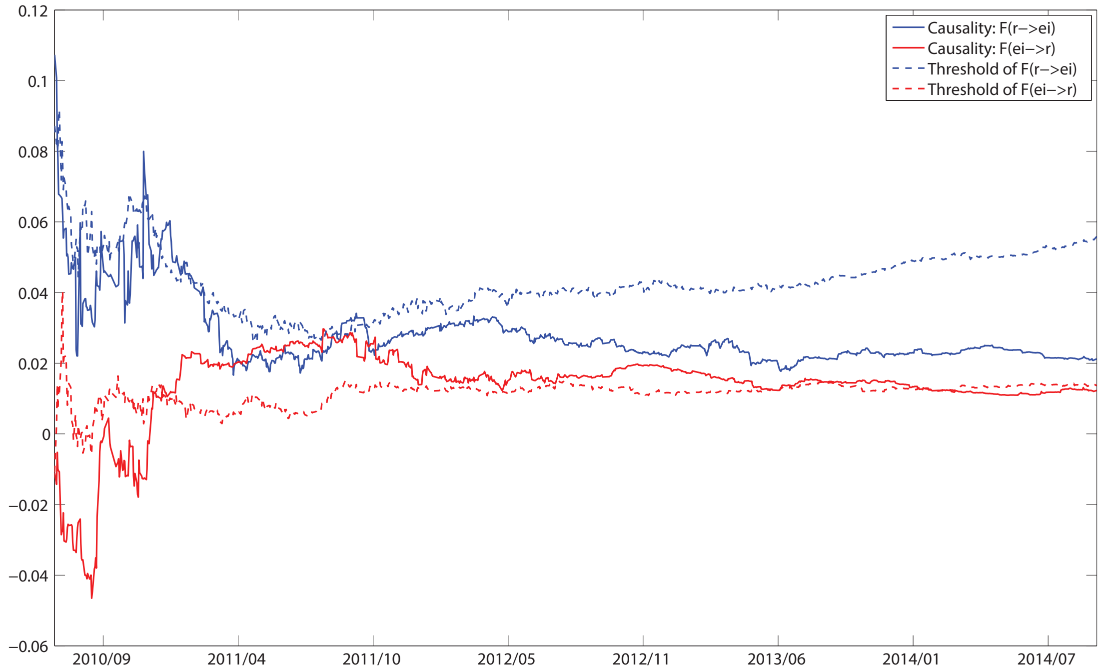

Figure 5.2: Time-varying Granger causality between the internal residue and EX

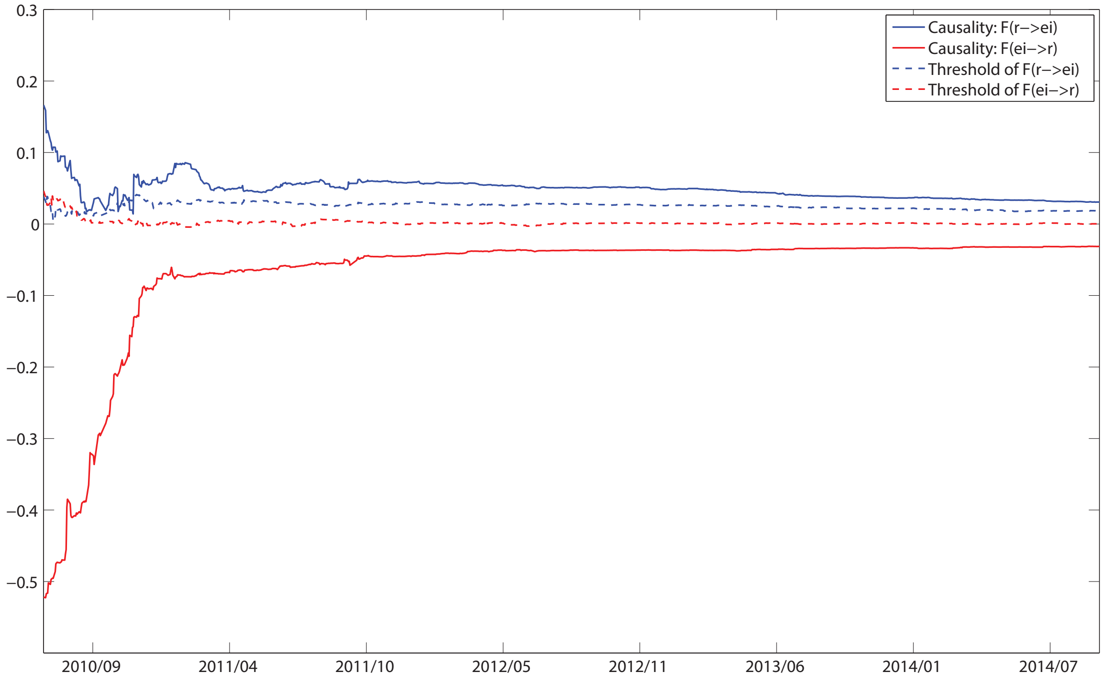

Figure 5.3: Time-varying Granger causality between the internal residue and DNDF

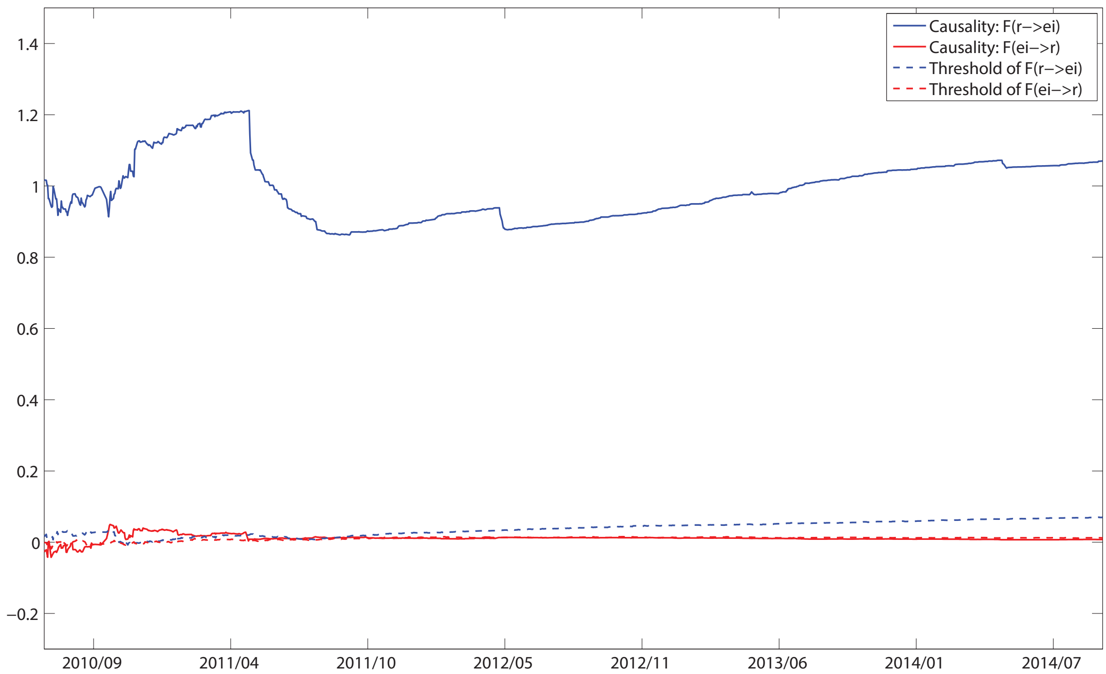

Figure 5.4: Time-varying Granger causality between the internal residue and PE

estimated OE model is given as below:

$$H(z) = \begin{bmatrix} \frac{-0.7433z^{-1}-1.483z^{-2}+3.23z^{-3}-1.626z^{-4}}{1-0.9897z^{-1}+0.2213z^{-2}} \\ \\ \frac{1.509z^{-1}+2.088z^{-2}+0.3219z^{-3}-1.587z^{-4}}{1-0.03759z^{-1}-0.3216z^{-2}} \\ \\ \frac{1.901z^{-1}-3.138z^{-2}+0.000206z^{-3}+1.244z^{-4}}{1-1.458z^{-1}+0.5993z^{-2}} \end{bmatrix}^{\mathrm{T}}. \tag{5.2}$$

The details of OE model estimation and internal model design can be found in [57, 121].

Figure 5.1 to Figure 5.7 report the time-varying Granger causality test results between internal residue e_i and selected indicator r. For each figure, we can observe the bidirectional causality strength and corresponding thresholds. The indicator is identified as a market force when its causality strength to internal residue exceeds the threshold. As shown in the results, three out of seven indicators significantly Granger cause the internal residue over the entire sampling period, including FUTURE, PE and HSIH. Moreover, it is interesting to find that the FUTURE and HSIH show unidirectional Granger causality to SSECI, but the variable PE has a bidirectional causality with SSE between 09/2010 and 10/2011. This bi-directional causality relationship indicates that there exists strong linkage between PE ratio and the stock prices during this period. The causality strength of DNDF to internal residue is significant nearly over the entire sample period, except that there is some fluctuation around October 2010. However, it is interesting to find that the internal residue weakly Granger cause EX between December 2010 and February 2014. As shown in Figure 5.7, there is a structural change in the Granger causality relationship from SP500 to the internal residue around May 2013. It indicates that the influences from the US markets to China markets become not significant since the middle of 2013.

