THRESHOLD EFFECTS IN VOLATILITY SPILLOVERS: THE CASE OF EQUITY, BOND AND FOREIGN EXCHANGE MARKETS

by

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Dedicated to my parents, guru,

family and friends for their

love and support

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ABSTRACT

THRESHOLD EFFECTS IN VOLATILITY SPILLOVERS: THE CASE OF EQUITY, BOND AND FOREIGN EXCHANGE MARKETS

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Most research on volatility spillovers across countries and various asset class returns model volatility as conditional variance and assume a linear relationship in spillovers. The risk measured as conditional variance is modeled as a function of own past innovations and own past conditional variances and fails to include lagged conditional variances from other assets. In this dissertation, for a bivariate set up, I estimate the conditional variance of the second country either as a GARCH (1, 1) or DCC (1, 1) type process. Using the estimated conditional variances, the non-linear or threshold parameter is computed by maximizing the log likelihood function and is included in the second stage estimation of spillovers in the newly specified extended conditional variance equation for the first country which allows for conditional variances from other assets to affect it. While it appears that spillovers and threshold effects should be positive I provide evidence of positive direct spillovers and negative indirect threshold effects across markets within three different asset classes.

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CHAPTER 1

INTRODUCTION

The vital and pressing concept of volatility has been an integral part of the field of finance ever since the field of finance developed as a unique paradigm and carved its niche from economics. In finance, “volatility” is defined as a measure for variation of price of a financial instrument over time. Andersen, Bollerslev, Christoffersen and Diebold (2005) define volatility as:

> *“…..The fluctuation observed in some phenomena over time. Within economics, it is used slightly more formally to describe, without a specific implied metric, the variability of the random component of a time series. More precisely or narrowly, in financial economics, volatility is often defined as the (instantaneous) standard deviation (or sigma) of the random Weiner-driven component in a continuous-time diffusion model……”*

Volatility can also be defined as risk or the chance of failure or loss of funds invested. This volatility in the financial market has an enormous impact on business transactions of different kinds. Owing to its enormous impact on business transactions, the concept of volatility has captured the attention of both academics as well as practitioners. Collective aggregation of various businesses and their activities constitute the market and uncertainties inherent in the market are a result of engaging in some activity for which one cannot be certain of the outcome. Campbell, Lo and MacKinlay (1997) state the importance of this volatility as:

> *“…what distinguishes financial economics is the central role that uncertainty or volatility plays in both financial theory and its empirical implementation….”*

The term “spillover”, captures the idea that some of the advantages or disadvantages of a particular activity accrue to the agents (markets) other than the party that undertakes the activity. Studies involving spillovers of volatility from one market to another have garnered significant mention with greater integration of markets across the globe. With globalization and reduction in regulations, markets are getting more and more integrated and volatility from one market seems to be spilling over to the other markets. Harvey and Bekaert (1994) use an innovative methodology to measure the degree of integration of markets and how these integrations progress over time. Understanding market integration and the relationship between volatility spillovers is paramount for risk management or hedging, optimal portfolio allocation strategies and analysis of market integration and inter-dependence. The financial concept of volatility spillover is not an easy one to define and hence both academics as well as practitioners have had great difficulty in understanding the dynamics of these volatility spillovers.

Empirical research has revolved to a significant part around stock, bond and foreign exchange market integration as measured by the interconnection and interdependence of these asset classes in different countries. These interconnections and interdependence has allowed for the so called volatility spillovers as defined above. The important questions that I ask are as follows:

> *Are there volatility spillovers from one market to another within a particular asset class like equity, bonds and foreign exchange? Are these direct volatility spillovers positive or negative? Are there some types of non-linearities in volatility spillover or threshold effects from one financial market to another within a particular asset class? Are these indirect threshold effects positive or negative?*

A definitive answer based on already existing literature on non-linearities in volatility spillovers is not transparent as most previous studies have assumed that the volatility spillover relationship is linear in nature and the idea of allowing for threshold effects in volatility spillovers is fairly new. The models employed in the existing literature revolve mostly around spillovers in the innovations; separating these innovations into positive and negative shocks and measuring their impact; using own lagged conditional variance and not looking at how the conditional variance term of other assets affect the dynamics of returns of an asset. This lays emphasis for the need to explicitly perform further analysis on threshold effects in volatility spillovers that clearly show the linkages and dynamics underlying this relationship. This dissertation is primarily focused on modeling volatility spillovers as conditional variance and allowing for threshold effects in volatility spillover adding significantly to the understanding in this area.

In analyzing how the conditional variance of asset returns can be modeled, Bauwens, Laurent and Rombouts (2006) raise certain interesting questions regarding this crucial concept of volatility in financial theory:

> *"Is the volatility of a market leading the volatility of other markets? Is the volatility of an asset transmitted to another asset directly (through its conditional variance) or indirectly (through its conditional covariances)? Does a shock on a market increase the volatility on another market, and by how much? Is the impact the same for negative and positive shocks of the same amplitude? A related issue is whether the correlations between asset returns change over time. Are they higher during periods of higher volatility (sometimes associated with financial crises)? Are they increasing in the long run, perhaps because of the globalization of financial markets?"*

They list the various types of models that could be used in modeling volatility spillovers and state the most obvious application of multivariate GARCH (generalized auto-regressive conditional heteroskedasticity) models in the study of the relations between the volatilities and co-volatilities of several markets.

