THE EMPIRICAL STUDY OF THE STOCK RETURNS AND THE VOLATILITY OF THE STOCK EXCHANGE OF THAILAND

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ABSTRACT

Title of Dissertation	The Empirical Study of the Stock Returns and the Volatility of the Stock Exchange of Thailand
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This study investigates the relationship between equity market risks and returns in various aspects. First, the implied volatility transmissions between international stock markets—the United States, European countries, Japan, and Thailand—are examined. The results from the VAR analysis with its application, including the causality tests, show that there exists a bi-directional causality between the returns of the SET50 index and its implied volatility such that both the leverage effect (return-driven) hypothesis and the volatility feedback effect (volatility-driven) hypothesis are satisfied. In addition, the dependencies of the implied volatility series across different countries exist such that changes in uncertainty in the U.S. stock market are transmitted to other markets, including Thailand stock returns and volatility.

Second, regarding the asymmetric property of volatility which is characterized by asymmetric GARCH models and the subprime effect, it was found that the subprime effect is significant in the volatility of the SET and eight industry group returns. Positive and negative shocks have different effects on the conditional variance of the agribusiness and food, consumer products, industrials, property and construction, and services industries. However, the ARCH effect was found in the SET index returns and all industries' returns such that the GARCH(1,1) model is appropriate in such a case. The leverage effect hypothesis and volatility feedback hypothesis are also satisfied at the industry level.

Third, the return-volatility tradeoff was found to be significantly positive at the aggregate level and 6 industries among all 8 industries, which are agribusiness and

food, consumer products, financials, property and construction, resources, and services. However, the interest rate effect on excess returns was statistically significant at the aggregate level and some industries: industrials, property and construction, and resources. The estimates of the relative risk aversion index implies that the industries whose index ranked from highest to lowest were services, agribusiness and food, consumer products, property and construction, financials, technology, resources, and industrials.

The major finding implies that volatility measured by conditional standard deviation or variance appear to be important in determining excess stock returns at the aggregate level and industry level for Thailand's stock market, and investors may obtain higher stock returns only by incurring additional risk. There exist instantaneous causal relations between returns and risk such that stock returns are caused by volatility, and returns also lead to stock volatility. In addition, it can be inferred from the negative relationship between the option-derived implied volatility and stock returns that an increase in stock volatility raises the expected risk premium, and lower stock prices through volatility-driven effect, and negative stock returns increases financial leverage, which makes the stock riskier and increases its volatility through a return-driven effect. Regarding the international perspective, the leading role of the U.S. market inferred from the VAR model, impulse response analysis, and variance decomposition can be utilized when predicting not only expected volatilities but also stock returns in Thailand's stock market. Finally, the global financial crisis effect on Thailand's stock returns volatility at both the aggregate level and all eight industries deduced from the modified GARCH models should lead to the development of measures to prevent another future crisis through coordinated crisis management and resolution, and regional cooperation.

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CHAPTER 1

INTRODUCTION

1.1 Statement and Significance of the Study

Stock markets play a key role in the economic positions of countries. Therefore, the analysis of stock return and its volatility has long attracted much attention in the financial economics literature. Particularly, stock market volatility is an important component in asset pricing theory, portfolio allocation, and risk management. Thus, accurate measures and good forecasts of volatility are critical for the implementation and evaluation of asset and derivative pricing theories as well as trading and hedging strategies.

Volatility refers to the spread of all likely outcomes of an uncertain variable (Goudarzi, 2011). Stock volatility is related to the risk and return concept where investors, within a given time period, require a larger expected return from a security that is riskier. An increase in stock market volatility brings about a larger stock price change of advances or declines. Investors interpret a raise in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets.

Besides aggregate volatility being important in almost any theory of risk and return, industry-level and firm-level shocks are also important components of individual stock returns (Campbell, Lettau, Malkiel and Xu, 2001). The first reason for being interested in the volatilities of these components is that many investors have large holdings of individual stocks; they may fail to diversify in the manner recommended by financial theory, or their holdings may be restricted by corporate compensation policies. Such investors are affected by shifts in industry-level and firm-level volatility, just as much as by shifts in aggregate volatility. The second reason is that investors that do try to diversify do so by holding a portfolio in which all unsystematic risks are eliminated. However, sufficiency of such approximation is affected by the firm-level volatility making up the portfolio. Thirdly, arbitrageurs that trade to exploit the mispricing of an individual stock (as opposed to a pattern of mispricing across many stocks) face risks that are related to firm-level volatility, not aggregate volatility. The fourth reason is that individual volatility is important in event studies in terms of events affecting individual stocks, and the statistical significance of an abnormal event-related return is determined by the individual stock return's volatility relative to the market or industry (Campbell, Lo and MacKinlay , 1997: 149 – 178). Fifth, the option price of an individual stock depends on the total volatility of the stock return, including industry-level and firm-level volatility as well as market volatility.

Measures of disaggregated volatility also have important implications for aggregate output in some macroeconomic models. Models of sectoral reallocation (Lilien, 1982) imply that an increase in the industry-level volatility of productivity growth may reduce output as resources are diverted from production to costly reallocation across sectors. Models of "cleansing recession" (Caballero and Hammour, 1994) emphasize similar effects at the level of the firm. Their models indicate that an exogeneous increase in the arrival rate of information about management quality may temporarily reduce output as resources are allocated from low-quality to high-quality firms; alternatively, a recession which occurs for some other reason may reveal information about management quality and increase the pace of reallocation across firms.

Many interesting issues concerning the risk and returns in stock markets have been studied. The first issue is the international transmission of the risk and returns across international stock markets (Äijö, 2008, Badshah, 2009; Chou, Wu and Yang, 2010; Dooley and Hutchison, 2009; Naoui, Liouane and Brahim, 2010; Nikkinen and Sahlström, 2004 and Wagner, and Szimayer, 2004). Secondly, the causal relations between risk and returns in the stock market have been widely studied (Bekaert and Wu, 2000; Bollerslev, 1987; Campbell and Hentschel, 1992; Christie, 1982; Dennis, Mayhew and Stivers, 2006; Duffee, 1995; Dufour, Garcia and Taamouti, 2008; Engle and Ng, 1993; Goudarzi, 2011 and Hatemi and Irandoust, 2011). The third issue is the tradeoff between risk and return across time (Baillie and DeGennaro, 1990; Chou, 1988; French, Schwert and Stambaugh 1987; Glosten, Jagannathan and Runkle 1993; Nelson, 1991; Poterba and Summers, 1986 and Tsuji, 2014).

The Stock Exchange of Thailand (SET) was established on April 30, 1975 in order to mobilize additional capital for national economic development, to support the promotion of economic growth and stability, as well as to develop Thailand's standard of living. The Securities and Exchange Act of 1992 states the SET's primary roles as "to serve as a center for the trading of listed companies, and to provide the essential systems needed to facilitate securities trading; to undertake any business relating to the Securities Exchange, such as a clearing house, a securities depository center, securities registrar, or similar activities; to undertake any other business approved by the Securities and Exchange Commission". In addition, the SET is a reliable barometer for the measurement of the economic conditions of a country since every major change in a country and economy is reflected in the price of shares. Moreover, the shares of profit-making companies are quoted at higher prices and are actively traded so such companies can easily raise capital from the stock market. The SET therefore facilitates the allocation of the investor's funds to profitable channels.

In addition to the SET index, the SET also provided 8 industry group indices comprising Agribusiness and Food (AGRO); Consumer Products (CONSUMP); Financials (FINCIAL); Industrials (INDUS); Property & Construction (PROPCON); Resources (RESOURC); Services (SERVICE); Technology (TECH) to make its classifications in line with international standards since 2004. Moreover, the SET mentions that "in order to accommodate the issuing of index futures and options (normally used for calculating the implied volatility index), and to provide a benchmark for investment in the Stock Exchange of Thailand, the SET provided the SET50 Index." The SET states that "such indices are calculated from the stock prices of the top 50 listed companies on the SET in terms of large market capitalization, high liquidity, and compliance with requirements regarding the distribution of shares to minor shareholders". The movement of the SET index, the SET50 index, and eight industry indices including their properties of changing volatility are expressed in Figure 1.1:

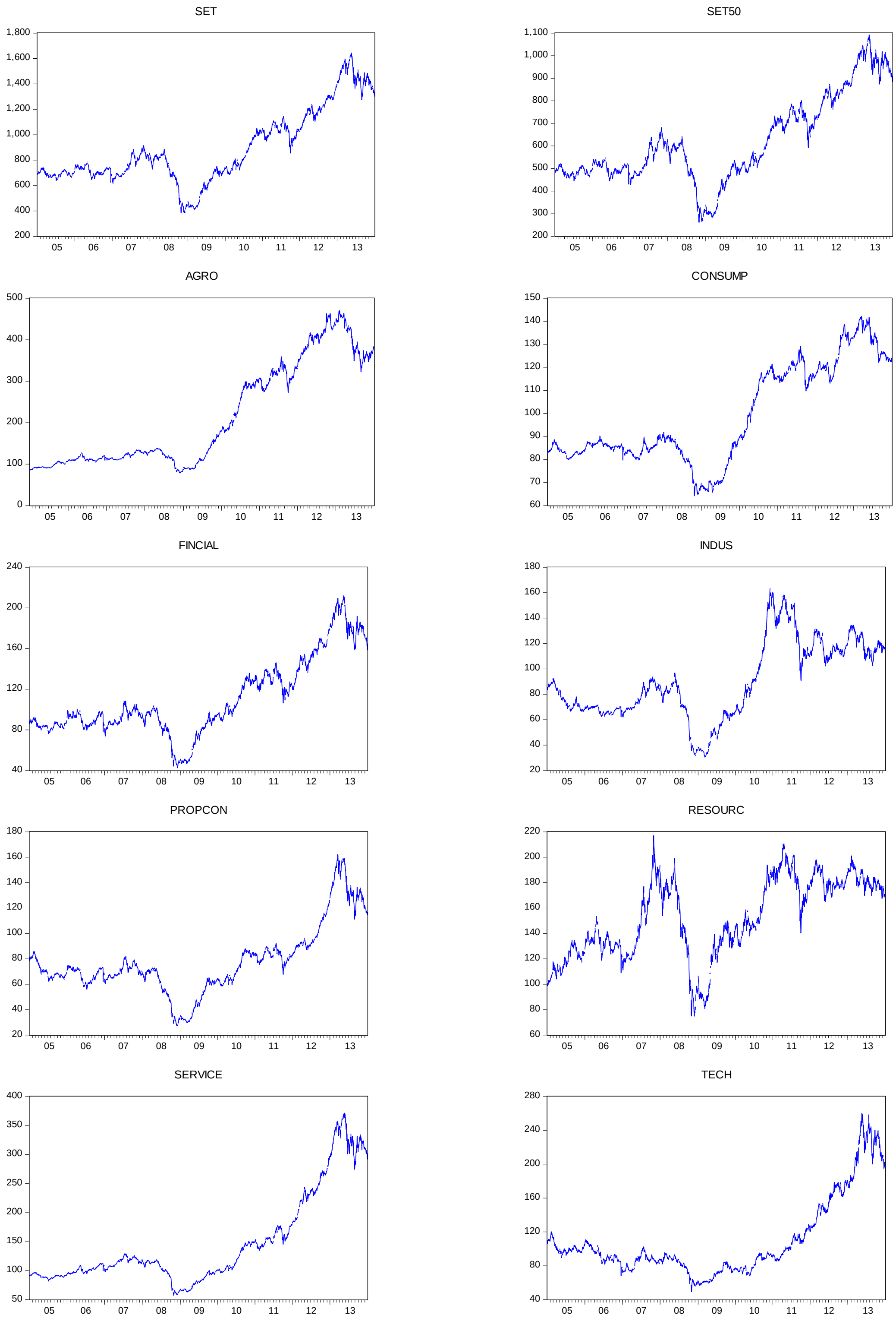

Figure 1.1 The Movement of the SET Index, the SET50 Index, and 8 Industry Indices

1.2 Objectives of the Study

This study aims to investigate the behaviors of stock returns in various aspects, especially the causal relationship between returns and volatility. Such volatility is a symptom of a liquid stock market (Goudarzi, 2011). While the price of securities is associated with the volatility of each asset, many researchers still differ on how this volatility predictability should be modeled. One interesting aspect of these approaches is the "leverage" volatility models, in which good news and bad news have different predictability for future volatility (Engle and Ng, 1993). Moreover, Merton (1976) proposes that "implied volatility can be interpreted as the market's expectation of the average asset's index return volatility over the remaining life of the option." As noted by Mayhew (1995), "implied volatilities provide a method to measure investors' expectations about uncertainty regarding future price movements." Another study by Nikkinen and Sahlström (2004), on integrated markets, they found that "the expectations of uncertainty regarding one international market should be reflected in the expectations for another market."

In summary, the aims of the study are:

1) To examine the international equity market integration with respect to uncertainty
2) To study the causal relations between volatility and stock returns
3) To analyze the effects of new information on the stock volatility
4) To investigate the tradeoff between the stock returns and their risk
5) To provide policy implications from the empirical results of the study for the private sector and responsible authorities in order to cope with critical situations

1.3 Methodology

1.3.1 Vector Auto Regressive (VAR) Model

For the study of the underlying link between the stock returns and their volatility coupled with the international transmission of uncertainty implicit in stock index option prices, the VAR model (Sims, 1980) will be used. The VAR model has many advantages, such as allowing investigation of the multivariate models and identifying structural shocks through variance decomposition. VAR model with its applications such as impulse response analysis, variance decomposition and causality analysis is motivated to choose the list of variables to capture importance sources of fluctuations in this study. Such a model is a popular approach and is widely used for multivariate time series analysis.

1.3.2 Granger Causality Test

The Granger Causality Test (Granger, 1969) explains the cause and effect between two variables or bi-directional causality. The causality test was employed in the study to examine the return-driven effect and the volatility-driven effect of Thailand's stock returns. Moreover, this test was implemented to examine the volatility transmission between international stock markets.

1.3.3 Impulse Response Analysis

Impulse response analysis is a practical approach to visually representing the behavior of time series in response to the various shocks at the time of the shock and over subsequent points in time (Enders, 2004). The impulse response function in this study was used to present the responses of Thailand's stock returns and the volatility to shocks of other international stock market volatility.

1.3.4 Variance Decomposition

Brooks (2002) suggests that "variance decomposition provides the proportion of the movements in the dependent variables that are due to their own shocks versus shocks to the other variables." Such an analysis is implemented in order to explain the impact of the shocks of the international stock markets on the countries' stock market volatilities in this study.

1.3.5 GARCH and Asymmetric GARCH Models

Some models of predictable volatility will be discussed: the GARCH model (Generalized Autoregressive Conditional Heteroskedasticity), the GJR model

(Glosten, Jagannathan and Runkle, 1989 and Zakoian, 1990), and the EGARCH model (Nelson, 1991). An interesting feature of asset prices is that a negative shock seems to have a more pronounced effect on volatility than do positive shocks. Models with asymmetry tend to allow the effects of good and bad news to have different effects on volatility.

1.3.6 GARCH in Mean Model

The GARCH in mean (GARCH-M) model allows the mean of time series to depend on its conditional variance or standard deviation (Tsay, 2010). The model was used in this study to investigate the price of risk for stock excess returns and to estimate the index of relative risk aversion.

1.3.7 The Black-Scholes Option Pricing Model

Since there is no volatility index calculated for Thailand's stock returns, which is the focus of the study, the Black-Scholes option pricing model (Black and Scholes, 1973) was applied to estimate the implied volatility derived from the option prices or the volatility index for Thailand's stock returns.

1.4 Scope of the Study

This research aims to empirically study the stock returns and volatility of the Stock Exchange of Thailand using the daily time series data for the Stock Exchange of Thailand and 8 industry groups, which are: 1) Agribusiness & Food 2) Consumer Products 3) Financials 4) Industrials 5) Property & Construction 6) Resources 7) Services 8) Technology in the period from 2005 to 2013. In addition, the daily international volatility indices were collected for 3 international stock markets: Japan (Nikkei 225 index), the U.S. (S&P 500 index), and the European stock market (Down Jones Euro STOXX 50 stock index) for the period from November, 2010 to December, 2013. To be consistent with such international volatility indices during the period, the daily option prices of the SET50 index options were obtained in order to calculate the volatility index of Thailand's stock returns.

1.5 Contributions of the Study

Several contributions of this study are expected as follows:

1) A new empirical model of the implied volatility linkages between international stock markets was developed for this study such that the causal relationship between Thailand's stock returns and the volatility was included in the model.

2) The asymmetric property of the Stock Exchange of Thailand's returns volatility at both the aggregate and industry levels was modelled, including the subprime crisis effect.

3) The model of return-volatility tradeoff was improved such that the interest rate effect and the crisis effect on each industry were combined.

1.6 Structure of Presentation

This dissertation consists of 5 chapters as follows:

1) Chapter 1 is the introduction, which provides an overview of the study on stock return behaviors incorporating the significance of the study, its objective, scope, methodology, and contributions and structure of presentation.

2) Chapter 2 investigates the causal relationship between returns and volatility, and international equity market integration with respect to volatility, including an introduction, a review of the literature, the theoretical framework, data and methodology, empirical models, results, and conclusion and implications.

3) Chapter 3 analyzes the effects of new information on the conditional variance of the Stock Exchange of Thailand by employing the GARCH and other models of predictable volatility. This chapter also consists of an introduction, a review of the literature, the theoretical framework, data and methodology, empirical models, results, and conclusion and implications.

4) Chapter 4 examines the tradeoff between stock returns and the volatility (as a measure of risk) at the aggregate and industry level, including an introduction, a review of the literature, the theoretical framework, data and methodology, empirical models, results, and conclusion and implications.

5) Chapter 5 provides the conclusions and policy implications that can be drawn from the study. All of the empirical results for the comparative stock return behaviors are concluded, and the significant policy implications are discussed.

CHAPTER 2

INTERNATIONAL IMPLIED VOLATILITY TRANSMISSION

2.1 Introduction

The relationships between stock returns and their volatility, especially asymmetric volatility property, stock returns, and volatility, are negatively correlated (Bekaert and Wu, 2000; Whaley, 2000; Simon, 2003; Skiadopoulos, 2004; Giot, 2005 and Hibbert; Daigler and Dupoyet, 2008) and has long been of interest to financial researchers. Hatemi and Irandoust (2011) states that "such a relationship is of fundamental importance for valuing financial assets, for identifying optimal hedging strategies, and for evaluating regulatory proposals on monitoring the impact of international capital flows." However, it is still controversial whether the relationship between returns and volatility is positive or negative. Although most asset pricing models highlight a positive relationship between stock returns and volatility (Baillie and DeGennarro, 1990) under the assumption of investor risk aversion, there is a long tradition in empirical finance of modeling stock return volatility as negatively correlated with stock returns (Cox and Ross, 1976, Whitelaw, 2000).

Implied volatility provides a method to measure investors' expectations of uncertainty regarding future stock price movements (Mayhew, 1995). It is established that implied volatilities outperform volatility measures based on historical stock price data when forecasting volatility (Blair, Poon and Taylor 2001; Christensen and Prabhala, 1998; and Fleming; Ostdiek and Whaley 1995). Since implied volatility is derived from option pricing theory (Cox and Rubinstein, 1985), SET50 indices, indices calculated from the stock prices of the top 50 listed companies on the SET in terms of large market capitalization, high liquidity, and compliance with requirements regarding the distribution of shares to minor shareholders, and SET50 index option prices will be the focus of this study due to the availability of the information on option prices and the representative of the Thailand stock market as the underlying asset of the option.

This chapter aims to investigate the sources of SET50 return's volatility in two aspects. First, the causal relationship between stock returns and their volatility is examined. Then, the asymmetric volatility property of stock returns is analyzed. The first hypothesis, called the leverage effect hypothesis, will be tested under the assumption that negative return increases financial leverage, which makes the stock riskier and increases its volatility (Black 1976 and Christie, 1982). Another hypothesis to be tested is called the volatility feedback effect hypothesis under the assumption that if volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to a negative return (French et al., 1987; Campbell and Hentschel, 1992). The second aspect is analyzing the transmission of volatility between the international stock markets. In other words, the study is intended to test whether the expectations of uncertainty for one stock market should be reflected in the expectations regarding another market with integrated equity markets such that news generated by the international stock market is relevant for the pricing of domestic securities as a result of the increased globalization of stock markets (Hamao, Masulis and Ng, 1990; Koutmos and Booth, 1995; Koutmos, 1996; Cifarelli and Paladino, 2005). Such international integration has been one of the most investigated issues in the recent finance literature due to its implications for globally-operating investors (Nikkinen and Sahlström, 2004) such that knowledge of the dependencies across markets provides information about the usefulness of international diversification for portfolio managers.

2.2 Review of the Literatures

Äijö (2008) investigated the econometric evidence on stock market integration by examining the implied volatility term structure linkages between the VDAX, VSMI, and VSTOXX volatility indices of the underlying stock indices, which are the German general index (DAX), the Swiss general index (SMI), and the pan-European blue chip index (Dow Jones EuroStoxx50), respectively, for the period of January 1, 2000 to December 31, 2004. The Vector Autoregressive (VAR(p)) model was applied to analyze the transmission of implied volatility term structures estimated from the VDAX, VSMI, and VSTOXX. It was found that the implied volatility term structures estimated from the VDAX, VSMI, and VSTOXX50 sub-indices varied a great deal over time. Moreover, the correlation structures indicated that they were closely correlated with each other, which is consistent with earlier studies of implied volatilities. The implied volatility term structure of the DAX Granger caused the implied volatility term structures of the SMI and the STOXX50. Finally, the variance of the forecast of the implied volatility term structure of the SMI and the STOXX can be explained as much as 35% and 65% respectively by the implied volatility term structure of the DAX.

Badshah (2009) suggested that "the volatility index is an excellent tool for examining the relationship between the market perception of volatility and returns." In addition, such a relation is asymmetric, implying that the volatility index reacts to negative and positive returns differently. This paper investigates the asymmetric return-volatility phenomenon with the VIX implied volatility index for the S&P 500 stock index, VXN for the NASDAQ 100 stock index, VDAX for DAX 30 stock index, and VSTOXX for the Dow Jones (DJ) Euro STOXX 50 stock index. In addition, the dynamic implied volatility transmission across the implied volatility index is also examined. The study used both the daily stock and implied volatility index for the S&P 500 stock index, the NASDAQ 100 index, the DAX 30 index, and the DJ Euro STOXX 50 index from February 2, 2001 to June 30, 2008 for a total of 1933 trading days. To investigate the implied volatility transmissions across the major volatility indexes, the vector autoregressive (VAR) model was used for investigating the daily changes in the volatility index of each country. After that, Granger causality, generalized impulse response function, and variance decomposition were used to examine the dynamic implied volatility transmissions across volatility indexes. It was found out that there was a negative and asymmetric return-volatility relationship between each volatility index and its corresponding stock market index. The VIX volatility index presented the highest asymmetry, followed by the VSTOXX, VDAX, and VXN volatility indices. There were significant spillover effects across volatility indexes, with bi-directional causality running between the volatility indexes. The VIX volatility index influenced the other three volatility indexes considerably. Nevertheless, VDAX was the dominant source of information in the European context.

Chou et al. (2010) analyzed and compared the volatility spillover effect based on two volatility measures, implied volatility and realized volatility, between U.S. and European equity markets. The study used both the daily stock index and implied volatility index for the S&P 500 stock (the U.S.) index, the NASDAQ 100 index (the U.S.), the DJIA index (the U.S.), the DAX 30 index (Germany), the FTSE 100 index (U.K.), and the CAC 40 index (France) from February 2001 to January 2010, for a total of 2,197 trading days. The corresponding volatility indices were the VIX, VXN, VXD, VDAXNEW, VFTSE and VCAC, respectively. The price range, a measure of realized volatility, was calculated by the difference between the highest price and the lowest price, $100 \times (\ln(P_{t,high}) - \ln(P_{t,low}))$. The multiplicative error model (MEM(p,q)), extended from the ARCH/GARCH model and based on the Gamma distribution, was implemented to examine the relationships between different assets. The results of the two volatility measures indicated that U.S. and Europe were interdependent. It was found that volatility spillovers existed from Germany and the U.K. to France based on the realized volatility measure. However, based on the implied volatility measure, it was seen that a volatility spillover existed from the U.K. to Germany. A structural break really existed between the pre- and the post-subprime crisis periods, except for France, based on the price range measure. After the crisis, France became independent of other countries based on both the volatility index and the price range measures. Furthermore, a maximum benefit of 6.02 bps and 20.06 bps was yielded by the volatility spillover effect based on the volatility index and price range measures, respectively, suggesting that the volatility spillover effect was economically significant. Finally, the volatility forecasts based on the price range measure exhibited better performance than those based on the volatility index measure.

Dooley and Hutchison (2009) studied how the financial markets in emerging markets respond to U.S. news during a period of intense financial turmoil by investigating the linkage between the U.S. equity market and the Mexican equity market. The research paper used a simple VAR (Vector autoregressive model), Granger-causality tests, and impulse response functions for the two subsample periods; 1/07 to 8/08 for the early period (phases 1 and 2) and 9/08 to 2/09 for the late period (phase 3). It was found that the emerging markets were decoupled from the U.S. for a period of time, but the linkages had dramatically recoupled (reemerged) by late summer or early fall 2008. In addition, volatility also rose dramatically beginning in September, 2008. U.S. financial and real news was transmitted strongly to emerging markets over the sample period, as reflected in 5-year CDS spreads on sovereign bonds. However, major news announcements by the Federal Reserve and the U.S. Treasury on plans to stabilize the U.S. financial system had little effect on emerging market CDS spreads. Using VAR methods, it was found that the linkages between the U.S. and Mexico equity markets became much stronger after September, 2008, when the U.S. financial crisis grew to critical proportions.

Naoui et al. (2010) examined the financial contagion phenomenon, the spread of market turmoil from one country to other financial markets, following the American subprime crisis by testing the financial contagion between the American market and several other financial markets of 5 developed countries (United Kingdom, French, Germany, the Netherlands, and Italy) and 10 emerging countries (India, Hong Kong, Malaysia, Korea, China, Singapore, Brazil, Mexico, Argentina, and Tunisia). The study used 1,074 daily returns of these stock markets observed over the period from January 3, 2007 to February 26, 2010. The dynamic conditional correlation method (DCC-GARCH) was applied to analyse the financial contagion phenomenon over the two sub-periods: a stable period between January 3, 2006 and July 31, 2007 and a crisis period starting August 1, 2007 and ending on February 26, 2010. They found that the conditional correlation of the S&P 500 stock index returns and the five developed markets (United Kingdom, French, Germany, the Netherlands, and Italy) considerably increased during the crisis period, with values sometimes exceeding 80%. For the emerging markets, the results showed that the conditional correlations of these countries can be classified into three groups. The first group included 3 countries with a high conditional correlation (correlation levels reach 80%) with the American market during the crisis: Brazil, Mexico, and Argentina. The second group included 3 countries with moderate conditional correlations approximating 50%: India, Malaysia, and Singapore. The third group, composed of China, Hong Kong, Korea, and Tunisia, recorded correlations level less than 20% and seemed to be unaffected by the subprime crisis.

Nikkinen and Sahlström (2004) examined the degree of international equity market integration with respect to uncertainty by using the implied volatilities estimated from the market prices of stock index options from the U.S., U.K., German, and Finnish markets. To proxy the market's assessment of expected volatility, the daily implied volatility from the U.S. (VIX: 100 S&P stock index option prices), German (VDAX: 30 stock index option prices), U.K. (FTSE 100 index option prices), and Finnish markets (Finnish 25 stock index options) for the period of July, 1996 to February, 2000 was used. The Vector Autoregressive (VAR(n)) model was applied to analyze the transmission of uncertainty between the markets. In order to examine the direction of the causality between the implied volatility of the U.S., U.K., German, and Finnish markets, the Granger causality test was applied. Impulse response analysis was implemented to reveal the speed and persistence of the effect in the VAR system, and the Variance Decomposition was analyzed in order to detect the fraction of the variation in one variable explained by a variation in another variable. The results of the study generally indicated a high degree of integration among the U.S., U.K., and German markets with respect to uncertainty. The Finnish stock market appeared to be less integrated. Since the changes in uncertainty regarding the U.S. stock market were transmitted to the other markets, the U.S. stock market was the leading source of uncertainty. In addition, the German market was the leading source of uncertainty among the European markets. Two important implications for investors are indicated. The results have important implications for international portfolio management since changes in risk levels in major markets are strongly related. Secondly, the leading role of the U.S. market can be utilized when predicting volatilities in the European markets.

Wagner and Szimayer (2004) discussed the idea that implied market volatility allows the monitoring of ex ante risk expectations in different markets. The research paper tested the jump events in the implied volatility of the U.S. and Germany as well as considered their relation to public news events, which are crucial for many applications of financial theory. For the period of January 2, 1992 to December 31, 2002, daily observations for the VIX (implied volatility indices for the U.S. market) and VDAX (implied volatility indices for the German market) were used to estimate changes in market volatility at discrete points of time. The evidence of a significant and positive jump component in implied market volatility has three implications. First, asset pricing theory suggests that changes in market risk measured by volatility should affect expected asset returns, which may also hold for jumps in risk expectations. Next, risk management, especially in volatility forecasting, should account for asymmetric error distributions stemming from positive jumps in volatility. Finally, jumps in implied market volatility have an impact on stock as well as on volatility option pricing. Jump events are mostly country-specific with some evidence of volatility spillover, such as with the Asian currency crisis in the fall of 1997, the terror attacks in the U.S. in September, 2001, the U.S. labor market report in March, 1996, and the Hewlett-Packard profit warning in July, 1996.

2.3 Theoretical Framework

2.3.1 International Volatility Transmission

Daniels, and Vanhoose (2002) postulates that "changes in communications technology, combined with the introduction of new financial instruments, have moved nations to liberalize their equity markets." In addition, instant and low-cost communications and information innovations allow a wider range of firms and individuals to participate in international equity markets and to manage their risk and increase potential returns. Das (2010) notes that "a functional definition of financial globalization is the integration of the domestic financial system of an economy with the global financial markets and intermediaries." In addition, he mentions that "such globalization entails increasing global linkages through trans-border financial flows, and it implies the liberalization of international transactions in financial instruments by a large number of integrating economies." He also notes that "enabling the framework of financial globalization essentially entails the liberalization and development of the domestic financial sector as well as the liberalization of the capital account, which implies a free flow of funds in and out of a country's economy." He proposes that "globalization unleashes market mechanisms and facilitates Adam Smith's invisible hand to operate globally." Das (2010) concludes that "globalization eradicates market barriers, eliminates countervailing pressures from governments and unleashes competitive forces."

As mentioned by Schmitz (2012), in time of increasing international integration of equity markets, both investment income flows and capital gains are channels that can potentially provide international risk sharing. According to Corbett and Maulana (2013), such a concept relies on the economic theory that "at the optimum, the consumer cannot gain from a feasible shift of consumption between periods." Moreover, Corbett (2010) states that "a sound financial system has been associated with consumers' improved ability to achieve consumption smoothing." The equity market is one of the mechanisms through which risk sharing can occur among countries. Through equity markets, citizens or the government of a country can own claims to output produced in other countries. Corbett and Maulana (2013) postulates the implication that "the consumption of a particular country depends on the world income rather than its own individual income." Corbett and Maulana (2013) illustrates the case that "there is a mutual fund of one country that invests all of its wealth by buying other countries' assets." So, it is expected that "the revenue of the firm will be closely related to the movements of other countries' income." They shows that "this implies that the firm will be insulated from some of the negative shocks that occur in the domestic economy, because it is insured through ownership of other countries' assets." Daniels and Vanhoose (2002) indicates that "this form of risk sharing is also known as income insurance or international diversification."

Stated by Peters (2004); Sheng (2009) and Das (2010), "the advanced industrial economies (e.g. U.S., Japan, and many European countries) are the most active participants in the global stock markets and are also the most financially globalized." They point out that this is due to many important facts. First, the participation of some groups of developing economies (e.g. Thailand, Korea) has grown and has become substantial. Second, one of the most significant aspects of financial globalization is the rapid growth of international liquidity such that there has been an enormous increase in the liquid assets available to global market participants. Third, new investors, such as the sovereign wealth funds, mutual fund, and hedge funds, have emerged on the global financial stage. Das (2008), and MGI (2008) emphasize that "such institutions are awash with liquid resources and are the new financial heavyweights that are changing the structure and character of global equity markets as well as capital movements."

It has been recognized that stock investors in a given market incorporate into their 'buy' and 'sell' decisions not only information generated domestically but also information produced by other stock markets. Such behavior is consistent with the efficient markets hypothesis, provided that news generated by the international stock market is relevant for the pricing of domestic securities as the result of the increased globalization of stock markets, brought about by the relatively free flow of goods and services as well as the revolution in information technology (Koutmos and Booth, 1995). In addition, international assets pricing postulates that any two economies are related through trade and investment, so that any news about economic fundamentals in one country most likely has implications for the other country (Lin, Engle and Ito, 1994). Next, the efficient markets hypothesis and international pricing of assets will be explained.

2.3.1.1 Efficient Markets Hypothesis

The Efficient Markets Hypothesis argues that competition among investors makes the equilibrium expected stock return, which is a function of its "risk," from using information on stock prices commensurate with the cost of that information (Fama, 1970). Therefore, if costs are zero, prices correctly reflect all relevant information. According to such a hypothesis, if we could easily predict that stock prices will rise tomorrow, we would all buy today, and prices would in fact rise today until they reflected the information we had received. In other words, short-run returns are mainly unpredictable, which is consistent with a market that incorporates information efficiently. However, it has been suggested that historical prices are excessively volatile relative to their future realized value (Shiller, 1981). This implies that although prices respond quickly to information, they change for other reasons as well. Such volatility is the result of investors' sentiment or is related to the rate of information flow (Ross, 1989). Subsequent work linked such excess volatility to predictable variation in long-run returns; short-term predictability was later found as well. Nevertheless, such findings are still consistent with the hypothesis that time-varying expected returns may be due to time-varying risk or volatility. Thus, news generated by the international stock market (e.g. market contagion) is relevant for the pricing of domestic securities as a result of the increased globalization of stock markets and in this way volatility can be used to examine the transmission of information across different markets (Hamao et al., 1990; Koutmos and Booth, 1995; Koutmos, 1996 and Cifarelli and Paladino, 2005).

2.3.1.2 International Pricing of Assets

The function of equity markets is the allocation of the bearing of risks. Adler and Dumas (1983) state that “when the financial market allows individuals to trade risks in every conceivable dimension of their choice, the allocation of risk bearing is Pareto optimal.” In addition, Solnik (1974) mentions that “if national stock markets are not perfectly (positive) correlated, investors should be able to reduce their unique country risk without sacrificing expected returns by international diversification.” Thus, Lin et al. (1994) conclude that “the international relations of stock prices take into account both the national and international factors so that international asset-pricing can incorporate the correlations between stock returns in different countries.” Moreover, growing financial integration will increase the degree of correlation between the stock returns of different countries by making investors in the home market more responsive to changes in foreign markets, and this causes the stock volatility of the international equity markets to be related.