5.3.2 Forecasting Capability of Identified Market Forces

The time-varying causality test results find four variables that can serve as driving forces in the China stock market, including CSI 300 index futures, PE ratio, DNDF and HSI-H share index. These variables are used as inputs for our system adaptation framework and two subperiod out-of-sample forecasting are conducted to test their forecasting capability. For each subperiod, the lag length of internal residue in our adaptive filter

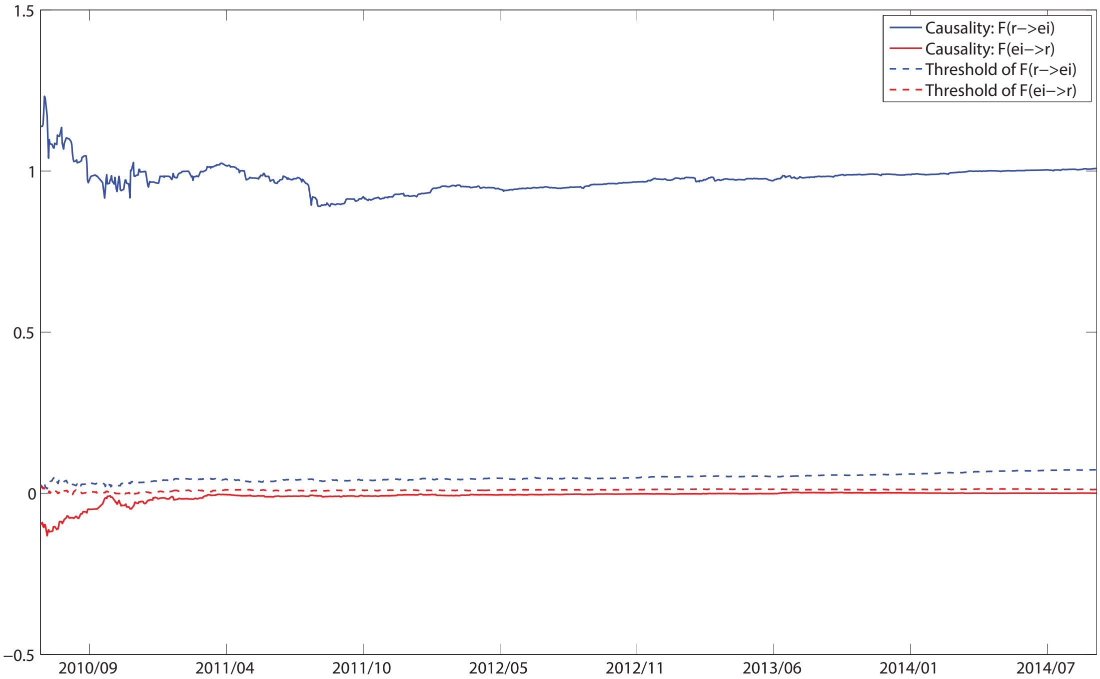

Figure 5.5: Time-varying Granger causality between the internal residue and FUTURE