In this dissertation I try to model volatility spillovers as the conditional variance of returns for a particular asset in a particular market to the same asset in a different market i.e., volatility spillovers within three different asset classes (equity, bond and foreign exchange) from the US market to South East Asian countries like China, India, Singapore, Japan, Thailand etc. or European markets like UK, Germany, Spain, Greece, Italy etc. I use a two-step estimation approach for measuring the spillover and threshold effects. A bivariate analysis is employed so that this study becomes computationally feasible. First I compute the conditional variance of the second asset. Then I employ a sequential grid search that maximizes the log likelihood function, to compute the threshold parameter for the second asset. In the second stage of the estimation I assume that the conditional variances and threshold in the first stage are observed and estimate the conditional variance of the first asset using an extended conditional variance specification. The data that is used in this analysis comes from DataStream International. Returns for the different assets in various markets are computed using daily data.

It is widely observed that conditional variances of an asset's return in the financial market move closely over time. Previous literature has shown extensively that there exist spillovers in volatility when volatility is measured as the conditional variance. Though it is clearly demonstrated that there exists a positive relationship in terms of volatility spillovers as the markets are integrated; there is also evidence of negative volatility spillovers and the behavior or dynamics for significantly greater levels of volatility is not analyzed in any previous research. My expectation is that though volatility spillovers have a positive relationship, the market that is a collective behavior of all investors should exhibit change in behavior for greater increases in risk. The change in behavior of volatility spillover dynamics will be reflective of how investors in various markets and in different assets behave. The very fact that there have been several crisis in the past, like the savings and loan crisis, or the east Asian financial crisis, or more recently the sub-prime mortgage crisis, and the events that have followed suit, is evidence enough for change in behavior of investors and hence the overall marketplace.

The remainder of this thesis is organized as follows. I have introduced the topic of volatility spillover, and the existing void in literature trying to understand the dynamics of the relationship of volatility spillover. I have also highlighted the relevance, importance and implications of understanding these volatility spillover dynamics in detail. A review of relevant research work and various methods used in these studies is presented in chapter two. Chapter three explains the empirical models and methods used in this dissertation and the hypothesized results for this analysis. Chapter four discusses the different data sources used for data gathering and outlines the generation of specific data that is employed in this analysis. Chapter five explores the empirical results of this analysis and the possible implications it might have in the field of finance. Finally, chapter six details the overall conclusions and possible extensions to this analysis, as part of future work.

CHAPTER 2

LITERATURE REVIEW

Ceteris paribus, it is conventional and widely accepted that volatilities in the financial markets move closely over time. Recognizing this feature, a detailed review of the research that has been conducted in this area is important. The purpose of this chapter of the dissertation is to review existing literature in the area of volatility spillovers across and within assets, define the models used in volatility spillover measurement mathematically, analyze the existence of volatility spillovers in different asset classes, discuss research findings showing the existence of both positive and negative spillovers and put in perspective the importance and contribution of this study.

This chapter is broadly organized into three sections 2.1 Univariate GARCH, 2.2 Multivariate GARCH, and 2.3 Summary of Section and multiple subsections. This chapter is not meant to be an exhaustive list of all the methodologies used in volatility spillover studies and is aimed at reviewing some of the important methods and literature that will aid in transitioning to the methodology section of this dissertation. Within every methodology discussed, I cite existing literature on equity, bond and foreign exchange market volatility spillovers. I also look at some of the cross asset spillovers literature, e.g., between stock and bond or stock and foreign exchange, etc. as I propose this as part of my future work.

2.1. Univariate GARCH

First, let me start by defining a GARCH model. In order to define a univariate GARCH model, consider the mean and variance of a return series. The return series is given by

$$y_t = \mu_t + \varepsilon_t \tag{2.1}$$

The return series has two components, a conditional mean return and an innovation. The innovation can be expressed as a standardized white noise process, scaled by time varying conditional volatility

$$\varepsilon_t = \sqrt{h_t} z_t \tag{2.2}$$

where, z_t ~ iid (0, 1), is the stochastic and serially uncorrelated part of the innovation. Hence, the conditional mean and variance for the process can be represented as

$$E(y_t \mid F_{t-1}) = \mu_t \tag{2.3}$$

$$Variance(y_t \mid F_{t-1}) = E(\varepsilon_t^2 \mid F_{t-1}) = h_t^2 \tag{2.4}$$

where, F_{t-1} denotes the information or filtration available at time 't-1'.

Most of the studies using a GARCH framework use a GARCH (1, 1) type model. The conditional variance for the GARCH (1, 1) model is defined as the recursive relationship

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \text{ where} \tag{2.5}$$

$$\varepsilon_t = \sqrt{h_t} z_t \tag{2.6}$$

and the parameters or coefficients are restricted by non-negativity constraint in order to make sure the conditional variance remains positive. Nelson and Cao (1992) state the necessary and sufficient condition for the univariate GARCH model, that is $\alpha + \beta < 1$, to ensure weak stationarity. The weights in the equation have to be positive, requiring $\alpha > 0$, $\beta > 0$ and $\omega > 0$.