2.3.2 Implied Volatility as a Measure of Uncertainty in Stock Returns

While historical volatilities are “backward looking.” implied volatilities are “forward looking.” Natenberg (1994) states that “implied volatility can be thought of as a consensus volatility among all market participants with respect to the expected amount of underlying price fluctuation over the remaining life of an option.” However, the implied volatility in the marketplace is constantly changing since option prices, as well as other market condition, are constantly changing. In addition, Natenberg (1994) also mentions that “it is as if the marketplace were continuously polling all participants to come up with a consensus volatility for the underlying asset or the stock.” Moreover, he states that “as bids and offers are made, the trade price of an option will represent the equilibrium between supply and demand.” Such equilibrium can be translated into an implied volatility. Thus, Natenberg (1994) concludes that “implied volatility is the volatility implied by an option price observed in the market.”

Hull (1997) postulates that “implied volatilities can be used to monitor the market’s opinion about the volatility of the stock.” Moreover, he shows that “several implied volatilities are obtained simultaneously from different options on the same stock and a composite implied volatility is then calculated by taking a weighted average of the individual implied volatilities." Hull (1997) emphasizes that "since the price of the at-the-money option is far more sensitive to volatility than the price of the deep-out-of-the-money option, it is therefore providing more information about the "true" implied volatility."

Basically, there are two types of option: calls and puts. A call option is a security giving the right to the buyer the option to purchase shares of the stock at a fixed price until the day the option expires. A put option is a security giving the right to the buyer the option to sell shares of the stock at a fixed price until the day the option expires. The price to be paid is called the "exercise price" or the "strike price," and the day the option is to expire is called the "expiration date" or "maturity date" (Chiras and Manaster, 1978). American options can be exercised at any time up to the maturity date. European options can be exercised only on the maturity date itself. Moreover, several exchanges trade options on stock indices which are used to track the movement of the stock market as a whole (Hull, 2011). Next, the option pricing theory will be explained.

2.3.2.1 The Option Pricing Theory

According to the option pricing theory, the option value, o_t, is usually defined as a function of five factors, often called the direct determinants of an option value (Cox & Rubinstein, 1985):

$$o_t = f(S_t, K, T-t, r, \sigma) \tag{2.1}$$

where S_t = stock price at time t

K = the strike price

r = the risk-free interest rate

$T-t$ = time to maturity of the option

σ = volatility of the stock returns over the remaining life of the option

Of these determinants mentioned above, all except volatility are observable in the market. When the market price of a stock option is known, it is possible to find such a volatility value that makes the option value, given by the option pricing model (e.g., the Black and Scholes, 1973, model), agree with the market price of the option. Such volatility value is called implied volatility or implied standard deviation, σ_{isd}, and is given by

$$\sigma_{isd} \quad = \quad f^{-1}(o_t, S_t, K, T-t, r) \qquad (2.2)$$

where f^{-1} = the inverse function

Merton (1976) and Heynen, Kemna and Vorst (1994) indicate that "such implied volatility can be interpreted as the market's expectation of the stock index's return volatility over the remaining life of the option." Thus, Mayhew (1995) states that "implied volatility provides a method to measure investors' expectations about uncertainty regarding future stock price movements." Moreover, Christensen and Prabhala (1998); Fleming (1998); Dumas, Fleming and Whaley (1998) and Blair et al. (2001) mention that "it is widely documented that implied volatility is superior to historical volatility when forecasting the future realized volatility of the underlying stock."

2.4 Data and Methodology

2.4.1 Data

The data used in this study consist of 634 daily data of the SET50 index, the prices of the SET50 index options, and the volatility index of 3 stock markets, which are the Japan (Nikkei 225 index), U.S. (S&P 500 index), and European stock market (Down Jones Euro STOXX 50 stock index) for the period November, 2010 to December, 2013. The information was derived from various sources such as SETSMART (SET Market Analysis and Reporting Tools) and Thomson Financial DataStream. The next section will present the empirical results.

2.4.2 Implied Volatility Measure

Whaley (2000) identifies that "each implied volatility index is often referred to as the "investors fear gauge" because the level of implied volatility index indicates the consensus view of the expected future realized stock index volatility." Many countries especially in advanced industrial economies calculate such implied volatility index (referred to as the volatility index). For example, the volatility index for the S&P 500 stock (the U.S.) index, the DAX 30 index (Germany), CAC 40 index (France), the Down Jones Euro STOXX 50 stock index (12 European countries including Germany, France, Italy, Austria, Belgium, Finland, Greece, Ireland, Luxembourg, the Netherlands, Portugal, and Spain), and the Nikkei 225 index (Japan) are VIX, VDAX, VCAC, VSTOXX, and JNIV, respectively. Although, there is no such volatility index calculated for the SET50 index options, it is feasible to calculate such a volatility index or implied volatility using the Black-Scholes pricing formula, which is the most widely-employed model and is consistent with the assumption of option pricing—that the options market is dominated by investors that behave as if they employ the Black and Scholes model (Latané and Rendleman, 1976; Chiras and Manaster, 1978; Christensen and Prabhala, 1998 and Nikkinen and Sahlström, 2004). Black and Scholes succeeded in solving their differential equation in order to obtain formulas for the equilibrium prices of European call and put options. The application of the integral calculus calculates the prices of the call option and put option as follows, respectively (Black and Scholes, 1973):

$$c = SN(d_1) - Xe^{-r(T-t)}N(d_2) \tag{2.3}$$

$$p = Xe^{-r(T-t)}\, N(-d_2) - SN(-d_1) \tag{2.4}$$

where

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}$$

$$d_2 = \frac{\ln\left(\frac{S}{X}\right) + \left(r - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}$$

$$= d_1 - \sigma\sqrt{T-t}$$

c = call option price

p = put option price

S = stock price

X = strike price or exercise price

r = risk-free rate of interest

$T-t$ = time to maturity

σ = volatility or standard deviation

Typically, $N(x)$ is the cumulative probability distribution function for a variable that is normally distributed with a mean of zero and a standard deviation of 1 (i.e., it is the probability that such a variable will be less than x). The expression

$N(d_2)$ is the probability that the option will be exercised so that $XN(d_2)$ is the strike price times the probability that the strike price will be paid. $SN(d_1)e^{-r(T-t)}$ is the expected value of a variable that equals S_T if $S_T > X$ and zero otherwise (Hull, 1997).

The one parameter in the Black-Scholes pricing formula that cannot be observed directly is the volatility or standard deviation of the stock price. When the market price of stock option is known, it is possible to find such a volatility value that makes the option value agree with the market price of the option of the model. Such volatility value is referred to as the implied volatility. Watsham and Parramore (1997) show that “implied volatility is first established by plugging in the value of all the parameters in the model (including the option price that is observed in the option market) except for volatility, and using the iterative procedures (e.g. Newton-Raphson method) to calculate the implied volatility such that the option price from the model is equal to the actual option price that is plugged in.” Since the implied volatility calculated is the implied volatility of each individual option at each exercise price, the volatility index or the implied volatility to be used in this study will be calculated by taking an average of the individual implied volatilities from the at-the-money options or near-the-money options. Hull (1997) mentions that “such a calculation is consistent with the fact that the at-the-money option is far more sensitive to volatility than the price of the deep-out-of-the-money option so that it provides more information about the “true” implied volatility.”

2.4.3 The Empirical Models

For the study of the relationship between stock returns and volatility, and the volatility transmission of international stock markets, previous literature employed several methodologies such as least squares analysis and VAR models. With several advantages of VAR models, such as allowing the investigation of the multivariate model and identifying structural shock through variance decomposition, the VAR model was chosen to capture the important sources of fluctuations in the research paper. It is one of the most popular methodologies and is widely used for the analysis of multivariate financial time series.

The VAR models have been much used in empirical macroeconomic and financial studies since they were launched for such purposes by Sims in 1980, who suggests that "it should be feasible to estimate economic models as unrestricted reduced forms." In addition, Sims (1980) states that "All of the variables in VAR model are treated as endogenous variables." Moreover, there are many tools employed by the VAR analysis such as Granger causality, the co-integration test, impulse response analysis, the error collection mechanism, and variance decomposition to explain the relationship among the variables and their behavior.

Based on these considerations, the VAR models in this study will be used in two ways. First, the relationship between SET50's index returns and their implied volatility will be presented. Then, the implied volatility transmission of international stock markets will be established.

2.4.3.1 The Relationship Between SET50 Index's Returns and the Implied Volatility

For the relationship between SET50 index's returns and volatility, the vector autoregressive model of order p, VAR(p), was applied, as proposed by Hatemi and Irandoust (2011), based on the assumption that there exist causal relations between stock returns and the first differences in the implied volatility:

$$\boldsymbol{x_t} = \boldsymbol{v} + \boldsymbol{A_1 x_{t-1}} + \boldsymbol{A_2 x_{t-2}} + \cdots + \boldsymbol{A_p x_{t-p}} + \boldsymbol{e_t} \quad (2.5)$$

where

$$\boldsymbol{x_t} = \begin{bmatrix} THR_t \\ \Delta THV_t \end{bmatrix}$$

$$\boldsymbol{v} = \begin{bmatrix} v_{01} \\ v_{02} \end{bmatrix}$$

$$\boldsymbol{A_i} = \begin{bmatrix} a_{11,i} & a_{12,i} \\ a_{21,i} & a_{22,i} \end{bmatrix},\ i = 1, \ldots, p$$

$$\boldsymbol{e_t} = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

= vector of residuals, which in general will have non-zero cross correlations

THR_t = SET50's index returns at time t

ΔTHV_t = First differences in the implied volatility of returns at time t

In other words, such VAR(p) can be alternatively expressed as:

$$THR_t = v_{01} + a_{11,1}THR_{t-1} + a_{12,1}\Delta THV_{t-1} + \cdots + a_{11,p}THR_{t-p} + a_{12,p}\Delta THV_{t-p} + e_{1t} \quad (2.6)$$

$$\Delta THV_t = v_{02} + a_{21,1}THR_{t-1} + a_{22,1}\Delta THV_{t-1} + \cdots + a_{21,p}THR_{t-p} + a_{22,p}\Delta THV_{t-p} + e_{2t} \quad (2.7)$$

The order of the VAR(p) model was selected based mainly on Akaike's Information Criterion (AIC), and Schwarz's Information Criterion (SIC).

2.4.3.2 The Volatility Transmission of International Stock Markets

Thai stock market (SET50 index) and the stock markets of three additional countries—Japan (Nikkei 225 index), the U.S. (S&P 500 index), and the European stock market (Euro STOXX 50 stock index)—were considered for the analysis of the volatility transmission of international stock markets. The U.S. market was selected since it is the world's largest. Japan and European countries are the most active participants in the global stock markets and also the most financially globalized (Peters, 2004; Sheng, 2009 and Das, 2010).

In order to examine the transmission of volatility between the international stock markets, the following VAR(*n*) system was applied for analyzing the time structure of transmissions proposed by Nikkinen and Sahlström (2004) under the assumption that there is bi-directional causality between SET50 returns and volatility changes, which will be tested later in the chapter, as follows:

$$THR_t = a^{THR} + \sum_{i=1}^{n} b_i^{THR}\, THR_{t-i} + \sum_{i=1}^{n} c_i^{THR}\, \Delta THV_{t-i} + \sum_{i=1}^{n} d_i^{THR}\, \Delta JPV_{t-i} + \sum_{i=1}^{n} e_i^{THR}\, \Delta USV_{t-i} + \sum_{i=1}^{n} f_i^{THR}\, \Delta EUV_{t-i} + \varepsilon_t^{THR} \quad (2.8)$$

$$\Delta THV_t = a^{\Delta THV} + \sum_{i=1}^{n} b_i^{\Delta THV}\, THR_{t-i} + \sum_{i=1}^{n} c_i^{\Delta THV}\, \Delta THV_{t-i} + \sum_{i=1}^{n} d_i^{\Delta THV}\, \Delta JPV_{t-i} + \sum_{i=1}^{n} e_i^{\Delta THV}\, \Delta USV_{t-i} + \sum_{i=1}^{n} f_i^{\Delta THV}\, \Delta EUV_{t-i} + \varepsilon_t^{\Delta THV} \quad (2.9)$$

$$\Delta JPV_t = a^{\Delta JPV} + \sum_{i=1}^{n} b_i^{\Delta JPV}\, THR_{t-i} + \sum_{i=1}^{n} c_i^{\Delta JPV}\, \Delta THV_{t-i} + \sum_{i=1}^{n} d_i^{\Delta JPV}\, \Delta JPV_{t-i} + \sum_{i=1}^{n} e_i^{\Delta JPV}\, \Delta USV_{t-i} + \sum_{i=1}^{n} f_i^{\Delta JPV}\, \Delta EUV_{t-i} + \varepsilon_t^{\Delta JPV} \quad (2.10)$$

$$\Delta USV_t = a^{\Delta USV} + \sum_{i=1}^{n} b_i^{\Delta USV}\, THR_{t-i} + \sum_{i=1}^{n} c_i^{\Delta USV}\, \Delta THV_{t-i} + \sum_{i=1}^{n} d_i^{\Delta USV}\, \Delta JPV_{t-i} + \sum_{i=1}^{n} e_i^{\Delta USV}\, \Delta USV_{t-i} + \sum_{i=1}^{n} f_i^{\Delta USV}\, \Delta EUV_{t-i} + \varepsilon_t^{\Delta USV} \quad (2.11)$$

$$\Delta EUV_t = a^{\Delta EUV} + \sum_{i=1}^{n} b_i^{\Delta EUV}\, THR_{t-i} + \sum_{i=1}^{n} c_i^{\Delta EUV}\, \Delta THV_{t-i} + \sum_{i=1}^{n} d_i^{\Delta EUV}\, \Delta JPV_{t-i} + \sum_{i=1}^{n} e_i^{\Delta EUV}\, \Delta USV_{t-i} + \sum_{i=1}^{n} f_i^{\Delta EUV}\, \Delta EUV_{t-i} + \varepsilon_t^{\Delta EUV} \quad (2.12)$$

where THR_t = the return of Thai stock market at time *t*

ΔTHV_t = the first differences in implied volatility of Thai stock market at time *t*

ΔJPV_t = the first differences in implied volatility of Japan stock market at time *t*

ΔUSV_t = the first differences in implied volatility of U.S. stock market at time *t*

ΔEUV_t = the first differences in implied volatility of European stock market at time *t*

As mentioned above, the lag order *p* is selected by minimizing Akaike's Information Criterion (AIC), and Schwarz's Information Criterion (SIC).

2.4.4 Granger Causality Tests

The concept of a causality test was first introduced by Granger (1969), which explains the cause and effect relation between two variables or bi-directional causality. Granger (1969) points out that "such causality test was carried out to create not only the direction of causality of the linkage between stock returns and their volatility, but also the volatility transmission between the international stock markets in this study." Such an approach is based on the regression of each volatility proxy on its lagged values and on the lagged values of all the other variables.

Granger (1969) also explains that "the Granger causality is a part of the VAR model such that as the degree to which the variable x can explain the behavior of variable y and reduce variable y's conditional variance: x causes y." On the other hand, the opposite circumstance will be expressed as y causes x. If both directions are true, both x and y maintain a feedback relationship or bi-directional causality. However, if neither is true then x and y have independent relations or no causality. This study employed the Granger causality test in order to examine the cause and effect relation among SET50 index returns and their implied volatility or the existence of the leverage effect and the volatility feedback effect. If the stock returns are caused by the volatility, the volatility feedback effect hypothesis is satisfied; and when the stock returns lead to volatility, the leverage effect hypothesis is satisfied. Moreover, the Granger causality test was employed in the study to examine the cause and effect relation among the implied stock volatilities in Thailand, a selected Asian country, the U.S., and some selected European countries or the international stock volatility transmission between the countries. Such a causality test will correspond to the efficient markets hypothesis and the international pricing of assets such that news generated by international stock markets is relevant to the pricing of domestic securities as a result of the increased globalization of stock markets.

2.4.5 Impulse Response Analysis

In the VAR model, a shock to any single variable transmits dynamically to all the endogenous variables. The impulse response analysis traces the effect of a one-time shock on the current as well as future values of the endogenous variables. Enders (2004) illustrates that "impulse response functions are a practical approach to visually representing the behavior of time series in response to the various shocks at the time of the shock and over subsequent points in time." In addition, the impulse responses reveal the speed and persistence of the effect. In this study, impulse response analysis presents the response of the stock return volatility to other international stock markets' shocks or innovations.

2.4.6 Variance Decomposition

The approach of variance decomposition is another way to characterize the dynamic behavior of the VAR model through forecasting future fluctuation. Enders (2004) emphasizes that "the forecast error variance decomposition shows the proportion of the movements in a sequence from its own shocks and shocks to other variables, which also helps to explain the impact of the shocks of the international stock markets on the countries' stock market volatilities in this study."

2.5 Empirical Results

2.5.1 Causal Directions Between Stock Returns and Implied Volatility

Box, Jenkins and Reinsel (1994) suggest that "before processing each financial time series, a test of each variable's unit root was required in order to investigate whether the time series variable was non-stationary." Figure 2.1 illustrates the SET50 index returns (THR) and the SET50 implied volatilities (THV) during the sample period, respectively:

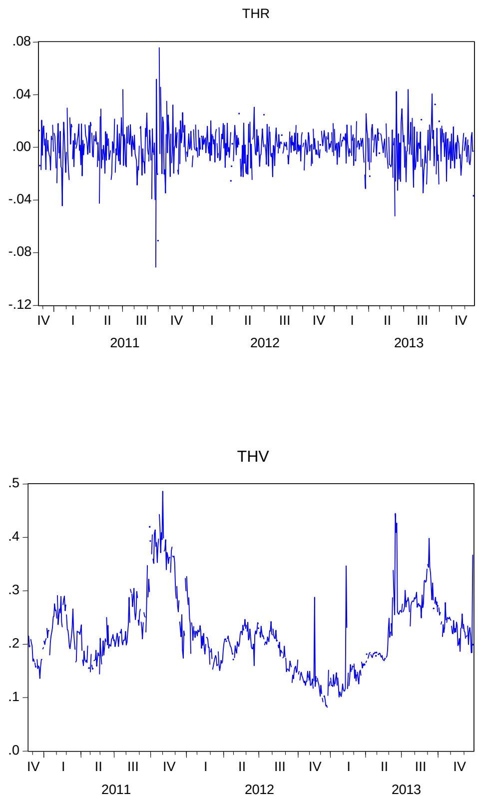

Figure 2.1 SET50 Index Returns (THR), and SET50 Implied Volatilities (THV) from November, 2010 to December, 2013

As can be seen in Figure 2.1, the mean of the daily SET50 index return series (THR) was close to zero. Moreover, the return series seemed to be stationary such that it tended to return to its mean value and fluctuated around it. On the other hand, the daily implied volatility series (THV) varied considerably over time, and there was no clear tendency for the series to revert to any mean value. The descriptive statistics for the SET50 index returns and the implied volatilities, including their daily changes, are given in Table 2.1.

Table 2.1 Descriptive Statistics of SET50 Index Returns (THR) and the Implied Volatilities (THV)

Statistics	**THR**	**THV**
Panel A: Levels		
Mean	0.00036	0.21757
Median	0.00147	0.21034
Maximum	0.07576	0.48624
Minimum	-0.09103	0.08150
Standard Deviation	0.01444	0.06784
Skewness	-0.42740	0.88177
Kurtosis	7.74415	3.96714
Panel B: First Differences (Δ)		
Mean		-0.00003
Median		-0.00043
Maximum		0.22802
Minimum		-0.16862
Standard Deviation		0.02949
Skewness		0.93732
Kurtosis		19.51249

Panel A of Table 2.1 presents the descriptive statistics for the daily SET50 index returns, and the volatilities. The sample mean is positive in both samples. The sample standard deviation is higher for the volatilities, which provides evidence for a larger variation in the volatility series. It is likely that the volatility series was non-stationary. A non-stationary series (or series contain a unit root) could cause spurious regression and therefore bias the study. However, differencing the unit-root nonstationary series leads to a stationary one (Tsay, 2010). Panel B of Table 2.1 shows the descriptive statistics for the differenced implied volatility or the daily volatility changes. The standard deviation of the implied volatility changes considerably declines compared to the levels of the volatilities. In order to investigate the stationarity of both the return and the volatility series, the augmented Dickey-

Fuller (ADF) and Phillips-Perron (PP) tests of a unit root were applied for the levels of the returns, and for the differences of the return volatilities, as shown in Table 2.2.

Table 2.2 Unit Root Tests of SET50 Index Returns (THR) and the Implied Volatilities (THV)

	Levels		**First Differences (Δ)**	
	ADF	**PP**	**ADF**	**PP**
THR	-26.283***	-26.313***		
THV	-2.840*	-4.813***	-20.241***	-43.294***

Note: The table reports the Augmented Dickey-Fuller and the Phillips-Perron unit root tests without a time trend. Critical values at the 1%, 5%, and 10% significance level are -3.440, -2.866, and -2.569, respectively.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

As can be seen in Table 2.2, the ADF and PP test statistics suggest that SET50 index returns do not have a unit root, but the SET50 return volatility series have a unit root. The null hypothesis of a unit root could not be rejected for the SET50 return volatilities at the 5% significance level. However, after differencing the volatility series, the results showed that the return volatilities had no unit root at the 1% significance level. This implies that the return volatility series were I (1) processes. Next, the correlation coefficients between the SET50 index returns and the return volatilities are reported in Table 2.3.

Table 2.3 Correlation Structures

Panel A: Levels	THR	THV
THR	1	
THV	-0.058 (0.144)	1

Panel B: First Differences in implied volatilities	THR	Δ THV
THR	1	
Δ THV	-0.155*** (0.000)	1

Note: p-value are reported in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

According to Table 2.3, there is an insignificant negative correlation between the SET50 index returns and the return volatilities. However, such a negative contemporaneous correlation between the returns and the volatility changes is significant at the 1% level. Such results are consistent with the asymmetric property of volatility in equity markets where stock returns and volatility are negatively correlated (Bekaert and Wu, 2000; Whaley, 2000; Simon, 2003; Skiadopoulos, 2004; Giot, 2005 Hibbert et al., 2008). However, it is still controversial whether such a negative relationship comes from return-driven or volatility-driven effects. One of the main objectives of the paper was to identify the causality between the returns and volatility for the Thai stock market. In order to achieve such an objective, the two-variable VAR(*p*) model was estimated. To define the appropriate lag lengths (*p*) of the VAR model, Akaike's information criteria (AIC), Schwartz's information criteria (SIC), and the Final Prediction Error (FPE) were used. The test statistics are shown in Table 2.4.

Table 2.4 Lag Order Selection for VAR(p) Model

Lag	AIC	SIC	FPE
0	-9.854	-9.840	1.80E-07
1	-9.996	-9.954	1.56E-07
2	-10.032	-9.960	1.51E-07
3	-10.062	-9.962	1.46E-07
4	-10.068	-9.939	1.45E-07
5	-10.065	-9.908	1.46E-07
6	-10.066	-9.881	1.46E-07
7	-10.061	-9.847	1.46E-07
8	-10.062	-9.820	1.46E-07
9	-10.066	-9.796	1.46E-07
10	-10.058	-9.759	1.47E-07

Note: The table reports Akaike's (AIC) and Schwarz's (SIC) information criteria, and final prediction error (FPE) for the lag order selection.

According to Table 2.4, the SIC suggests a lag length of three, and according to the AIC and FPE, a lag length of four is appropriate. Table 2.5 presents the Granger causality test results for testing the causality between the SET50 returns (THR) and the first differences in implied volatility.

Table 2.5 Results of Granger Causality Tests

Null hypothesis	4 lags		3 lags	
	F statistics	p-value	F statistics	p-value
THR does not Granger cause ΔTHV	4.314	0.002	2.933	0.033
ΔTHV does not Granger cause THR	4.024	0.003	5.049	0.002

Note: THR denotes SET50 index returns, and ΔTHV denotes the first difference in SET50 return volatilities

As can be seen in Table 2.5, the test statistics are reported for lag orders three and four. It was found that the stock returns Granger causes implied volatilities and vice versa at least at the 5% significance level. Thus, there was bi-directional causality between the returns and implied volatility. This suggests that both the leverage effect hypothesis and the volatility feedback effect hypothesis are satisfied for the Thai stock market. Finally, the serial correlation in the residuals was tested for the appropriateness of the VAR(*p*) model. Using the information criterion from Table 2.4, VAR(4) model was chosen. The summary statistics of the Ljung-Box Q statistic for testing autocorrelation in the residuals are presented in Table 2.6.

Table 2.6 Ljung-Box Statistics (Qh, h > 4)

lag (h)	Ljung-Box Q_h statistic	p-value
1	0.071	NA
2	0.310	NA
3	0.702	NA
4	1.339	NA
5	11.253	0.024
6	19.217	0.014
7	24.590	0.017
8	30.728	0.015
9	36.308	0.014
10	37.981	0.035

Note: NA denotes not available since the test is valid only for lags larger than the VAR Lag Order

According to Table 2.6, the probability value (p-value) of the Ljung-Box Q statistic is greater than 0.01 for all lag orders of one to ten. This implies that no residual autocorrelation remains for the VAR(4) model at the 1% significance level, suggesting that no longer lag lengths for the variable are needed. In the next section, the study will investigate the degree of international equity market integration with respect to volatility.

2.5.2 International Implied Volatility Transmission

In this section, the volatility transmission between international stock markets will be analyzed. Figure 2.2 illustrates the implied volatilities during the sample period.

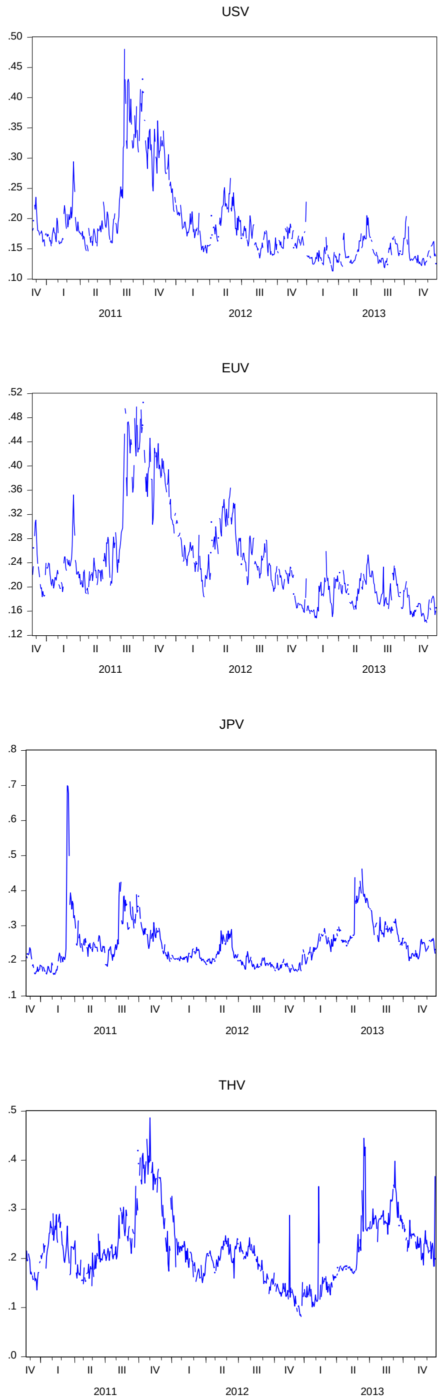

Figure 2.2 Implied Volatilities from November, 2010 to December, 2013

As can be seen in Figure 2.2, the implied volatility series for the US, EU, Japan, and Thailand during the sample period from November, 2010 to December, 2013 are presented. The sample covers the periods of high and low stock market uncertainty. It can be observed that the implied volatilities varied considerably over time, and that there was no clear tendency for the series to revert to any mean value. The descriptive statistics for the implied volatilities, including their daily changes of four international stock markets, are given in Table 2.7.

Table 2.7 Descriptive Statistics of Implied Volatilities from November, 2010 to December. 2013

Statistics	USV	EUV	JPV	THV
Panel A: Levels				
Mean	0.187	0.243	0.245	0.218
Median	0.170	0.223	0.233	0.210
Maximum	0.480	0.504	0.699	0.486
Minimum	0.113	0.141	0.161	0.082
Standard Deviation	0.063	0.075	0.065	0.068
Skewness	1.862	1.362	2.267	0.882
Kurtosis	6.333	4.441	13.234	3.967
Panel B: First Differences (Δ)				
Mean	-8.8E-05	-8.8E-05	2.9E-05	-2.7E-05
Median	-0.0007	-0.0008	-0.0009	-0.0004
Maximum	0.1600	0.1213	0.2916	0.2280
Minimum	-0.0889	-0.1066	-0.1773	-0.1686
Standard Deviation	0.0179	0.0191	0.0242	0.0295
Skewness	1.6249	0.3512	3.1148	0.9373
Kurtosis	17.8339	9.0204	50.4753	19.5125

Panel A and Panel B of Table 2.7 report the descriptive statistics for the implied volatilities at the levels, and the differences, respectively. The first difference in the implied volatilities or the implied volatility changes results in a lower standard deviation or variation for each country's stock market. Then, the ADF and PP tests of a unit root were applied to the levels and for the differences of the variables, as shown in Table 2.8.

Table 2.8 Unit Root Tests of Implied Volatilities

	Levels		First Differences (Δ)	
	ADF	PP	ADF	PP
USV	-2.046	-3.274**	-17.783***	-29.897***
EUV	-2.170	-2.546	-16.472***	-26.881***
JPV	-3.807***	-4.706***	-17.416***	-27.444***
THV	-2.840*	-4.813***	-20.241***	-43.294***

Note: The table reports the Augmented Dickey-Fuller and the Phillips-Perron unit root tests without a time trend. Critical values at the 1%, 5%, and 10% significance level are -3.440, -2.866, and -2.569, respectively.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

As shown in Table 2.8, using the ADF test, the null hypothesis of a unit root was rejected in the case of Japan at the 5% significance level, whereas the unit root was not rejected for other countries' series. After differencing, it can be seen that none of the series had a unit root at the 1% significance level. Table 2.9 reports the correlation coefficients between the implied volatilities at the levels, and the changes.

Table 2.9 Correlation Coefficients Between Implied Volatilities

Panel A: Levels	USV	EUV	JPV
EUV	0.945*** (0.000)		
JPV	0.361*** (0.000)	0.318*** (0.000)	
THV	0.523*** (0.000)	0.512*** (0.000)	0.395*** (0.000)
Panel B: First Differences	**Δ USV**	**Δ EUV**	**Δ JPV**
Δ EUV	0.670*** (0.000)		
Δ JPV	0.198*** (0.000)	0.330*** (0.000)	
Δ THV	0.063 (0.111)	0.130*** (0.001)	0.098** (0.013)

Note: p-value are Reported in Parentheses.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Table 2.9 shows the significant positive contemporaneous correlations between the implied volatility at the levels, and the changes at least at the 5% significance level except for Thailand and the US, whose correlation was marginally significantly positive at the 12% significance level. This implies that the uncertainty in equity markets changes in the same way, and there exists a moderate to high degree of financial integration among international stock markets with respect to the implied volatility at the levels. The highest correlation (0.67) was observed between the US and EU implied volatility changes. For Thailand, the differences of the implied volatility were lowly correlated with other markets, ranging from 0.063 to 0.13. In order to estimate the VAR(*p*) model of the implied volatility changes and Thailand's stock returns, inferred from the causal directions between the Thailand stock returns and the volatilities in section 4.3.1, the test statistics for the AIC, SIC, and FPE are reported in Table 2.10.

Table 2.10 AIC, SIC, and FPE for VAR(p) Order Selection

Lag	AIC	SIC	FPE
0	-19.800	-19.771	2.96E-14
1	-20.226	-20.083	1.93E-14
2	-20.315	-20.059	1.77E-14
3	-20.384	-20.013	1.65E-14
4	-20.451	-19.966	1.54E-14
5	-20.418	-19.819	1.59E-14
6	-20.391	-19.677	1.64E-14
7	-20.362	-19.534	1.69E-14
8	-20.363	-19.421	1.68E-14
9	-20.351	-19.295	1.71E-14
10	-20.313	-19.143	1.77E-14

Note: The table reports Akaike's (AIC) and Schwarz's (SIC) information criteria, and final prediction error (FPE) for the lag order selection.

As can be seen in Table 2.10, while the AIC and FPE suggest the lag length of four to be used in the VAR(*p*), SIC suggests the lag length of one. Since the significance of serial correlation in the residual in the VAR(1) model was indicated, the lag order of four was applied in the examination. The Granger causality tests between the implied volatility changes and Thailand's stock returns are presented in Table 2.11.

Table 2.11 Granger Causality Test Between the First Differences in Implied Volatility

Null hypothesis	F statistic	p-value
Δ EUV does not Granger Cause Δ USV	0.531	0.713
Δ USV does not Granger Cause Δ EUV	12.226	0.000
Δ JPV does not Granger Cause Δ USV	7.243	0.000
Δ USV does not Granger Cause Δ JPV	16.999	0.000
THR does not Granger Cause Δ USV	1.715	0.145
Δ USV does not Granger Cause THR	12.447	0.000
Δ THV does not Granger Cause Δ USV	1.314	0.263
Δ USV does not Granger Cause Δ THV	2.273	0.060
Δ JPV does not Granger Cause Δ EUV	3.368	0.010
Δ EU does not Granger Cause Δ JPV	11.420	0.000
THR does not Granger Cause Δ EUV	0.777	0.541
Δ EUV does not Granger Cause THR	4.295	0.002
Δ THV does not Granger Cause Δ EUV	1.186	0.316
Δ EUV does not Granger Cause Δ THV	1.023	0.395
THR does not Granger Cause Δ JPV	1.171	0.322
Δ JPV does not Granger Cause THR	0.639	0.635
Δ THV does not Granger Cause Δ JPV	2.442	0.046
Δ JPV does not Granger Cause Δ THV	0.406	0.804
Δ THV does not Granger Cause THR	4.024	0.003
THR does not Granger Cause Δ THV	4.314	0.002

Note: THR denotes SET50 index returns, and Δ THV denotes first difference in SET50 implied volatilities.

Δ USV, ΔEUV, and Δ JPV denote the first difference in implied volatilities of the U.S., European, and Japanese stock markets, respectively.

In Table 2.11 it can be seen that U.S.-implied volatility changes caused other markets at the 1% significance level, except for Thailand's implied volatility changes, such that the U.S.-implied volatility changes caused Thailand's implied volatility changes at the 6% significance level. This implies that the changes in uncertainty in the U.S. stock market were transmitted to other markets. Moreover, the E.U.-implied volatility changes Granger causes Thailand stock returns at the 1% significance level, indicating that uncertainty flows from E.U. to Thailand. There was bi-directional causality between Thailand's stock returns and volatilities at the 1% significance level, as mentioned in section 2.5.1. Next, the Ljung-Box Q statistics are reported in Table 2.12 in order to investigate the serial correlation in residuals of the VAR(4) model.

Table 2.12 Ljung-Box Qh Statistics (h > 4)

lag (h)	Ljung-Box Q_h statistic	p-value
1	0.504	NA
2	2.385	NA
3	3.687	NA
4	9.183	NA
5	30.781	0.196
6	59.970	0.158
7	89.453	0.122
8	122.225	0.065
9	150.281	0.061
10	176.298	0.070

Note: NA denotes not available since the test is valid only for lags larger than the VAR lag order.