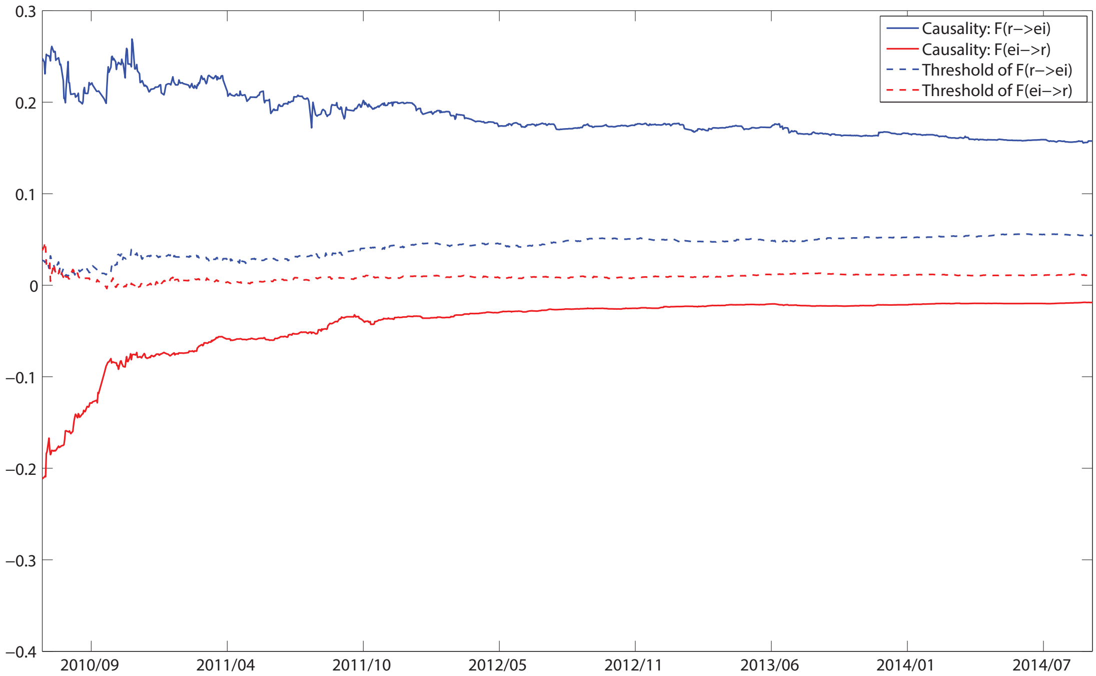

Figure 5.6: Time-varying Granger causality between the internal residue and HSIH

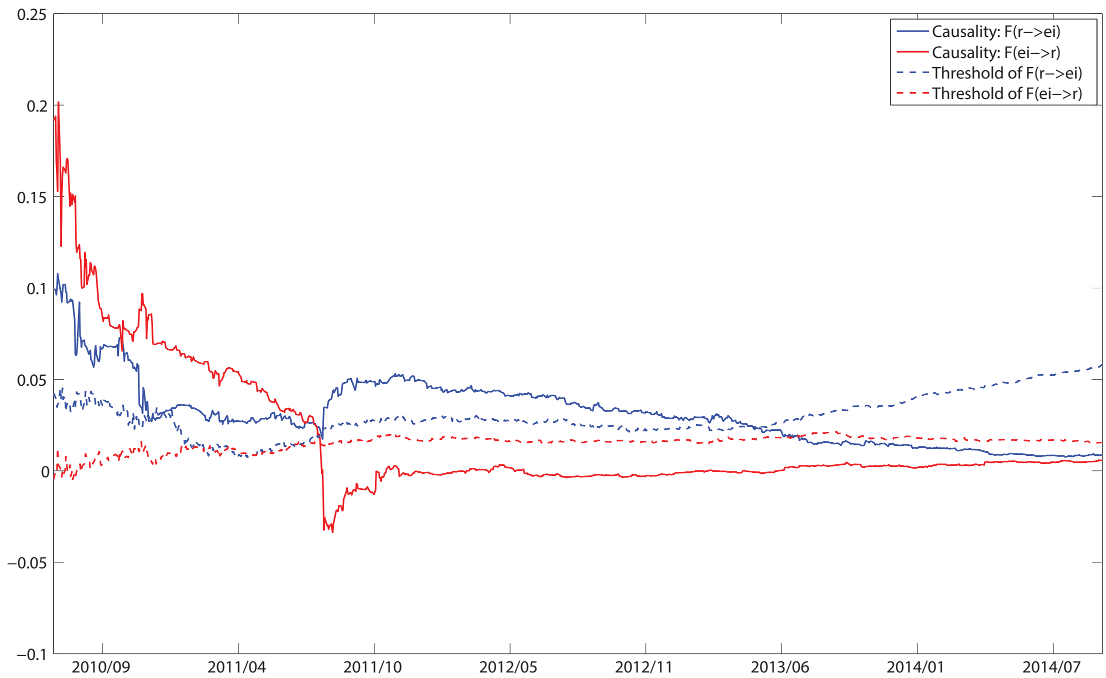

Figure 5.7: Time-varying Granger causality between the internal residue and SP500

is selected to be 4, and the lag length of each external input is selected to be 10. Two subperiods are selected to be from August 2012 to August 2013, and from September 2013 to September 2014 respectively. Table 5.1 reports the forecasting capability of the identified market forces by using our system adaptation framework. It is clear that the inputs significantly improve the forecasting performance. In subperiod S1, the selected market forces explain for 60.4% of RMSE and 64.7% of MAE respectively. In subperiod S2, these indicators can explain for 61.3% of RMSE and 64.3% of MAE. Furthermore, we compare the forecasting performance of our system adaptation framework with the commonly adopted ARMAX model, see Table 5.2. The lag length of the ARMAX model is set similarly as those in our system adaptation framework, i.e., 4 for AR and MA terms and 10 for all the exogenous inputs. Using the system adaptation framework the RMSE and MAE are correspondingly improved by 30.2% and 35.1% in subperiod S1 compared with that of the ARMAX model. Similarly, in subperiod S2 the RMSE and MAE are improved by 34.5% and 38.4% respectively.

5.3.3 Long-term Equilibrium between Market Forces and Stock Prices

In addition to identifying the dynamic short-term interactions we also examine the existence of long-term equilibrium between the economic variables and stock prices. In

Table 5.1: Forecasting capability of the selected market forces

Model inputs	Subperiod S1 Aug. 2012 - Aug. 2013		Subperiod S2 Sep. 2013 - Sep. 2014	
	RMSE	MAE	RMSE	MAE
No inputs	44.9	34	37.2	28.4
FUTURE HSIH DNDF PE	17.8	12	14.4	10.4
Improvement	60.4%	64.7%	61.3%	64.3%

Table 5.2: Forecasting performance of the system adaptation framework

Model	Subperiod S1 Aug. 2012-Aug. 2013		Subperiod S2 Sep. 2013-Sep.2014	
	RMSE	MAE	RMSE	MAE
ARMAX	25.5	18.5	22.0	16.9
System adaptation framework	17.8	12	14.4	10.4
Improvement	30.2%	35.1%	34.5%	38.4%

this study, we employ Engle-Granger cointegration test [196, 197] to examine the long-run equilibrium relationship. Two individually non-stationary time series are called cointegrated if a linear combination of them is stationary. The economic explanation of the cointegrated relationship is that there exists a long-run comovement between the two variables.

The Engle-Granger test for cointegration consists of two steps. First, a unit root test is conducted to examine whether each individual series is integrated of the same order. Second, the cointegration test is applied to the non-stationary series to determine whether a linear combination of them is stationary or not.