The necessary and sufficient conditions for positivity of the conditional variance in higher-order GARCH models are more complicated than the sufficient conditions for the GARCH (1, 1) framework and have been discussed in detail in Nelson and Cao (1992). It is important to note that the basic GARCH model framework for the conditional variance works well for analyzing financial data under the normality assumption. In some cases, the normality assumption may not be appropriate and there are studies [Lee and Long (2009), Nakatani and

Terasvirta (2009), Otranto (2010), etc.] that talk about this aspect as well as the nonlinear behavior in conditional variance. So, in some cases there are aspects of the model which can be improved by extending the conditional variance framework so that it can better capture the characteristics and dynamics of a particular time series.

Engle et al. (1990, 1992, 1994), Hamao et al. (1990), Cheung and Ng (1996), Pyun et al. (2000) and Alaganar and Bhar (2002), all have used GARCH (1, 1) type models in their studies on volatility.[1] The interesting point to note in these studies is that they show evidence of positive volatility spillovers. Though Pyun et al. (2000) show evidence of positive spillovers in the lagged conditional variance coefficient; they include a dummy variable in the conditional variance specification which has a negative coefficient. This is evidence of change in behavior or relationship. The dummy variable which takes on a value of one if the day follows a weekend or holiday and zero otherwise has a negative coefficient in every sample period they have examined. The reason why this is interesting is because they show evidence, for the existence of negative spillovers in volatility on days following the weekend and holidays. The limitation in their model though, is that the days are fixed or static and do not capture the entire dynamic effects of volatility spillovers.

Baillie and Bollerslev (1990) use a seasonal GARCH model and four foreign exchange rate series, recorded on an hourly basis. They do not find any evidence for the presence of volatility spillovers between different currencies or foreign exchange markets through time. Their results seem very contrary to what one would expect in terms of spillovers. The robust LM test they use avoids the misspecification problem but offers no evidence of spillovers as well. They state that this contradictory finding is not surprising and the reason they attribute for the

[1] Engle et al. (1990) uses a univariate GARCH model for the variance equation and a combination of maximum likelihood (ML) and Berndt, Hall, Hall, and Hausman (BHHH -1974) for their estimation. Hamao et al. (1990) uses a variation of the univariate GARCH model and a dummy variable for the variance equation and does a two stage estimation using ML and BHHH. Engle et al. (1992) uses a univariate GARCH model for the variance equation and quasi-maximum likelihood (QML) technique for estimation. Cheung and Ng (1996) use a univariate GARCH model for the variance equation and a two stage estimation using ML and cross correlation. Pyun et al. (2000) uses a univariate GARCH model for the variance equation and two stage maximum likelihood estimation.

lack of evidence is the hourly sampling frequency they use in their study. Huang and Yang (2002) in their paper on exchange rate volatility transmission, analyze the volatility spillover of different exchange rates in a particular market as well as particular exchange rate volatility across different markets. Using a causality-in-variance method developed by Cheung and Ng (1996) and a univariate GARCH model, they find evidence of positive volatility spillovers in exchange rate within and across markets.

In a fairly recent paper on volatility spillover transmission mechanism, Gray and Treepongkaruna (2009) apply the speculative trading model of Fleming et al. (1998) (a generalization of the Tauchen and Pitts (1983) trading model) and a univariate GARCH model to test if any volatility spillover exists. The trading model they have used has two primary information links. First is the information spillover from one currency to another and the second is common information available between currencies. They employ a Generalized Method of Moments (GMM) estimation technique and use tick by tick data of different foreign exchange markets and examine twenty one bivariate systems. In their test of hypotheses (Null hypothesis that correlation between two series tested is zero), they reject the null hypothesis, meaning the model helps in identifying volatility spillovers.

Volatility spillovers in the bond markets have not been researched as extensively as the equity markets or the foreign exchange markets. One of the possible reasons for this is that the bond markets have historically not been as integrated globally as the equity or the foreign exchange markets. Before looking at some volatility spillover studies that delve into this, it is important to define the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model used in studies related to Bond market spillovers. The EGARCH model can be depicted as below.

$$\log h_t = \omega + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_i \log h_{t-j} \quad \text{where} \tag{2.7}$$

$$\varepsilon_t = h_t^{1/2} z_t \text{ and} \tag{2.8}$$

$$g(z_{t-i}) = \theta z_{t-i} + \xi(|z_{t-i}| - E|z_{t-i}|) \tag{2.9}$$

Skintzi and Refenes (2006) use the EGARCH model to measure volatility spillovers from the US and the aggregate Euro bond market to twelve individual European bond markets. They find significant evidence for the existence of volatility spillovers from the aggregate Euro and the US Bond markets to eleven out of the twelve individual European markets examined. Their results also suggest that the aggregate Euro bond volatilities influence the individual Euro country volatilities more than the US bond volatilities. The evidence that the European bond markets are more integrated makes spillover studies focusing on European countries, more interesting. I would like to briefly introduce the reader that this was one of the factors I took into consideration while choosing the countries for this study.

Adding support to Skintzi and Refenes (2006), Christiansen (2007) studied volatility spillovers from the US and the aggregate Euro bond markets to individual European bond markets. His findings are very similar; volatility spillovers from aggregate Euro bond market to individual European bond markets seem to be stronger than the US bond market, which re-establishes the finding that regional spillovers may have a greater significance.