As can be seen in Table 2.12, the p-value of the Ljung-Box Q statistic is greater than 0.01 for all lag orders of one to ten. This indicates no residual autocorrelation remains for VAR(4) model at the 1% significance level, suggesting that no longer lag lengths for the variable are needed. Then, the response of the stock return volatility to other international stock markets' shocks or innovations was analyzed using the impulse response functions. Figures 2.3 to 2.6 present the estimation results from the impulse response analysis, which shows the response of the first differences of one stock return volatility to another volatility shock, as follows:

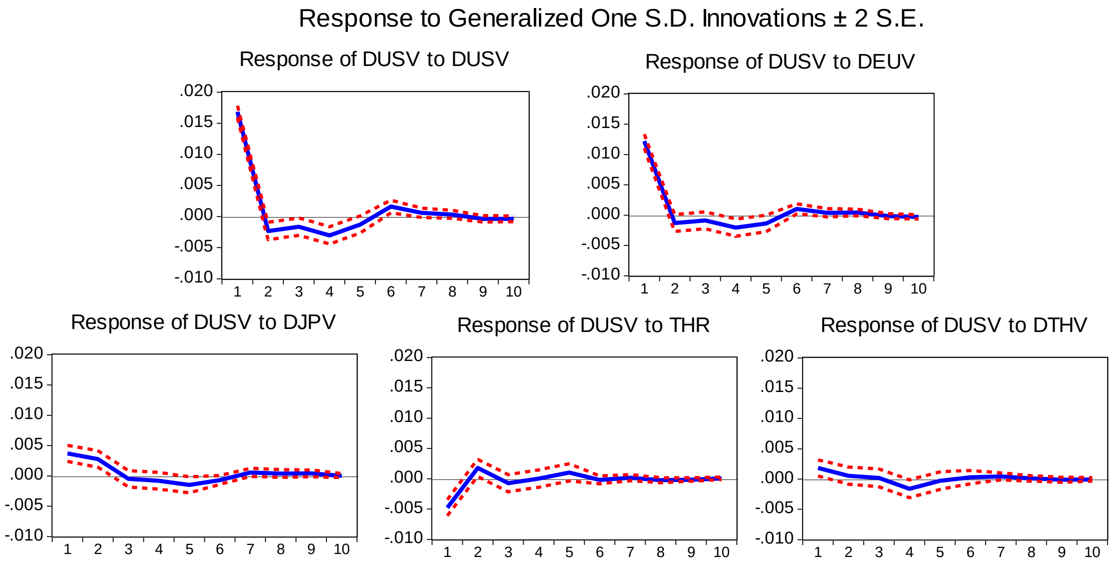

Figure 2.3 The US's Impulse Responses of the First Differences in Implied Volatility to Another Market

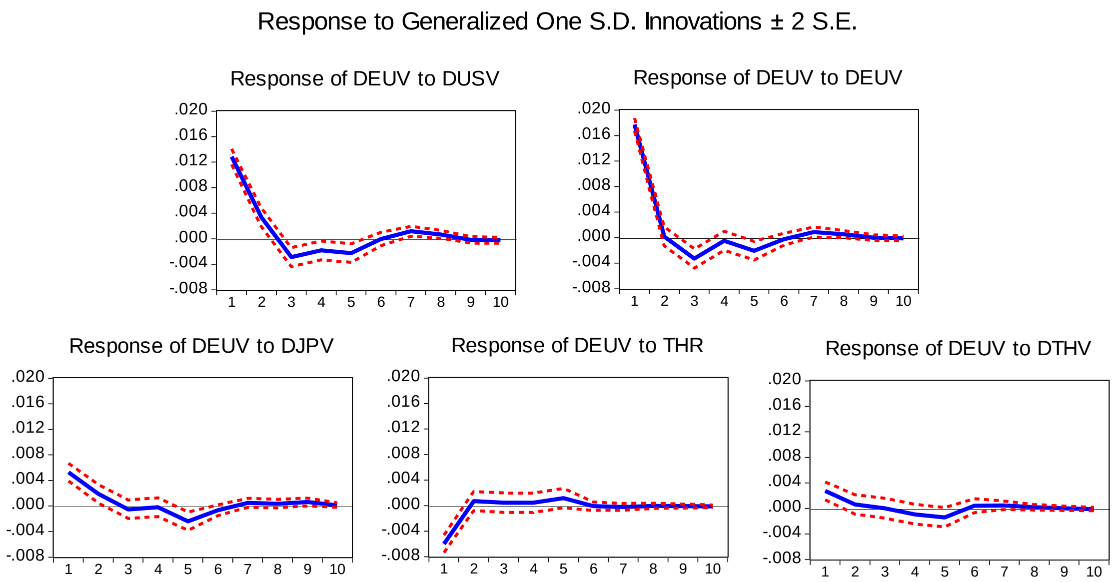

Figure 2.4 The EU's Impulse Responses of the First Differences in Implied Volatility to Another Market

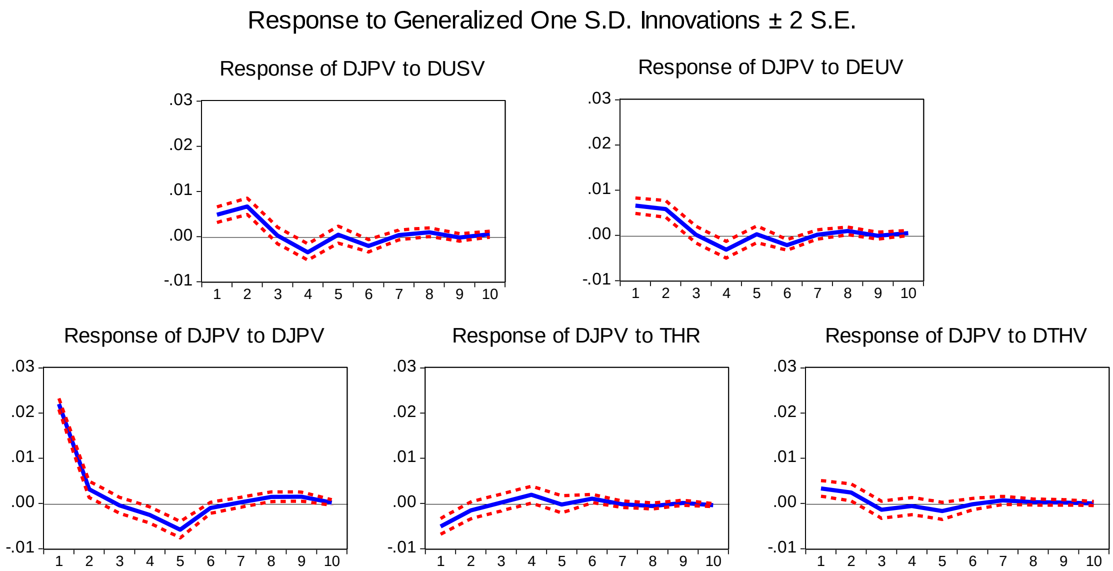

Figure 2.5 Japan's Impulse Responses of the First Differences in Implied Volatility to Another Market

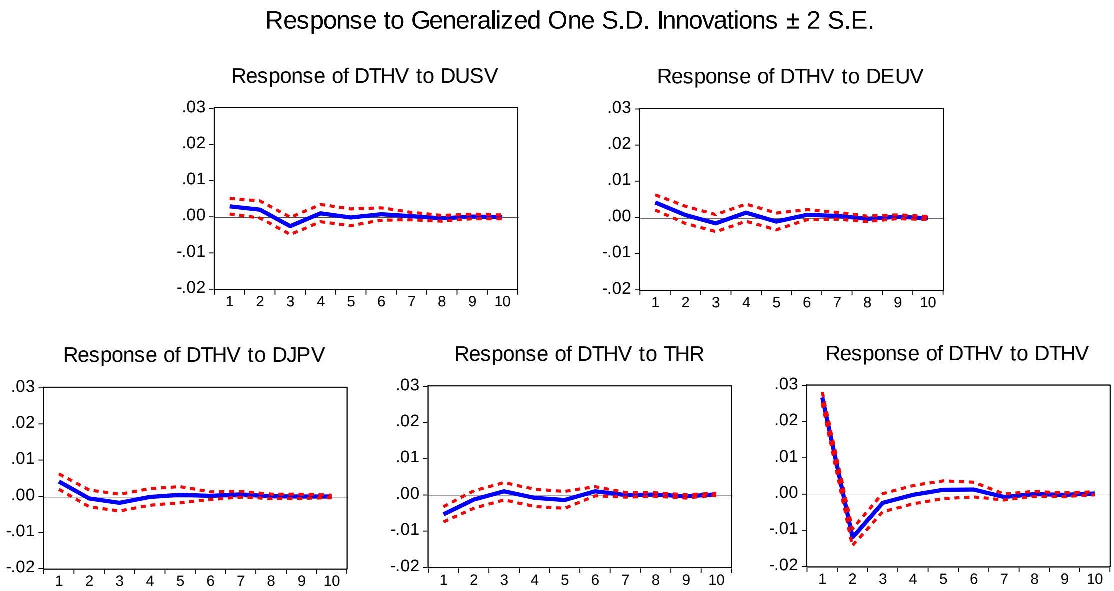

Figure 2.6 Thailand's Impulse Responses of the First Differences in Implied Volatility to Another Market

As can be seen in Figure 2.3 – 2.6, the impulse responses of implied volatility in one market to a shock in implied volatility on the other markets are presented. In addition, 95% confidence intervals are reported. Day 1 indicates contemporaneous effect, and Day 2 is a 1-day lagged effect, etc. The responses of the implied volatility of the E.U., Japan, and Thailand to a shock in the implied volatility of the U.S. indicate that the volatility of E.U., Japan, and Thailand also increase on the next day following the contemporaneous effect. Then, the impact starts to decay and the whole impact is incorporated within 2 days. The responses of the implied volatility of the U.S. to shocks of the E.U., Japan, and Thailand are incorporated within the same day. Such findings indicate that the implied volatility of the U.S. leads the other implied volatility by one day. Next, variance decomposition analysis is used to ascertain how important the innovations of the other variables in the VAR model are in explaining the fraction of a variable at different step ahead forecast variances. The results of the variance decomposition tests are presented in Table 2.13 to 2.16 as follows:

Table 2.13 US's Variance Decomposition of the First Differences in Implied Volatility

Period	Δ USV	Δ EUV	Δ JPV	THR	Δ THV
1	100.0000	0.0000	0.0000	0.0000	0.0000
2	95.0594	0.0971	3.6639	1.0432	0.1364
3	94.5443	0.1565	3.6302	1.5278	0.1414
4	93.8299	0.1614	3.5035	1.7158	0.7894
5	93.3168	0.2891	3.8585	1.7509	0.7848
6	93.0242	0.2987	4.1445	1.7328	0.7998
7	92.8795	0.2992	4.2009	1.7766	0.8437
8	92.8449	0.3181	4.2169	1.7770	0.8431
9	92.7590	0.3241	4.2812	1.7835	0.8522
10	92.7554	0.3244	4.2839	1.7835	0.8528

Note: THR denotes SET50 index returns, and Δ THV denotes first difference in SET50 implied volatilities.

Δ USV, ΔEUV, and Δ JPV denote the first difference in implied volatilities of the U.S., European, and Japanese stock markets, respectively.

From Table 2.13, the U.S.'s variance decomposition of implied volatility analysis reveals that the largest share of shock comes from its own shock at least 93%. Next is the implied volatility of Japan which accounts for about 4%. E.U., and Thailand shocks also account for about 1% each.

Table 2.14 EU's Variance Decomposition of the First Differences in Implied Volatility

Period	Δ USV	Δ EUV	Δ JPV	THR	Δ THV
1	52.4645	47.5355	0.0000	0.0000	0.0000
2	51.4679	46.7908	1.0687	0.5583	0.1144
3	52.0320	46.0469	1.0984	0.6704	0.1523
4	52.1613	45.7376	1.0821	0.6691	0.3500
5	52.1567	44.6389	1.9960	0.6587	0.5497
6	52.0400	44.5663	2.0993	0.6758	0.6186
7	52.1840	44.3773	2.1067	0.6820	0.6499
8	52.2287	44.3124	2.1154	0.6916	0.6519
9	52.1685	44.2618	2.2274	0.6907	0.6516
10	52.1648	44.2460	2.2341	0.6979	0.6572

Note: THR denotes SET50 index returns, and Δ THV denotes first difference in SET50 implied volatilities.

Δ USV, ΔEUV, and Δ JPV denote the first difference in implied volatilities of the U.S., European, and Japanese stock markets, respectively.

As can be seen in Table 2.14, the E.U.'s variance decomposition of implied volatility analysis is different from the previous one. This shows that 1% of the U.S. volatility shock had the most influence on the E.U. stock volatility, which accounted for about 52%. The second largest was the E.U. own shock, which accounted for about 45%. Japan's and Thailand's shocks accounted for about 2% and 1%, respectively.

Table 2.15 Japan's Variance Decomposition of the First Differences in Implied Volatility

Period	Δ USV	Δ EUV	Δ JPV	THR	Δ THV
1	4.8229	4.0800	91.0972	0.0000	0.0000
2	12.6691	4.0680	82.6582	0.1592	0.4455
3	12.6264	4.0516	82.3607	0.1649	0.7965
4	14.4282	4.1017	80.4717	0.2194	0.7791
5	13.4713	3.8232	81.3639	0.3798	0.9618
6	14.0710	3.9233	80.6522	0.3903	0.9631
7	14.0756	3.9214	80.5844	0.3910	1.0277
8	14.1558	3.9377	80.4930	0.3902	1.0233
9	14.1015	3.9229	80.5492	0.4056	1.0208
10	14.1333	3.9292	80.5029	0.4117	1.0229

Note: THR denotes SET50 index returns, and Δ THV denotes first difference in SET50 implied volatilities.

Δ USV, ΔEUV, and Δ JPV denote the first difference in implied volatilities of the U.S., European, and Japanese stock markets, respectively.

Table 2.15 presents Japan's variance decomposition of implied volatility analysis. It indicates that the largest share of shock came from its own shock at about 80%. Next is the implied volatility of the U.S., which accounted for about 14%. The E.U.'s and Thailand's shocks also accounted for about 4% and 1%, respectively.

Table 2.16 Thailand's Variance Decomposition of the First Differences in Implied Volatility

Period	Δ USV	Δ EUV	Δ JPV	THR	Δ THV
1	1.1711	1.2330	1.2106	2.0667	94.3186
2	1.4004	1.1439	1.0742	1.8248	94.5567
3	2.1265	1.1417	1.2668	1.8011	93.6638
4	2.2252	1.2184	1.3085	1.8256	93.4224
5	2.2110	1.4525	1.3693	2.1554	92.8117
6	2.2567	1.4558	1.3639	2.3511	92.5726
7	2.2560	1.4759	1.3807	2.3524	92.5351
8	2.2778	1.4769	1.3811	2.3521	92.5122
9	2.2774	1.4795	1.3823	2.3690	92.4919
10	2.2777	1.4848	1.3822	2.3698	92.4855

Note: THR denotes SET50 index returns, and Δ THV denotes first difference in SET50 implied volatilities.

Δ USV, ΔEUV, and Δ JPV denote the first difference in implied volatilities of the U.S., European, and Japanese stock markets, respectively.

Table 2.16 presents Thailand’s variance decomposition of implied volatility analysis. It indicates that the largest share of shock to Thailand’s volatility came from their own shock at about 93%. The second largest was the U.S. volatility shock, which accounted for about 2%. The E.U. volatility shock accounted for about 1%. The Japan volatility shock also accounted for about 1%. Next, the estimation results from the impulse response analysis, which shows the response of Thailand’s stock returns to another volatility shock, and the variance decomposition of the stock returns, are presented in Figure 2.7 and Table 2.17, respectively, as follows:

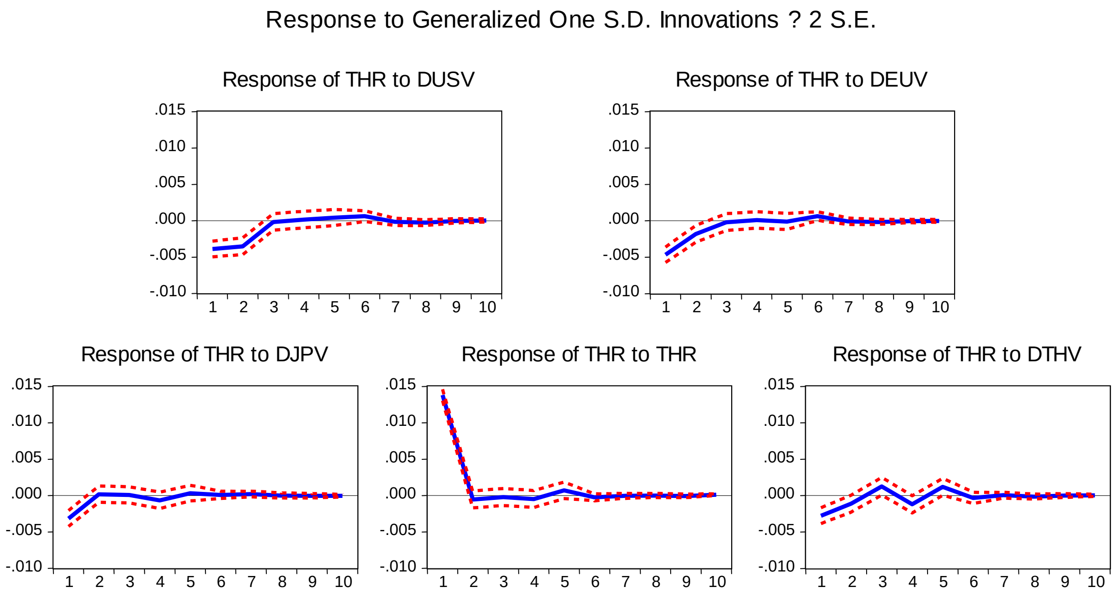

Figure 2.7 Thailand’s Impulse Responses of Stock Returns to Another Market

Table 2.17 Thailand's Variance Decomposition of Returns

Period	Δ USV	Δ EUV	Δ JPV	THR	Δ THV
1	8.0628	3.7158	1.8194	86.4020	0.0000
2	13.3947	3.9600	1.9498	80.0444	0.6511
3	13.2979	3.9291	1.9428	79.4035	1.4267
4	13.1477	3.8825	2.1800	78.6293	2.1605
5	13.0357	3.9891	2.2095	77.8077	2.9581
6	13.1623	4.0185	2.2101	77.5727	3.0365
7	13.1702	4.0186	2.2331	77.5423	3.0358
8	13.2013	4.0181	2.2322	77.5060	3.0423
9	13.2010	4.0194	2.2325	77.5051	3.0421
10	13.1999	4.0199	2.2336	77.5031	3.0434

Note: THR denotes SET50 index returns, and Δ THV denotes first difference in SET50 implied volatilities.

Δ USV, ΔEUV, and Δ JPV denote the first difference in implied volatilities of the U.S., European, and Japanese stock markets, respectively.

As can be seen in Figure 2.7 and Table 2.17, Thailand's stock returns responded negatively to the contemporaneous change from other implied volatility shocks in the system. The largest share of shock to Thailand's stock returns came from their own shock at about 78%. The second largest was the U.S. volatility shock, which accounted for about 13%. In addition, the E.U. volatility shock to Thailand's returns accounted for about 4%, while Japan's volatility shock accounted for about 2%.

2.6 Conclusion and Implications

This paper examined the interaction between the SET50 index returns and options-derived implied volatility by using a two-variable VAR model. It was found that the correlation between the returns and the volatility changes was significantly negative or the asymmetric property of volatility exists. Such a finding is consistent with the related literature (Bekaert and Wu, 2000; Whaley, 2000; Simon, 2003, Skiadopoulos, 2004; Giot, 2005 and Hibbert et al., 2008). The application of the Granger causality test implies that there is a bi-directional causality between the returns and the volatility such that both the return-driven effect and the volatility-driven effect were satisfied.

From the international point of view, the paper aimed to investigate the stock implied volatility transmission between international countries, namely the U.S. (S&P 500 index), Japan (Nikkei 225 index), and European stock markets (Down Jones Euro STOXX 50 stock index), and Thailand (SET50 index) or the existence of such financial markets integration. A five variable VAR model was used with the application of the Granger causality test, impulse response analysis, and variance decomposition. The results of the study showed two important issues. First, the correlation structures indicated that the implied volatility correlations were moderately correlated with each other, especially the correlation between the U.S. and the E.U. Second, the dependencies of the implied volatility series across different countries existed such that changes in uncertainty in the U.S. stock market were transmitted to other markets, including Thailand's stock returns and volatility. This is supported by the efficient markets hypothesis, which suggests that news generated by the international stock market is relevant for the pricing of domestic securities as the result of the increased globalization of stock markets (Koutmos and Booth, 1995). In addition, such dependencies is consistent with the international assets pricing such that any two economies are related through trade and investment such that the international relations of stock prices takes into account both the national and international factors so that international asset-pricing can incorporate the correlations between stock returns in different countries (Lin et al., 1994).

The empirical results of the present study have a number of implications. First, the expectations of uncertainty on one stock market are reflected in the expectations on the other market under the integrated equity markets. The empirical result is consistent with Hamao et al. (1990); Koutmos and Booth (1995); Koutmos (1996) and Cifarelli and Paladino, (2005) such that changes in the volatility generated by an international stock market are relevant to the volatility of domestic securities as a result of the increased globalization of stock markets through the international implied volatility-driven effect . Second, the results have important implications for international portfolio management since they show that changes in risk levels in major markets are moderately related. Forming an optimal portfolio of international and domestic securities should also take into consideration the responses of option-derived implied volatilities, in addition to the correlations between international stock returns, which are one of the most concerns among global investors in terms of managing their international portfolios. Third, volatility and returns prediction methods can be improved by taking into account the dependencies between options-derived implied volatilities across different markets. The leading role of the U.S. market in particular can be utilized when predicting both stock volatilities and returns in Thailand’s stock market.

CHAPTER 3

STOCK RETURNS AND CONDITIONAL VOLATILITY

3.1 Introduction

The ability to forecast financial market volatility is important for portfolio selection and asset management as well as for the pricing of primary and derivative assets. While most researchers agree that volatility is predictable in many asset markets (see for example the survey by Bollerslev (1992)), they differ on how volatility predictability should be modeled. The most interesting of these approaches is the "asymmetric" volatility model, where good news and bad news have different predictability for future volatility (Engle and Ng, 1993). In addition, news impact curve is estimated to model such volatility.

Asymmetric volatility usually occurs when contemporaneous returns and conditional return volatility are negatively correlated. In other words, negative returns are generally associated with upward revisions of conditional volatility, and vice versa. Such asymmetric volatility is most apparent during stock market crashes (e.g. a subprime crisis) when a large decline in stock prices is associated with a significant increase in stock market volatility (Wu, 2001). While volatility and its relationship with stock prices in developed financial markets have been well studied, little attention has been paid to the extensive study of the volatility of emerging stock markets, including Thailand. For the reasons mentioned above, this chapter aims to investigate the asymmetric relation between stock returns and their volatility of the SET as one of the emerging stock markets. In addition to aggregate volatility, measures of stock volatility at the industry level are also important because they help to forecast economic activity and reduce the significance of other commonly-used forecasting variables, especially for investors whose decision making is affected by a shift in industry-level volatility (Campbell et al., 2001). In addition, Campbell and Lettau (1999) mention that "a stock market dispersion measure computed at industry-level returns is a leading indicator of real economic activity." Thus, the relation between Thailand's stock returns and volatility will be investigated at the aggregate level and with eight industry group indices in this chapter. Such a causal relationship will be examined as to whether it will satisfy the leverage effect hypothesis or the volatility feedback effect hypothesis. According to the theoretical framework, the volatility feedback effect hypothesis states that returns are caused by stock volatility or volatility-driven effects, and the leverage effect hypothesis claims that returns lead to stock volatility or a return-driven effect.

3.2 Review of the Literature

Bekaert and Wu (2000) discussed the idea that "two important determinants of asymmetric volatility are the leverage effect and volatility feedback effect." While the leverage effect hypothesis claims that return shocks lead to changes in conditional volatility, the volatility feedback effect claims that if volatility is priced, an anticipated increase in volatility raises the required return on equity leading to an immediate stock price decline. Wu (2001) applied the Efficient Method of Moment (EMM), a method developed by Gallant and Tauchen (1996, 1998a, 1998b), to test the specification of the structural model for the monthly returns on the value weighted CRSP index from January 1926 to December 1997 and the weekly returns from July 1962 to December 1997. It was found that both the leverage effect and volatility feedback were important determinants of asymmetric volatility. Moreover, Wu (2001) found out that "volatility feedback is both statistically and economically significant."

Bollerslev (1987) claimed that "the distribution of speculative price changes and rates of return data tend to be uncorrelated over time but characterized by volatile and tranquil periods." Applying the extension of the Generalized ARCH (GARCH) models by allowing for conditionally t-distributed errors to the monthly stock price indices of Standard and Poor's 500 Composite Index, and 4 industry group indices, composed of Industrial, Capital Goods, Consumer Goods and Public Utilities price indices, during 1947 to 1984, it was found that the GARCH(1,1)-*t* model fit the data series quite well.

Campbell and Hentschel (1992) stated that “the volatility feedback hypothesis which implies that stock price movements are correlated with future volatility.” They estimated a model of volatility feedback for stock returns. Two assumptions were relied on for the analysis of the volatility feedback effect. First, news about stock dividends followed an QGARCH (Quadratic GARCH) model. Second, the expected return on a stock was a linear function of the conditional variance of the news about dividends. The monthly and daily CRSP (Center for Research in Securities Prices) value-weighted index returns in excess of one-month Treasury bill returns during the period 1926-1988 were estimated using the maximum likelihood parameter. All of the returns were measured in logarithms. Based on the QGARCH-M model, a negative correlation between the U.S. stock returns and the future volatility of returns was found but changing volatility had little effect on the level of stock prices. However, during the periods of high volatility, the volatility feedback effect can become dramatically more important. In addition, the volatility feedback effect explained somewhat less than half of the skewness and excess kurtosis of the QGARCH model residuals without introducing any new parameters specifically to fit these moments.

Christie (1982) investigated the relation between the variance of equity returns (referred to as the volatility of the rate of return on equity) and the value of equity. The elasticity of variance with respect to the value of equity was also examined in order to test the financial leverage effect hypothesis—that volatility is an increasing function of financial leverage (defined as the ratio of market value of debt to market value of equity) and that this relation can cause the elasticity of volatility with respect to value of equity to be negative under a broad range of circumstances. The study used the price per share of equity and the number of shares outstanding obtained from a CRSP monthly file. Quarterly variances were generated from the daily file by summing the squared daily returns for all days in each quarter based on the assumption that the quarterly mean returns were zero. There were 66 quarters of data for each of 379 firms from January 7, 1962 to December 31, 1978. The paper focused on risky debt models, also called the consol model, which treats the common stock of levered firms as a claim (option) on the value of the firm as a whole that can be exercised by paying off bondholders. The firm has one class of consol bonds (or nonconvertible, non-callable preferred stock) paying a continuous coupon bond; the bond covenants prohibit the sale of assets of the firm to make coupon or dividend payments. It was assumed further that the instantaneous movement in the value of the firm is lognormal with a constant variance rate, that the firm pays no dividends, that markets are perfect and frictionless, and that market participants can trade continuously. The estimated version of the consol model assumes the volatility of equity to be a function of financial leverage and interest rate. Because volatility is a function of financial leverage, the elasticity of the equity volatility with respect to the stock price can be estimated in the constant elasticity of variance (CEV) models for equity. It was found that "riskless interest rate and financial leverage jointly have a substantial impact on the volatility of the equity." Moreover, financial leverage is a dominant, although probably not the only, determinant of the elasticity of variance with respect to the value of equity, which is consistent with the leverage effect hypothesis—that a positive stock return enhances the market value of the firm's equity, which in turn reduces its financial leverage ratio. The diminished leverage ratio will result in a lower volatility of stock returns. In addition, while the paper focuses on the direction from the level of equity to volatility, it is also possible for exogenous changes in volatility to cause changes in the value of equity.

Dennis et al. (2006) studied the dynamic relation between daily stock returns and daily innovations in option-derived implied volatilities using daily dividend-adjusted returns from the CRSP for the period January 4, 1988 through December 31, 1995 of 50 firms that had the highest total option trading volume on the Chicago Board Options Exchange (CBOE). Stock returns and volatility innovations in a specification that included own-firm IV innovations and index IV innovations were simultaneously estimated by the mean equation and conditional variance equation. Four primary results were found concerning the dynamic relation between stock returns and expected volatility innovations. First, index returns had a large negative relation with innovations in expected index volatility. Second, individual stock returns had only a modest negative relation with innovations in their own expected volatility. The negative relation between individual stock returns and index volatility innovations was stronger than the negative relation between individual stock returns and their own-firm volatility innovations. Fourth, the relation between individual stock returns and their respective idiosyncratic volatility innovation was near zero. Moreover, the systematic market-level influences were more important in understanding the asymmetric volatility phenomenon, suggesting that volatility feedback effect was the best known systematic explanation.

Duffee (1995) examined the relation between firm stock returns and firm volatility at monthly and daily frequencies by using ordinary least squares (OLS) to estimate the relation between returns and return volatility for the daily stock returns of 2,494 firms from the CRSP Amex/ NYSE tape during the period 1997 to 1991. The researcher found that "firm stock returns and future changes in stock return volatility were negatively correlated, while firm stock returns and volatility were contemporaneously positively correlated." At the daily frequency, the positive relation between returns and volatility was even stronger. Moreover, the paper also reported the rank correlations between each of the regression coefficients and firms' debt/equity ratios (D/E). First, there was a positive correlation between the coefficient of the firm's stock return and D/E. Second, the highly-leveraged firms exhibited stronger negative relations between stock returns and volatility than did the less highly-leveraged firms. Third, there is some reason other than the leverage effect that underlies at least part of the correlation between firm debt/equity ratios and the regression coefficients. Finally, there was a well-known negative contemporaneous relation between returns and volatility at the aggregate level.

Dufour et al. (2008) used high-frequency data to study the dynamic relationship between volatility and equity returns. Sample data consisted of 5-minute transaction prices for the S&P Index futures contracts traded on the Chicago Mercantile Exchange over the period of January 1988 to December, 2005 for a total of 4,494 trading days. An autoregressive linear model was used. Using only returns and realized volatility, they measured a weak dynamic leverage effect for the first four hours for the hourly data and a strong dynamic leverage effect for the first three days for the daily data. However, the volatility feedback effect was found to be negligible at all horizons. Remeasuring the leverage and volatility feedback effects using implied volatility, they found that a volatility feedback effect appeared, while the leverage effect remained almost the same. This was due to the power of implied volatility to predict the future volatility and because of the fact that the volatility feedback effect was related to the ability of implied volatility. The dynamic impact of good and bad news on volatility was tested. The impact of bad news was statistically significant for the first four days, while the impact of good news was negligible at all horizons. Finally, the concept of news based on the difference between implied and realized volatilities (the variance risk premium) was introduced. Such empirical results showed that "a positive variance risk premium (an anticipated increase in variance) has more impact on returns than a negative variance risk premium."

Engle and Ng (1993) defined the news impact curve which measured how new information was incorporated into volatility estimates. Various news and existing ARCH models, including a partially-nonparametric estimators were compared and estimated using daily Japanese stock return data. New diagnostics tests were presented which emphasized the asymmetric volatility response to news. Their results suggested that "the model by Glosten, Jagannathan, and Runkle (GJR) was the best parametric model." The EGARCH model also could captured most of the asymmetry; there was evidence that "the variablilty of the conditional variance implied by the EGARCH methodology was too high."

Goudarzi (2011) studied the effects of good and bad news on volatility in the Indian stock markets using asymmetric ARCH models during the global financial crisis of 2008-2009. The BSE 500 stock index was used as a proxy for the Indian stock market to study the asymmetric volatility over a 10-year period. EGARCH and TGARCH models were used. The return series were found to react to the good and bad news asymmetrically. The presence of the leverage effect suggested that a negative innovation (news) had a greater impact on volatility than a positive innovation (news). This fact indicated that "the sign of innovation had a significant influence on the volatility of returns and that the arrival of bad news in the market would result in the increase in volatility more than good news."

Hatemi and Irandoust (2011) discussed the importance of the relationship between returns on a financial asset and its variance such that further analysis is required for identifying optimal hedging strategies and for evaluating regulatory proposals on monitoring the impact of international capital flows. They applied the causality test method by estimating the VAR model and generating simulated data with a bootstrap test for the daily data of the US stock market over the period 2004 to

2009. They found that "volatility causes returns negatively and returns cause volatility positively." In other words, bidirectional causality exists such that return-driven and volatility driven effects might well coexist.

3.3 Theoretical Framework

Campbell et al. (1997) states that "most financial studies involve stock returns instead of prices of stocks." There are two main reasons for using returns. First, for most investors, the stock return is a complete and scale-free summary of the investment opportunity. Second, return series are easier to handle than price series since the former have more attractive statistical properties. For instance, Tsay (2010) points out that "the natural logarithm of the simple gross return of the stock, called the continuously compounded return or the log return, satisfies the statistical properties such that log returns are more tractable." The log returns are often referred to as the return in this dissertation.

Aydemir (1998) stresses that "volatility estimates are widely used as simple risk measures in many asset pricing models." In addition, Baillie and DeGennaro (1990) state that "stock return variance or standard deviation is an intuitively-appealing measure of risk." French et al. (1987) and Campbell and Hentschel (1992) illustrate that "investors use the best conditional forecasts of variables, such as the conditional variance of stock returns that affect equilibrium-expected returns." It is typical that stock returns contain periods of high volatility followed by periods of lower volatility (visually, there are clusters of extreme values in the returns followed by periods in which such extreme values are not present). Engle (1982) and Harris and Sollis (2003) claim that "such volatility is referred to as conditional volatility, and the time-varying volatility typical of stock returns is referred to as conditional heteroscedasticity."

Stock volatility is related to the risk and return concept, which has long been an important topic in asset pricing research. It is generally agreed that investors, within a given time period, require a larger expected return from a security that is riskier. Nevertheless, Glosten et al. (1993) and Hatemi and Irandoust (2011) state that "there is no such agreement about the causal relation between returns and risk across time.” In other words, it is still controversial whether there is bi-directional causality between stock returns and volatility.

Bekaert and Wu (2000), Whaley (2000), Simon (2003), Skiadopoulos (2004), Giot (2005) and Hibbert et al. (2008) postulate that "it appears that volatility in equity markets is asymmetric: stock returns and volatility are negatively correlated." In addition, many models have been developed to characterize such asymmetric volatility (Pagan and Schwert, 1990; Nelson, 1991; Glosten et al., 1993; Engle and Ng, 1993 and Hentschel, 1995). Typically, there are 2 hypotheses that explain such asymmetric volatility property of stock returns: the volatility feedback effect hypothesis, and the leverage effect hypothesis. The volatility feedback effect hypothesis argues that if volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to immediate stock price decline (Pindyck, 1984; French et al., 1987 and Campbell and Hentschel, 1992). Conversely, the leverage effect hypothesis states that a drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increase its volatility (Black, 1976 and Christie, 1982). The causal relationship between stock returns and volatility is shown in Figure 3.1.

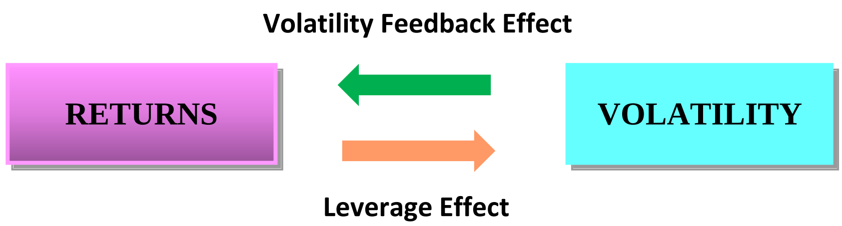

Figure 3.1 The Causal Relations between Stock Returns and Volatility

In Figure 3.1, the bi-directional causality between stock returns and volatility is depicted. Whereas the volatility feedback effect hypothesis states that returns are caused by the stock volatility or volatility-driven effect, the leverage effect hypothesis claims that returns leads to stock volatility or return-driven effect. Which effect exists in such asymmetric volatility property of stock returns remains an open question and is one of the important focuses of this study. Next, the hypotheses of volatility feedback effect and leverage effect will be explained.