In this study, we use the augment Dickey-Fuller (ADF) unit root test for the first step [198]. The ADF regression equation is as below

$$\Delta x_t = \alpha + \beta t + \gamma x_{t-1} + \sum_{i=1}^{m} \lambda_i \Delta x_{t-i} + \varepsilon_t \tag{5.3}$$

where x_t is the variable interested at time t and $\Delta x_t = x_t - x_{t-1}$; β is the coefficient on a series of time trend; $i = 1, 2, ...m$ is the lag length of Δx_t, which is determined by Schwarz criterion; ε_t is the residue and i.i.d. with mean zero and variance σ^2. If γ is significantly different from zero the series is stationary, and if $\gamma = 0$ the series is nonstationary. A pseudo t statistic can be used as the test statistic for γ. As Schwert [199] points out that the t statistics might be misleading if the time series models of the tested variables are not pure autoregressive processes. Schwert gives corrections to the test statistics using Monte Carlo simulation which allows for more general time series process. Mackinnon [200] provides an corresponding critical values for the corrected test statistics.

The second step is to test the cointegration by estimating the equilibrium equation:

$$x_{1,t} = c + \rho x_{2,t} + \mu_t \tag{5.4}$$

where $x_{1,t}$ and $x_{2,t}$ are the variables tested; c is a constant term; ρ is coefficient of $x_{2,t}$; μ_t is an error term. The test of cointegration is to examine whether the OLS regression residue $\widehat{\mu}_t = x_{1,t} - c - \rho x_{2,t}$ is stationary. This is determined by ADF test on $\widehat{\mu}_t$ with Mackinnon critical values [200].

The ADF unit root test results for SSECI and the selected variables are shown in Panel A of Table 5.3. The SHIBOR and exchange indicator DNDF are significant at 1% level. The spot USD/CNY exchange rate, EX, is significant at 5% level. These results imply that the series of SHIBOR, DNDF and spot exchange rate are stationary. However, the testing results of all of the other variables can not reject the null hypothesis of having unit roots.

We take first order difference for all the variables and their ADF unit root test results are presented in Panel B of Table 5.3. After taking first difference, all the ADF tests are significant at 1% level, which indicates that the variables of SSECI, FUTURE, HSIH, PE and SP500 are first order integrated, namely I(1). The cointegration tests are performed between SSECI and the other four I(1) series using Equation 5.4. Table 5.4 reports the ADF test results from the cointegration regression. The residue from PE ratios, HSI H-share index and CSI 300 index futures are significant at 5% level, which indicates the existence of cointegration between these variables and SSE. However, the result from SP500 is not significant. Therefore, the null hypothesis of no cointegration between SSE and SP500 can not be rejected.

5.3.4 Interest Rate Policy Impact on Stock Prices

It is surprising to find that SHIBOR does not show time-varying Granger causality or cointegration with stock prices in the China stock markets. The results indicate that the linkage between stock market and interbank market is not as strong as that in most of

Table 5.3: ADF unit root test of the selected variables

	SSECI	FUTURE	SHIBOR	EX	DNDF	HSIH	PE	SP500
Panel A: Stationary test of the selected variables								
ADF	−1.95	−1.94	−7.97*	−2.92**	−6.68*	−2.26	−1.67	−0.11
Panel B: Stationary test of the first order difference of selected variables								
ADF	−32.74*	−33.50*	−21.70*	−30.12*	−23.64*	−32.29*	−32.54*	−35.06*

Notes: Critical values are −3.44(1%), −2.86(5%), −2.57(10%).
* indicates significant at level of 1%.
** indicates significant at level of 5%.
*** indicates significant at level of 10%.

Table 5.4: Cointegration test between SSECI and the I(1) variables

Dependent Variable	Independent Variable	ADF
SSECI	FUTURE	−2.89**
	HSIH	−3.13**
	PE	−3.08**
	SP500	−2.11

Notes: Critical values are −3.44(1%), −2.86(5%), −2.57(10%).
* indicates significant at level of 1%.
** indicates significant at level of 5%.
*** indicates significant at level of 10%.

the developed markets [201]. In addition to the market interest rate, official interest rate is another crucial interest rate in the financial markets of China, It is a key instrument of monetary policy and macro-control. The announcement of official interest rate change is usually associated with significant fluctuations on financial markets. Considering the specific role of monetary policy in the financial markets, this study also employs an event study to access the effect of official interest rate change on stock prices. The event study is to find empirical evidence that a security return is statistically different from the expected value. Its assumption is that, in a rational market, the effect of an event can be immediately reflected by the asset prices.

We define that the interest rate announcement day is the event date $t = 0$. If it is not a trading day the event date is shifted to the following trading day. We use $p_{i,t}$ to denote stock index price on date t, where i is an event, $i = 1, 2...N$. The logarithmic return of stock price on day t is

$$R_{i,t} = ln(p_{i,t}) - ln(p_{i,t-1}) \tag{5.5}$$

Since this study investigates the stock index we apply the market-adjusted return model, which assumes that the mean market return is fixed without the event. We have

$$R_{i,t} = a_i + \xi_{i,t} \tag{5.6}$$

$$E(\xi_{i,t}) = 0, D(\xi_{i,t}) = \sigma_i^2 \tag{5.7}$$

where a_i is the normal return, which is assumed to be sample average return in the estimation period. For event i, the estimation period is selected to be $T_{es} = 30$ trading days (-40,-11), and the event window is selected to be $T_{ev} = 21$ trading days (-10, 10). For the event date t the conditional abnormal return $AR_{i,t}$ is given by:

$$AR_{i,t} = R_{i,t} - \widehat{a}_i \tag{5.8}$$

where $\widehat{a}_i$ is estimated average return in the estimation period.