Ng (2000) tries to find the volatility spillover relationship from Japan, which she treats as a regional developed market and the US, a global developed market, to the Pacific Basin (PB) equity markets. She employs a GARCH model and finds evidence that both regional and global factors affect volatility in the PB markets. Though the regional and global factors play a vital role, the magnitude of these spillovers is small and positive. In four out of six PB countries, the volatility spillover from the US and Japan accounts for less than 10% of the local variation in returns. She uses capital market reforms and closed-end country fund launch dates as her information variable. She states, one of the main reasons for this spillover of lesser magnitude is that the information variables used in her empirical model may not be able to explain the volatility in the global and regional markets. She suggests that using other information variables that could better measure, how investment barriers are changing over time would increase the magnitude of the spillover and leaves it as part of future work.

McMillan and Speight (2010) in their paper argue against the modeling of volatility spillovers under the univariate or multivariate GARCH framework for high frequency intra-day data. They state that the volatility spillovers measured in such ways would be inefficient, because of the market microstructure noise. Alternately, they use realized volatility, initially proposed by Andersen and Bollerslev (1998) for their study. Based on Engle et al. (1990), who propose that volatility may possess dual aspects, both country-specific autocorrelation (which they call as the 'heat-wave' hypothesis) and also correlation from one market to another (which they call as the 'meteor shower' hypothesis). McMillan and Speight use realized volatility of different frequencies (10-min, 1-hour, half day and daily) to construct a spillover index that measures the extent of spillovers. Overall their results show evidence for the existence of positive volatility spillovers in foreign exchange markets. Since I will not be using across asset class spillovers in any of the applications in this study, a brief review of literature in this area is deemed sufficient. Melvin and Melvin (2003) find that volatility spillovers in foreign exchange from yesterday affect today's volatility positively within the same region greater than that from a different region. Using a similar measure of realized volatility, their study employs high frequency data and provides evidence that regional effects in spillovers have greater significance and magnitude compared to inter-regional spillovers.

Thimann et al. (2009) in their study identify Emerging Market Economic (EME) shocks and find out the extent to which these shocks affect the global equity markets. They find that spillovers from fourteen of the EME's affect global markets by 0.3%. They also find heterogeneity in the responses to shocks (large versus small; positive versus negative; political versus economic). It is important to note that, the detection of large degree of heterogeneity in the response of global equity markets enhances their study. Steeley (2006) studies volatility transmission between the stock and bond markets. He uses a GARCH framework and finds evidence of volatility spillovers between the stock and bond markets. An important contribution of his study is that, to capture volatility transmission effects, he shows, it is possible to augment the conditional variance equation of the GARCH model with terms representing volatility shocks from another market. His extended conditional variance specification of a particular return series, say stock returns is explained by past innovations and past conditional variance of that series, past innovations of a second return series (bonds) and dummy variables for specific days of the week for both the series innovations. The limitation of his model is that, he does not allow the past conditional variances of the second series to affect the conditional variance of the first series and restricts his model to only innovations of the second series.

This extension of the conditional variance specification recognizes and shows evidence for the possibility of asymmetries in the conditional variance specification. Another limitation of this study is that he considers only one country, the UK (within country across asset classes). Though he finds evidence of volatility spillover across asset classes, his study could easily be expanded to include multiple countries, aiding in examining the volatility transmission process, across markets and across asset classes. In examining the UK stock and bond markets he finds that the correlation between short-term and long term bond yield shocks was relatively stable during the sample period but the correlation between each of these markets and the equity markets reversed sign indicating the increased hedging potential.

Kanas (2000) tests volatility spillovers between stock returns and exchange rate changes for six countries (US, UK, Canada, Japan, France and Germany) using a bivariate EGARCH model. He follows the bivariate EGARCH specification of Nelson (1991) which is defined as below.

$$\log h_{S,t} = \omega_S + \sum_{j=1}^{p} \beta_{S,i} \log h_{S,t-j} + \sum_{i=1}^{q} \alpha_{S,i} g(z_{S,t-i}) + \sum_{i=1}^{q} \eta_{E,i} g(z_{S,t-i}) \tag{2.10}$$

$$\log h_{E,t} = \omega_S + \sum_{j=1}^{p} \beta_{E,i} \log h_{E,t-j} + \sum_{i=1}^{q} \alpha_{E,i} g(z_{E,t-i}) + \sum_{i=1}^{q} \eta_{S,i} g(z_{E,t-i}) \tag{2.11}$$

where, the subscripts “E” and “S” represent the foreign exchange and stock asset classes respectively. He finds evidence of symmetric spillovers across asset classes for all the countries examined except Germany. While the volatility spillovers from stock returns to exchange rates are significant, the reverse i.e., the spillover from exchange rates to stock returns is insignificant for all countries. It is not misplaced to make the inference from his findings that certain asset classes might have its volatility spillover to another asset in a unidirectional sense.

The Glosten-Jagannathan-Runkle-GARCH (GJR-GARCH) model can be defined as below.