3.3.1 Volatility Feedback Effect Hypothesis

One dominant characteristic of the stock market is that the volatility of returns can be very different at different times. Campbell and Hentschel (1992) emphasize that "changes in volatility may have important effects on required stock returns and thus on the levels of stock prices." French et al. (1987) postulate that "due to the fact that expected risk premiums are positively related to predictable volatility, a positive change in volatility increases the future expected risk premium and lowers the current stock prices." Such an effect is referred to as the "volatility feedback" effect. Thus, the volatility feedback effect hypothesis implies that stock price movements are correlated with future volatility such that an increase in stock market volatility raises required stock returns, and thus lowers stock prices (negative return).

3.3.2 Leverage Effect Hypothesis

Christie (1982) states that "one dominant source of variation in the volatility of equity is the changes in financial leverage such that volatility is an increasing function of financial leverage (defined as the ratio of market value of debt to market value of equity)." In addition, this relation can cause the elasticity of volatility with respect to value of equity to be negative under a broad range of circumstances. Thus, a positive stock return enhances the equity's market value, which in turn reduces its financial leverage ratio. The diminished leverage ratio will result in a lower volatility of stock returns. Conversely, a drop in the value of the stock (negative return) increases the financial leverage, which makes the stock riskier and increases its volatility (Bekaert, and Wu, 2000).

In summary, the difference between the leverage effect hypothesis and volatility feedback effect hypothesis for volatility asymmetry is related to a causality issue (Bekaert and Wu, 2000 and Bollerslev et al., 2006). While the leverage effect explains why a negative return leads to higher subsequent volatility, the volatility feedback effect justifies how an anticipated increase in volatility may result in a negative return. Therefore, volatility asymmetry may result from various causal links: from returns to volatility, from volatility to returns, instantaneous causality.

3.4 Data and Methodology

3.4.1 Data

This study collected 2,195 daily return series for the SET, and returns of 8 industry group indices comprising Agribusiness and Food (AGRO); Consumer Products (CONSUMP); Financials (FINCIAL); Industrials (INDUS); Property & Construction (PROPCON); Resources (RESOURC); Services (SERVICE); Technology (TECH) for the sample period from January, 2005 to December, 2013.

3.4.2 The Empirical Models

3.4.2.1 Mean and Variance Equation of Stock Returns

Most financial time series, including stock returns, exhibit conditionally heteroskedastic (Enders, 2004) such that there exists a period where the stock market seems tranquil alongside periods with large increases and decreases in the market. Moreover, there is the tendency for stock returns to have distributions that exhibit fat tails and excess peakedness at the mean (Brooks, 2002), referred to as Leptokurtosis. Such properties can be characterized by ARCH (Engle, 1982) or GARCH models (Bollerslev, 1986 and Taylor, 1986). ARCH or GARCH models can simultaneously estimate the mean and the variance of the stock return series. In addition, asymmetric GARCH models such as EGARCH (Nelson, 1991), GJR (Glosten et al., 1989) are introduced to capture the asymmetric property of volatility such that there is a tendency for stock volatility to rise more following a large price fall than following a price rise of the same magnitude. The present study will estimate the predictable stock volatility from alternatives of parametric models, and examine the subprime crisis effect on volatility as follows.

1) Building the ARMA Model: the Box-Jenkins Methodology

Box and Jenkins (1976) were the first to approach the task of estimating an autoregressive moving average (ARMA) model in a systematic manner, which involves three steps:

(1) Identification: determining the order of the model required to capture the dynamic features of the stock return series. Graphical procedures are used (e.g. plotting the data over time and plotting the autocorrelation function (ACF) and

the partial autocorrelation function (PACF)) to determine the most appropriate specification.

(2) Estimation: estimating the parameters of the model specified in step 1 such as least squares, etc. A general ARMA(p,q) model (Tsay, 2010) is in the form:

$$\begin{aligned} r_t &= \mu + \phi_1 r_{t-1} + \cdots + \phi_p r_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q} \\ &= \mu + \sum_{i=1}^{p} \phi_i\, r_{t-i} + u_t - \sum_{j=1}^{q} \theta_i\, u_{t-j} \end{aligned} \tag{3.1}$$

where r_t = stock return at time t

u_t = innovation or shock at time t ; $u_t \sim$ i.i.d.$(0, \sigma_u^2)$

Such a model states that "the current value of return series depends linearly on its own previous values, and a combination of current and previous values of a white noise error term." An autoregressive process has a geometrically-decaying ACF, and a number of non-zero points of PACF equals to AR order, while a moving average process has a number of non-zero points of ACF equal to MA order, and a geometrically decaying PACF. Thus, a combination autoregressive moving average process has both a geometrically decaying ACF and PACF (Brooks, 2002). The distribution theory underlying the use of the sample ACF and PACF as approximations to those of the true data generating process assumes that the $\{r_t\}$ sequence is stationary (Enders, 2004).

(3) Diagnostic checking: determining whether the model specified and estimated is adequate, for instance, checking the residuals for evidence of linear dependence which, if present, would suggest that the model originally specified was inadequate for capturing the features of the return series.

2) GARCH (1,1) model

One important assumption of the Classical Linear Regression Model (CLRM)—that the variance of the errors in constant—is known as homoscedacticity (i.e. it is assumed that $var(u_t) = \sigma_u^2$) (Gujarati, 1995). If the variance of the errors is not constant, also called heteroscedascity, an implication would be that standard error estimates could be wrong. Most financial time series, including stock returns, have the property of volatility clustering or the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes. Thus, it is unlikely that in the context of financial time series that the variance of the errors will be constant over time or that the ARCH (Autoregressive Conditional Heteroscedascity) effects exist (Brooks, 2002). This implies that it is important to test for the ARCH effect by testing the null hypothesis that the lags of squared residuals have coefficient values that are not significantly different from zero. If the null hypothesis is rejected, ARCH or GARCH models should be applied.

Under the ARCH(*m*) model (Engle, 1982), the "autocorrelation in volatility" is estimated by allowing the conditional variance of the error term, σ_t^2, to depend on the m lags of squared errors. Instead of calling the conditional variance σ_t^2, in the literature it is often called h_t. The GARCH(*l*,*m*) model, developed independently by Bollerslev (1986) and Taylor (1986), allows the conditional variance to be dependent upon its own lags and lags of squared errors:

$$\begin{aligned} \sigma_t^2 &= h_t \\ &= \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_m u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_l \sigma_{t-l}^2 \\ &= \alpha_0 + \textstyle\sum_{i=1}^{m} \alpha_i u_{t-i}^2 + \sum_{j=1}^{l} \beta_j \sigma_{t-j}^2 \end{aligned} \tag{3.2}$$

The GARCH model is a better and therefore more widely-used model than the ARCH since the GARCH is more parsimonious and avoids overfittng. For instance, GARCH(1,1), the most widely-used for financial asset returns, contains only three parameters in the conditional variance equation such that the model allows an infinite number of past squared errors to influence the current conditional variance (Brooks, 2002). This study will typically use the GARCH(1,1) model to simultaneously estimate the mean and variance equations of stock returns as follows:

$$r_t = \mu + \textstyle\sum_{i=1}^{p} \phi_i r_{t-i} + u_t - \sum_{j=1}^{q} \theta_i u_{t-j} \tag{3.3}$$

$$u_t = v_t \sqrt{h_t}\,,\ v_t \sim \text{i.i.d. N(0,1)} \tag{3.4}$$

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{3.5}$$

where r_t = stock return at time *t*

h_t = conditional variance at time *t*

u_t = an unexpected increase (decrease) in price suggesting the arrival of good (bad) news

It is required that $\alpha_1 + \beta_1 < 1$, and $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta_1 \geq 0$ such that stationarity in variance and non-negativity in variance be satisfied, respectively.

3) The Sign Bias Test

For several stocks, there is a strong negative correlation between the current return and the predictable volatility or the asymmetric property of volatility exists (Enders, 2004). There is the tendency for volatility to decline when the stock returns rise and to rise when returns fall. Thus, there exists such an asymmetric volatility effect in the residuals after estimating the ARCH or GARCH models. Engle and Ng (1993) developed the Sign Bias Test to determine whether positive and negative shocks have different effects on the conditional variance as follows.

(1) Estimate the ARCH/GARCH models and generate the standardized residuals (s_t)

$$s_t = \hat{u}_t / \hat{h}_t^{1/2} \tag{3.6}$$

where s_t = standardized residual at time *t*

$\hat{h}_t$ = the estimated conditional variance at time *t*

$\hat{u}_t$ = the estimated residual at time *t*

(2) Regress the square of standardized residuals on a constant and dummy variable:

$$s_t^2 = a_0 + a_1 d_{t-1} + u_{1,t} \tag{3.7}$$

where d_{t-1} = 1 if $\hat{u}_{t-1} < 0$, and 0 otherwise

(3) Test for the significance of a_1 using a *t*-statistic. If the *t*-statistic indicates that a_1 is statistically different from zero, a specific form of the asymmetric GARCH model (i.e. EGARCH, GJR) can be estimated.

4) Exponential-GARCH (EGARCH) Model

A model that allows for the asymmetric property of predictable volatility is the exponential-GARCH (EGARCH). Nelson (1991) introduced a specification that does not require nonnegativity constraints like the GARCH model as follows:

$$\ln(h_t) \quad = \quad \alpha_0 + \alpha_1\left(\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right) + \gamma_1\left|\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta_1 \ln(h_{t-1}) \qquad (3.8)$$

where h_t = conditional variance at time *t*

u_{t-1} = an unexpected increase (decrease) in price suggesting the arrival of good (bad) news

Three interesting issues to take note of concerning the EGARCH (1,1) model are:

(1) The conditional variance equation is in log-linear form. The implied value of h_t can never be negative regardless of the magnitude of $\ln(h_t)$.

(2) The model uses the level of standardized value of u_{t-1} (i.e. $u_{t-1}/\sqrt{h_{t-1}}$) instead of u_{t-1}^2. This standardization allows for a more natural interpretation of the size and persistence of shocks. After all, the standardized value of u_{t-1} is a unit-free measure.

(3) EGARCH model allows for the asymmetric property of volatility such that if $u_{t-1}/\sqrt{h_{t-1}} > 0$, the effect of the shock on the log of the conditional variance is $\alpha_1 + \gamma_1$, and if $u_{t-1}/\sqrt{h_{t-1}} < 0$, the effect of the shock on the log of the conditional variance is $-\alpha_1 + \gamma_1$.

The news impact curves of the above asymmetric volatility models capture the leverage or asymmetric effect by allowing either the slope of the two sides of the news impact curve to differ or the center of the news impact curve to locate at a point where u_{t-1} is positive (Engle and Ng, 1993). The news impact curve of the EGARCH(1,1) is compared with GARCH(1, 1), as shown in Figure 3.2.

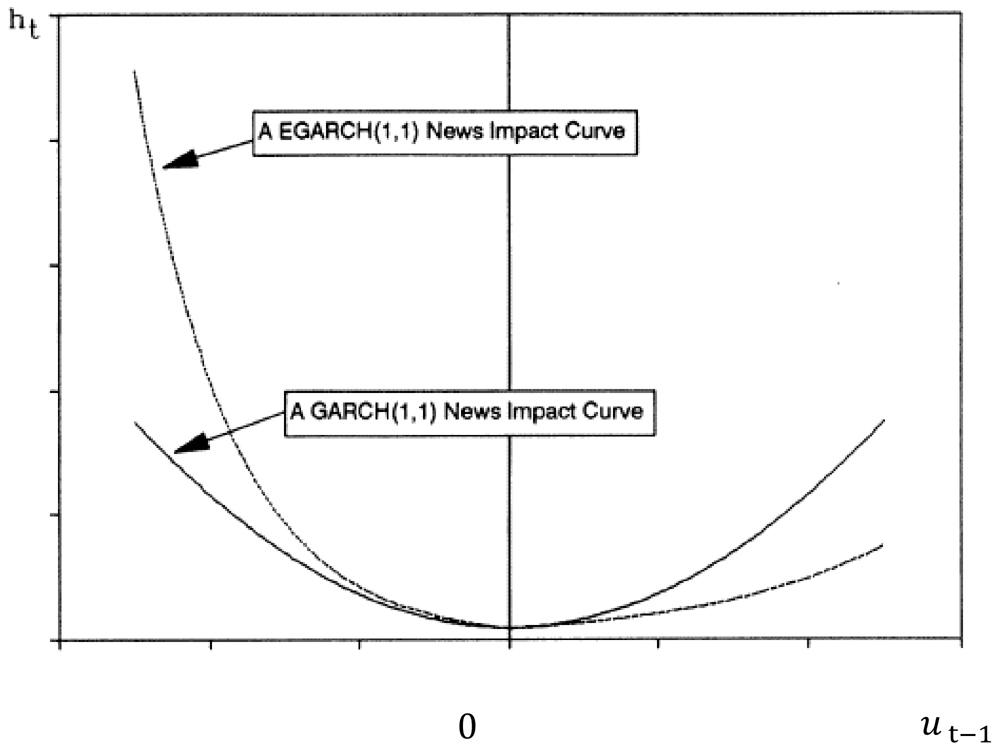

Figure 3.2 The News Impact Curves of the GARCH(1,1) and EGARCH(1,1) Models

5) Threshold-GARCH (TARCH) Model

Another widely-used model that allows for the asymmetric property of stock volatility is the Threshold-GARCH (TARCH) model, which was introduced by Glosten, Jagannathan, and Runkle in 1989. Sometimes it is called the GJR model. In the model, $u_{t-1} = 0$ is a threshold such that shocks greater than the threshold have different effects than shocks below the threshold:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 d_{t-1} u_{t-1}^2 + \beta_1 h_{t-1} \qquad (3.9)$$

where h_t = conditional variance at time t

u_{t-1} = an unexpected increase (decrease) in price suggesting the arrival of good (bad) news

d_{t-1} = 1 if $u_{t-1} < 0$, and 0 if $u_{t-1} \geq 0$

The positive values of u_{t-1} are associated with a zero value of d_{t-1}. Thus, if $u_{t-1} \geq 0$, the effect of an u_{t-1} shock on h_t is $\alpha_1 u_{t-1}^2$. If $u_{t-1} < 0$, then $d_{t-1} = 1$, and the effect on u_{t-1} shock on $h_t$is $\alpha_1 u_{t-1}^2 + \gamma_1 u_{t-1}^2$ or $(\alpha_1 + \gamma_1) u_{t-1}^2$. If $\gamma_1 > 0$, the negative shocks will have larger effect on volatility than positive shocks. When estimating the volatility using the TARCH model, if γ_1 is significantly different from zero, it can be concluded that the stock return series contain a threshold effect (Enders, 2004).

6) Subprime Crisis Effect on Volatility

Wu. (2001) emphasizes one important issue concerning stock volatility such that "asymmetric volatility is most apparent during stock market crashes when a large decline in stock prices is associated with a significance increase in stock market volatility." Since the sample period for analyzing Thailand's stock volatility in the chapter is from January, 2005 to December, 2013. Such a sample period includes the subprime crisis originated from the U.S. during the years 2007 to 2009. However, Dooley (2009) states that "the phase of the subprime crisis which had an impact on the international stock markets, especially on the emerging markets (including Thailand), was the period from September 15, 2008 to February, 2009." During such a phase of the crisis, trade credit to support exports and imports was disrupted by the counter party risk and deleveraging generated by the bankruptcy of a major player in the international credit markets (i.e. the bankruptcy of the Lehman Brothers). This phase was hypothesized to be a recoupling of financial markets in the U.S. and emerging markets. Thus, in order to test for the subprime crisis effect on Thailand's stock return volatility, the conditional volatility of the stock returns estimated from GARCH(1,1), EGARCH(1,1), and TARCH will be modified such that the dummy variable for the subprime crisis effect on the stock volatility will be included in the models as follows:

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + u_t - \sum_{j=1}^{q} \theta_i u_{t-j} \tag{3.10}$$

$$u_t = v_t \sqrt{h_t}\,, \ v_t \sim \text{i.i.d. N(0,1)} \tag{3.11}$$

GARCH(1,1) model

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D_{SP} \tag{3.12}$$

EGARCH(1,1) model

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right) + \gamma_1 \left|\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta_1 \ln(h_{t-1}) + \delta_1 D_{SP} \tag{3.13}$$

TARCH model

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 d_{t-1} u_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D_{SP} \tag{3.14}$$

where r_t = stock return at time *t*

h_t = conditional variance at time *t*

u_t = an unexpected increase (decrease) in price suggesting the arrival of good (bad) news

d_{t-1} = 1 if $u_{t-1} < 0$, and 0 if $u_{t-1} \geq 0$

D_{SP} = 1 if during the Subprime crisis, and 0 otherwise

3.4.2.2 The Causal Relationship between Returns and Conditional Volatility at the Aggregate and Industry Level

In order to examine the relationship between the stock returns and the volatility at the aggregate and industry level, the vector autoregressive model of order *m*, VAR(*m*) was applied:

$$\boldsymbol{y_t} = \boldsymbol{\omega} + \boldsymbol{B_1 y_{t-1}} + \boldsymbol{B_2 y_{t-2}} + \cdots + \boldsymbol{B_m y_{t-m}} + \boldsymbol{\varepsilon_t} \qquad (3.15)$$

where $\boldsymbol{y_t} = \begin{bmatrix} r_t \\ \sqrt{h_t} \end{bmatrix}$

$\boldsymbol{\omega} = \begin{bmatrix} \omega_{01} \\ \omega_{02} \end{bmatrix}$

$\boldsymbol{B_j} = \begin{bmatrix} b_{11,j} & b_{12,j} \\ b_{21,j} & b_{22,j} \end{bmatrix}, \ j = 1, \ldots, m$

$\boldsymbol{\varepsilon_t} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$

= vector of stochastic disturbance terms, which in general will have non-zero cross correlations

r_t = the stock returns at time *t*

$\sqrt{h}_t$ = conditional volatility of the stock returns at time *t* (estimated from GARCH(1,1), EGARCH(1,1), and TARCH models)

In other words, such VAR(*m*) can be alternatively expressed as:

$$r_t = \omega_{01} + b_{11,1} r_{t-1} + b_{12,1}\sqrt{h}_{t-1} + \cdots + b_{11,m} r_{t-m} + b_{12,m}\sqrt{h}_{t-m} + \varepsilon_{1t} \qquad (3.16)$$

$$\sqrt{h}_t = \omega_{02} + b_{21,1} r_{t-1} + b_{22,1}\sqrt{h}_{t-1} + \cdots + b_{21,m} r_{t-m} + b_{22,m}\sqrt{h}_{t-m} + \varepsilon_{2t} \qquad (3.17)$$

The order of the VAR(*m*) model was selected based mainly on Akaike's Information Criterion (AIC).

From the VAR(*m*) model, the study employed the Granger causality test in order to examine the cause and effect among the stock returns and the conditional volatility or the existence of the leverage effect and the volatility feedback effect. If the stock returns lead to its volatility, the leverage effect hypothesis is satisfied. And when the stock returns are caused by volatility, the volatility feedback effect hypothesis is satisfied.

3.5 Empirical Results

3.5.1 Estimation of Stock Conditional Volatilities

In this section, the conditional volatility of stock returns at the aggregate level and the industry level will be analyzed. Figure 3.3 - 3.4 illustrates the stock returns of the SET index and 8 industry group indices during the sample period, respectively:

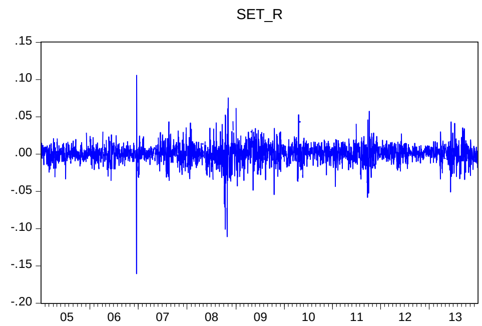

Figure 3.3 The Stock Returns of SET Index During the Period 2005 – 2013

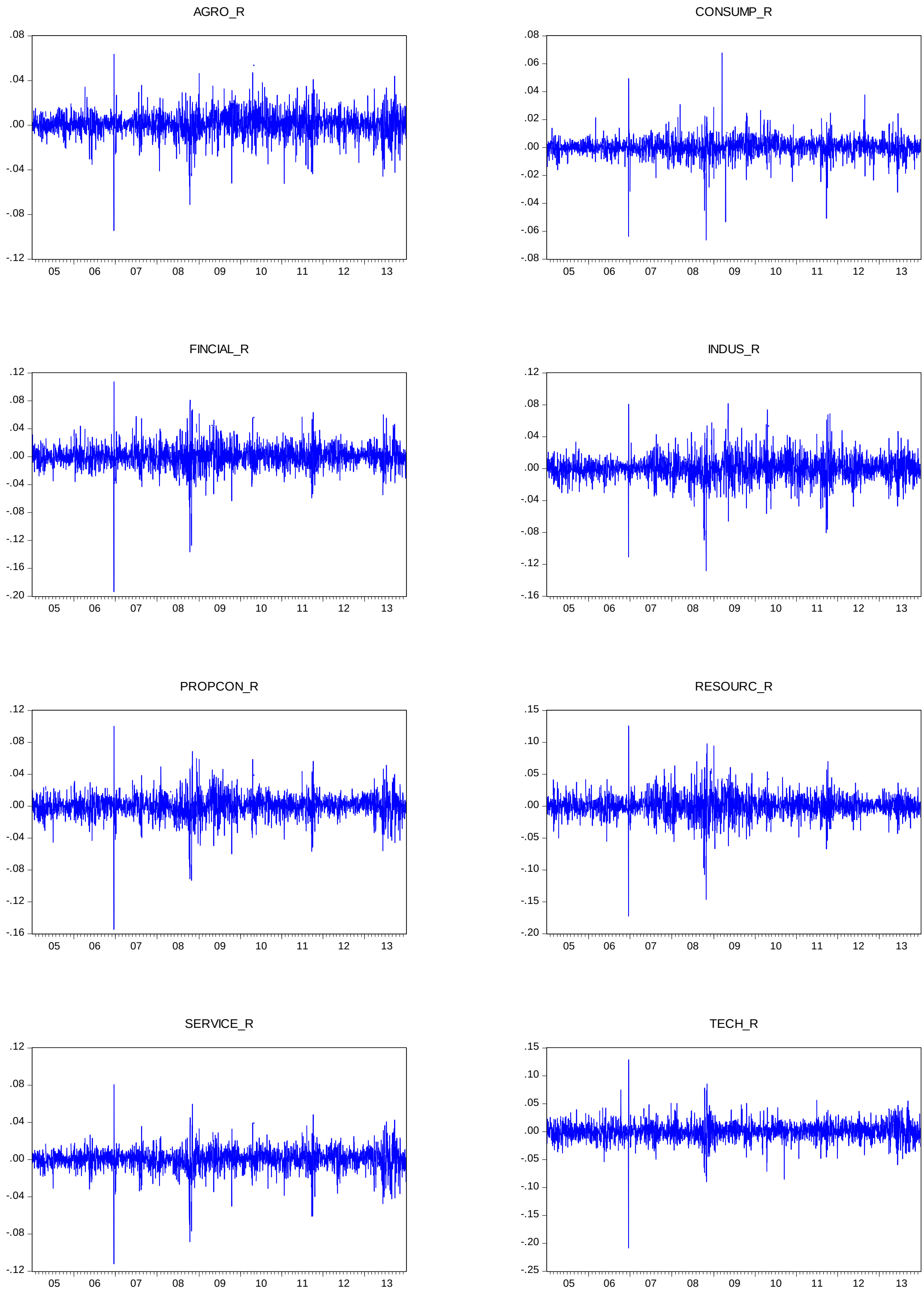

Figure 3.4 The Stock Returns of 8 Industry Group Indices During the Period 2005 – 2013

As can be seen from Figure 3.3 and 3.4, the means of the daily SET index return series (SET_R), and all eight industry group indices, are close to zero. In addition, all of the stock return series seem to be stationary and tend to return to their average and fluctuate around the mean values. The descriptive statistics for the SET index returns, and all eight industry group returns, are given in Table 3.1 and 3.2, respectively.

Table 3.1 Descriptive Statistics of the SET Index Returns

Statistics	SET index returns
Mean	0.0003
Median	0.0007
Maximum	0.1058
Minimum	-0.1606
Standard Deviation	0.0140
Skewness	-1.0097
Kurtosis	17.2127

Table 3.2 Descriptive Statistics of the Industry Group Indices' Returns

Statistics	AGRO	CONSUMP	FINCIAL	INDUS
Mean	0.0007	0.0002	0.0003	0.0001
Median	0.0009	0.0004	0.0002	0.0004
Maximum	0.0635	0.0678	0.1073	0.0816
Minimum	-0.0945	-0.0663	-0.1936	-0.1282
Standard Deviation	0.0113	0.0070	0.0169	0.0162
Skewness	-0.5772	-0.7052	-0.8685	-0.4703
Kurtosis	8.4430	19.7291	16.0913	8.7971
Statistics	**PROPCON**	**RESOURC**	**SERVICE**	**TECH**
Mean	0.0002	0.0002	0.0005	0.0003
Median	0.0006	0.0003	0.0012	0.0005
Maximum	0.1003	0.1260	0.0806	0.1290
Minimum	-0.1547	-0.1725	-0.1121	-0.2084
Standard Deviation	0.0146	0.0180	0.0116	0.0165
Skewness	-0.7929	-0.5099	-1.0825	-0.8395
Kurtosis	12.8097	12.2658	13.1384	18.3998

According to Table 3.1 and 3.2, it is quite clear that all of the stock returns have a zero mean, and all of the series exhibit leptokurtosis such that there exists positive excess kurtosis (Kurtosis > 3), and the distribution has heavy tails and excess peakedness around the mean (Brooks, 2002 and Tsay, 2010). Next, the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests of a unit root were applied to the stock returns in order to investigate the stationarity of the return series, as shown in Table 3.3.

Table 3.3 Unit Root Tests of the Stock Returns

	ADF	PP
SET	-46.089***	-46.093***
AGRO	-44.943***	-45.036***
CONSUMP	-47.117***	-47.117***
FINCIAL	-45.653***	-45.639***
INDUS	-43.157***	-43.445***
PROPCON	-43.809***	-43.963***
RESOURC	-46.638***	-46.646***
SERVICE	-29.716***	-43.440***
TECH	-48.067***	-48.163***

Note: The table reports the Augmented Dickey-Fuller and the Phillips-Perron unit root tests without a time trend. Critical values at the 1%, 5%, and 10% significance level are -3.433, -2.863, and -2.567, respectively.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Table 3.3 indicates that the null hypothesis of a unit root was rejected for all stock returns at the 1% significance level using both ADF and PP tests. Thus, the SET index returns, and eight industry group index returns, are statistically stationary. In order to estimate the order of ARMA(p,q) model for the stock return series, ACF and PACF were plotted for each stock return series, as shown in Appendix A. The appendix implies that none of the stock return series is white noise processes. In addition, the ACF and PACF for most of the return series indicated no clear pattern of the ARMA(p,q) model. Thus, the extended sample autocorrelation function (ESACF), introduced by Tsay and Tiao, 1984, was applied by R programming to investigate the appropriate order of the ARMA(p,q) model, as shown in Appendix B. The statistical summary of the residuals from the estimated ARMA(p,q) models for the SET index returns and the industry group index returns, implied by ESACF from Appendix B, are reported in Tables 3.4 and 3.5, respectively, as follows:

Table 3.4 Descriptive Statistics of the Residuals for SET Indices' Returns

Residuals	SET index returns
Model	ARMA(3,14)
Mean	0.0000
Median	0.0004
Maximum	0.1045
Minimum	-0.1608
Standard Deviation	0.0140
Skewness	-0.9548
Kurtosis	16.9590

Table 3.5 Descriptive Statistics of the Residuals for Industry Group Indices' Returns

Residuals	AGRO	CONSUMP	FINCIAL	INDUS
Model	ARMA(2,13)	ARMA(22,22)	ARMA(1,20)	ARMA(1,20)
Mean	0.0000	0.0000	0.0000	0.0001
Median	0.0001	0.0001	0.0000	0.0002
Maximum	0.0648	0.0676	0.1118	0.0896
Minimum	-0.0958	-0.0664	-0.1936	-0.1207
Standard Deviation	0.0113	0.0070	0.0169	0.0160
Skewness	-0.5274	-0.6744	-0.8311	-0.3462
Kurtosis	8.4993	19.8470	16.1503	8.3410
Residuals	PROPCON	RESOURC	SERVICE	TECH
Model	ARMA(3,14)	ARMA(2,15)	ARMA(1,14)	ARMA(0,0)
Mean	0.0000	0.0000	0.0000	0.0000
Median	0.0004	0.0002	0.0005	0.0002
Maximum	0.1104	0.1280	0.0874	0.1287
Minimum	-0.1542	-0.1736	-0.1116	-0.2087
Standard Deviation	0.0146	0.0179	0.0115	0.0165
Skewness	-0.6856	-0.5048	-0.7797	-0.8395
Kurtosis	13.0378	12.2020	12.5440	18.3998

As can be seen from Table 3.4 and 3.5, the means of the residuals for the SET index returns and the industry group index returns from the estimated model are approximately zero. However, all of the residuals for each industry's return series have a property such that the kurtosis is greater than 3. This implies that the ARCH effect existed for all industries' returns, including the SET returns, and that the model capturing ARCH effect was required. The LM test for the ARCH effect was conducted in order to confirm the implication as reported in Table 3.6 as follows:

Table 3.6 L.M Test for ARCH Effect of Index's Return Volatility

Index	LM Test for ARCH effect	
	Obs*R-squared	Probability
SET	231.995	0.000
AGRO	100.836	0.000
CONSUMP	63.222	0.000
FINCIAL	215.988	0.000
INDUS	202.265	0.000
PROP	250.293	0.000
RESOURC	254.397	0.000
SERVICE	223.212	0.000
TECH	203.365	0.000

As can be seen in Table 3.6, the LM test implies that there exists an ARCH effect at the 1% level for all return series. Then, the GARCH(1,1) model was applied in order to estimate the conditional variance with a mean equation for each industry index return, as shown in Table 3.7:

Table 3.7 Mean & Variance Equation of Index' Returns from GARCH (1,1) Model

Index	Mean equation	Variance equation
SET	$r_t = 0.0011 + 0.4770\ r_{t-1} - 0.7354\ r_{t-3} - 0.4391\ u_{t-1} + 0.7640\ u_{t-3} + 0.0564\ u_{t-13} - 0.0415\ u_{t-14} + u_t$	$h_t = 1.27E\text{-}05 + 0.1336\ u^2_{t-1} + 0.8038\ h_{t-1}$
	(p-value) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.01)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 15.976
		Ljung-Box Q^2(15) statistic = 0.658
AGRO	$r_t = 0.0011 + 0.4871\ r_{t-1} - 0.2612\ r_{t-2} - 0.4266\ u_{t-1} + 0.2736\ u_{t-2} + 0.1055\ u_{t-13} + u_t$	$h_t = 8.17E\text{-}06 + 0.1543\ u^2_{t-1} + 0.7923\ h_{t-1}$
	(p-value) (0.00) (0.00) (0.07) (0.01) (0.05) (0.00)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 7.328
		Ljung-Box Q^2(15) statistic = 4.198
CONSUMP	$r_t = 0.0005 + 0.0491\ r_{t-2} - 0.0635\ r_{t-6} - 0.0527\ r_{t-21} + 0.0523\ r_{t-22} + u_t$	$h_t = 1.14E\text{-}05 + 0.1866\ u^2_{t-1} + 0.5918\ h_{t-1}$
	(p-value) (0.00) (0.06) (0.00) (0.00) (0.00)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 14.860
		Ljung-Box Q^2(15) statistic = 4.428
FINCIAL	$r_t = 0.0009 + 0.0841\ u_{t-1} + u_t$	$h_t = 1.24E\text{-}05 + 0.0850\ u^2_{t-1} + 0.8719\ h_{t-1}$
	(p-value) (0.02) (0.00)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 13.088
		Ljung-Box Q^2(15) statistic = 2.078
INDUS	$r_t = 1.4720\ r_{t-1} - 0.5346\ r_{t-2} - 1.3842\ u_{t-1} + 0.4437\ u_{t-2} + 0.0247\ u_{t-7} + u_t$	$h_t = 1.22E\text{-}05 + 0.1066\ u^2_{t-1} + 0.8445\ h_{t-1}$
	(p-value) (0.00) (0.00) (0.00) (0.02) (0.00)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 8.386
		Ljung-Box Q^2(15) statistic = 5.227
PROPCON	$r_t = 0.0009 + 0.1404\ r_{t-1} + u_t$	$h_t = 1.39E\text{-}05 + 0.1851\ u^2_{t-1} + 0.7631\ h_{t-1}$
	(p-value) (0.01) (0.00)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 21.423
		Ljung-Box Q^2(15) statistic = 1.578
RESOURC	$r_t = 0.0009 + 0.0386\ r_{t-1} - 0.6938\ r_{t-2} + 0.7035\ u_{t-2} - 0.0634\ u_{t-6} - 0.0464\ u_{t-8} + u_t$	$h_t = 1.57E\text{-}05 + 0.1137\ u^2_{t-1} + 0.8382\ h_{t-1}$
	(p-value) (0.01) (0.07) (0.00) (0.00) (0.01) (0.06)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 11.312
		Ljung-Box Q^2(15) statistic = 1.611
SERVICE	$r_t = 0.0011 + 0.0912\ u_{t-1} + 0.0443\ u_{t-2} + 0.059\ u_{t-3} + 0.0585\ u_{t-13} + u_t$	$h_t = 8.57E\text{-}06 + 0.1317\ u^2_{t-1} + 0.8042\ h_{t-1}$
	(p-value) (0.00) (0.00) (0.07) (0.02) (0.01)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 14.401
		Ljung-Box Q^2(15) statistic = 2.652
TECH	$r_t = u_t$	$h_t = 7.29E\text{-}05 + 0.1221\ u^2_{t-1} + 0.6019\ h_{t-1}$
	(p-value)	(p-value) (0.00) (0.00) (0.00)
		Ljung-Box Q(15) statistic = 6.740
		Ljung-Box Q^2(15) statistic = 0.974

Table 3.7 indicates that the parameters corresponding to the u_{t-1}^2 term and h_{t-1} term in the GARCH(1,1) model are non-negative and significant at the 1% level for the SET index returns and 8 industry group index returns. In addition, the sum of the 2 parameters is less than one for all index returns. This indicates that the non-negativity and stationarity in variance in variance are satisfied for the GARCH(1,1) model. Then, the GARCH(1,1) model was modified by introducing the dummy variable of the subprime crisis effect, as shown in Table 3.8 as follows:

Table 3.8 Mean & Variance Equation of Index' Returns from the Modified GARCH (1,1) Model

Index		Mean equation		Variance equation
SET	r_t	$= 0.0012 + 0.4709\, r_{t-1} - 0.7349\, r_{t-3} - 0.4314\, u_{t-1} + 0.7621\, u_{t-3} + 0.0575\, u_{t-13} - 0.0420\, u_{t-14} + u_t$	h_t	$= 1.90E\text{-}05 + 0.1675\, u^2_{t-1} + 0.7252\, h_{t-1} + 6.28E\text{-}05\, D_{sp}$
	(p-value)	(0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 10.804
				Ljung-Box Q^2(15) statistic = 0.766
AGRO	r_t	$= 0.0011 + 0.4938\, r_{t-1} - 0.2683\, r_{t-2} - 0.4323\, u_{t-1} + 0.2792\, u_{t-2} + 0.1037\, u_{t-13} + u_t$	h_t	$= 8.79E\text{-}06 + 0.1595\, u^2_{t-1} + 0.7782\, h_{t-1} + 1.19E\text{-}05\, D_{sp}$
	(p-value)	(0.00) (0.00) (0.06) (0.01) (0.04) (0.00)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 7.188
				Ljung-Box Q^2(15) statistic = 3.804
CONSUMI	r_t	$= 0.0004 + 0.0487\, r_{t-2} - 0.0673\, r_{t-6} - 0.0256\, r_{t-21} + 0.0439\, r_{t-22} + u_t$	h_t	$= 1.76E\text{-}06 + 0.0671\, u^2_{t-1} + 0.8915\, h_{t-1} + 1.56E\text{-}05\, D_{sp}$
	(p-value)	(0.01) (0.04) (0.01) (0.19) (0.05)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 15.072
				Ljung-Box Q^2(15) statistic = 2.138
FINCIAL	r_t	$= 0.0009 + 0.0834\, u_{t-1} + u_t$	h_t	$= 1.68E\text{-}05 + 0.0846\, u^2_{t-1} + 0.8480\, h_{t-1} + 4.05E\text{-}05\, D_{sp}$
	(p-value)	(0.02) (0.00)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 12.016
				Ljung-Box Q^2(15) statistic = 2.177
INDUS	r_t	$= 1.4687\, r_{t-1} - 0.5308\, r_{t-2} - 1.3808\, u_{t-1} + 0.4393\, u_{t-2} + 0.0249\, u_{t-7} + u_t$	h_t	$= 1.30E\text{-}05 + 0.1071\, u^2_{t-1} + 0.8366\, h_{t-1} + 1.96E\text{-}05\, D_{sp}$
	(p-value)	(0.00) (0.00) (0.00) (0.02) (0.00)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 7.338
				Ljung-Box Q^2(15) statistic = 4.630
PROPCON	r_t	$= 0.0009 + 0.1385\, r_{t-1} + u_t$	h_t	$= 1.87E\text{-}05 + 0.2056\, u^2_{t-1} + 0.7093\, h_{t-1} + 5.93E\text{-}05\, D_{sp}$
	(p-value)	(0.00) (0.00)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 20.267
				Ljung-Box Q^2(15) statistic = 1.626
RESOURC	r_t	$= 0.0009 + 0.0412\, r_{t-1} - 0.6699\, r_{t-2} + 0.6802\, u_{t-2} - 0.0708\, u_{t-6} - 0.0528\, u_{t-8} + u_t$	h_t	$= 2.48E\text{-}05 + 0.1326\, u^2_{t-1} + 0.7759\, h_{t-1} + 1.09E\text{-}04\, D_{sp}$
	(p-value)	(0.00) (0.06) (0.00) (0.00) (0.00) (0.03)	(p-value)	(0.00) (0.00) (0.00) (0.00)
				Ljung-Box Q(15) statistic = 10.634
				Ljung-Box Q^2(15) statistic = 1.348
SERVICE	r_t	$= 0.0011 + 0.0913\, u_{t-1} + 0.0441\, u_{t-2} + 0.0598\, u_{t-3} + 0.0600\, u_{t-13} + u_t$	h_t	$= 8.95E\text{-}06 + 0.1293\, u^2_{t-1} + 0.7987\, h_{t-1} + 1.04E\text{-}05\, D_{sp}$
	(p-value)	(0.00) (0.00) (0.07) (0.02) (0.00)	(p-value)	(0.00) (0.00) (0.00) (0.06)
				Ljung-Box Q(15) statistic = 13.423
				Ljung-Box Q^2(15) statistic = 2.640
TECH	r_t	$= u_t$	h_t	$= 9.18E\text{-}05 + 0.1144\, u^2_{t-1} + 0.5163\, h_{t-1} + 8.97E\text{-}05\, D_{sp}$
	(p-value)		(p-value)	(0.00) (0.00) (0.00) (0.01)
				Ljung-Box Q(15) statistic = 7.002
				Ljung-Box Q^2(15) statistic = 0.933

According to Table 3.8, the modified GARCH(1,1) model indicates that the parameter corresponding to the dummy variable of the subprime effect is significant at the 1% level (except for the service industry) for the SET index returns and 7 industry group index returns. Moreover, the summation of the parameters corresponding to the u_{t-1}^2 term and h_{t-1} was moderately reduced compared to the original GARCH(1,1) model for all of the index returns except for the consumer products industry.