We apply a t-test to examine whether the abnormal return is statistically significant. The null hypothesis is that the interest rate change has no influence on the stock index price. Following Patell [202], we use a standardized abnormal return (SAR) where each return is normalized by the standard deviation of return in the estimation period:

$$SAR_{i,t} = \frac{AR_{i,t}}{S_i^*} \tag{5.9}$$

where S_i^* is the sample standard deviation and given by:

$$S_i^* = \sqrt{\frac{1}{T_{es} - 1} \sum_{t=1}^{T_{es}} AR_{i,t}^2} \tag{5.10}$$

The standardized t-test on day t is given by:

$$\theta_t = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} SAR_{i,t} \tag{5.11}$$

Moreover, we also examine the effect of each interest rate announcement individually by:

$$\widehat{\theta}_i = \frac{1}{\sqrt{T_{ev}}} \sum_{t=-10}^{10} SAR_{i,t} \tag{5.12}$$

Table 5.5 reports the t-test results of abnormal return on each day in the event period. The tests are separately performed on interest rate rise and reduction. For the category of interest rate rise, the abnormal return is only significant on the ninth day after the announcement. Moreover, our results do not find any significant abnormal return when the interest rate reduces. The evidence from overall interest rate changes indicates that the abnormal return is only significant (at 5% level) on the eighth day before the announcement. This result implies that there might exist information leak before the announcement. In addition, the t-tests are significant at level of 10% on the third day before and ninth day after the event day.

Table 5.5: T-test of interest rate on each day during the event period

Day	t-statistic		
	Interest rates rise	Interest rates reduction	Interest rate change
−10	1.876	−1.006	1.048
−9	0.838	−0.022	0.697
−8	1.667	2.092	2.527**
−7	−0.351	1.566	0.541
−6	−0.492	0.179	−0.321
−5	0.838	1.598	1.562
−4	−0.613	0.545	−0.226
−3	0.863	2.305	1.962***
−2	0.028	−0.333	−0.154
−1	0.146	0.245	0.254
0	−0.747	0.918	−0.141
1	0.880	−2.216	−0.441
2	0.468	−0.324	0.222
3	0.806	2.189	1.851
4	0.787	0.234	0.790
5	1.718	−0.880	0.982
6	0.290	−1.351	−0.477
7	−0.602	0.257	−0.371
8	0.261	2.051	1.316
9	−2.757**	0.462	−2.083 ***
10	−0.822	−0.796	−1.121

Notes: * indicates significant at level of 1%;
** indicates significant at level of 5%;
*** indicates significant at level of 10%.

Table 5.6 presents the t-test results of each interest rates announcement. According to the results, there are two announcements associated with significant influences to the stock market. However, the other five interest rate changes do not have any significant influences.

Table 5.6: T-test of each interest rate change

Event i	Date	Interest rate changes	t-statistic
1	20/10/2010	-0.27%	2.89*
2	26/12/2010	$+0.25\%$	0.26
3	09/02/2011	$+0.25\%$	1.58
4	06/04/2011	$+0.25\%$	-0.08
5	07/07/2011	$+0.25\%$	-2.36**
6	08/06/2012	$+0.25\%$	1.64
7	06/07/2012	-0.25%	0.51

Notes: Critical values are 2.861(1%), 2.093(5%) and 1.729(10%).
* indicates significant at level of 1%.
** indicates significant at level of 5%.
*** indicates significant at level of 10%.

5.4 Discussions and Conclusions

This chapter conducts a comprehensive study of the driving forces on the China stock markets. We select seven indicators from macroeconomics and microeconomics to investigate their interaction with SSECI. Their cointegration and time-varying Granger causality relationships are empirically tested. Our time-varying Granger causality results suggest that four out of the seven indicators have significant causal linkage to SSECI, including CSI 300 index futures, DNDF, PE ratio and HSI H-share index. The forecasting results imply that these market forces can explain for more than sixty percentage of the prediction variance.

The ADF unit-root test reports that SHIBOR is stationary while the SSECI is an I(1) process, which indicates that there exists no cointegration between these two variables. Furthermore, our time-varying Granger causality tests do not find evidence to show Granger causal linkage between stock prices and SHIBOR. These results imply that SHIBOR, as a new benchmark of the market interest rates, does not have the similar influences as the long-term interest rates that are reported to have Granger causality or cointegration with stock prices [172, 173]. This is different from the developed markets, where the overnight interbank interest rates usually play a crucial role in equity markets [57]. In this study, we also employ an event study to investigate the effect of interest rate policy on the China stock markets. The event study results find that two out of seven interest rate changes in our sample period are associated with significant abnormal returns. However, the daily effects of abnormal returns in the event window are generally not significant. It indicates that the China stock markets are weakly sensitive to the monetary policy.