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta\varepsilon_{t-1}^2 I_{t-1} + \delta h_{t-1} \text{ where} \tag{2.12}$$

$$I_{t-1} = 0 \text{ if } \varepsilon_{t-1} > 0 \text{ and} \tag{2.13}$$

$$I_{t-1} = 1 \text{ if } \varepsilon_{t-1} < 0 \tag{2.14}$$

Chang et al. (2009) study the volatility transmission mechanism between the exchange rate and stock market in Vietnam. They find asymmetric effects in spillovers using a bivariate GJR-GARCH model which is defined below.

$$h_{S,t} = \omega_{S,0} + \delta_S h_{S,t-1} + \alpha_S \varepsilon_{S,t-1}^2 + \beta_S \varepsilon_{S,t-1}^2 I_{S,t-1} + \eta_S \varepsilon_{E,t-1}^2 I_{S,t-1} \tag{2.15}$$

$$h_{E,t} = \omega_{E,0} + \delta_E h_{E,t-1} + \alpha_E \varepsilon_{E,t-1}^2 + \beta_E \varepsilon_{E,t-1}^2 I_{E,t-1} + \eta_E \varepsilon_{S,t-1}^2 I_{E,t-1} \tag{2.16}$$

where, the subscripts “S” stands for stock and “E” stands for exchange rate. Their study has the similar limitation as Steeley (2006); they consider only one country (Vietnam).

Harris and Pisedtasalasai (2006) look at the volatility spillovers from large cap equity index to small cap equity index within the UK using a multivariate AR-GJR-GARCH model. The GJR-GARCH they use, models asymmetry in the ARCH process. They find evidence of positive spillovers from large cap to small cap stocks, consistent with the theory that information gets incorporated into prices and hence the returns for bigger firms before being incorporated into smaller firm prices. The spillovers vice versa from small cap to large cap are much less in magnitude and not as significant. An interesting point to note in their research is that, they include time dummies in the conditional variance specification and one of the time dummies has a negative coefficient which indicates the presence of negative spillovers as well.

Major focus in terms of volatility spillovers in the equity markets has been on the South East Asian countries. One of the possible reasons for that is the resounding emergence of these economies after the Asian financial crisis of 1998. Wu (2005) uses a bivariate EGARCH (similar to equation 2.10 and 2.11) specification found in Nelson (1991) and an EGARCH-X model, which is an extension of Lee (1994) GARCH-X model, in his study. The EGARCH-X model can be used to detect the asymmetry in the volatility transmission between markets. He uses the models to examine the volatility spillover relationship between two different asset classes (stocks and foreign exchange) for seven countries (Indonesia, Japan, South Korea, Philippines, Singapore, Thailand, Taiwan), during and after the Asian financial crisis. He finds evidence of a bi-directional positive volatility spillover relationship between these two asset classes. In his examination of the relationship, during and after the East Asian financial crisis, he finds important evidence that the spillover relationship becomes stronger for the period after the crisis compared to before the crisis. His findings lend the motivation to research further into volatility spillovers and how the dynamics change due to large increases in volatility.

Mishra et al. (2007) focus on the volatility spillovers between the equity and foreign exchange markets in India. They find a strong, positive and bi-directional relationship for spillovers between these two asset classes which acts as evidence for their integration. Though in this research I do not delve into cross asset spillovers, I would like to highlight the significance of integration that exists across asset classes and leave that investigation as part of future work. Porfiris et al. (2007) study the effect of derivative trading on the volatility of the underlying asset. They find evidence of negative spillovers which they highlight as attestation to reinforce diversification benefits across assets. Using an EGARCH model described earlier, they show considerable reduction in conditional volatility of the FTSE/ASE20 index when options and futures trading is introduced into the market place. The only limitation in their study is that they show evidence only from the Greek stock market, which might have other explanations in terms of the timing of Greece joining the Economic Monetary Union of Europe or European Monetary Union. Nevertheless, their findings can be interpreted with caution as support for the diversification benefit argument.

In a more recent study, Bhar and Nikolva (2009) use index return volatility to find negative conditional volatility spillovers from India and China to the Asia-Pacific region and the World respectively. They use a bivariate EGARCH model defined similar to equations 2.10 and 2.11 in this section, with time varying correlations relating equity index returns from the Brazil, Russia, India and China (BRIC) countries and both the regional equity index and the world index returns. They attribute the reason for these negative spillovers from India to the Asia-Pacific region to the low impact of the Asian financial crisis on India. The negative spillovers from China to the Asia-Pacific region, they suggest is due to the lack of evidence of regional integration of China with the other markets and the possibility of market segmentation in China leading to the negative spillovers.

Audrino and Trojani (2006) in their research emphasize the need for allowing, asymmetries in the volatility spillovers specification. In their paper, they use a tree structured AR-GARCH methodology to estimate thresholds in the global stock market volatility spillovers. The model they use is defined as below.

$$f_\theta(\varepsilon, x, x^{US}, \sigma^2) = f_\theta^p(\varepsilon, x, x^{US}, \sigma^2) = \sum_{j=1}^{k}(\alpha_{0,j} + \alpha_{1,j}\varepsilon^2 + \beta_j\sigma^2)I_{[x, x^{US}, \sigma^2 \in R_j]} \qquad (2.17)$$

This model defines a single threshold in the conditional volatilities of the returns. The threshold also depends on domestic and foreign index returns. Therefore, the lagged US market information can affect the conditional means and variances in the model. The lagged US and domestic returns impact the threshold only through a weighted sum, which strongly constrains the model dynamics. They first significantly point out the fact that their estimated threshold in volatility spillover may involve multiple thresholds rather than a single one and that the local variance estimated in their model may involve different dependencies across regimes. They lay the groundwork and suggest extensions to their model to include multiple regime switches. The limitation in the model they use is the confinement to a single threshold.