At this point, the Sign Bias Test was applied in order to determine whether the positive and negative shocks had different effects on the conditional variance from the estimated GARCH(1,1) and the modified GARCH(1,1) models for each index return, as shown in Table 3.9 as follows:

Table 3.9 The Sign Bias Test for the Conditional Variance of the Index Returns

	Sign Bias Test							
Industry	**The GARCH(1,1) model**				**The modified GARCH(1,1) Model**			
SET	s^2_t	=	0.7961 +	0.3943 d_{t-1}	s^2_t	=	0.8188 +	0.3502 d_{t-1}
	(p-value)		(0.00)	(0.13)	(p-value)		(0.00)	(0.16)
AGRO	s^2_t	=	0.8054 +	0.3797 d_{t-1}	s^2_t	=	0.9063 +	0.1817 d_{t-1}
	(p-value)		(0.00)	(0.00)	(p-value)		(0.00)	(0.18)
CONSUMP	s^2_t	=	0.7583 +	0.4671 d_{t-1}	s^2_t	=	0.7887 +	0.4219 d_{t-1}
	(p-value)		(0.00)	(0.03)	(p-value)		(0.00)	(0.02)
FINCIAL	s^2_t	=	0.8704 +	0.2493 d_{t-1}	s^2_t	=	0.8709 +	0.2491 d_{t-1}
	(p-value)		(0.00)	(0.26)	(p-value)		(0.00)	(0.26)
INDUS	s^2_t	=	0.8659 +	0.2731 d_{t-1}	s^2_t	=	0.8709 +	0.263 d_{t-1}
	(p-value)		(0.00)	(0.04)	(p-value)		(0.00)	(0.05)
PROPCON	s^2_t	=	0.8235 +	0.3461 d_{t-1}	s^2_t	=	0.8361 +	0.3215 d_{t-1}
	(p-value)		(0.00)	(0.07)	(p-value)		(0.00)	(0.08)
RESOURC	s^2_t	=	0.8892 +	0.2117 d_{t-1}	s^2_t	=	0.8881 +	0.1840 d_{t-1}
	(p-value)		(0.00)	(0.27)	(p-value)		(0.00)	(0.24)
SERVICE	s^2_t	=	0.8387 +	0.3227 d_{t-1}	s^2_t	=	0.8445 +	0.313 d_{t-1}
	(p-value)		(0.00)	(0.09)	(p-value)		(0.00)	(0.10)
TECH	s^2_t	=	0.9224 +	0.1597 d_{t-1}	s^2_t	=	0.9335 +	0.1370 d_{t-1}
	(p-value)		(0.00)	(0.46)	(p-value)		(0.00)	(0.52)

As can be seen in Table 3.9, the coefficient of the d_{t-1} for the SET, financial, resources, and technology industries is not statistically different from zero in either the GARCH (1,1) or the modified GARCH (1,1) model. However, the coefficient is different from zero by at least a 10% significance level for the consumer products, industrials, property and construction, and services industries. For the agribusiness and food industry, the parameter corresponding to the d_{t-1} term is non-zero at the 1% significance level in the GARCH(1,1) model but insignificant in the modified GARCH(1,1) model. Thus, a specific form of the TARCH or EGARCH(1,1) can be estimated for the agribusiness and food, consumer products, industrials, property and construction, and services industries, which are shown in Table 3.10 to Table 3.14, respectively, as follows:

Table 3.10 Estimation Results of Mean & Conditional Variance for AGRO's Return

Panel A: Without D_{sp}		**Mean equation**									**Variance equation**			
GARCH(1,1)														
r_t	$= 0.0011 +$	$0.4871\ r_{t-1}$	$-\ 0.2612\ r_{t-2}$	$-\ 0.4266\ u_{t-1}$	$+\ 0.2736\ u_{t-2}$	$+\ 0.1055\ u_{t-13}$	$+\ u_t$	h_t	$= 8.17E\text{-}06 +$	$0.1543\ u^2_{t-1}$	$+\ 0.7923\ h_{t-1}$			
(p-value)	(0.00)	(0.00)	(0.07)	(0.01)	(0.05)	(0.00)		(p-value)	(0.00)	(0.00)	(0.00)			
									AIC = -6.275		Ljung-Box Q(15) statistic =		7.328	
TARCH									logL = 6890		Ljung-Box Q^2(15) statistic =		4.198	
r_t	$= 0.0009 +$	$0.5152\ r_{t-1}$	$-\ 0.1363\ r_{t-2}$	$-\ 0.4408\ u_{t-1}$	$+\ 0.1416\ u_{t-2}$	$+\ 0.1089\ u_{t-13}$	$+\ u_t$	h_t	$= 1.04E\text{-}05 +$	$0.0900\ u^2_{t-1}$	$+\ 0.7607\ h_{t-1}$	$+\ 0.1570\ d_{t-1}u^2_{t-1}$		
(p-value)	(0.00)	(0.00)	(0.34)	(0.01)	(0.30)	(0.00)		(p-value)	(0.00)	(0.00)	(0.00)	(0.00)		
									AIC = -6.285		Ljung-Box Q(15) statistic =		6.930	
EGARCH(1,1)									logL = 6901		Ljung-Box Q^2(15) statistic =		6.918	
r_t	$= 0.0007 +$	$0.6114\ r_{t-1}$	$-\ 0.2129\ r_{t-2}$	$-\ 0.5554\ u_{t-1}$	$+\ 0.2211\ u_{t-2}$	$+\ 0.0965\ u_{t-13}$	$+\ u_t$	$\ln(h_t)$	$= -1.08E{+}00\ -$	$0.0932\ (u_{t-1}/\sqrt{h_{t-1}})$	$+\ 0.9062\ \ln(h_{t-1})$	$+\ 0.2965\ \lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$		
(p-value)	(0.01)	(0.00)	(0.16)	(0.00)	(0.13)	(0.00)		(p-value)	(0.00)	(0.00)	(0.00)	(0.00)		
									AIC = -6.294		Ljung-Box Q(15) statistic =		7.236	
									logL = 6911		Ljung-Box Q^2(15) statistic =		6.358	
Panel B: With D_{sp}		**Mean equation**									**Variance equation**			
GARCH(1,1)														
r_t	$= 0.0011 +$	$0.4938\ r_{t-1}$	$-\ 0.2683\ r_{t-2}$	$-\ 0.4323\ u_{t-1}$	$+\ 0.2792\ u_{t-2}$	$+\ 0.1037\ u_{t-13}$	$+\ u_t$	h_t	$= 8.79E\text{-}06 +$	$0.1595\ u^2_{t-1}$	$+\ 0.7782\ h_{t-1}$	$+\ 1.19E\text{-}05\ D_{sp}$		
(p-value)	(0.00)	(0.00)	(0.06)	(0.01)	(0.04)	(0.00)		(p-value)	(0.00)	(0.00)	(0.00)	(0.00)		
									AIC = -6.278		Ljung-Box Q(15) statistic =		7.188	
TARCH									logL = 6893		Ljung-Box Q^2(15) statistic =		3.804	
r_t	$= 0.0009 +$	$0.5195\ r_{t-1}$	$-\ 0.1506\ r_{t-2}$	$-\ 0.4465\ u_{t-1}$	$+\ 0.1550\ u_{t-2}$	$+\ 0.1063\ u_{t-13}$	$+\ u_t$	h_t	$= 1.11E\text{-}05 +$	$0.0933\ u^2_{t-1}$	$+\ 0.7472\ h_{t-1}$	$+\ 0.1568\ d_{t-1}u^2_{t-1}$		$+\ 8.65E\text{-}06\ D_{sp}$
(p-value)	(0.00)	(0.00)	(0.30)	(0.01)	(0.26)	(0.00)		(p-value)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
									AIC = -6.286		Ljung-Box Q(15) statistic =		18.068	
EGARCH(1,1)									logL = 6904		Ljung-Box Q^2(15) statistic =		3.746	
r_t	$= 0.0008 +$	$0.6484\ r_{t-1}$	$-\ 0.3009\ r_{t-2}$	$-\ 0.5885\ u_{t-1}$	$+\ 0.3077\ u_{t-2}$	$+\ 0.0918\ u_{t-13}$	$+\ u_t$	$\ln(h_t)$	$= -1.19E{+}00\ -$	$0.0915\ (u_{t-1}/\sqrt{h_{t-1}})$	$+\ 0.8949\ \ln(h_{t-1})$	$+\ 0.3033\ \lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$		$+\ 6.99E\text{-}02\ D_{sp}$
(p-value)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)		(p-value)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
									AIC = -6.295		Ljung-Box Q(15) statistic =		17.961	
									logL = 6914		Ljung-Box Q^2(15) statistic =		4.806	

Note: D_{sp} denotes the dummy variable of the Subprime Effect

Table 3.11 Estimation Results of Mean & Conditional Variance for CONSUMP's Return

Panel A: Without D_{sp}		**Mean equation**						**Variance equation**			
GARCH(1,1)											
r_t =	0.0005 +	0.0491 r_{t-2} −	0.0635 r_{t-6} −	0.0527 r_{t-21} +	0.0523 r_{t-22} + u_t	h_t =	1.14E-05 +	0.1866 u^2_{t-1}	+ 0.5918 h_{t-1}		
(p-value)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(p-value)	(0.00)	(0.00)	(0.00)		
						AIC	= -7.208		Ljung-Box Q(15) statistic =	14.860	
TARCH						logL	= 7840		Ljung-Box Q^2(15) statistic =	4.428	
r_t =	0.0003 +	0.0422 r_{t-2} −	0.0658 r_{t-6} −	0.0526 r_{t-21} +	0.0507 r_{t-22} + u_t	h_t =	1.15E-05 +	0.0567 u^2_{t-1}	+ 0.5883 h_{t-1} +	0.2468 $d_{t-1}u^2_{t-1}$	
(p-value)	(0.03)	(0.08)	(0.00)	(0.00)	(0.01)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	
						AIC	= -7.227		Ljung-Box Q(15) statistic =	16.426	
EGARCH(1,1)						logL	= 7861		Ljung-Box Q^2(15) statistic =	4.270	
r_t =	0.0004 +	0.0398 r_{t-2} −	0.0573 r_{t-6} −	0.0470 r_{t-21} +	0.0507 r_{t-22} + u_t	$\ln(h_t)$ =	-1.24E+00 −	0.1254 $(u_{t-1}/\sqrt{h_{t-1}})$ +	0.8909 $\ln(h_{t-1})$ +	0.2092 $\lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$	
(p-value)	(0.00)	(0.09)	(0.01)	(0.00)	(0.01)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	
						AIC	= -7.232		Ljung-Box Q(15) statistic =	14.750	
						logL	= 7867		Ljung-Box Q^2(15) statistic =	2.971	
Panel B: With D_{sp}		**Mean equation**						**Variance equation**			
GARCH(1,1)											
r_t =	0.0004 +	0.0487 r_{t-2} −	0.0673 r_{t-6} −	0.0256 r_{t-21} +	0.0439 r_{t-22} + u_t	h_t =	1.76E-06 +	0.0671 u^2_{t-1}	+ 0.8915 h_{t-1}	+ 1.56E-05 D_{sp}	
(p-value)	(0.01)	(0.04)	(0.01)	(0.19)	(0.05)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	
						AIC	= -7.247		Ljung-Box Q(15) statistic =	15.072	
TARCH						logL	= 7883		Ljung-Box Q^2(15) statistic =	2.138	
r_t =	0.0003 +	0.0469 r_{t-1} −	0.0648 r_{t-6} −	0.0291 r_{t-21} +	0.0475 r_{t-22} + u_t	h_t =	1.87E-06 +	0.0522 u^2_{t-1}	+ 0.8856 h_{t-1} +	0.0351 $d_{t-1}u^2_{t-1}$	+ 1.60E-05 D_{sp}
(p-value)	(0.02)	(0.05)	(0.01)	(0.12)	(0.03)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
						AIC	= -7.248		Ljung-Box Q(15) statistic =	15.577	
EGARCH(1,1)						logL	= 7885		Ljung-Box Q^2(15) statistic =	5.5042	
r_t =	0.0003 +	0.0476 r_{t-1} −	0.0514 r_{t-6} −	0.0375 r_{t-21} +	0.0527 r_{t-22} + u_t	$\ln(h_t)$ =	-7.98E-01 −	0.0722 $(u_{t-1}/\sqrt{h_{t-1}})$ +	0.9327 $\ln(h_{t-1})$ +	0.1616 $\lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$	+ 1.23E-01 D_{sp}
(p-value)	(0.03)	(0.04)	(0.03)	(0.00)	(0.02)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
						AIC	= -7.247		Ljung-Box Q(15) statistic =	14.557	
						logL	= 7883		Ljung-Box Q^2(15) statistic =	2.153	

Note: D_{sp} denotes the dummy variable of the Subprime Effect

Table 3.12 Estimation Results of Mean & Conditional Variance for INDUS's Return

Panel A: Without D_{sp}	**Mean equation**	**Variance equation**
GARCH(1,1)		
	$r_t = 1.4720\ r_{t-1} - 0.5346\ r_{t-2} - 1.3842\ u_{t-1} + 0.4437\ u_{t-2} + 0.0247\ u_{t-7} + u_t$	$h_t = 1.22E{-}05 + 0.1066\ u^2_{t-1} + 0.8445\ h_{t-1}$
(p-value)	(0.00) (0.00) (0.00) (0.02) (0.00)	(0.00) (0.00) (0.00)
		AIC = -5.618 ; Ljung-Box Q (15) statistic = 8.386
		logL = 6168 ; Ljung-Box Q^2(15) statistic = 5.227
TARCH		
	$r_t = 1.4231\ r_{t-1} - 0.4894\ r_{t-2} - 1.3306\ u_{t-1} + 0.3961\ u_{t-2} + 0.0253\ u_{t-7} + u_t$	$h_t = 1.42E{-}05 + 0.0770\ u^2_{t-1} + 0.8304\ h_{t-1} + 0.0733\ d_{t-1}u^2_{t-1}$
(p-value)	(0.00) (0.01) (0.00) (0.05) (0.00)	(0.00) (0.00) (0.00) (0.00)
		AIC = -5.624 ; Ljung-Box Q (15) statistic = 8.384
		logL = 6176 ; Ljung-Box Q^2(15) statistic = 3.952
EGARCH(1,1)		
	$r_t = 1.3955\ r_{t-1} - 0.5009\ r_{t-2} - 1.3106\ u_{t-1} + 0.4207\ u_{t-2} + 0.0278\ u_{t-7} + u_t$	$\ln(h_t) = -8.42E{-}01 - 0.0623\ (u_{t-1}/\sqrt{h_{t-1}}) + 0.9203\ \ln(h_{t-1}) + 0.2277\ \lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$
(p-value)	(0.00) (0.01) (0.00) (0.02) (0.00)	(0.00) (0.00) (0.00) (0.00)
		AIC = -5.608 ; Ljung-Box Q (15) statistic = 9.355
		logL = 6159 ; Ljung-Box Q^2(15) statistic = 3.006

Panel B: With D_{sp}	**Mean equation**	**Variance equation**
GARCH(1,1)		
	$r_t = 1.4687\ r_{t-1} - 0.5308\ r_{t-2} - 1.3808\ u_{t-1} + 0.4393\ u_{t-2} + 0.0249\ u_{t-7} + u_t$	$h_t = 1.30E{-}05 + 0.1071\ u^2_{t-1} + 0.8366\ h_{t-1} + 1.96E{-}05\ D_{sp}$
(p-value)	(0.00) (0.00) (0.00) (0.02) (0.00)	(0.00) (0.00) (0.00) (0.00)
		AIC = -5.621 ; Ljung-Box Q (15) statistic = 7.338
		logL = 6172 ; Ljung-Box Q^2(15) statistic = 4.630
TARCH		
	$r_t = 1.4642\ r_{t-1} - 0.5215\ r_{t-2} - 1.3700\ u_{t-1} + 0.4260\ u_{t-2} + 0.025\ u_{t-7} + u_t$	$h_t = 1.43E{-}05 + 0.0761\ u^2_{t-1} + 0.8241\ h_{t-1} + 0.0792\ d_{t-1}u^2_{t-1} + 1.79E{-}05\ D_{sp}$
(p-value)	(0.00) (0.01) (0.00) (0.02) (0.00)	(0.00) (0.00) (0.00) (0.00) (0.01)
		AIC = -5.626 ; Ljung-Box Q (15) statistic = 11.017
		logL = 6179 ; Ljung-Box Q^2(15) statistic = 2.636
EGARCH(1,1)		
	$r_t = 1.3365\ r_{t-1} - 0.4383\ r_{t-2} - 1.2522\ u_{t-1} + 0.3579\ u_{t-2} + 0.0286\ u_{t-7} + u_t$	$\ln(h_t) = -9.53E{-}01 - 0.0592\ (u_{t-1}/\sqrt{h_{t-1}}) + 0.9083\ \ln(h_{t-1}) + 0.2332\ \lvert u_{t-1}/\sqrt{h_{t-1}}\rvert + 7.94E{-}02\ D_{sp}$
(p-value)	(0.00) (0.03) (0.00) (0.08) (0.00)	(0.00) (0.00) (0.00) (0.00) (0.00)
		AIC = -5.612 ; Ljung-Box Q (15) statistic = 8.377
		logL = 6164 ; Ljung-Box Q^2(15) statistic = 2.447

Note: D_{sp} denotes the dummy variable of the Subprime Effect

Table 3.13 Estimation Results of Mean & Conditional Variance for PROPCON's Return

Panel A: Without D_{sp}	**Mean equation**	**Variance equation**	
GARCH(1,1)			
	$r_t = 0.0009 + 0.1404\, r_{t-1} + u_t$	$h_t = 1.39E\text{-}05 + 0.1851\, u^2_{t-1} + 0.7631\, h_{t-1}$	
(p-value)	(0.01) (0.00)	(0.00) (0.00) (0.00)	
		AIC = -5.826	Ljung-Box Q (15) statistic = 21.423
		logL = 6396	Ljung-Box Q^2(15) statistic = 1.578
TARCH			
	$r_t = 0.0005 + 0.1456\, r_{t-1} + u_t$	$h_t = 1.43E\text{-}05 + 0.0987\, u^2_{t-1} + 0.7596\, h_{t-1} + 0.1711\, d_{t-1}u^2_{t-1}$	
(p-value)	(0.11) (0.00)	(0.00) (0.00) (0.00) (0.00)	
		AIC = -5.839	Ljung-Box Q (15) statistic = 21.495
		logL = 6411	Ljung-Box Q^2(15) statistic = 1.372
EGARCH(1,1)			
	$r_t = 0.0006 + 0.1510\, r_{t-1} + u_t$	$\ln(h_t) = -8.59E\text{-}01 - 0.0976\, (u_{t-1}/\sqrt{h_{t-1}}) + 0.9247\, \ln(h_{t-1}) + 0.2737\, \lvert u_{t-1}/\sqrt{h_{t-1}} \rvert$	
(p-value)	(0.07) (0.00)	(0.00) (0.00) (0.00) (0.00)	
		AIC = -5.840	Ljung-Box Q (15) statistic = 22.815
		logL = 6412	Ljung-Box Q^2(15) statistic = 1.261
Panel B: With D_{sp}	**Mean equation**	**Variance equation**	
GARCH(1,1)			
	$r_t = 0.0009 + 0.1385\, r_{t-1} + u_t$	$h_t = 1.87E\text{-}05 + 0.2056\, u^2_{t-1} + 0.7093\, h_{t-1} + 5.93E\text{-}05\, D_{sp}$	
(p-value)	(0.00) (0.00)	(0.00) (0.00) (0.00) (0.00)	
		AIC = -5.833	Ljung-Box Q (15) statistic = 20.267
		logL = 6404	Ljung-Box Q^2(15) statistic = 1.626
TARCH			
	$r_t = 0.0006 + 0.1439\, r_{t-1} + u_t$	$h_t = 1.95E\text{-}05 + 0.1103\, u^2_{t-1} + 0.7033\, h_{t-1} + 0.1901\, d_{t-1}u^2_{t-1} + 5.73E\text{-}05\, D_{sp}$	
(p-value)	(0.08) (0.00)	(0.00) (0.00) (0.00) (0.00) (0.00)	
		AIC = -5.844	Ljung-Box Q (15) statistic = 20.261
		logL = 6418	Ljung-Box Q^2(15) statistic = 1.507
EGARCH(1,1)			
	$r_t = 0.0006 + 0.1499\, r_{t-1} + u_t$	$\ln(h_t) = -1.23E{+}00 - 0.1055\, (u_{t-1}/\sqrt{h_{t-1}}) + 0.8866\, \ln(h_{t-1}) + 0.3079\, \lvert u_{t-1}/\sqrt{h_{t-1}} \rvert + 1.50E\text{-}01\, D_{sp}$	
(p-value)	(0.06) (0.00)	(0.00) (0.00) (0.00) (0.00) (0.00)	
		AIC = -5.848	Ljung-Box Q (15) statistic = 21.192
		logL = 6422	Ljung-Box Q^2(15) statistic = 1.798

Note: D_{sp} denotes the dummy variable of the Subprime Effect

Table 3.14 Estimation Results of Mean & Conditional Variance for SERVICE's Return

Panel A: Without D_{sp}			**Mean equation**						**Variance equation**		
GARCH(1,1)											
r_t	$= 0.0011 +$	$0.0912\ u_{t-1} +$	$0.0443\ u_{t-2} +$	$0.059\ u_{t-3} +$	$0.0585\ u_{t-13} + u_t$	h_t	$= 8.57E\text{-}06 +$	$0.1317\ u^2_{t-1}$	$+\ 0.8042\ h_{t-1}$		
(p-value)	(0.00)	(0.00)	(0.07)	(0.02)	(0.01)	(p-value)	(0.00)	(0.00)	(0.00)		
							AIC	= -6.302	Ljung-Box Q(15) statistic	= 14.401	
TARCH							logL	= 6925	Ljung-Box Q^2(15) statistic	= 2.652	
r_t	$= 0.0007 +$	$0.0972\ u_{t-1} +$	$0.0487\ u_{t-2} +$	$0.0719\ u_{t-3} +$	$0.0659\ u_{t-13} + u_t$	h_t	$= 9.70E\text{-}06 +$	$0.0466\ u^2_{t-1}$	$+\ 0.7965\ h_{t-1}$	$+\ 0.1540\ d_{t-1}u^2_{t-1}$	
(p-value)	(0.01)	(0.00)	(0.04)	(0.00)	(0.00)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	
							AIC	= -6.319	Ljung-Box Q(15) statistic	= 14.524	
EGARCH(1,1)							logL	= 6945	Ljung-Box Q^2(15) statistic	= 2.329	
r_t	$= 0.0006 +$	$0.1089\ u_{t-1} +$	$0.0507\ u_{t-2} +$	$0.0849\ u_{t-3} +$	$0.0655\ u_{t-13} + u_t$	$\ln(h_t)$	$= -8.10E\text{-}01 -$	$0.1134\ (u_{t-1}/\sqrt{h_{t-1}})$	$+\ 0.9271\ \ln(h_{t-1})$	$+\ 0.1949\ \lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$	
(p-value)	(0.05)	(0.00)	(0.03)	(0.00)	(0.00)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	
							AIC	= -6.316	Ljung-Box Q(15) statistic	= 15.858	
							logL	= 6941	Ljung-Box Q^2(15) statistic	= 2.486	
Panel B: With D_{sp}			**Mean equation**						**Variance equation**		
GARCH(1,1)											
r_t	$= 0.0011 +$	$0.0913\ u_{t-1} +$	$0.0441\ u_{t-2} +$	$0.0598\ u_{t-3} +$	$0.0600\ u_{t-13} + u_t$	h_t	$= 8.95E\text{-}06 +$	$0.1293\ u^2_{t-1}$	$+\ 0.7987\ h_{t-1}$	$+\ 1.04E\text{-}05\ D_{sp}$	
(p-value)	(0.00)	(0.00)	(0.07)	(0.02)	(0.00)	(p-value)	(0.00)	(0.00)	(0.00)	(0.06)	
							AIC	= -6.304	Ljung-Box Q(15) statistic	= 13.423	
TARCH							logL	= 6927	Ljung-Box Q^2(15) statistic	= 2.640	
r_t	$= 0.0007 +$	$0.0976\ u_{t-1} +$	$0.0484\ u_{t-2} +$	$0.0722\ u_{t-3} +$	$0.0674\ u_{t-13} + u_t$	h_t	$= 1.01E\text{-}05 +$	$0.0462\ u^2_{t-1}$	$+\ 0.7894\ h_{t-1}$	$+\ 0.1541\ d_{t-1}u^2_{t-1}$	$+\ 8.65E\text{-}06\ D_{sp}$
(p-value)	(0.01)	(0.00)	(0.04)	(0.00)	(0.00)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)
							AIC	= -6.320	Ljung-Box Q(15) statistic	= 13.805	
EGARCH(1,1)							logL	= 6947	Ljung-Box Q^2(15) statistic	= 2.358	
r_t	$= 0.0006 +$	$0.1086\ u_{t-1} +$	$0.0504\ u_{t-2} +$	$0.0866\ u_{t-3} +$	$0.0683\ u_{t-13} + u_t$	$\ln(h_t)$	$= -8.72E\text{-}01 -$	$0.1132\ (u_{t-1}/\sqrt{h_{t-1}})$	$+\ 0.9205\ \ln(h_{t-1})$	$+\ 0.1936\ \lvert u_{t-1}/\sqrt{h_{t-1}}\rvert$	$+\ 1.23E\text{-}01\ D_{sp}$
(p-value)	(0.04)	(0.00)	(0.03)	(0.00)	(0.00)	(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
							AIC	= -6.317	Ljung-Box Q(15) statistic	= 15.219	
							logL	= 6943	Ljung-Box Q^2(15) statistic	= 2.612	

Note: D_{sp} denotes the dummy variable of the Subprime Effect

From Table 3.10 to 3.14, it can be seen that the asymmetric property of volatility exists for the stock returns of consumer products, industrials, property and construction, services, and agribusiness and food industries as the parameter corresponding to the $(d_{t-1}u_{t-1}^2)$ term in the TARCH model, and the parameter corresponding to the $(u_{t-1}/\sqrt{h_{t-1}})$ term in the EGARCH(1,1) model is statistically different from zero at the 1% significance level. This is consistent with the sign bias test in Table 3.9. In addition, the dummy variable of the subprime effect is different from zero at at least a 10% significance level for the consumer products, industrials, property and construction, services, and agribusiness and food industries.

3.5.2 The Causal Relationship between Returns and Conditional Volatility

In this section, the leverage effect hypothesis and the volatility feedback effect hypothesis will be tested for the SET index returns and 8 industry group index returns. In other words, the Granger causality test will be applied to examine the causal relationship between the stock returns and conditional volatility. First, a unit root test was conducted for the conditional volatility of the SET index returns and eight industry group index returns which were estimated from the models mentioned in the last section in 3.5.1. As mentioned in Table 3.3, the SET index returns, and eight industry group index returns, are statistically stationary. The augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests of a unit root were applied for the stock conditional volatility, estimated from the GARCH(1,1) model and the modified GARCH(1,1) model, which includes the dummy variable of the subprime effect, in order to investigate the stationarity of the volatility series, as shown in Table 3.15.