The second finding is that the spot exchange rate, EX, does not Granger cause or cointegrate with stock prices. These findings are consistent with Zhao's study [174], which suggests that there is no stable long-term equilibrium between real effective exchange rates and stock prices in the China markets. Nevertheless, the NDF exchange rates based indicator, DNDF, is found to have significant time-varying Granger causality to stock prices. It suggests that the China stock market responds to the currency market by assessing the premium between the spot and the expected future exchange rates. The reason might be that the China economy is export-oriented which is susceptible to the risk of future exchange rates.

Third, our tests find unidirectional Granger causality from CSI 300 index futures to SSECI, and the causal strength is strong. Although only part of the constituent stocks of CSI 300 index are overlapped with that of SSECI, this index futures still present strong leading role between their interactions. This result implies that the index futures market is more efficient than spot market in price discovery in the China equity markets. This is similar to the finding of Hou and Li [191], in which they use high-frequency data to reveal that the new information disseminates more rapidly on CSI 300 index futures markets than that on the underlying stock markets. Furthermore, the cointegration tests report that there exists long-term equilibrium between SSECI and CSI 300 index futures. This is not surprising because of the comovement characteristics between index futures and spot markets.

PE ratio is believed to reflect the bias between the stock valuation and price. In value investment, PE ratio is an important indicator for asset's future performance. Our time-varying causality test also shows that the PE ratio is a leading indicator to the movements of SSECI. The cointegration results also reveal long-run equilibrium between SSECI and PE ratio. These findings indicate that PE ratio functions well in the China stock market. Moreover, we find that the stock prices weakly Granger cause PE ratios over the period of 09/2010-10/2011. To the best of our knowledge, this is the first study to examine the PE ratio's effect as driving force in the China stock markets.

Regarding the relationship between the China and international stock markets, our time-varying Granger causality results show that HSI H-share index has causal linkage to SSECI over the whole sampling period. However, SP500 only has Granger causality to

SSECI before May 2013, and subsequently the causality become not significant any more. The cointegration test also indicates that SSECI has long-term equilibrium with HSI-H share index rather than with SP500. These results suggest that the Hong Kong stock markets, as regional developed markets, are more influential to the China stock markets. Our results are similar to the findings of Li [180], which suggests that there exists unidirectional spillovers of volatility from Hong Kong to the China markets. However, his results do not find any direct evidence of significant linkage between the US and China markets. The reason might be that a number of China firms have cross listing of shares both in the Shanghai Stock Exchange and Hong Kong Exchange. However, the market efficiency and information processing rate in Hong Kong markets are higher than that of the relatively isolated China stock markets. Thus Hong Kong markets are faster in price discovery and play leading roles between their interactions.

Chapter 6

Concluding Remarks and Future Work

6.1 Concluding Remarks

Benefiting from the development of system economics, many advanced approaches have been introduced to financial market studies. In this thesis, we employ a system adaptation framework together with conventional econometrics approaches to investigate the stock market dynamics in two sub-horizons: long-run cycles and short-run fluctuations. In particular, the tasks and contributions of this thesis mainly focus on three aspects. First, based on the system adaptation framework and wavelet MRA, an empirical model is developed to forecast the market turning points. Our previous studies indicate that the internal residue of system adaptation framework contain rich information for stock market turning points forecasting [122, 57, 142]. In this study, the MRA of the DWT and MODWT are used to decompose the internal residue and further extract its middle-frequency signals. By analyzing the slope of retrieved signals, an empirical index is proposed to forecast the market turning points. To examine the performance of this index, we conduct a set of empirical tests on US, UK and China markets, where all major turning points are well forecasted. Compared the results of the DWT with the MODWT, it is found that the DWT works better for this index. The testing results of US, UK and China markets demonstrate that nearly all the major turning points in the testing periods can be well forecasted by our index with the DWT, even including some smooth transition timings.

Second, we conduct an empirical study to investigate the time-varying Granger causality of intermarkets under 9/11 terrorist attack. To the best of our knowledge, this is the first study to reveal the time-varying causal linkage between markets under drastic environments of terrorist attack. There are some important findings that are worthy to note. First, the terrorist attack had distinct influences to the causal linkage between different markets, but in general, the Granger causality strength experienced fast changes after 9/11. Furthermore, some causality directions even changed, e.g. the results from FTSE 100, as shown in Figure 4.6. Second, the explanatory capability of the US stock market forces significantly increased after 9/11. The time-varying Granger causality tests find four driving forces for DJIA over the whole testing period, including USD/major, EMEU, DAX and HSI. After 9/11, all of their causal strength to DJIA significantly increased. It indicates that the terrorist attack increased the spillover effect from these variables to the US stock markets. This dynamic change allows the shareholders and policy marker to more efficiently track the time-varying price spillover and information diffusion among markets. Furthermore, the identified forces significantly improve the performance of market forecasting.