These models can easily be extended to higher order GARCH models as well. Though there might be computational difficulties, the main reason for moving to multivariate models rather than using univariate GARCH models is because it is widely accepted that volatilities across markets and asset classes often move together over time. Also, modeling the temporal dependence of second order moments among returns is challenging and important. Hence using multivariate models in volatility studies should lead to more efficient and relevant empirical results. There are various multivariate GARCH models that have been used in volatility spillover studies. I will discuss some of these models below.

2.2. Multivariate GARCH

A substantial portion of the literature analyzes volatility spillovers using univariate GARCH models. Some of the more recent literature uses multivariate GARCH models. The multivariate GARCH models are classified into three major categories. First is the direct generalization of the univariate GARCH model e.g. VEC and BEKK (Baba, Engle, Kraft and Kroner) models. Second is the linear combination of univariate GARCH models e.g. Factor GARCH or F-GARCH. Third is the nonlinear combination of univariate GARCH models e.g. constant conditional correlation model (CCC) and dynamic conditional correlation model (DCC). Engle and Kroner (1995) introduced a new theoretical formulation and estimation of the multivariate GARCH model. Ever since, this methodology has gained notability in the volatility spillover literature. Along the lines of multivariate GARCH models, a restricted version of the Bollerslev, Engle and Wooldridge (1988) VEC model is the Baba-Engle-Kraft-Kroner (BEKK) model. The number of parameters in the BEKK model is considerably less in comparison to the regular VEC model and that makes it easier to estimate. The BEKK is a direct generalization of the univariate GARCH models. The other variations of the BEKK model are the diagonal-BEKK and the scalar-BEKK. The inherent computational issues in allowing for dynamic changes in correlations and parameter estimations have led many studies on volatility spillovers to use the constant conditional correlation (CCC) GARCH introduced by Bollerslev (1990). The limitation imposed on having constant conditional correlation where the conditional correlations are not time varying has led researchers to use the dynamic conditional correlation (DCC) GARCH framework introduced by Engle (2002). The DCC model used in volatility spillover studies is a non-linear combination of univariate GARCH models.

First, let me introduce some terminology before looking at various multivariate GARCH models. For an 'N' asset return series which has dynamic time varying means, variances and covariances

$$y_t = (y_{1t}, y_{2t}, y_{3t}, y_{4t}, \ldots\ldots y_{Nt})', \tag{2.18}$$

The return can be partitioned as $y_t = \mu_t + \varepsilon_t$ (2.19)

where, each of the terms in 2.19 are vectors. The innovation in this partition, ε_t, can be represented as

$$\varepsilon_t = H_t^{1/2} z_t \tag{2.20}$$

where, $H_t^{1/2}$ can be defined as any positive definite symmetric N×N matrix such that H_t is the conditional variance-covariance matrix of y_t. z_t, is the stochastic part and is serially uncorrelated disturbance which is iid ($E(z_t) = 0$ and $Var(z_t) = E(\varepsilon_t \varepsilon_t^{'}) = I_N$). The mean of the return process can be defined as

$$\mu_t = E(y_t \mid F_{t-1}) = E_{t-1}(y_t) \tag{2.21}$$

where, F_{t-1} is the information available at time 't – 1', at least having $\{y_{1t-1}, y_{2t-1}, \ldots\ldots y_{Nt-1}\}$ information. The conditional variance is expressed as

$$H_t = H_t^{1/2} (H_t^{1/2})' = E(\varepsilon_t \varepsilon_t^{'} \mid \Omega_t). \tag{2.22}$$

There are many challenges that one has to address in this multivariate representation. The first important challenge is to restrain the positive definiteness of the conditional variance. The second challenge is to avoid too many parameters but at the same time maintain enough flexibility in the dynamics of the conditional variance, so as to allow for direct spillover type effects from past conditional variance terms. The reason, effort is made to avoid many parameters is that it leads to computational difficulties in the convergence of the optimization routines and the estimation of the parameters.

2.2.1. VEC Model

The VEC model is a direct generalization of the univariate GARCH model. In this model h_{ijt} is a linear function of the lagged squared errors, cross product of errors and lagged values of all the elements of H_t. The vech can be defined as an operator that stacks the lower triangle of an N×N matrix as an N(N+1)/2 × 1 vector. Using this, the VEC (1, 1) model can be defined as

$$h_t = c + A\eta_{t-1} + Gh_{t-1} \text{ where} \tag{2.23}$$

$$h_t = \text{vech } H_t \text{ and } \eta_t = \text{vech } (\varepsilon_t \varepsilon_t^{'}) \tag{2.24}$$

and c is an N*×1 vector of parameters [with N* = N (N+1)/2] and A and G are N*×N* matrices of parameters.