Table 3.15 Unit Root Tests of the Stock Volatility

	GARCH(1,1)		The modified GARCH(1,1)	
	ADF	PP	ADF	PP
SET	-8.592***	-7.973***	-8.946***	-8.855***
AGRO	-9.472***	-9.311***	-9.576***	-9.317***
CONSUMP	-16.312***	-16.244***	-5.416***	-5.049***
FINCIAL	-7.024***	-6.605***	-6.911***	-6.233***
INDUS	-7.669***	-6.988***	-7.513***	-6.775***
PROPCON	-9.672***	-9.079***	-9.784***	-9.658***
RESOURC	-7.714***	-6.950***	-7.764***	-6.845***
SERVICE	-8.830***	-8.156***	-8.681***	-7.968***
TECH	-15.846***	-15.544***	-15.425***	-15.039***

Note: The table reports the Augmented Dickey-Fuller and the Phillips-Perron unit root tests without a time trend. Critical values at the 1%, 5%, and 10% significance level are -3.433, -2.863, and -2.567, respectively.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Table 3.15 indicates that the null hypothesis of a unit root was rejected in all stock volatilities at the 1% significance level using both ADF and PP tests. Thus, the SET returns' volatility, and eight industry group returns' volatilities, are statistically stationary. Since the asymmetric property of volatility exists for the stock returns of consumer products, industrials, property and construction, services, and agribusiness and food industries mentioned in the last section, the ADF and PP tests of a unit root were also applied to the stock conditional volatility estimated from the EGARCH(1,1) model and the TARCH model in order to investigate the stationarity of the volatility series, as shown in Table 3.16 as follows:

Table 3.16 Unit Root Tests of the Stock Volatility for CONSUMP, INDUS, PROPCON, SERVICE, and AGRO

	TARCH		Modified TARCH		EGARCH(1,1)		Modified EGARCH(1,1)	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
AGRO	-21.490***	-23.034***	-10.829***	-10.641***	-12.126***	-11.864***	-12.269***	-11.909***
CONSUMP	-16.820***	-16.764***	-5.662***	-5.310***	-12.997***	-12.649***	-6.544***	-6.166***
INDUS	-8.122***	-7.504***	-7.978***	-7.331***	-9.129***	-8.921***	-8.861***	-8.626***
PROPCON	-9.890***	-9.751***	-10.653***	-10.567***	-12.519***	-12.070***	-14.451***	-13.859***
SERVICE	-9.037***	-9.033***	-9.067***	-9.009***	-10.467***	-10.281***	-10.293***	-10.072***

Note: The table reports the Augmented Dickey-Fuller and the Phillips-Perron unit root tests without a time trend. Critical values at the 1%, 5%, and 10% significance level are -3.433, -2.863, and -2.567, respectively.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

From Table 3.16, the null hypothesis of a unit root was rejected for consumer products, industrials, property and construction, services, and agribusiness and food returns' volatilities at the 1% significance level applying the conditional volatility estimated from the TARCH, and EGARCH(1,1) models. The hypothesis was also rejected for the modified TARCH and modified EGARCH(1,1) models allowing the dummy variable of the Subprime effect. Thus, the five industry return volatilities mentioned above are statistically stationary. Next, the two-variable VAR(p) model was estimated using the appropriate lag lengths (p) of the VAR model suggested by Akaike's information criteria (AIC). The test statistics for the symmetric GARCH models of all industries, and the asymmetric GARCH models (e.g., TARCH, EGARCH(1,1)) of the agribusiness and food, consumer products, industrials, property and construction, and services industries, are shown in Table 3.17 to 3.18, respectively:

Table 3.17 Lag Order Selection for VAR(m) Model Using Akaike's Information Criteria (AIC) of all Industries - Symmetric GARCH(1,1) Models

	SET		AGRO		CONSUMP		FINCIAL		INDUS		PROPCON		RESOURC		SERVICE		TECH	
Lag	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)	GARCH(1,1)	Modified GARCH(1,1)
0	-13.3741	-13.2528	-14.4555	-14.4260	-16.5498	-15.9848	-12.8840	-12.8878	-13.1750	-13.1537	-13.0657	-13.0166	-12.4917	-12.3450	-14.2555	-14.2606	-13.9284	-13.9868
1	-15.6855	-15.3486	-16.3911	-16.3411	-17.5327	-19.1572	-15.6125	-15.6305	-15.6736	-15.6745	-15.0776	-14.9165	-14.9973	-14.7766	-16.5617	-16.5897	-15.0088	-15.0712
2	-15.7138	-15.3689	-16.4043	-16.3537	-17.5449	-19.1787	-15.6397	-15.6555	-15.6965	-15.6953	-15.0974	-14.9321	-15.0215	-14.7938	-16.5898	-16.6165	-15.0217	-15.0781
3	-15.7231	-15.3780	-16.4073	-16.3560	-17.5430	-19.1779	-15.6491	-15.6648	-15.6993	-15.6979	-15.1035	-14.9381	-15.0304	-14.8018	-16.5969	-16.6235	-15.0209	-15.0797
4	-15.7265	-15.3819	-16.4062	-16.3548	-17.5403	-19.1752	-15.6483	-15.6640	-15.6989	-15.6977	-15.1046	-14.9398	-15.0303	-14.8027	-16.5981	-16.6249	-15.0246	-15.0825
5	-15.7272	-15.3840	-16.4035	-16.3524	-17.5378	-19.1725	-15.6463	-15.6625	-15.6956	-15.6946	-15.1030	-14.9387	-15.0308	-14.8049	-16.5963	-16.6235	-15.0296	-15.0899
6	-15.7319	-15.3888	-16.4009	-16.3498	-17.5401	-19.1739	-15.6495	-15.6658	-15.6949	-15.6941	-15.1031	-14.9401	-15.0387	-14.8136	-16.5997	-16.6266	-15.0291	-15.0901
7	-15.7301	-15.3877	-16.4023	-16.3516	-17.5443	-19.1752	-15.6485	-15.6649	-15.7006	-15.7001	-15.1011	-14.9381	-15.0355	-14.8113	-16.5974	-16.6245	-15.0275	-15.0901
8	-15.7301	-15.3893	-16.4014	-16.3509	-17.5412	-19.1729	-15.6478	-15.6646	-15.6992	-15.6986	-15.1023	-14.9404	-15.0353	-14.8119	-16.5996	-16.6270	-15.0284	-15.0944
9	-15.7295	-15.3901	-16.4043	-16.3541	-17.5405	-19.1727	-15.6468	-15.6637	-15.6976	-15.6971	-15.1041	-14.9425	-15.0338	-14.8114	-16.5993	-16.6266	-15.0288	-15.0960
10	-15.7300	-15.3902	-16.4014	-16.3512	-17.5394	-19.1711	-15.6532	-15.6699	-15.6977	-15.6975	-15.1027	-14.9409	-15.0328	-14.8103	-16.6009	-16.6279	-15.0263	-15.0943
11	-15.7287	-15.3891	-16.3996	-16.3495	-17.5431	-19.1698	-15.6511	-15.6678	-15.6971	-15.6971	-15.1018	-14.9405	-15.0356	-14.8133	-16.5987	-16.6258	-15.0259	-15.0951
12	-15.7294	-15.3908	-16.3979	-16.3478	-17.5420	-19.1689	-15.6496	-15.6667	-15.6979	-15.6980	-15.1006	-14.9395	-15.0362	-14.8144	-16.5985	-16.6254	-15.0236	-15.0933
13	-15.7303	-15.3934	-16.4045	-16.3545	-17.5388	-19.1661	-15.6488	-15.6666	-15.6995	-15.6990	-15.1039	-14.9435	-15.0357	-14.8146	-16.6036	-16.6305	-15.0212	-15.0910
14	-15.7301	-15.3930	-16.4043	-16.3544	-17.5360	-19.1632	-15.6482	-15.6657	-15.7013	-15.7011	-15.1034	-14.9425	-15.0365	-14.8148	-16.6019	-16.6288	-15.0182	-15.0890
15	-15.7305	-15.3948	-16.4014	-16.3517	-17.5335	-19.1614	-15.6494	-15.6665	-15.7005	-15.7004	-15.1029	-14.9426	-15.0372	-14.8159	-16.6018	-16.6288	-15.0160	-15.0875
16	-15.7316	-15.3952	-16.3997	-16.3499	-17.5301	-19.1584	-15.6529	-15.6686	-15.6997	-15.6994	-15.1046	-14.9434	-15.0345	-14.8127	-16.6027	-16.6294	-15.0126	-15.0839
17	-15.7289	-15.3930	-16.3979	-16.3482	-17.5270	-19.1553	-15.6511	-15.6673	-15.6961	-15.6958	-15.1034	-14.9425	-15.0316	-14.8102	-16.6004	-16.6272	-15.0106	-15.0831
18	-15.7283	-15.3918	-16.3950	-16.3454	-17.5238	-19.1521	-15.6500	-15.6662	-15.6934	-15.6929	-15.1006	-14.9395	-15.0321	-14.8105	-16.6001	-16.6269	-15.0091	-15.0816
19	-15.7263	-15.3896	-16.3944	-16.3448	-17.5222	-19.1500	-15.6482	-15.6640	-15.6913	-15.6908	-15.0977	-14.9367	-15.0290	-14.8074	-16.5982	-16.6247	-15.0069	-15.0792
20	-15.7267	-15.3901	-16.3926	-16.3431	-17.5204	-19.1475	-15.6492	-15.6649	-15.6891	-15.6887	-15.0970	-14.9358	-15.0280	-14.8067	-16.6004	-16.6270	-15.0037	-15.0761

Table 3.18 Lag Order Selection for VAR(m) Model Using AIC of AGRO, CONSUMP, INDUS, PROPCON, SERVICE - Asymmetric GARCH Models

	AGRO				CONSUMP				INDUS				PROPCON				SERVICE			
Lag	TARCH	Modified TARCH	EGARCH(1,1)	Modified EGARCH(1,1)	TARCH	Modified TARCH	EGARCH(1,1)	Modified EGARCH(1,1)	TARCH	Modified TARCH	EGARCH(1,1)	Modified EGARCH(1,1)	TARCH	Modified TARCH	EGARCH(1,1)	Modified EGARCH(1,1)	TARCH	Modified TARCH	EGARCH(1,1)	Modified EGARCH(1,1)
0	-71.1066	-14.2793	-14.4961	-14.4684	-16.3201	-15.9372	-16.6603	-16.3366	-13.0855	-13.0385	-13.4567	-13.3779	-12.9180	-12.8889	-13.0000	-12.8204	-14.0960	-14.1028	-14.3796	-14.3607
1	-71.5262	-16.2093	-16.2402	-16.1841	-17.6323	-19.0753	-18.5692	-19.3696	-15.5640	-15.5444	-15.6339	-15.5947	-15.0610	-14.9001	-14.6980	-14.2561	-16.5908	-16.5937	-16.6642	-16.6841
2	-71.5887	-16.2102	-16.2398	-16.1829	-17.6383	-19.0918	-18.5750	-19.3797	-15.5771	-15.5553	-15.6397	-15.5979	-15.0662	-14.9023	-14.7013	-14.2557	-16.6000	-16.6016	-16.6711	-16.6895
3	-71.5976	-16.2104	-16.2384	-16.1818	-17.6385	-19.0915	-18.5796	-19.3843	-15.5792	-15.5572	-15.6390	-15.5976	-15.0718	-14.9076	-14.7031	-14.2591	-16.6008	-16.6021	-16.6715	-16.6901
4	-71.5967	-16.2078	-16.2349	-16.1784	-17.6350	-19.0887	-18.5764	-19.3812	-15.5771	-15.5550	-15.6364	-15.5953	-15.0701	-14.9058	-14.7027	-14.2597	-16.5998	-16.6014	-16.6722	-16.6915
5	-71.5955	-16.2049	-16.2326	-16.1764	-17.6336	-19.0863	-18.5758	-19.3806	-15.5740	-15.5522	-15.6334	-15.5927	-15.0674	-14.9036	-14.7012	-14.2594	-16.5978	-16.5997	-16.6716	-16.6912
6	-71.5926	-16.2021	-16.2297	-16.1737	-17.6362	-19.0877	-18.5785	-19.3828	-15.5734	-15.5518	-15.6341	-15.5942	-15.0683	-14.9058	-14.7025	-14.2623	-16.6017	-16.6034	-16.6726	-16.6923
7	-71.5934	-16.2019	-16.2297	-16.1738	-17.6415	-19.0895	-18.5828	-19.3841	-15.5779	-15.5562	-15.6374	-15.5976	-15.0650	-14.9024	-14.6995	-14.2599	-16.5990	-16.6008	-16.6692	-16.6890
8	-71.5939	-16.2017	-16.2302	-16.1747	-17.6397	-19.0868	-18.5805	-19.3824	-15.5772	-15.5557	-15.6371	-15.5975	-15.0664	-14.9055	-14.6985	-14.2603	-16.6013	-16.6034	-16.6714	-16.6918
9	-71.5910	-16.2041	-16.2318	-16.1769	-17.6404	-19.0868	-18.5804	-19.3838	-15.5768	-15.5555	-15.6378	-15.5983	-15.0689	-14.9088	-14.6984	-14.2604	-16.6013	-16.6035	-16.6707	-16.6912
10	-71.5878	-16.2016	-16.2296	-16.1747	-17.6382	-19.0850	-18.5775	-19.3819	-15.5758	-15.5546	-15.6367	-15.5978	-15.0663	-14.9059	-14.6954	-14.2576	-16.6005	-16.6026	-16.6692	-16.6895
11	-71.5845	-16.1995	-16.2275	-16.1728	-17.6420	-19.0836	-18.5790	-19.3808	-15.5746	-15.5534	-15.6361	-15.5972	-15.0652	-14.9054	-14.6952	-14.2581	-16.5986	-16.6008	-16.6687	-16.6895
12	-71.5810	-16.1967	-16.2244	-16.1697	-17.6402	-19.0827	-18.5775	-19.3819	-15.5768	-15.5558	-15.6386	-15.5997	-15.0648	-14.9053	-14.6947	-14.2587	-16.5976	-16.5997	-16.6672	-16.6878
13	-71.5878	-16.2041	-16.2322	-16.1777	-17.6371	-19.0800	-18.5744	-19.3794	-15.5774	-15.5558	-15.6378	-15.5989	-15.0683	-14.9098	-14.7000	-14.2644	-16.6047	-16.6069	-16.6732	-16.6940
14	-71.5864	-16.2077	-16.2348	-16.1801	-17.6342	-19.0772	-18.5716	-19.3776	-15.5796	-15.5582	-15.6391	-15.6001	-15.0687	-14.9096	-14.6998	-14.2642	-16.6041	-16.6063	-16.6716	-16.6926
15	-71.5838	-16.2057	-16.2338	-16.1792	-17.6319	-19.0754	-18.5692	-19.3760	-15.5788	-15.5573	-15.6381	-15.5991	-15.0678	-14.9093	-14.6996	-14.2647	-16.6023	-16.6047	-16.6707	-16.6919
16	-71.5813	-16.2039	-16.2327	-16.1778	-17.6289	-19.0725	-18.5665	-19.3732	-15.5787	-15.5573	-15.6392	-15.6001	-15.0698	-14.9105	-14.6986	-14.2629	-16.6039	-16.6062	-16.6700	-16.6912
17	-71.5781	-16.2019	-16.2306	-16.1759	-17.6255	-19.0695	-18.5631	-19.3700	-15.5753	-15.5539	-15.6358	-15.5966	-15.0684	-14.9093	-14.6962	-14.2606	-16.6014	-16.6037	-16.6669	-16.6881
18	-71.5747	-16.1993	-16.2284	-16.1736	-17.6233	-19.0663	-18.5603	-19.3667	-15.5726	-15.5510	-15.6332	-15.5939	-15.0652	-14.9059	-14.6929	-14.2573	-16.5997	-16.6020	-16.6650	-16.6863
19	-71.5718	-16.1990	-16.2280	-16.1734	-17.6206	-19.0643	-18.5573	-19.3645	-15.5706	-15.5489	-15.6317	-15.5923	-15.0623	-14.9031	-14.6896	-14.2541	-16.5972	-16.5993	-16.6620	-16.6832
20	-71.5689	-16.1970	-16.2255	-16.1710	-17.6191	-19.0623	-18.5544	-19.3620	-15.5683	-15.5469	-15.6290	-15.5897	-15.0613	-14.9018	-14.6879	-14.2521	-16.5993	-16.6015	-16.6619	-16.6831

As can be seen in Table 3.17, the AIC suggests the lag lengths of six, three, two, ten, fourteen, sixteen, six, thirteen, and five to be used in the VAR (*m*) for SET, AGRO, CONSUMP, FINCIAL, INDUS, PROPCON, RESOURC, SERVICE, and TECH, respectively, in the stock returns and volatility estimated from the GARCH (1,1) model. For the stock returns and volatility estimated from the modified GARCH (1,1) model allowing for the dummy variable of the subprime effect, the AIC suggests the lag lengths of sixteen, three, two, ten, fourteen, thirteen, fifteen, thirteen, and nine to be used in the VAR(*m*) for SET, AGRO, CONSUMP, FINCIAL, INDUS, PROPCON, RESOURC, SERVICE, and TECH, respectively. Table 3.18 suggests that the lag lengths of three, three, one, and one be used in the VAR(*m*) for AGRO's return and volatility estimated from the TARCH, the modified TARCH, EGARCH (1,1), and the modified EGARCH (1,1) models, respectively. The AIC statistics suggest that the lag lengths of eleven, two, seven and three be used in the VAR(*m*) for CONSUMP's return and volatility estimated from TARCH, the modified TARCH, EGARCH(1,1), and the modified EGARCH(1,1) models, respectively. Moreover, Table 3.18 suggests that the lag lengths of fourteen, fourteen, two, and sixteen be used in the VAR (*m*) for INDUS's return and volatility estimated from TARCH, the modified TARCH, EGARCH (1,1), and the modified EGARCH (1,1) models, respectively. The lag lengths of three, sixteen, three, and fifteen are suggested by AIC to be used in the VAR (*m*) for PROPCON's return and volatility estimated from TARCH, the modified TARCH, EGARCH (1,1), and the modified EGARCH (1,1) models, respectively. Lastly, the lag length of fourteen is suggested to be used in the VAR (*m*) for SERVICE's return and volatility estimated from TARCH, the modified TARCH, EGARCH (1,1), and the modified EGARCH (1,1) models.

According to the lag order of VAR(*m*) mentioned above, the Granger causality tests between the stock returns and conditional volatility estimated from the GARCH (1,1), and the modified GARCH (1,1) models, were then applied and are presented in Table 3.19 as follows:

Table 3.19 Granger Causality Test Results between Stock Returns and Volatility – Symmetric GARCH (1,1) Models

Null hypothesis	GARCH(1,1)			Modified GARCH(1,1)		
	lags	F statistics	p-value	lags	F statistics	p-value
SET						
Returns does not Granger Cause Volatility	6	47.509	0.000	16	18.038	0.000
Volatility does not Granger Cause Returns		5.407	0.000		3.188	0.000
AGRO						
Returns does not Granger Cause Volatility	3	39.810	0.000	3	39.774	0.000
Volatility does not Granger Cause Returns		2.922	0.033		3.035	0.028
CONSUMP						
Returns does not Granger Cause Volatility	10	14.553	0.000	10	14.074	0.000
Volatility does not Granger Cause Returns		4.772	0.000		5.003	0.000
INDUS						
Returns does not Granger Cause Volatility	14	4.451	0.000	14	4.474	0.000
Volatility does not Granger Cause Returns		2.120	0.009		2.117	0.009
PROPCON						
Returns does not Granger Cause Volatility	4	42.818	0.000	13	13.828	0.000
Volatility does not Granger Cause Returns		6.408	0.000		3.528	0.000
RESOURC						
Returns does not Granger Cause Volatility	6	19.036	0.000	15	8.160	0.000
Volatility does not Granger Cause Returns		4.731	0.000		3.252	0.000
SERVICE						
Returns does not Granger Cause Volatility	13	23.558	0.000	13	23.479	0.000
Volatility does not Granger Cause Returns		2.430	0.003		2.456	0.003
TECH						
Returns does not Granger Cause Volatility	5	27.354	0.000	9	14.374	0.000
Volatility does not Granger Cause Returns		1.875	0.096		2.548	0.007

Note: The Lags Denote the Lag Order of VAR(m) to be Used in the Granger Causality Tests

As can be seen in Table 3.19, it was found that the stock returns Granger causes the stock volatilities, and vice versa, at at least a 10% significance level for the GARCH (1,1) model, and at at least a 5% significance level for the modified GARCH (1,1) model. Next, the Granger causality tests between stock returns and conditional volatility estimated from the asymmetric GARCH models were applied for the agribusiness and food, consumer products, industrials, property and construction, and services industries and are reported in Table 3.20 as follows:

Table 3.20 Granger Causality Test Results between Stock Returns and Volatility - Asymmetric GARCH Models for AGRO, CONSUMP, INDUS, PROPCON, and SERVICE

Null hypothesis	TARCH			Modified TARCH			EGARCH(1,1)			Modified EGARCH(1,1)		
	lags	F statistics	p-value	lags	F statistics	p-value	lags	F statistics	p-value	lags	F statistics	p-value
AGRO												
Returns does not Granger Cause Volatility	3	31.673	0.000	3	234.555	0.000	1	739.833	0.000	1	715.890	0.000
Volatility does not Granger Cause Returns		0.166	0.919		3.387	0.017		1.370	0.242		2.116	0.146
CONSUMP												
Returns does not Granger Cause Volatility	11	104.147	0.000	2	151.823	0.000	7	254.298	0.000	3	418.011	0.000
Volatility does not Granger Cause Returns		1.479	0.132		0.667	0.513		2.455	0.017		2.283	0.077
INDUS												
Returns does not Granger Cause Volatility	14	24.642	0.000	14	26.739	0.000	2	258.918	0.000	16	30.945	0.000
Volatility does not Granger Cause Returns		2.172	0.007		2.184	0.007		1.876	0.154		1.613	0.058
PROPCON												
Returns does not Granger Cause Volatility	3	275.527	0.000	16	51.855	0.000	3	241.951	0.000	15	43.181	0.000
Volatility does not Granger Cause Returns		8.640	0.000		3.137	0.000		5.014	0.002		2.578	0.001
SERVICE												
Returns does not Granger Cause Volatility	13	110.479	0.000	13	110.886	0.000	13	125.664	0.000	13	127.767	0.000
Volatility does not Granger Cause Returns		2.242	0.007		2.303	0.005		1.820	0.035		1.975	0.019

Note: The Lags Denote the Lag Order of VAR(m) to be Used in the Granger Causality Tests

As seen in Table 3.20, a return-driven effect exists in all 5 mentioned industries at a 1% significance level in the 4 asymmetric GARCH models. However, a volatility-driven effect exists at a 5% significance level for AGRO's modified TARCH model, at at least a 10% significance level for CONSUMP's EGARCH(1,1) and modified EGARCH(1,1) models, and at at least a 10% significance level for INDUS's TARCH, modified TARCH, and modified EGARCH(1,1) models. There exist bi-directional causality between stock returns and volatilities at the 1% significance level for all 4 asymmetric GARCH models for PROPCON, and at least a 5% significance level for all 4 asymmetric GARCH models for SERVICE.

3.6 Conclusion and Implications

This paper investigated the relationship between stock index returns and conditional volatility at the aggregate and industry levels by using a two-variable VAR model. Moreover, the asymmetric property of volatility was also examined using the sign bias test and characterized by the asymmetric GARCH models and the subprime effect. It was found that the subprime effect was statistically significant in the stock volatility for the SET and eight group industry returns. The positive and negative shocks had different effects on the conditional variance of the agribusiness and food, consumer products, industrials, property and construction, and services industries. However, the effect of autoregressive conditional heteroscedascity was found in the SET index returns and all of the industries' returns such that the GARCH(1,1) model was appropriate in such a case. Finally, the return-driven (leverage effect) hypothesis and volatility-driven (volatility feedback) hypothesis were satisfied. There exist bi-directional causality between the stock returns and volatilities at the aggregate and industry levels.

The results of the study have some implications. First, asymmetric volatility is primarily attributed to the industry level rather than the aggregate level for Thailand's stock market. Second, stock returns are caused by volatility, and returns lead to stock volatility. Such instantaneous causal relations should be useful to both institutional and retail investors, whose investment achievement depends on the ability to forecast volatility movements and the related returns in stock market, and accordingly, to construct their equity portfolios based on these predictions. Third, the global financial crisis effect on Thailand's stock returns volatility at both the aggregate level and industry level should lead to the development of measures to prevent another future crisis through coordinated crisis management and resolution, and regional cooperation.

CHAPTER 4

RETURNS AND VOLATILITY TRADEOFF

4.1 Introduction

As Bawa and Lindenberg (1977) noted, portfolio management is a decision problem involving a choice among elements of a set of known probability distributions of returns. Based on the assumption of Fama and Macbet (1973) and Merton (1980), “investors are assumed to be risk averse and to behave as if they choose among portfolios on the basis of maximum expected utility, the positive tradeoff between return and risk is expected in the equilibrium.” In other words, Sharpe (1964) postulates that “they may obtain a higher expected rate of return on their holdings only by incurring additional risk.” Many research papers found the positive tradeoff between return and risk (Sharpe, 1964; Lintner, 1965; Fama and Macbeth, 1973; Merton, 1973; Merton, 1980; Engle et al., 1987; French et al., 1987; Chou, 1988; Baillie and DeGennaro, 1990; Ghysels, Santa-Clara and Valkanov, 2005 and Tsuji, 2014). However, Rotschild and Stiglitz (1970) argued that “the demand for a risky asset in an optimal portfolio which combines such an asset with a riskless asset need not be a decreasing function of the risk of the asset.” Thus, it is possible that an increase in the riskiness of the market will not require a corresponding increase in its equilibrium expected return. The negative tradeoff between return and risk has been empirically found (Poterba and Summers (1986); Campbell (1987); Glosten et al. (1993); Nelson (1991); Engle and Ng (1993); Bekaert and Wu (2000) and Brandt and Kang (2004)). Such a tradeoff between risk and return will be investigated at the aggregate and industry level in the present research paper.

4.2 Review of the Literatures

Baillie and DeGennaro (1990) investigated the econometric evidence for the relationship between stock returns and its conditional variance or standard deviation by estimating the stock returns and conditional variance using 4,542 daily observations and 683 monthly observations of the CRSP (Center for Research in Security Prices) value weighted index from January 1, 1970 through December 22, 1987. They used GARCH in the mean models to jointly estimate the mean and variance processes. For both daily and monthly data, the empirical results showed that the estimated GARCH in the mean parameter, representing the relation between the market excess return and conditional standard deviation, was statistically significant under the assumption of conditional normality and provided some evidence for the mean-variance relationship. However, it was statistically insignificant under the more appropriate assumption of a conditional student t density. Accordingly, the results suggested that “any relationship between mean returns and own variance or standard deviation is weak and investors should consider some other risk measure to be more important than the variance of portfolio returns.”

Chou (1988) studied the issue of volatility persistence and its relationship with market fluctuations. Moreover, the index of relative risk aversion was also estimated in this study. Using the weekly returns of the NYSE value-weighted index with dividends reinvested from the CRSP (Center for Research in Security Prices) from July 1962 through December 1985, the GARCH-in-mean estimation technique showed that the point estimate of the index of relative risk aversion was 4.5, and the existence of changing equity premiums in U.S. from 1962 to 1985 was confirmed. Such a value of the index of risk aversion is within the reasonable range of 2 to 6. Under the assumption of stationarity, the half-life of volatility shocks is about 1 year. The persistence of shocks to the stock return volatility is so high that the data cannot reject a non-stationary volatility process specification.

French et al. (1987) examined the intertemporal relation between risk and expected returns by measuring whether the expected market risk premium was related to risk as measured by the volatility of the stock market. The study used the daily values of the Standard and Poor’s (S&P) composite portfolio to estimate the monthly standard deviation of stock market returns from January 1928 through December 1984. The relation between expected risk premiums and volatility was estimated by regressing excess holding period returns on the predictable components of the stock market volatility, and contemporaneous unexpected changes in market volatility. Finally, GARCH-in-mean models for excess holding period returns to the S&P's composite portfolio were conducted. It was found out that "there was a positive relation between the expected risk premium on common stocks and the predictable level of volatility." In addition, there was also a strong negative relation between the unpredictable component of stock market volatility and excess holding period returns. When expected risk premiums are positively related to predictable volatility, a positive unexpected change in volatility (an upward revision in predicted volatility) increases future expected risk premiums and lowers current stock prices. Since the magnitude of the negative relation between contemporaneous returns and changes in volatility was too large to be attributed solely to the leverage effect, the paper implies this negative relation as evidence of a positive relation between expected risk premiums and *ex ante* volatility.

Glosten et al. (1993) empirically characterized the nature of the relation between the conditional mean and the conditional variance of the excess return on stocks. The research paper used monthly excess returns on the Center for Research in Security Prices (CRSP) value-weighted of the New York Stock Exchange (NYSE) during the period 1951:4 to 1989:12 in order to estimate the conditional mean and conditional variance of the excess return on stocks using the Modified GARCH-M model and the Modified EGARCH-M model. From the modified GARCH-M models that allow positive and negative unanticipated returns to have different impacts on the conditional variance, it was found that "1) the relation between conditional mean and conditional variance was negative and statistically significant; 2) the risk-free rate contained information about future volatility, within the Modified GARCH-M framework; 3) the October and January seasonals in volatility were statistically significant; 4) the conditional volatility of the monthly excess return is not highly persistent; and 5) the negative residuals were associated with an increase in variance, while positive residuals were associated with a slight decrease in variance." The paper's conclusions do not change when EGARCH-M is conducted with the modified model including the risk-free rate or seasonals or both.

Nelson (1991) applied the GARCH model for modeling the relationship between the conditional and asset risk premium of the CRSP Value-Weighted Market Index from 1962 to 1987. It was found that "the GARCH models had at least 3 major drawbacks in asset pricing applications. 1) Research has revealed a negative correlation between current returns and future return volatility. GARCH models rule this out by assumption. 2) GARCH models impose parameter restrictions that are often violated by estimated coefficients and that may unduly restrict the dynamics of the conditional variance process. 3) Interpreting whether shocks to conditional variance "persist" or not is difficult with the GARCH models because the usual norms measuring persistence often do not agree."

Poterba and Summers (1986) argued that "changes in risk are responsible for a significant part of the variation in share prices." The changing risk premium hypothesis suggests that market movements reflect in substantial part changing risk premia induced by movements in stock market volatility. The research paper evaluated the changing risk premium hypothesis and examined the influence of changing stock market volatility on the level of stock prices. Using the daily return data on the Standard and Poor's Composite Index for the period 1928 – 1984, the link between return volatility and equity risk premium was estimated using two-stage least squares, and the regression of the change in the implied forward volatility on the current three-month "spot" implied volatility changes was estimated. It was found that "shocks to stock market volatility did not persist for long periods since the estimates based on the actual and ex ante volatilities indicated that these volatility shocks had half-lives of less than six months, and in some cases as short as one month." Most of the estimates suggested that "the elasticity of the market price with respect to a volatility shock was much smaller, between -0.02 and -0.05." Such estimates imply that a doubling of volatility, which is a large shock by historical standards, would reduce the level of stock prices by at most 23 percent and probably by much less.

Tsuji (2014) investigated the relationship between risk and return in the Latin American equity markets from June 2001 to November 2013 by applying the GARCH-in-mean model and the EGARCH-in-mean model to the daily, weekly, monthly, and quarterly data. It was found that "in Brazilian and Colombian equity markets, positive relations between risk and return were relatively often observed. However, no positive risk-return tradeoff was observed in the stock markets in Chile."

4.3 Theoretical Framework

Engle et al. (1987), and French et al. (1987) emphasize that "the valuation of risk is the central feature of financial economics such that the expected market risk premium (sometimes called the stock excess return) is related to risk as measured by the volatility of the stock market." The excess return was the stock return less the riskless rate of interest. In addition, Sharpe (1964); Lintner (1965); Fama (1970); Fama and Macbeth (1973); Merton (1980); Engle et al. (1987); French et al. (1987); Baillie and DeGennaro (1990) and Tsay (2010) claim that "the standard deviation of stock returns is one of the most common measures of stock market risk." According to Sharpe (1964), "an individual is assumed to view the outcome of any investment in probabilistic terms and prefers a high expected future wealth to a lower value, ceteris paribus." Moreover, the risk aversion is assumed such that he chooses an investment offering a lower value of standard deviation to one with a greater value, given the level of expected value. The market presents the individual with two prices: the price of time, or the interest rate, and the price of risk, the additional expected return per unit of risk borne. Sharpe (1964) point out that "in equilibrium, capital asset prices have adjusted so that the investor, after following rational procedures, may obtain a higher expected rate of return on his or her holdings only by incurring additional risk." Thus, Sharpe (1964); Lintner (1965), Engle et al. (1987) and French et al. (1987) point out that "the equilibrium tradeoff between risk and return for the portfolios takes the expected excess return to be approximately proportional to its estimated volatility" as follows:

$$E_{t-1}\,(ER_t) \;=\; Y\widehat{\sigma_t} \tag{4.1}$$

where ER_t = the excess return at time t

Y = the price of risk

$\widehat{\sigma_t}$ = the expected volatility at time t

The specification allows for changes in the expected excess return as the risk level for the stock market changes. Merton (1980) states that "the price of risk is assumed to be a slowly-varying function of time relative to the time scale of changes in standard deviation such that such the price of risk can be treated as essentially constant over intervals of time length." French et al. (1987) and Chou et al. (1992) illustrate that "the index of relative risk aversion can be obtained from the variance specification instead of standard deviation specification in the mentioned equation."

As opposed to the positive tradeoff between risk and return mentioned above, Glosten et al. (1993) stated that "it may first appear that investors would require a relatively larger risk premium during times when investors are better able to bear particular types of risk. However, a larger risk premium may not be required since time periods that are relatively more risky could coincide with time periods when investors are better able to bear particular types of risk." In addition, Glosten et al. (1993) argued that "a larger risk premium may not be required due to the fact that investors may want to save relatively more periods when the future is more risky." Thus, Glosten et al. (1993) concludes that "if all the productive assets available for transferring income to the future carry risk and no risk-free investment opportunities are available, then the price of the risky asset may be bid up considerably, thereby reducing the risk premium." Poterba and Summers (1986), Campbell (1987), Nelson (1991), Engle and Ng (1993), Bekaert and Wu (2000), and Brandt and Kang (2004) also found such a negative relationship between risk and return. The intertemporal tradeoff between risk and return can be clarified with 2 hypotheses, a positive relationship hypothesis and a negative relationship hypothesis as follows.

4.3.1 The Positive Tradeoff Hypothesis

Fama and Macbeth (1973) emphasize that "investors look at assets in terms of their contributions to the expected value and standard deviation or risk of the stock returns." In addition, they postulate that "investors are assumed to be risk averse and to behave as if they choose among portfolios on the basis of maximum expected utility." Then, Sharpe (1964); Lintner (1965); Fama and Macbeth (1973); Merton (1973); Merton (1980); Engle et al. (1987); French et al. (1987); Chou (1988); Baillie and DeGennaro (1990); Ghysels et al. (2005) and Tsuji (2014) show that "in equilibrium, there will be a linear relationship between the expected excess return and standard deviation of the return such that on average there seems to be a positive tradeoff between return and risk."

4.3.2 The Negative Tradeoff Hypothesis

Black (1976) and Christie (1982) point out that "a decline in the stock market should increase volatility through the leverage effect such that a drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increase its volatility." In addition, they illustrate that "stock price movements are correlated with future volatility such that an increase in stock market volatility raises required stock returns, and thus, lowers stock prices (negative return)." Thus, Poterba and Summers (1986); Campbell (1987); Glosten et al. (1993); Nelson (1991); Engle and Ng (1993); Bekaert and Wu (2000) and Brandt and Kang (2004) conclude that "a negative tradeoff between return and risk is expected."

The positive or negative intertemporal linkage between risk and return as mentioned by the two hypotheses was investigated at the aggregate and industry level in this study. However, French et al. (1987) and Campbell (1987) suggested that "other variables that could affect expected risk premiums should be integrated into this analysis, such as short-term interest rate changes." Merton (1973) argued that "interest rate change is an important factor to shift in the investment opportunity set, and it is conventional to assume that there exists a financial asset whose return is negatively correlated with changes in interest rate." Stulz (1986) stated that "there exists a negative relation between stock returns and changes in interest rate." Campbell (1987) suggested that "there may be a payoff to simultaneous analysis of interest rate changes and stock returns." When the interest rate is higher, the expected stock excess return is lower. Thus, Campbell (1987) concluded that "a higher interest rate is associated with a lower conditioner mean of excess stock returns." In addition, Engle et al. (1987) and Enders (2004) claimed that "the expected volatility can be subjected to changes in policy regimes, economic crises, or any observable variables."

4.4 Data and Methodology

4.4.1 Data

The GARCH-M models mentioned above were applied to the 2,195 daily return series of SET, and returns of 8 industry group indices comprising Agribusiness and Food (AGRO), Consumer Products (CONSUMP), Financials (FINCIAL); Industrials (INDUS), Property and Construction (PROPCON), Resources

(RESOURC), Services (SERVICE), Technology (TECH) for the sample period from January, 2005 to December, 2013. The daily data including the 1-day repurchase rates were derived from various sources such as SETSMART (SET Market Analysis and Reporting Tools), and Thomson Financial DataStream. The next section presents the empirical results.

4.4.2 The Empirical Models

1) GARCH(1,1)-M Model

Merton (1980) pointed out that "the equilibrium risk-return tradeoff is the linear relationship between the excess return and its volatility or standard deviation, and estimators should be adjusted for heteroscedasticity." French et al. (1987); Chou (1988); Baillie and DeGennaro (1990); Glosten et al. (1993); Bali and Peng (2006); Zakaria and Abdalla (2012) and Tsuji (2014) illustrate that "such a phenomenon is usually modeled by GARCH in the mean." The mean and conditional variance of the excess returns were estimated as follows:

$$ER_t = \delta\sigma_t + \mu + \sum_{i=1}^{p} \phi_i ER_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} , \qquad (4.2)$$

$$\varepsilon_t \sim N(0, \sigma_t^2) \qquad (4.3)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (4.4)$$

where ER_t = excess stock return at time *t*

σ_t^2 = variance of the excess return at time *t*

ε_t = stochastic disturbance term

Usually, the model uses conditional normal distribution. However, the student t distribution was also applied since Bollerslev (1987) and Baillie and Bollerslev (1989) argued that "it can be more appropriate to use a student *t* density since much of the financial market data possess substantial kurtosis such that *t*-distributed errors are found to provide a good representation to the leptokurtosis and time dependent conditional heteroscedasticity."