In addition to time-varying causal linkage, the dynamic comovement among markets are also studied. we apply a DCC-GARCH model to test the dynamic correlation fluctuations between the US stock markets and other financial markets. There are some critical findings to note. First, only two markets present the contagion phenomena, i.e. the Hong Kong and Australia markets. For the other markets, following the terrorist attack is a sudden fall of the correlation rather than increase. Second, our results find that the terrorist attack generally shocked comovement of financial markets, but the rebounds took different time for different markets. In some markets, it took around three month to return to the pre-crisis level, e.g. the GOLD and SPTSX. However, for the others, e.g. FTSE 100 and DAX, the fluctuation only lasted for a very short period.

Third, we conducts a comprehensive study to examine the driving forces on the China stock markets. We select seven indicators from macroeconomics and microeconomics to investigate their interaction with SSECI. The cointegration and time-varying Granger causality relationships are empirically tested. Four of these indicators are identified as market forces over the whole testing period, including CSI 300 index futures, DNDF, PE ratio and HSI H-share index. The forecasting results imply that these market forces can explain for more than sixty percentage of the prediction variance. In addition to the identified forces, there are some other important findings which deserve more attention. First, our empirical results indicates that the SHIBOR, which is considered to be a new benchmark of market interest rates in China, does not show short-run causal linkage or long-run equilibrium with the stock prices. Second, the spot CNY/USD exchange rates does not Granger cause or cointegrated with stock prices, but the NDF exchange rates based indicator, DNDF, significantly Granger cause stock prices. This result suggests that the China stock markets respond to the currency market by assessing the premium between the spot and the expected future exchange rates. Third, we find that HSI H-share index Granger causes SSECI over the whole testing period. However, SP 500 only Granger causes SSECI before May 2013, and subsequently the causality become not significant any more. The cointegration test also indicates that SSECI has long-term equilibrium with HSI-H share index rather than with SP 500. These results suggest that the Hong Kong stock markets, as regional developed markets, are more influential to the China stock markets.

6.2 Future Work

In this thesis, we have some new findings in revealing the stock market dynamics. There are still a lot of work which can be done in both the long-run cycles and short-term dynamics. Below are some directions that deserve more efforts in the future work.

1. Forecasting market turning points

Our study find that the middle frequency signals of the internal residue contain rich signals in forecasting the turning points. Inspired by the non-parametric approaches [12, 57], we propose some rules to forecast the market turning points from the retrieved middle frequency signals. It is worthy to note that these rules might not be the optimal in timing the markets. Therefore, some similar index can be constructed based on different rules that may improve the forecasting performance. In addition, the signals in different frequency bands might contain more useful information, which also deserve more examinations. These two directions still need more explorations. Furthermore, considering some advantages of MODWT, it is essential to conduct more studies to explore its application in detecting oscillation of stock markets, which may shed more light in market turning points forecasting. Last, although this model is developed for stock markets, many other financial markets, e.g. bond and commodity markets, also show similar cyclical patterns. Some variants of this model may be applied to these markets to detect the corresponding turning points, which is also a future direction.

2. Investigating short-run market dynamics under unexpected shocks

In this thesis, we investigate the short-run market dynamics by studying the case of 9/11 terrorist attack. More efforts are still needed in this line. First, the intermarkets we study are limited, many other markets can be investigated, e.g. the derivatives markets and other international stock markets. Second, some other terrorist attack event can also be studied to compare with the 9/11 terrorist attack. This will allow us to examine whether there exists some regular patterns under similar terrorist activities. Third, some other unexpected shocks, like market crashes or earthquakes, also deserve further studies.

3. Analyzing emerging market dynamics

Although we have conducted a comprehensive study regarding the market driving forces in China markets, much space is still left for future work. First, This study mainly focuses on empirical tests of daily frequency data. Further studies in monthly or quarterly data might show more interesting results. In addition, more macroeconomic data will be available at the monthly or quarterly frequency, such as GDP, CPI and employment rate. Second, in addition to the China markets, many important emerging markets from other countries, e.g. Brazil and India, also deserve studies. Third, we mainly study the driving forces for the market index. In the future, more studies can be conducted towards some specific sections, for instance, banking, energy and property. This will reveal more details of the market dynamics and benefit for equity portfolio construction.

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List of Author's Publications

1. L. Bai, S. Yan, X. Zheng, and B. M. Chen, "Market turning points forecasting using wavelet analysis," *Physica A: Statistical Mechanics and its Applications*, vol. 437, pp. 184-197, 2015.

2. L. Bai, X. Zheng, and B. M. Chen,"Identification of China stock market forces under system adaptation framework," in *Proceedings of Computing in Economics and Finance, 2015*, Taipei, Taiwan, 2015.

3. L. Bai, S. Yan, X. Zheng and B. M. Chen, "Market turning points forecasting using wavelet analysis," in *Proceedings of the 2014 International Conference of Financial Engineering*, London, U.K., pp. 940-945, 2014, "Best Student Paper Award."

4. L. Bai, X. Zheng, J. Zhao, and B. M. Chen, "Study of economic forces in China stock market," In preparation.

5. L. Bai, X. Zheng, J. Zhao, D. S. Rosenblum, and B. M. Chen, "Transient reaction of intermarket relationship-under 9/11 terrorist attack," In preparation.

6. L. Bai, L. Goncalves-Pinto, and D. S. Rosenblum, "Information asymmetry and the interaction of dealer markets with crossing networks," In preparation.