The vech operator stacks the lower triangle of an N×N symmetric matrix as an N(N+1)/2 × 1 vector and this can be depicted as below.

$$\text{vech } H_t = (h_{11t}, h_{21t}, h_{22t}, h_{31t}, ...h_{NNt})' \tag{2.25}$$

vec is the operator that stacks a matrix as a column vector

$$\text{vec } H_t = (h_{11t}, h_{21t}, ...h_{N1t,} h_{12t}, h_{22t}, ...h_{NNt})' \tag{2.26}$$

For example, the elements for a bivariate VEC (1, 1) model can be expressed as below:

$$\left.\begin{aligned} h_{11t} &= c_1 + a_{11}\varepsilon_{1,t-1}^2 + a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{13}\varepsilon_{2,t-1}^2 + g_{11}h_{11,t-1} + g_{12}h_{21,t-1} + g_{13}h_{22,t-1} \\ h_{21t} &= c_2 + a_{21}\varepsilon_{1,t-1}^2 + a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{23}\varepsilon_{2,t-1}^2 + g_{21}h_{11,t-1} + g_{22}h_{21,t-1} + g_{23}h_{22,t-1} \\ h_{22t} &= c_3 + a_{31}\varepsilon_{1,t-1}^2 + a_{32}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{33}\varepsilon_{2,t-1}^2 + g_{31}h_{11,t-1} + g_{32}h_{21,t-1} + g_{33}h_{22,t-1} \end{aligned}\right\} \quad (2.27)$$

The conditional variance spillover from the second series to the first can be measured by the coefficients on the lagged conditional variance term (e.g. g_{13}) from the second series. In examining the elements of the bivariate VEC-GARCH model, there is evident concern regarding the number of parameters it involves and the difficulties it might pose in terms of computation of the parameter estimates.

A larger number of parameters, results in a lower probability for the estimation of those values converging and the indefinite time and computational capacity it would require. To reduce the number of parameters in the VEC model, Bollerslev et al. (1988) suggest the use of a diagonal VEC (DVEC) model. The matrices A and G in the DVEC model are diagonal. Each variance in the DVEC model depends only on its own past squared errors and own lagged variances. The covariance in the DVEC model depends only on its own past cross product of errors. Using matrices A and G that are diagonal, mitigates the problem due to numerous parameters, which is called “Curse of Dimensionality”. The DVEC model is quite restrictive and it might not lend as much flexibility to study volatility spillovers. This might be the reason for the lack of literature that uses the VEC model to study volatility spillovers. Yang and Allen (2004) use the DVEC model to test the hedging effectiveness in the Australian futures market. They find that the hedge ratios generated from the DVEC model perform better than the constant hedge ratios in terms of minimizing risks and when return effects are included the results are inconclusive. Though their study does not involve volatility spillover measurements, nevertheless it is evidence for the use of the DVEC model in an empirical analysis. Balli (2009) also finds evidence of positive spillovers in the bond markets. The interesting thing to note, in addition to the evidence of spillovers is that he models market integration by considering both the global and local factors. After controlling for the market specific risk factors (liquidity, default, maturity, etc.) and employing a VEC type MVGARCH model, he finds that the European bond markets are not fully integrated, in spite of having the European Monetary Union. Findings by Balli are contradictory to the studies that claim European bond market integration. The amount of literature on bond market spillovers is comparatively less and most of the research, centers on European bond market spillovers.

2.2.2. BEKK Model

The BEKK model is also a direct generalization of the univariate GARCH model. The BEKK (1, 1, K) model can be defined as below:

$$H_t = C^{*\prime}C^* + \sum_{k=1}^{K} A_k^{*\prime}\varepsilon_{t-1}\varepsilon_{t-1}^{\prime}A_k^* + \sum_{k=1}^{K} G_k^{*\prime}H_{t-1}G_k^* \tag{2.28}$$

where, C^*, A_k^* and G_k^* are N×N matrices of parameters which are upper triangular. You can also write $C^{*\prime}C^* > 0$ to ensure positivity of the parameters. A_k^* and G_k^* in the BEKK model are square matrices without restrictions. The advantage of the BEKK model is that, it ensures the positive definiteness of H_t. The disadvantages are dimensionality (as the number of parameters and lags grow) and the effect of dimensionality on the dynamic relations over time.

The bivariate BEKK (1, 1, 1) has the same linear structure as the VEC model seen earlier but the constraints on the parameters are slightly different. The conditional variance for a bivariate BEKK (1, 1, 1) model can be expressed as below:

$$\left.\begin{aligned}
&h_{11t} = \omega_{11} + a_{11}^{*2}\varepsilon_{1,t-1}^2 + 2a_{11}^*a_{21}^*\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^{*2}\varepsilon_{2,t-1}^2 + g_{11}^{*2}h_{11,t-1} \\
&+ 2g_{11}^*g_{21}^*h_{21,t-1} + g_{21}^{*2}h_{22,t-1} \\
&h_{21t} = \omega_{21} + a_{11}^*a_{12}^*\varepsilon_{1,t-1}^2 + (a_{11}^*a_{22}^* + a_{12}^*a_{21}^*)\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^*a_{21}^*\varepsilon_{2,t-1}^2 \\
&+ g_{11}^*g_{12}^*h_{11,t-1} + (g_{11}^*g_{22}^* + g_{21}^{*2})h_{21,t-1} + g_{22}^*g_{21}^*h_{22,t-1} \\
&h_{22t} = \omega_{22} + a_{22}^{*2}\varepsilon_{2,t-1}^2 + 2a_{22}^*a_{21}^*\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^{*2}\varepsilon_{2,t-1}^2 + g_{22}^{*2}h_{22,t-1} \\
&+ 2g_{22}^*g_{21}^*h_{21,t-1} + g_{21}^{*2}h_{11,t-1}
\end{aligned}\right\} \tag{2.29}$$