2) Alternative GARCH(1,1)-M Model

Even though the stock riskiness represented by the standard deviation of its excess return is the dominant factor that affects excess stock returns, Merton (1973); Merton (1980) and Stulz (1986) emphasize that "interest rate changes might be another factor that can also affect excess returns such that the higher interest rate is associated with the lower conditioner mean of excess stock returns." Campbell (1987) points out that "there exists a negative tradeoff between excess stock returns and changes in interest rate." Hausman and Wongswan (2007) and Ehrmann and

Fratzscher (2009) show that "the stock return will exhibit a response to changes in the policy interest rate (i.e. the federal funds rate)." The 1-day repurchase rate announced by the Bank of Thailand is equivalent to such a policy interest rate. In addition, since the data collected for analyzing the Thailand's stock volatility in the chapter includes the sample period from January, 2005 to December, 2013, such a sample period subsumes the subprime crisis originated from the U.S. during the years 2007 to 2009. Thus, the dummy variable of the subprime crisis effect on the stock volatility was also included in the model. The alternative GARCH in the mean model was estimated as follows:

$$ER_t = \delta\sigma_t + \gamma drp_t + \mu + \sum_{i=1}^{p} \phi_i ER_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} \quad (4.5)$$

$$\varepsilon_t \sim N(0, \sigma_t^2) \quad (4.6)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \partial D_{SUB} \quad (4.7)$$

where ER_t = excess stock return at time *t*

σ_t^2 = variance of the excess return at time *t*

drp_t = changes in 1-day repurchase rate

D_{SUB} = dummy variable of the Subprime crisis effect

ε_t = stochastic disturbance term

The student t distribution was also applied for the residual term, as mentioned before.

4.5 Empirical Results

4.5.1 Descriptive Statistics for Excess Stock Returns

The annualized excess returns (referred to as "the excess returns") of the SET index, 8 industry group index returns, and the 1-day repurchase rate during the sample period are shown in Figure 4.1, 4.2, and 4.3, respectively:

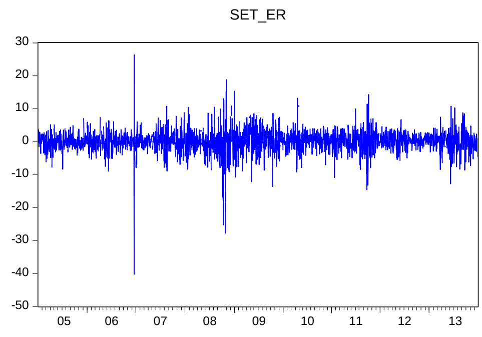

Figure 4.1 Excess Returns for the SET Index During the Period 2005 – 2013

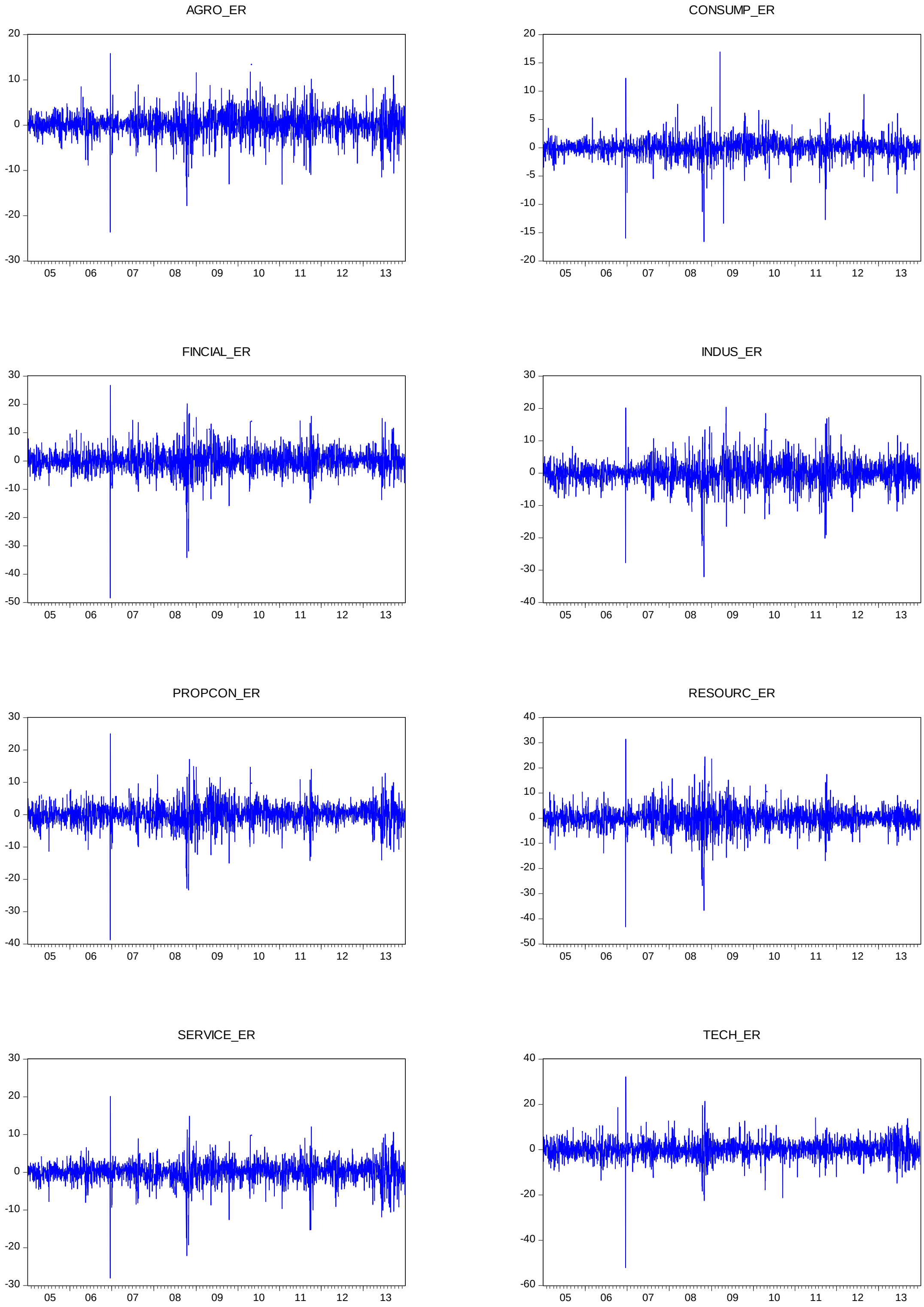

Figure 4.2 Excess Returns for the 8 Industry Group Indices During the Period 2005 - 2013

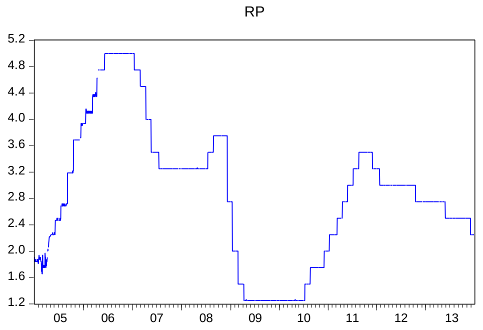

Figure 4.3 The One-Day Repurchase Rate (RP) During the Period 2005 – 2013

According to Figure 6.1 and 6.2, the means of the daily SET index excess return series (SET_ER), and all eight industry group excess returns, are close to zero. In addition, all of the excess return series seem to be stationary such that they tend to return to their average and fluctuate around mean values. The one-day repurchase rate from Figure 6.3 seems to be stationary if the first difference of such interest rate series is conducted. The descriptive statistics for the SET index returns, and all eight industry group returns, are given in Table 4.1, and 4.2, respectively.

Table 4.1 Descriptive Statistics of the SET Excess Returns

Statistics	SET excess returns
Mean	0.0457
Median	0.1548
Maximum	26.3937
Minimum	-40.2066
Standard Deviation	3.5005
Skewness	-1.0109
Kurtosis	17.2174

Table 4.2 Descriptive Statistics of the Industry Group Excess Returns

Statistics	AGRO	CONSUMP	FINCIAL	INDUS
Mean	0.1433	0.0159	0.0419	0.0077
Median	0.1844	0.0583	0.0340	0.0690
Maximum	15.8362	16.9436	26.7657	20.3890
Minimum	-23.6694	-16.6067	-48.4393	-32.0960
Standard Deviation	2.8371	1.7487	4.2251	4.0400
Skewness	-0.5763	-0.7042	-0.8696	-0.4690
Kurtosis	8.4451	19.7271	16.0984	8.7991
Statistics	**PROPCON**	**RESOURC**	**SERVICE**	**TECH**
Mean	0.0159	0.0327	0.1048	0.0366
Median	0.1284	0.0562	0.2795	0.0914
Maximum	25.0141	31.4507	20.1082	32.1907
Minimum	-38.7296	-43.1725	-28.0762	-52.1574
Standard Deviation	3.6614	4.5054	2.9079	4.1258
Skewness	-0.7933	-0.5107	-1.0837	-0.8415
Kurtosis	12.8144	12.2684	13.1441	18.4072

In Table 4.1 – 4.2, all of the excess return distributions are leptokurtic. Unit root tests were conducted for such excess returns and interest rate, as shown in Table 4.3.

Table 4.3 Unit Root Tests of the Excess Returns, and the Interest Rate (RP)

	ADF	PP
Panel A: Excess Returns		
SET	-46.073***	-46.079***
AGRO	-44.915***	-45.015***
CONSUMP	-47.076***	-47.075***
FINCIAL	-45.641***	-45.627***
INDUS	-43.141***	-43.437***
PROPCON	-43.794***	-43.955***
RESOURC	-46.628***	-46.635***
SERVICE	-29.702***	-43.428***
TECH	-48.059***	-48.153***
Panel B: Interest Rates		
RP (Levels)	-1.136	-1.127
RP (Changes)	-47.039***	-47.041***

Note: The table reports the Augmented Dickey-Fuller and the Phillips-Perron unit root tests without a time trend. Critical values at the 1%, 5%, and 10% significance level are -3.433, -2.863, and -2.567, respectively.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

4.5.2 Analysis of the Excess Returns Volatility

As mentioned in the last section, that all excess return series are stationary, the GARCH (1,1)-M models were estimated for all industry excess returns, as shown in Table 4.4 to 4.12 as follows:

Table 4.4 Estimation of GARCH in Mean Models for AGRO Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-1} + \phi_2 ER_{t-13} + \varepsilon_t, \quad (4.8)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.9)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-1} + \phi_2 ER_{t-13} + \varepsilon_t, \quad (4.10)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.11)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's *t*	Normal	Student's *t*
δ	0.097***	0.094***	0.097***	0.094***
	(0.028)	(0.022)	(0.028)	(0.022)
ϕ_1	0.069***	0.019	0.070***	0.019
	(0.026)	(0.022)	(0.026)	(0.022)
ϕ_2	0.102***	0.069***	0.100***	0.070***
	(0.018)	(0.019)	(0.017)	(0.019)
γ	--	--	-0.865	0.077
			(1.329)	(0.985)
α_0	0.513***	0.311***	0.549***	0.321***
	(0.044)	(0.076)	(0.050)	(0.079)
α_1	0.148***	0.138***	0.152***	0.139***
	(0.013)	(0.021)	(0.015)	(0.021)
β_1	0.797***	0.833***	0.784***	0.829***
	(0.013)	(0.021)	(0.015)	(0.022)
τ	--	--	0.669***	0.127
			(0.003)	(0.539)
Log Likelihood	-5202.32	-5089.54	-5198.66	-5089.43
AIC	4.77	4.67	4.77	4.67
Q(15)	11.14	17.73	10.94	17.48
$Q^2(15)$	4.33	3.78	3.97	3.69

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Table 4.4 implies that the AGRO price of risk coefficient (δ) is positive at the 1% significance level, and the subprime effect (∂) exists at the 1% significance level with the normal distribution of ε_t.

Table 4.5 Estimation of GARCH in Mean Models for CONSUMP Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-2} + \phi_2 ER_{t-6} + \phi_3 ER_{t-21} + \varepsilon_t, \quad (4.12)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.13)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-2} + \phi_2 ER_{t-6} + \phi_3 ER_{t-21} + \varepsilon_t, \quad (4.14)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.15)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's t	Normal	Student's t
δ	0.048**	0.035**	0.036	0.035**
	(0.022)	(0.016)	(0.022)	(0.016)
ϕ_1	0.053**	0.028	0.050**	0.028
	(0.026)	(0.021)	(0.024)	(0.021)
ϕ_2	-0.063***	-0.063***	-0.066***	-0.062***
	(0.023)	(0.019)	(0.025)	(0.019)
ϕ_3	-0.056***	-0.047***	-0.025	-0.047***
	(0.009)	(0.016)	(0.019)	(0.016)
γ	--	--	-0.508	-0.501
			(0.989)	(0.598)
α_0	0.650***	0.387***	0.107***	0.429***
	(0.044)	(0.077)	(0.010)	(0.084)
α_1	0.167***	0.207***	0.067***	0.208***
	(0.012)	(0.037)	(0.005)	(0.038)
β_1	0.629***	0.687***	0.893***	0.658***
	(0.022)	(0.040)	(0.006)	(0.045)
τ	--	--	0.963***	0.526*
			(0.129)	(0.273)
Log Likelihood	-4165.34	-3866.92	-4120.03	-3864.06
AIC	3.84	3.56	3.80	3.56
Q(15)	17.23	16.73	17.35	17.18
$Q^2(15)$	3.66	2.35	6.74	2.11

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

For the Consumer Products industry, Table 4.5 indicates that the price of the risk coefficient is positive at the 5% significance level for all GARCH-M models (except for the alternative GARCH (1,1)-M with the normal distribution of ε_t). The dummy variables of the subprime effect are significant at a 1% and 10% significance level for residual normal distribution and student *t* density, respectively.

Table 4.6 Estimation of GARCH in Mean Models for FINCIAL Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-1} + \varepsilon_t , \quad (4.16)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.17)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-1} + \varepsilon_t , \quad (4.18)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.19)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's *t*	Normal	Student's *t*
δ	0.052**	0.039*	0.050**	0.038*
	(0.025)	(0.022)	(0.025)	(0.022)
ϕ_1	0.081***	0.054**	0.080***	0.055**
	(0.024)	(0.022)	(0.025)	(0.023)
γ	--	--	-0.301	0.111
			(2.167)	(1.684)
α_0	0.794***	0.600***	1.081***	0.747***
	(0.133)	(0.154)	(0.242)	(0.200)
α_1	0.086***	0.109***	0.086***	0.111***
	(0.010)	(0.017)	(0.012)	(0.019)
β_1	0.870***	0.855***	0.845***	0.837***
	(0.015)	(0.020)	(0.025)	(0.026)
τ	--	--	2.565***	2.157**
			(0.880)	(1.036)
Log Likelihood	-6076.23	-5946.08	-6069.05	-5942.90
AIC	5.54	5.43	5.54	5.42
Q(15)	13.48	14.16	12.38	13.08
$Q^2(15)$	1.97	1.66	2.07	1.67

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

In Table 4.6, it is shown that the FINCIAL's price of risk coefficient is statistically positive at at least the 10% significance level for all GARCH (1,1)-M models. Moreover, the dummy variables of the subprime effect are significant at at least the 5% significance level.

Table 4.7 Estimation of GARCH in Mean Models for INDUS Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-1} + \varepsilon_t - \theta_1\varepsilon_{t-1}, \tag{4.20}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{4.21}$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-1} + \varepsilon_t - \theta_1\varepsilon_{t-1}, \tag{4.22}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \tag{4.23}$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's t	Normal	Student's t
δ	0.033	0.028	0.032	0.027
	(0.229)	(0.216)	(0.239)	(0.226)
ϕ_1	0.463**	0.448*	0.450**	0.418
	(0.192)	(0.254)	(0.197)	(0.267)
θ_1	0.377*	0.392	0.364*	0.361
	(0.202)	(0.262)	(0.207)	(0.276)
γ	--	--	-2.917	-2.624**
			(1.857)	(1.288)
α_0	0.774***	0.320***	0.811***	0.332***
	(0.079)	(0.090)	(0.086)	(0.094)
α_1	0.109***	0.118***	0.108***	0.118***
	(0.013)	(0.017)	(0.013)	(0.017)
β_1	0.842***	0.868***	0.836***	0.865***
	(0.015)	(0.017)	(0.017)	(0.017)
τ	--	--	1.207***	0.625
			(0.426)	(0.481)
Log Likelihood	-5947.41	-5858.81	-5941.75	-5856.03
AIC	5.43	5.35	5.42	5.35
Q(15)	20.53	23.34	19.35	21.99
$Q^2(15)$	4.80	2.70	4.25	2.64

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Being quite different from other industries, the Industrial's price of risk coefficients in Table 4.7 are all positive but insignificant. The interest rate changes coefficient is negative at the 5% significance level with the student *t* density of ε_t. The subprime dummy variable is statistically significant at the 1% significance level with the residual's normal distribution.

Table 4.8 Estimation of GARCH in Mean Models for PROPCON Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-1} + \phi_2 ER_{t-13} + \varepsilon_t , \quad (4.24)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (4.25)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-1} + \phi_2 ER_{t-13} + \varepsilon_t , \quad (4.26)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \tau D_{SUB} \quad (4.27)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's *t*	Normal	Student's *t*
δ	0.062***	0.058***	0.061***	0.057***
	(0.028)	(0.023)	(0.028)	(0.023)
ϕ_1	0.134***	0.072***	0.133***	0.075***
	(0.024)	(0.023)	(0.025)	(0.023)
ϕ_2	0.063***	0.032*	0.061***	0.032*
	(0.019)	(0.019)	(0.019)	(0.019)
γ	--	--	-2.771*	-2.339*
			(1.595)	(1.265)
α_0	0.841***	0.462***	1.111***	0.502***
	(0.087)	(0.106)	(0.131)	(0.119)
α_1	0.184***	0.134***	0.203***	0.134***
	(0.019)	(0.019)	(0.022)	(0.020)
β_1	0.767***	0.832***	0.717***	0.825***
	(0.016)	(0.020)	(0.022)	(0.023)
τ	--	--	3.430***	1.066
			(0.941)	(0.668)
Log Likelihood	-5687.05	-5572.14	-5677.38	-5569.31
AIC	5.22	5.11	5.21	5.11
Q(15)	17.78	24.53	16.52	22.77
$Q^2(15)$	1.65	1.28	1.61	1.28

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

As can be seen in Table 4.8, the price of risk coefficients of the Property and Construction industry are all positive at the 5% significance level. In addition, the coefficients of interest rate changes are all negative at v10% significance level. The dummy variable of the subprime effect is significant at the 1% significance level with the residual's normal distribution.

Table 4.9 Estimation of GARCH in Mean Models for RESOURC Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-1} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-3} - \theta_3\varepsilon_{t-9}, \quad (4.28)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.29)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-1} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-3} - \theta_3\varepsilon_{t-9}, \quad (4.30)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.31)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's t	Normal	Student's t
δ	0.050**	0.031	0.052**	0.032
	(0.023)	(0.019)	(0.023)	(0.019)
ϕ_1	0.593**	0.789***	0.594***	0.781***
	(0.244)	(0.167)	(0.227)	(0.170)
θ_1	0.569**	0.775***	0.568**	0.765***
	(0.248)	(0.168)	(0.231)	(0.172)
θ_2	0.049**	0.045**	0.052**	0.046**
	(0.021)	(0.019)	(0.021)	(0.019)
θ_3	-0.031*	-0.022	-0.033*	-0.022
	(0.018)	(0.014)	(0.018)	(0.014)
γ	--	--	-4.852***	-5.191***
			(1.822)	(1.379)
α_0	0.972***	0.465***	1.441***	0.547***
	(0.090)	(0.121)	(0.213)	(0.149)
α_1	0.111***	0.119***	0.125***	0.120***
	(0.014)	(0.018)	(0.019)	(0.019)
β_1	0.841***	0.861***	0.790***	0.850***
	(0.014)	(0.018)	(0.029)	(0.022)
τ	--	--	6.143***	2.447*
			(1.555)	(1.293)
Log Likelihood	-6168.67	-6044.33	-6151.16	-6037.78
AIC	5.63	5.52	5.62	5.51
Q(15)	15.54	17.46	13.83	16.11
$Q^2(15)$	1.53	1.23	1.30	1.23

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Table 4.9 indicates that the risk-return tradeoff of the Resources industry is positive at the 5% significance level with the residual's normal distribution. The coefficients of interest rate changes are all negative at v1% significance level, and the subprime effect exists at least the 10% significance level.

Table 4.10 Estimation of GARCH in Mean Models for SERVICE Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \theta_3\varepsilon_{t-3} - \theta_4\varepsilon_{t-13}, \quad (4.32)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.33)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \theta_3\varepsilon_{t-3} - \theta_4\varepsilon_{t-13}, \quad (4.34)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.35)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's *t*	Normal	Student's *t*
δ	0.098***	0.114***	0.097***	0.113***
	(0.029)	(0.024)	(0.029)	(0.024)
θ_1	-0.093***	-0.059***	-0.093***	-0.060***
	(0.025)	(0.022)	(0.025)	(0.022)
θ_2	-0.046*	-0.032	-0.045*	-0.030
	(0.024)	(0.022)	(0.025)	(0.022)
θ_3	-0.061**	-0.039*	-0.062**	-0.039*
	(0.025)	(0.023)	(0.025)	(0.023)
θ_4	-0.058***	-0.037*	-0.060***	-0.037*
	(0.021)	(0.019)	(0.021)	(0.019)
γ	--	--	-1.187	-1.443
			(1.236)	(0.907)
α_0	0.539***	0.318***	0.559***	0.338***
	(0.064)	(0.073)	(0.067)	(0.077)
α_1	0.130***	0.129***	0.128***	0.129***
	(0.013)	(0.019)	(0.014)	(0.019)
β_1	0.805***	0.832***	0.800***	0.826***
	(0.019)	(0.022)	(0.020)	(0.023)
τ	--	--	0.603*	0.585
			(0.324)	(0.377)
Log Likelihood	-5195.91	-5072.38	-5192.87	-5069.33
AIC	4.74	4.63	4.74	4.63
Q(15)	16.02	21.64	15.21	20.65
$Q^2(15)$	2.63	1.90	2.63	1.88

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

Table 4.10 shows that the services's risk-return tradeoff coefficients are all positive at the 1% significance level, and the subprime effect exists at the 10% significance level with residual's normal distribution.

Table 4.11 Estimation of GARCH in Mean Models for TECH Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \varepsilon_t, \quad (4.36)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.37)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \varepsilon_t, \quad (4.38)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.39)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's *t*	Normal	Student's *t*
δ	0.027	0.031	0.024	0.031
	(0.023)	(0.019)	(0.023)	(0.020)
γ	--	--	-2.264	-2.280
			(2.128)	(1.625)
α_0	4.513***	2.665***	5.536***	3.129***
	(0.629)	(0.571)	(0.978)	(0.706)
α_1	0.124***	0.145***	0.115***	0.143***
	(0.020)	(0.028)	(0.023)	(0.030)
β_1	0.603***	0.685***	0.530***	0.643***
	(0.053)	(0.053)	(0.080)	(0.064)
τ	--	--	5.196***	3.464*
			(1.945)	(1.960)
Log Likelihood	-6124.95	-5965.63	-6118.89	-5960.99
AIC	5.58	5.44	5.58	5.44
Q(15)	6.83	6.29	6.90	6.39
$Q^2(15)$	0.96	0.80	0.93	0.76

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

As can be seen in Table 4.11, the price of risk coefficients of the Technology industry are all positive but marginally significant at the 12% significance level with the student *t* density of ε_t. The coefficient of the interest rate changes is negative but insignificant. The coefficients of the subprime dummy variable are all significant at at least the 10% significance level.

Table 4.12 Estimation of GARCH in Mean Models for SET Excess Returns

GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \phi_1 ER_{t-1} + \varepsilon_t, \quad (4.40)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (4.41)$$

Alternative GARCH(1,1)-M:

$$ER_t = \delta\sigma_t + \gamma drp_t + \phi_1 ER_{t-1} + \varepsilon_t, \quad (4.42)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \tau D_{SUB} \quad (4.43)$$

Parameters and Diagnostic Statistics	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's *t*	Normal	Student's *t*
δ	0.078***	0.078***	0.079***	0.078***
	(0.024)	(0.021)	(0.024)	(0.021)
ϕ_1	0.073***	0.043*	0.074***	0.046**
	(0.026)	(0.023)	(0.026)	(0.023)
γ	--	--	-2.634*	-2.636**
			(1.575)	(1.065)
α_0	0.881***	0.317***	1.257***	0.360***
	(0.082)	(0.077)	(0.152)	(0.090)
α_1	0.124***	0.126***	0.145***	0.126***
	(0.015)	(0.018)	(0.021)	(0.019)
β_1	0.803***	0.849***	0.736***	0.839***
	(0.018)	(0.018)	(0.033)	(0.021)
τ	--	--	3.749***	1.275*
			(0.993)	(0.671)
Log Likelihood	-5620.78	-5449.00	-5606.20	-5444.63
AIC	5.13	4.97	5.12	4.97
Q(15)	18.54	18.83	17.34	17.70
$Q^2(15)$	0.72	0.48	0.67	0.48

Note: Normal, and Student's *t* denote residuals follow the normal distribution, and student *t* density, respectively. Q(15) and $Q^2(15)$ are the Box Pierce Q statistics applied to residuals and Standard errors are in parentheses.

***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

At the aggregate level, Table 4.12 indicates that the SET's risk-return tradeoff is positive at the 1% significance level, and the coefficient of interest rate changes is negative at at least the 10% significance level. Moreover, the subprime effect exists at at least the 10% significance level.

4.5.3 Estimation of the Index of Risk Aversion

According French et al. (1987) and Chou et al. (1992), the index of relative risk aversion for each stock index can be obtained from regressing the excess returns on the conditional variance estimated from the GARCH in the mean model. Following such a procedure, the indices of risk aversion for SET, and 8 industry group index, were estimated, as shown in Table 4.13 as follows:

Table 4.13 Estimation of Index of Risk Aversion for SET, and 8 Industry Group

	GARCH(1,1)-M		Alternative GARCH(1,1)-M	
	Normal	Student's t	Normal	Student's t
SET	0.018***	0.016***	0.018***	0.015**
	(0.007)	(0.006)	(0.007)	(0.006)
AGRO	0.027***	0.026***	0.026***	0.026***
	(0.010)	(0.008)	(0.010)	(0.008)
CONSUMP	0.024**	0.018**	0.015	0.018*
	(0.012)	(0.009)	(0.013)	(0.009)
FINCIAL	0.011*	0.008	0.010*	0.007
	(0.006)	(0.005)	(0.006)	(0.005)
INDUS	0.007	0.004	0.006	0.004
	(0.007)	(0.006)	(0.007)	(0.006)
PROPCON	0.014*	0.012**	0.012*	0.011*
	(0.007)	(0.006)	(0.007)	(0.006)
RESOURC	0.009*	0.005	0.009*	0.005
	(0.005)	(0.004)	(0.005)	(0.004)
SERVICE	0.028***	0.030***	0.027***	0.029***
	(0.010)	(0.008)	(0.010)	(0.008)
TECH	0.008	0.009*	0.007	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)

Note: Normal, and Student's t denote residuals follow the normal distribution, and student t density, respectively. Standard errors are in parentheses.
***, **, and * indicate significance at 1%, 5%, and 10% significance level, respectively.

As can be seen in Table 4.13, applying the SET's index of risk aversion as the benchmark, the group whose average index of risk aversion is higher than of the SET consists of the Services, Agribusiness and Food, and Consumer Products. The group whose average index of risk aversion is lower than of the SET consists of the Property and Construction, Financials, Technology, Resources, and Industrials.

4.6 Conclusion and Implications

This research paper examined the returns and volatility tradeoff at the aggregate and industry levels by using the GARCH-M models. In addition, the effects of the interest rate changes and the subprime crisis were also investigated. The study find that the risk-return tradeoff was positive in all industries, which is consistent with Sharpe (1964); Lintner(1965); Fama and Macbeth (1973); Merton (1973); Merton (1980), Engle et al. (1987); French et al. (1987); Chou (1988); Baillie and DeGennaro (1990); Ghysels et al. (2005) and Tsuji (2014). Such a positive tradeoff is significant at the aggregate level and 6 industries from all 8 industries, which are Agribusiness & Food, Consumer Products, Financials, Property & Construction, Resources, and Services. While it was found that the subprime effect on volatility was statistically significant for the SET index returns and all eight group industry returns, the interest rate effect on excess returns was statistically significant at the aggregate level and some industries: Industrials, Property & Construction, and Resources. Finally, the estimates of the relative risk aversion index indicated that the industries whose index ranking was from highest to lowest were Services, Agribusiness & Food, Consumer Products, Property & Construction, Financials, Technology, Resources, and Industrials.

The findings regarding the significant positive price of risk at the aggregate level and industry level have some implications. First, asset pricing theory referred by Sharpe (1964), French et al. (1987) and Wagner (2004) predicts that "changes in risk measured by volatility should affect excess returns." Assuming the investors to be risk averse, they may obtain higher stock returns only by incurring additional risk. Second, conditional standard deviation or variance appears to be important in determining excess stock returns at the aggregate and industry level for Thailand's stock market.

Third, the positive constant of the relative risk aversion index leading to the percentage invested in stocks or risky assets is unchanged as investors' wealth increases which is consistent with Elton et al. (2003). This implies that the investors exhibit decreasing absolute risk aversion. In other words, as wealth increases, investors hold more dollars in risky assets. Such an implication is consistent with Blume and Friend (1975) and Cohn et al. (1975).

CHAPTER 5

CONCLUSIONS AND POLICY IMPLICATIONS

5.1 Conclusions

Stock returns volatility is central to the theory and practice of asset pricing, asset allocation, and risk management. This study has examined three aspects of stock returns volatility. First, the asymmetric property of volatility was also examined using the sign bias test and characterized by the asymmetric GARCH models and the subprime effect. The subprime effect was statistically significant in the stock volatility for the SET and eight-group industry returns. The positive and negative innovations had different effects on the conditional variance of agribusiness and food, consumer products, industrials, property and construction, and services industries. Nevertheless, the effect of autoregressive conditional heteroscedascity was found in the SET index returns and all industries' returns and the GARCH (1,1) model was appropriate in such a case. Then, the causal relationship between conditional volatility and returns was investigated at the SET index and 8 industry group levels. The leverage effect hypothesis and volatility feedback hypothesis were satisfied as there existed bi-directional causality between stock returns and volatilities for the SET index and all eight industry group indices. While the volatility feedback effect hypothesis states that stock price movements are correlated with future volatility such that an increase in stock market volatility raises required stock returns and thus lowers stock prices (negative return), the leverage effect hypothesis argues that a drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility. In addition, the negative relationship between the implied volatility derived from the SET50 index option prices and the SET50 index returns also confirmed these results at the aggregate level.

Secondly, the tradeoff between stock excess returns and their risk as measured by the volatility was investigated both at the aggregate level and the industry level due to its importance for portfolio management. The positive tradeoff hypothesis referred by Sharpe (1964); Lintner (1965); Fama and Macbeth (1973); Merton (1973); Merton (1980); Engle et al. (1987); French et al. (1987); Chou (1988); Baillie and DeGennaro (1990); Ghysels et al. (2005) and Tsuji (2014) states that "assuming the risk averse preference of investors, the equilibrium capital asset prices can be adjusted so that the investor, after following rational procedures, may obtain a higher expected rate of return on his or her holdings only by incurring additional risk." On the other hand, the negative tradeoff hypothesis claims that a decline in the stock market should increase volatility through the leverage effect such that a drop in the value of the stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility. Moreover, the stock price movements are correlated with future volatility such that an increase in stock market volatility raises required stock returns, and thus lowers stock prices (negative return). Thus, claimed by Black (1976); Christie (1982); Poterba and Summers (1986); Campbell (1987); Glosten et al. (1993); Nelson (1991); Engle and Ng (1993), Bekaert and Wu (2000) and Brandt and Kang (2004), "a negative tradeoff between return and risk was expected." It was revealed empirically that the positive tradeoff was statistically satisfied at the aggregate level and for the 6 industries from all 8 industries, which were agribusiness and food, consumer products, financials, property & construction, resources, and services. In addition, the interest rate effect on excess returns was statistically significant at the aggregate level and for some industries—industrials, property and construction, and resources. Moreover, the estimation of the relative risk aversion index implies that the industries whose index ranking was from the highest to lowest were services, agribusiness and food, consumer products, property & construction, financials, technology, resources, and industrials.

Finally, the transmission of implied volatility transmission between the international stock markets, namely the U.S. (S&P 500 index), Japan (Nikkei 225 index), the European stock market (Down Jones Euro STOXX 50 stock index), and Thailand (SET50 index) were analyzed. It was found that the implied volatility of each stock market was moderately correlated with others, especially the correlation between the U.S. and the E.U. The international stock markets were integrated or financially globalized such that changes in uncertainty in the U.S. stock market were transmitted to other markets, including Thailand's stock returns and volatility. Such volatility transmission can be explained using the efficient market hypothesis and the international pricing of assets. The efficient markets hypothesis referred by Koutmos and Booth (1995) claims that "the news generated by the international stock market is relevant for the pricing of domestic securities as a result of the increased globalization of stock markets." International assets pricing mentioned by Lin et al. (1994) states that "any two economies are related through trade and investment such that the international relations of stock prices takes into account both the national and international factors so that international asset-pricing can incorporate correlations between stock returns in different countries."

5.2 Policy Implications

Based on the assumption of risk averse investors and constant relative risk aversion following Sharpe (1964); Lintner (1965); Engle et al. (1987) and French et al. (1987), the asset pricing theory predicts that "changes in risk measured by volatility should affect excess stock returns through a volatility-driven effect." The application of GARCH-M models implies that volatility measured according to conditional standard deviation or variance appears to be important in determining excess stock returns at the aggregate and industry level for Thailand's stock market, and investors may obtain higher stock returns only by incurring additional risk. Moreover, the positive constant relative risk aversion index also implies that as wealth increases, investors hold more dollars in risky assets, which is in line with Blume and Friend (1975) and Cohn et al. (1975).

In another aspect, the intertemporal relations between Thailand's stock returns and volatility estimated by the VAR model and Granger causality tests imply that there exist instantaneous causal relations between returns and risk such that stock returns are caused by volatility, and returns also lead to stock volatility. In addition, it can be inferred from the negative relationship between option-derived implied volatility and stock returns that an increase in stock volatility raises expected risk premiums and lowers stock prices through a volatility-driven effect, and negative stock returns increase financial leverage, which makes the stock riskier and increases its volatility through a return-driven effect. Moreover, the Sign Bias test and EGARCH models suggests that negative unanticipated returns result in an upward revision of stock volatility for the industry level rather than the aggregate level. The TARCH models also yielded such a consistent pattern. Such a relationship between stock returns and volatility should be useful to both institutional and retail investors, whose investment achievement depends on the ability to forecast volatility movements and the related returns in the stock market, and accordingly, to construct their equity portfolios based on these predictions.

Regarding the international perspective as stated by Mayhew (1995) and Nikkinen and Sahlström (2004), “the option-derived implied volatilities transmission represents the international stock market integration with respect to uncertainty.” The correlation coefficients between option-derived implied volatilities in the U.S. (S&P 500 index), Japan (Nikkei 225 index), the European stock market (Down Jones Euro STOXX 50 stock index), and Thailand (SET50 index) and the Granger causality tests indicate that expectations of uncertainty regarding one stock market are reflected in expectations of other markets. In addition, such results have important implications for international portfolio management since they show that changes in risk levels in major markets are moderately related. Additionally, when forming an optimal portfolio of international and domestic securities, the responses of option-derived implied volatilities in addition to the correlations between the international stock returns should be considered, which are of great concern among global investors in terms of managing international portfolios. Moreover, the leading role of the U.S. market inferred from the VAR model, impulse response analysis, and variance decomposition can be utilized when predicting not only expected volatilities but also stock returns in Thailand’s stock market. Finally, the global financial crisis effect on Thailand’s stock returns volatility at both the aggregate level and for all eight industries deduced from the modified GARCH models should lead to the development of measures to prevent another future crisis through coordinated crisis management and resolution, and regional cooperation. A sound and efficient financial system with well-developed liquid capital markets can contribute to efficient intermediation of financial flows. This also will help to reduce serious stock fluctuations. It is important for policy makers to pursue closer monitoring as well as develop early warning systems of the emergence of risks and vulnerabilities in the financial system in order to lessen loss from crises during the financial globalization era

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APPENDICES

APPENDIX A

ACF and PACF of SET index returns, and 8 industry group index returns

ACF and PACF of SET Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.016	0.016	0.5375	0.463
		2	0.051	0.051	6.3023	0.043
		3	0.001	-0.001	6.3035	0.098
		4	-0.009	-0.012	6.4985	0.165
		5	-0.014	-0.013	6.9137	0.227
		6	-0.065	-0.064	16.264	0.012
		7	0.017	0.020	16.900	0.018
		8	-0.035	-0.029	19.603	0.012
		9	0.044	0.043	23.903	0.004
		10	0.041	0.041	27.541	0.002
		11	0.010	0.003	27.743	0.004
		12	0.057	0.049	34.796	0.001
		13	0.044	0.044	39.042	0.000
		14	0.059	0.050	46.687	0.000
		15	-0.041	-0.040	50.475	0.000
		16	-0.020	-0.022	51.390	0.000
		17	-0.014	-0.005	51.801	0.000
		18	0.010	0.022	52.037	0.000
		19	0.014	0.016	52.487	0.000
		20	-0.045	-0.043	56.926	0.000
		21	0.002	-0.008	56.938	0.000
		22	-0.012	-0.013	57.254	0.000
		23	0.026	0.016	58.704	0.000
		24	0.011	0.009	58.977	0.000
		25	0.037	0.035	62.025	0.000
		26	0.036	0.026	64.966	0.000
		27	0.023	0.020	66.138	0.000
		28	0.027	0.021	67.769	0.000
		29	-0.023	-0.013	68.931	0.000
		30	-0.025	-0.024	70.373	0.000

ACF and PACF of AGRO Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.041	0.041	3.6147	0.057
		2	0.024	0.022	4.8637	0.088
		3	0.019	0.017	5.6738	0.129
		4	-0.006	-0.008	5.7416	0.219
		5	0.011	0.011	6.0296	0.303
		6	-0.019	-0.020	6.8222	0.338
		7	0.038	0.039	9.9454	0.192
		8	-0.005	-0.008	10.008	0.264
		9	0.031	0.031	12.157	0.205
		10	0.032	0.028	14.406	0.155
		11	0.009	0.007	14.584	0.202
		12	0.020	0.016	15.487	0.216
		13	0.091	0.091	33.834	0.001
		14	0.052	0.042	39.789	0.000
		15	-0.007	-0.014	39.896	0.000
		16	-0.027	-0.032	41.458	0.000
		17	-0.013	-0.013	41.838	0.001
		18	0.012	0.013	42.166	0.001
		19	0.005	0.006	42.223	0.002
		20	-0.015	-0.022	42.753	0.002
		21	0.013	0.010	43.103	0.003
		22	0.055	0.050	49.917	0.001
		23	0.037	0.028	53.018	0.000
		24	-0.010	-0.018	53.224	0.001
		25	0.034	0.030	55.732	0.000
		26	0.019	0.009	56.546	0.000
		27	0.009	0.001	56.742	0.001
		28	0.039	0.037	60.080	0.000
		29	0.008	0.011	60.229	0.001
		30	-0.024	-0.025	61.562	0.001

ACF and PACF of CONSUMP Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0893	0.765
		2	0.055	0.055	6.8124	0.033
		3	-0.018	-0.017	7.4872	0.058
		4	-0.018	-0.021	8.1912	0.085
		5	-0.015	-0.013	8.6688	0.123
		6	-0.066	-0.064	18.220	0.006
		7	0.034	0.034	20.717	0.004
		8	-0.015	-0.008	21.186	0.007
		9	0.049	0.043	26.479	0.002
		10	0.039	0.039	29.799	0.001
		11	0.038	0.033	33.005	0.001
		12	0.017	0.011	33.630	0.001
		13	0.017	0.021	34.294	0.001
		14	0.004	0.004	34.327	0.002
		15	0.000	0.007	34.327	0.003
		16	-0.018	-0.015	35.052	0.004
		17	0.003	0.007	35.077	0.006
		18	-0.011	-0.011	35.352	0.009
		19	0.023	0.021	36.476	0.009
		20	0.013	0.009	36.827	0.012
		21	-0.051	-0.058	42.669	0.003
		22	0.045	0.038	47.152	0.001
		23	0.016	0.022	47.716	0.002
		24	-0.004	-0.013	47.747	0.003
		25	0.020	0.023	48.658	0.003
		26	0.028	0.030	50.378	0.003
		27	0.002	-0.004	50.389	0.004
		28	-0.001	0.005	50.392	0.006
		29	0.009	0.007	50.565	0.008
		30	0.003	0.006	50.581	0.011

ACF and PACF of FINCIAL Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.025	0.025	1.3650	0.243
		2	-0.001	-0.002	1.3667	0.505
		3	0.007	0.007	1.4606	0.691
		4	-0.003	-0.004	1.4837	0.830
		5	-0.021	-0.021	2.4948	0.777
		6	-0.065	-0.064	11.792	0.067
		7	-0.004	-0.001	11.830	0.106
		8	-0.035	-0.035	14.590	0.068
		9	0.039	0.042	18.004	0.035
		10	0.037	0.034	20.950	0.021
		11	-0.007	-0.011	21.071	0.033
		12	0.040	0.036	24.597	0.017
		13	0.053	0.049	30.748	0.004
		14	0.040	0.036	34.301	0.002
		15	-0.042	-0.038	38.202	0.001
		16	-0.018	-0.014	38.932	0.001
		17	0.005	0.009	38.994	0.002
		18	0.034	0.043	41.579	0.001
		19	0.002	0.005	41.593	0.002
		20	-0.056	-0.052	48.657	0.000
		21	-0.010	-0.013	48.866	0.001
		22	-0.004	-0.010	48.907	0.001
		23	0.021	0.017	49.905	0.001
		24	0.006	0.009	49.989	0.001
		25	0.050	0.051	55.630	0.000
		26	0.037	0.025	58.643	0.000
		27	0.030	0.024	60.637	0.000
		28	0.022	0.018	61.724	0.000
		29	-0.013	-0.003	62.076	0.000
		30	-0.021	-0.019	63.099	0.000

ACF and PACF of INDUS Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.081	0.081	14.512	0.000
		2	0.064	0.058	23.657	0.000
		3	0.006	-0.003	23.743	0.000
		4	0.016	0.012	24.312	0.000
		5	-0.006	-0.009	24.396	0.000
		6	-0.047	-0.048	29.206	0.000
		7	0.067	0.076	39.206	0.000
		8	0.023	0.018	40.374	0.000
		9	0.025	0.014	41.797	0.000
		10	0.026	0.022	43.293	0.000
		11	0.038	0.030	46.548	0.000
		12	0.049	0.040	51.875	0.000
		13	0.041	0.038	55.633	0.000
		14	0.075	0.062	68.206	0.000
		15	0.024	0.008	69.483	0.000
		16	-0.014	-0.027	69.941	0.000
		17	-0.004	-0.003	69.975	0.000
		18	0.019	0.021	70.812	0.000
		19	0.022	0.017	71.895	0.000
		20	-0.012	-0.018	72.198	0.000
		21	0.007	-0.005	72.320	0.000
		22	0.026	0.017	73.873	0.000
		23	0.019	0.011	74.700	0.000
		24	-0.002	-0.010	74.709	0.000
		25	0.016	0.008	75.273	0.000
		26	0.020	0.007	76.161	0.000
		27	0.049	0.043	81.579	0.000
		28	0.032	0.022	83.825	0.000
		29	-0.015	-0.028	84.319	0.000
		30	-0.038	-0.042	87.547	0.000

ACF and PACF of PROPCON Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.067	0.067	9.7808	0.002
		2	0.041	0.037	13.555	0.001
		3	0.026	0.021	15.013	0.002
		4	0.014	0.010	15.468	0.004
		5	0.003	0.000	15.494	0.008
		6	-0.028	-0.030	17.205	0.009
		7	0.024	0.028	18.515	0.010
		8	-0.020	-0.021	19.360	0.013
		9	0.039	0.042	22.785	0.007
		10	0.037	0.033	25.810	0.004
		11	0.054	0.048	32.323	0.001
		12	0.052	0.041	38.312	0.000
		13	0.070	0.061	49.253	0.000
		14	0.059	0.044	56.992	0.000
		15	-0.032	-0.043	59.272	0.000
		16	-0.027	-0.031	60.827	0.000
		17	0.002	0.007	60.840	0.000
		18	0.013	0.015	61.210	0.000
		19	0.008	0.010	61.359	0.000
		20	-0.020	-0.025	62.281	0.000
		21	0.029	0.022	64.101	0.000
		22	-0.005	-0.015	64.152	0.000
		23	0.041	0.029	67.825	0.000
		24	0.016	0.003	68.403	0.000
		25	0.047	0.039	73.414	0.000
		26	0.021	0.009	74.395	0.000
		27	0.036	0.033	77.357	0.000
		28	0.052	0.046	83.323	0.000
		29	-0.041	-0.041	87.108	0.000
		30	-0.028	-0.032	88.813	0.000

ACF and PACF of RESOURC Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0331	0.856
		2	0.051	0.051	5.8524	0.054
		3	-0.029	-0.029	7.6804	0.053
		4	-0.028	-0.031	9.4339	0.051
		5	-0.017	-0.014	10.099	0.072
		6	-0.079	-0.077	23.767	0.001
		7	0.013	0.014	24.142	0.001
		8	-0.032	-0.026	26.448	0.001
		9	0.048	0.041	31.442	0.000
		10	0.033	0.033	33.892	0.000
		11	-0.032	-0.041	36.198	0.000
		12	0.050	0.043	41.613	0.000
		13	0.013	0.021	41.965	0.000
		14	0.059	0.052	49.695	0.000
		15	-0.029	-0.023	51.613	0.000
		16	-0.017	-0.017	52.216	0.000
		17	-0.012	-0.008	52.555	0.000
		18	-0.017	-0.006	53.161	0.000
		19	0.013	0.010	53.540	0.000
		20	-0.024	-0.013	54.805	0.000
		21	0.004	-0.004	54.849	0.000
		22	-0.031	-0.035	57.038	0.000
		23	0.015	0.009	57.505	0.000
		24	0.012	0.011	57.838	0.000
		25	0.030	0.034	59.794	0.000
		26	0.030	0.019	61.764	0.000
		27	0.002	0.000	61.774	0.000
		28	0.007	-0.000	61.878	0.000
		29	0.001	0.011	61.881	0.000
		30	-0.009	-0.002	62.043	0.001

ACF and PACF of SERVICE Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.079	0.079	13.705	0.000
		2	0.071	0.065	24.774	0.000
		3	0.044	0.034	29.079	0.000
		4	-0.019	-0.030	29.891	0.000
		5	-0.002	-0.004	29.899	0.000
		6	-0.035	-0.033	32.593	0.000
		7	0.017	0.025	33.220	0.000
		8	-0.031	-0.030	35.278	0.000
		9	0.058	0.063	42.728	0.000
		10	0.055	0.047	49.371	0.000
		11	0.034	0.022	51.897	0.000
		12	0.055	0.038	58.632	0.000
		13	0.084	0.075	74.174	0.000
		14	0.034	0.015	76.743	0.000
		15	-0.030	-0.041	78.670	0.000
		16	-0.027	-0.030	80.227	0.000
		17	-0.026	-0.012	81.670	0.000
		18	0.002	0.014	81.675	0.000
		19	0.009	0.011	81.856	0.000
		20	-0.027	-0.034	83.504	0.000
		21	-0.002	-0.006	83.514	0.000
		22	0.021	0.013	84.495	0.000
		23	0.042	0.030	88.464	0.000
		24	0.022	0.010	89.536	0.000
		25	0.013	0.003	89.932	0.000
		26	0.050	0.043	95.587	0.000
		27	0.029	0.026	97.507	0.000
		28	0.024	0.021	98.805	0.000
		29	-0.020	-0.019	99.675	0.000
		30	-0.032	-0.027	101.91	0.000

ACF and PACF of TECH Index Returns:

Sample: 1/04/2005 12/27/2013
Included observations: 2195

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.026	-0.026	1.5134	0.219
		2	0.001	0.000	1.5149	0.469
		3	-0.020	-0.020	2.4214	0.490
		4	-0.006	-0.007	2.5019	0.644
		5	-0.027	-0.027	4.1165	0.533
		6	-0.017	-0.019	4.7456	0.577
		7	0.015	0.014	5.2584	0.628
		8	-0.028	-0.028	6.9582	0.541
		9	-0.006	-0.009	7.0458	0.632
		10	0.001	-0.000	7.0466	0.721
		11	0.019	0.017	7.8731	0.725
		12	0.026	0.027	9.3383	0.674
		13	0.024	0.025	10.655	0.640
		14	0.021	0.021	11.600	0.638
		15	-0.035	-0.033	14.388	0.496
		16	-0.000	0.000	14.388	0.570
		17	-0.025	-0.022	15.758	0.541
		18	-0.035	-0.036	18.457	0.426
		19	0.030	0.030	20.498	0.365
		20	-0.019	-0.018	21.258	0.382
		21	-0.009	-0.012	21.439	0.432
		22	-0.002	-0.001	21.452	0.493
		23	0.018	0.012	22.187	0.509
		24	-0.000	-0.001	22.187	0.568
		25	0.028	0.025	23.877	0.526
		26	0.011	0.008	24.132	0.568
		27	0.009	0.012	24.325	0.612
		28	0.018	0.023	25.043	0.626
		29	-0.023	-0.018	26.251	0.612
		30	-0.007	-0.006	26.361	0.657

APPENDIX B

ESACF of the SET Index Returns, and 8 Industry Group Index Returns

ESACF of SET Index Returns:

```
> eacf(SET,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  o x o o o x o o x o o  x  x  x  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
1  x x o o o x o o o o o  o  o  x  x  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
2  o x o o o x o o x o o  o  o  x  x  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
3  x x o o o x o o x o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
4  x x o x o o o o x o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
5  x x x x x o o o x o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
6  x x x x x x o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
7  x o x x x x o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
8  x o x x o x o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
9  x x x x x x x x x o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
10 x x x x o x x x x x o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
11 x x x x x x x x x x x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x x x x x x x x x x x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
13 x x x x x x x x o x x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
14 x x x o x x x x o x x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
15 x x x o o x o x x x x  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
16 x x x x o x o x o x x  x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x x x x x x o x x  x  x  x  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x x o x x o x x x x  x  o  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x x x x x x x o o x  x  x  x  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x x x x x o o  x  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
21 x x x x x x o x x o o  x  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
22 x x x o x o x x x o x  x  o  x  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
23 x x x o x o o o x o x  x  o  x  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
24 x x x x x o o o x o x  x  x  o  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
25 x o x x x o o o o x x  x  x  o  o  x  o  x  o  o  x  o  x  o  x  o  o  o  o  o  o
26 x x o x x o x x o x x  x  x  x  o  x  o  o  x  o  x  o  o  o  x  x  o  o  o  o  o
27 x x o x x o x x o x x  o  o  x  x  x  o  o  o  o  x  o  x  x  o  o  o  o  o  o  o
28 x x x x x o x o x x x  o  o  o  o  o  x  o  o  o  x  o  x  x  o  x  o  o  o  o  o
29 x x x x x x x o x o x  o  o  o  o  o  x  o  o  o  x  x  o  o  o  x  o  x  x  o  o
30 x o x o x x o x x o o  x  x  o  o  o  o  x  o  x  x  x  o  x  o  o  o  o  x  o  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of AGRO Index Returns:

```
> eacf(AGRO,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  o o o o o o o o o o o  o  x  x  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o
1  x o o o o o o o o o o  o  x  x  o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o
2  x x o o o o o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
3  x x x o o o o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
4  x o o x o o o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
5  x x o x x o o o o o o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
6  x o o x x x o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
7  x x x x x x o o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
8  x x x x x x x x o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
9  x x x x x x x o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
10 x x x x x o x o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
11 x o x x o x x o x o x  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x x x x x x x x x o x  x  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
13 x x x o o x x x o o o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
14 x x x o o o x x x o o  x  x  o  o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o
15 x x x x o o o x x o o  x  x  x  o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o
16 x x x x o o o x o o o  x  x  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x x o o o x x x x  o  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x o x o o x o o x x  o  o  x  x  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x o o x o x o o x x  o  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x o x o o x o  x  o  x  o  x  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o
21 x x x x x x x o x o x  x  x  x  o  o  x  x  x  o  x  o  o  o  o  o  o  o  o  o  o
22 x x x x x x x x x o x  x  x  x  o  o  x  x  x  x  o  x  o  o  o  o  o  o  o  o  o
23 x x x x x x x x x x o  o  o  o  x  x  x  o  x  x  x  x  o  o  o  o  o  o  o  o  o
24 x x x x x x x x x x x  o  o  o  x  x  x  o  x  x  o  x  o  x  o  o  o  o  o  o  o
25 x x x x x x o x x x x  x  o  o  x  o  x  x  o  x  o  x  x  o  x  o  o  o  o  o  o
26 x o x x x x o x x x o  o  o  o  x  o  o  x  x  o  x  x  x  o  o  x  o  o  o  o  o
27 o x x x x o x x x x o  o  o  o  x  x  x  x  x  o  x  x  o  o  o  x  x  o  o  o  o
28 x x x x o x o x x o o  o  x  x  o  x  o  o  o  x  o  x  o  o  o  x  o  o  o  o  o
29 x x x x o x o x o x o  o  x  x  x  x  o  o  o  x  o  x  o  o  o  x  o  o  x  o  o
30 x x x x x o x o x x x  x  o  x  x  x  o  o  o  x  o  x  o  o  x  x  o  o  x  o  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of CONSUMP Index Returns:

```
> eacf(CONSUMP,ar.max=30,ma.max=30)
```

AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
0	o	x	o	o	o	x	o	o	x	o	o	o	o	o	o	o	o	o	o	o	x	x	o	o	o	o	o	o	o	o	o
1	x	x	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o
2	x	x	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o
3	x	x	x	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
4	x	x	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
5	x	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
6	x	x	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
7	x	x	x	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
8	x	x	x	x	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
9	x	o	x	x	x	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
10	x	x	x	x	x	x	o	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
11	x	x	x	o	x	x	x	o	o	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
12	x	x	x	o	x	o	o	o	o	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
13	x	x	x	x	x	o	o	o	o	x	o	o	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o
14	x	x	x	x	x	x	o	o	o	x	x	o	o	o	o	o	o	o	x	o	x	o	o	o	o	o	o	o	o	o	o
15	x	x	x	x	o	x	o	o	o	x	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
16	x	x	x	x	x	o	x	x	o	o	o	x	x	o	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
17	x	x	x	x	o	o	o	o	x	o	o	x	x	o	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o
18	x	o	x	x	o	o	o	o	o	o	o	o	x	o	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o
19	x	x	x	x	x	o	o	o	x	o	x	o	x	o	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o
20	x	x	x	x	o	o	o	o	x	o	x	x	x	o	x	x	x	o	x	x	o	o	o	o	o	o	o	o	o	o	o
21	x	x	x	x	o	o	o	o	x	x	x	o	x	x	x	x	x	o	x	x	x	o	o	o	o	o	o	o	o	o	o
22	x	x	x	o	x	o	o	x	x	x	x	o	x	x	x	x	o	x	x	x	x	x	o	o	o	o	o	o	o	o	o
23	x	x	x	o	x	x	o	o	x	x	x	x	o	x	x	o	o	x	x	x	x	x	x	o	o	o	o	o	o	o	o
24	x	x	x	x	x	o	o	o	o	x	x	x	o	x	x	o	o	x	x	x	x	o	x	o	o	o	o	o	o	o	o
25	x	x	x	x	x	o	x	o	o	x	x	x	x	x	x	o	o	x	x	x	x	o	o	o	x	o	o	o	o	o	o
26	x	x	x	x	x	o	x	o	o	x	x	x	x	x	o	x	x	x	x	x	x	o	o	x	o	o	o	o	o	o	o
27	x	x	x	x	x	x	x	x	x	x	o	o	x	x	o	x	x	x	x	x	o	o	o	x	o	x	x	o	o	o	o
28	x	x	o	x	x	x	x	x	x	x	x	o	x	o	x	o	o	x	o	o	o	o	x	o	o	o	o	o	o	o	o
29	x	x	x	x	x	x	x	x	o	x	x	x	x	x	x	o	o	x	o	x	x	x	x	x	o	x	o	o	o	o	o
30	x	x	x	x	x	o	x	x	o	x	x	x	x	o	x	o	o	o	o	x	x	x	x	x	x	o	o	o	o	o	o

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of FINCIAL Index Returns:

```
> eacf(FINCIAL,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  o o o o o x o o o o o  o  x  o  o  o  o  o  o  x  o  o  o  o  x  o  o  o  o  o  o
1  x o o o o x o o o o o  o  o  x  x  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
2  x x o o o x o o o o o  o  o  x  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
3  x x x o o o o x x o o  o  o  x  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
4  x x x o o o o o x o o  o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
5  x x x x x o o o x o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
6  o x x x x x o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
7  o x x x x o x o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
8  x x x x x x x x o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
9  x x x x x x x x x o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
10 x x x x o x x o x x o  o  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o  o  o  o
11 x x x x x x x o x o x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x x x x x o x x x x x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
13 x x x x x o o x o x x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
14 x x x x x o x x o x x  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
15 x x x x x o x o o x x  o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
16 x x x o x x x o o x o  x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x o o x x o x x x  o  x  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x x x o x x x x o x  x  o  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x x x x x x o x o x  x  o  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x x x o x x o  x  o  x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o
21 x x x o x o x x x o o  x  o  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
22 x x x o x o x x x o x  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
23 x x x o x o x x x o x  x  o  x  x  o  o  x  o  x  o  o  o  o  x  o  o  o  o  o  o
24 x x x x x x o o x o x  x  o  x  o  o  o  o  x  o  o  o  o  o  x  o  o  o  o  o  o
25 x x o x x x x o x x x  x  x  o  x  o  o  x  x  o  o  o  x  o  x  o  o  o  o  o  o
26 x x o x x x x o x x x  x  o  o  x  o  x  x  x  o  o  o  x  o  o  x  o  o  o  o  o
27 x x x o x x x x x x x  o  x  o  x  x  x  x  x  o  x  o  o  o  x  o  o  o  o  o  o
28 x x x o x o o x o x x  x  x  o  o  o  x  x  x  o  x  o  o  o  x  x  o  x  o  o  o
29 x x x x x x o o o x x  x  o  o  o  x  o  x  x  o  x  o  o  o  x  o  o  x  o  o  o
30 x x o x x o o o o x x  x  o  o  o  x  o  x  x  o  o  o  o  o  o  o  o  x  o  o  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of INDUS Index Returns:

```
> eacf(INDUS,ar.max=30,ma.max=30)
```

AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
0	x	x	o	o	o	x	x	o	o	o	o	x	o	x	o	o	o	o	o	o	o	o	o	o	o	o	x	o	o	o	o
1	x	x	o	o	o	o	x	o	o	o	o	o	o	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
2	x	x	o	o	o	o	x	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
3	x	x	o	o	o	o	x	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
4	x	x	o	x	o	o	x	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
5	x	x	x	o	x	x	x	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
6	x	x	x	x	x	x	x	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
7	x	x	x	x	x	o	x	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
8	x	x	o	o	x	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
9	x	x	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
10	x	o	o	o	o	o	o	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
11	x	o	x	o	o	o	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
12	x	x	x	o	o	o	x	x	o	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
13	x	x	o	o	o	x	x	x	x	o	o	x	o	o	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o
14	x	x	x	x	x	x	x	x	x	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
15	x	x	x	o	x	o	x	x	x	o	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
16	x	x	x	x	x	o	x	o	o	o	o	o	o	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
17	x	x	x	x	x	x	x	o	o	o	o	o	o	x	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
18	x	x	x	x	x	o	x	o	x	o	o	o	o	x	o	x	o	x	o	o	o	o	o	o	o	o	o	o	o	o	o
19	x	x	x	x	x	o	x	o	o	o	o	o	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
20	x	x	x	x	x	x	x	o	o	o	o	o	x	o	x	x	o	o	o	x	o	o	o	o	o	o	o	o	o	o	o
21	x	x	x	x	x	x	x	o	x	o	o	o	x	x	x	x	x	o	o	o	x	o	o	o	o	o	o	o	o	o	o
22	x	x	x	x	x	o	x	x	o	o	o	o	x	x	x	x	o	o	o	o	o	o	o	o	o	o	o	o	o	o	o
23	x	o	x	x	x	x	o	x	x	o	o	o	x	x	x	x	x	o	x	o	o	x	x	o	o	o	o	o	o	o	o
24	x	o	o	x	x	x	o	x	o	x	x	x	x	x	x	x	x	o	o	o	o	x	x	o	o	o	o	o	o	o	o
25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	o	x	x	x	o	x	o	x	o	x	x	o	o	o	o	o	o
26	x	x	x	x	x	o	x	x	x	x	x	x	o	x	o	x	x	x	o	o	o	x	o	o	x	x	o	o	o	o	o
27	x	x	o	x	x	x	x	x	o	x	x	x	o	x	x	o	o	x	o	o	x	x	o	o	x	o	o	o	o	o	o
28	x	x	o	o	x	o	x	x	o	x	o	x	x	x	x	x	o	x	o	o	x	x	o	o	x	o	o	o	o	o	o
29	x	x	x	o	x	x	x	o	x	o	o	x	x	o	x	x	x	x	o	o	o	o	x	o	o	o	o	o	x	o	o
30	x	x	x	x	x	x	x	o	x	o	o	x	o	o	x	x	x	x	o	o	o	o	x	o	o	o	o	o	x	o	o

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of PROPCON Index Returns:

```
> eacf(PROPCON,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  x o o o o o o o o o x  x  x  x  o  o  o  o  o  o  o  o  o  o  x  o  o  x  o  o  o
1  x o o o o o o o o o o  o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  x  x  o  o
2  x x o o o o o o o o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o
3  x x x o o o o o o o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  x  x  o  o
4  o x o o o o o o o o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  x  o  x  o
5  o x x o x o o o o o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o
6  x x x o x x o o o o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o
7  x x o x o x x o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o
8  x x x x o x x o o o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
9  x x x x x x x x x o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  x
10 x x o o x x x o x x o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  x
11 x x x o x x x x x x x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x x o o x x x x x x x  x  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o  o  o  o
13 x x x x x x x x x x x  x  x  o  o  o  o  o  o  o  o  o  o  o  x  o  o  x  o  o  o
14 x x x x o x x x x x x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
15 x x o x o o o x x x x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
16 x x o o x o o o o x x  o  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x x o x o o o x x  o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x x x o x o o o x o  o  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x x x x o o x o o o  o  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x o x x o o o  o  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
21 x x x x o o x x o o o  o  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
22 x x x o x o x x o x o  o  o  x  x  x  x  o  o  o  o  x  o  o  o  o  o  o  o  o  o
23 x x x o o o o o x o x  o  o  x  x  x  x  o  x  o  o  x  x  o  o  o  o  o  o  o  o
24 x x x x o o o o o o x  o  x  x  x  x  x  o  x  x  x  x  x  x  o  o  o  o  o  o  o
25 x x x x x x o o x x x  x  o  x  x  x  x  x  x  x  x  o  x  o  x  o  o  o  o  o  o
26 x x x o x x o x x x x  x  o  x  x  x  x  x  x  x  x  x  x  o  x  x  o  o  o  o  o
27 x x x x x x o o x x x  x  x  x  o  x  x  x  x  x  x  x  o  o  x  x  o  o  o  o  o
28 x x x x x x x o x x x  x  o  x  o  x  x  x  x  x  x  x  x  o  o  x  x  o  o  o  o
29 x x x x x x o o x x o  x  o  x  o  x  o  x  x  o  o  x  o  o  o  x  x  o  o  o  o
30 x x o o x x x x x x x  x  x  x  o  x  x  x  x  x  o  x  o  o  o  x  o  o  o  x  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of RESOURC Index Returns:

```
> eacf(RESOURC,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  o x o o o x o o x o o  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
1  x o o o o x o o x o o  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
2  x x o o o x o o o o o  o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
3  x x x o o x o x x o o  o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
4  x x x x o o o o x o o  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
5  x x x x x o o o o o o  x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
6  x x x x x x o o o o x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
7  x o x x x x x o o o x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
8  x o x x x x x x o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
9  x x x x x x x x x o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
10 x x x x x x x x x o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
11 x x x x x x x x x o x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x x x x x x x x x x x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
13 x x x x x x x x o x o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
14 x x x x x x x x x x x  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
15 x x o x x x x x x x o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
16 x x o x x x o x x o x  x  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x o x x o x x x x  x  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x x x x o x x x o x  x  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x x x x o o x x o x  x  x  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x x o x x x x  o  x  x  x  x  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
21 x x x x x o x x x x x  x  o  x  x  x  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
22 x x x x x x x o x o x  x  x  x  o  x  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
23 x x x x x x x x o x x  x  x  o  x  x  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o
24 x x x x x x x x x x x  x  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
25 x x x x x x x x x x x  x  o  x  x  x  x  x  x  o  o  o  o  x  o  o  o  o  o  o  o
26 o o x x o x x x x x x  x  o  x  x  x  o  x  x  o  o  o  o  x  o  o  o  o  o  o  o
27 x o x x o x x x o o x  x  x  o  x  o  o  x  x  o  o  o  o  x  o  o  o  o  o  o  o
28 o o x o x x x x o o x  x  o  x  x  o  o  x  x  o  o  o  o  x  o  o  x  x  o  o  o
29 x x x o x x x x x o x  o  o  x  o  x  x  o  o  x  x  o  o  o  o  x  x  o  o  o  o
30 x x x x x x x o x x x  o  o  x  o  x  x  o  o  x  x  x  o  o  o  o  x  x  o  o  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of SERVICE Index Returns:

```
> eacf(SERVICE,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  x x x o o o o o x x o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  x  o  o  o  o  o
1  x o x o o o o o x o o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
2  x x x o o o o o x o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
3  x x x o o o o o x o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
4  x x x x o o o o x o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
5  x x x x o o o o o o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
6  x x x o o o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
7  x x x x x x x o x o o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
8  x x x x x x x o o o o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
9  x x x x x x x o x o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
10 x x x x x o x o x o o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
11 x o x o x o o o x x o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x o x x x x o x x o o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
13 x x o x x x x o x x x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
14 x x o x x x x x o x o  x  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
15 x x x o x x x o o o o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
16 x x x o x x x x o o o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x x x x x x x o o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x x x x x x x x o x  x  o  o  o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x x x x x x x o x o  x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x x x x x o o  o  x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
21 x x x x x x o x x o o  o  x  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o
22 x x x x x x x o o o o  o  x  x  o  x  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o
23 x o x x x x x x o o o  o  x  o  x  o  o  x  o  x  x  o  o  o  o  o  o  o  o  o  o
24 x o x x o x x o x o x  o  x  o  x  x  o  x  o  x  o  o  o  o  o  o  o  o  o  o  o
25 x x x x x x x x x x x  x  x  o  o  o  o  o  o  x  o  o  o  x  o  o  o  o  o  o  o
26 x x x x x x x x o o x  x  o  x  o  o  x  o  o  o  o  o  o  o  x  o  o  o  o  o  o
27 x x x x x x x x o o x  x  o  x  o  o  o  o  o  o  o  o  o  o  x  o  x  o  o  o  o
28 x x x x o x o x o o o  x  o  o  o  o  x  x  o  o  o  o  o  o  o  o  x  o  o  o  o
29 x x x x o x x o x x o  x  o  o  x  o  x  o  o  o  o  o  o  o  o  o  x  o  o  o  o
30 x o x o x x o x x o x  x  o  o  o  o  x  o  o  o  o  o  o  o  o  o  x  x  o  o  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

ESACF of TECH Index Returns:

```
>  eacf(TECH,ar.max=30,ma.max=30)
AR/MA
   0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
0  o o o o o o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
1  o o o o o o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
2  o x o o o o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
3  x x o o o o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
4  x x o x o o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
5  x x x x x o o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
6  x x x x o x o o o o o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
7  x x x x o x x o o o o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o
8  x x x x x x x x o o o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o
9  o o x o o x o x x o o  o  o  o  o  o  o  o  x  o  o  o  o  o  o  o  o  o  o  o  o
10 o x x o o x o x x x o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
11 x x x x o o o x x x o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
12 x x o x o o x x x x o  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
13 x o x x x x x x x x o  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
14 x x x x x x x x x x o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
15 o x x x x x x x o x o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
16 o x x x x x x x x o x  x  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
17 x x x x x x x x x o x  x  o  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o  o  o
18 x x x x x x x x x x x  x  x  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o  o
19 x x x x x o x x x x x  x  x  o  o  x  x  x  x  o  o  o  o  o  o  o  o  o  o  o  o
20 x x x x x x x x o x x  o  o  o  x  o  x  o  x  x  o  o  o  o  o  o  o  o  o  o  o
21 x x x x x o x x x x x  o  o  x  x  o  x  o  o  x  o  o  o  o  o  o  o  o  o  o  o
22 x x x x x o x o o x o  o  x  x  x  o  x  o  o  x  x  o  o  o  o  o  o  o  o  o  o
23 o x o x x o x x o x x  x  o  x  x  o  x  x  o  x  o  o  o  o  o  o  o  o  o  o  o
24 o x o x x o x o o x o  x  o  x  x  x  x  x  x  x  x  o  x  x  o  o  o  o  o  o  o
25 x x x x o x x x o x o  o  x  x  o  x  x  x  x  o  x  x  o  x  x  o  o  o  o  o  o
26 x o x x x x x x x x o  o  x  x  o  x  x  x  x  x  o  x  o  x  x  o  o  o  o  o  o
27 x o x x x x o x x x o  o  x  o  x  x  x  x  x  o  o  o  x  x  x  x  o  o  o  o  o
28 x x x x x x o x o x o  o  x  o  o  x  x  x  x  x  x  o  x  o  x  o  o  o  o  o  o
29 x x x x x o x x o o o  o  x  x  o  x  x  x  o  x  x  o  x  o  x  x  o  x  o  o  o
30 x o o x x x x x o o x  o  x  x  o  x  x  x  o  o  o  o  x  o  x  x  o  x  o  o  o
```

Note: The function prints a coded ESACF table with significant values denoted by x and nonsignificant values by o.

BIOGRAPHY

NAME	Supachok Thakolsri
ACADEMIC BACKGROUND	Bachelor of Business Administration (Finance and Banking) Assumption University, 1995
	Master of Business Administration (Finance) National Institute of Development Administration, 2001
	Master of Economics Sukhothai Thammathirat Open University, 2009
PRESENT POSITION	State Enterprise Analyst, Professional Level State Enterprise Policy Office Ministry of Finance