Using this model, the spillover effects can be tested by the significance of the conditional variance and covariance terms of the second asset affecting the first asset. Allowing for lagged covariances in the conditional variance equation complicates the testing and interpretation of the coefficients. The interpretation of the basic parameters is not obvious in the BEKK, which poses a significant problem for model consideration. The diagonal BEKK is similar to the DVEC model where matrices A_k^* and G_k^* are diagonal matrices. Darbar and Deb (1997), Kearney and Patton (2000), Caporale et al. (2002), Ewing et al. (2002) and Worthington and Higgs (2004, 2005) have used BEKK (1, 1, 1) type models for their research on volatility spillovers and find evidence of positive volatility spillovers.[2]

Darbar and Deb (1997) look at the equity returns from Canada, Japan, the US and the UK using a BEKK (1, 1, 1) model. Though this model is flexible and parsimonious, they stress the difficulty in testing it, in its current form without imposing restrictions on the variance functions. So they use a bivariate model to obtain a convenient parameterization, which allows for testing the hypothesis on the covariance terms without imposing restrictions on the variance terms. The conditional variance equation for the bivariate case is defined as below.

$$h_{11t} = \omega_{11}^2 + a_{1,11}^2 \varepsilon_{1,t-1}^2 + g_{1,11}^{*2} h_{11,t-1} \tag{2.30}$$

$$h_{12t} = \omega_{12}\omega_{11} + a_{1,11}a_{1,22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + g_{1,11}g_{1,22}h_{12,t-1} \tag{2.31}$$

$$h_{22t} = \omega_{22}^2 + \omega_{12}^2 + (a_{1,22}^2 + a_{2,22}^2)\varepsilon_{2,t-1}^2 + (g_{1,22}^2 + g_{2,22}^2)h_{22,t-1} \tag{2.32}$$

Worthington and Higgs (2004) examine the volatility spillovers in equity returns. They look at three developed markets (Hong Kong, Japan and Singapore) and six emerging markets (Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand). They find evidence of

[2] Darbar and Deb (1997) use BEKK type model for the variance equation and maximum likelihood (ML) technique for their estimation of results. They use an AR (1) model for the mean equation. Kearney and Patton (2000), Ewing et al. (2002) and Worthington and Higgs (2004) use BEKK (1, 1, 1) model for the variance equation and a combination of ML and Berndt, Hall, Hall, and Hausman (BHHH -1974) for the estimation of results. Caporale et al. (2002) use BEKK (1, 1, 1) model for the variance equation and quasi-maximum likelihood (QMLE) estimation for their results. They use an AR (1) model in the mean equation similar to Darbar and Deb (1997).

positive spillover relationships in both mean and volatility of returns between these markets by employing a BEKK model and sample duration from 1988 to 2000. Following on their earlier study in 2004, Worthington and Higgs (2005) examine the spillovers in Australian electricity spot markets and find positive spillovers once again.

Allowing for asymmetries in volatility modeling enriches the empirical study and throws light on the actual dynamics of volatility spillovers. It is common understanding that, investing in equities, bonds and foreign exchange markets internationally provides a greater opportunity set in terms of diversification. Any evidence of negative volatility spillovers lends support to the benefits that can be derived from diversification. Persand et al. (2002), study the effect of allowing for asymmetries in the stock return on optimal hedge ratios. They show evidence of a more effective hedging performance in allowing for asymmetries in the return volatility by using an extended BEKK framework. The model they use can be defined as below.

$$H_t = C^{*\prime} C^* + \sum_{k=1}^{K} A_k^{*\prime} \varepsilon_{t-1} \varepsilon_{t-1}^{\prime} A_k^* + \sum_{k=1}^{K} G_k^{*\prime} H_{t-1} G_k^* + \sum_{k=1}^{K} D_k^{*\prime} \xi_{t-1} \xi_{t-1}^{\prime} D_k^* \tag{2.33}$$

The better hedging performance suggests considerable portfolio diversification benefits. A hedge can be achieved by using derivative instruments. Any adverse movement in the prices leading to a decline in returns can be offset by hedging the exposure with another instrument, adding strength to the diversification benefits argument. Due to the complexity involved and the computational difficulties not many studies have examined the effect of volatility spillover allowing for asymmetries in return volatility.

Shamiri and Isa (2009) look at the equity asset class and employ a bivariate GARCH model, using the BEKK representation and find evidence of positive volatility spillovers from the US to all the south East Asian countries used in their sample. It is important to note that volatility spillovers in the foreign exchange markets have been researched extensively. Kearney and Patton (2000) use a BEKK multivariate GARCH model to test the exchange rate volatility spillovers in the European Monetary System (EMS). They highlight the difficulty in estimating a multivariate set up and the necessity for simplifying assumptions to aid in estimating the system. They find some spillover effects when they use daily data and no spillover effects when they use weekly data. Their research draws attention to the fact that the periodicity of the data used in measuring spillover effects might play a significant role on the results.

In practice, the BEKK log-likelihood function is not always well behaved, especially when the number of parameters increases. Adding to this is the problem of reaching a global maximum of the log-likelihood function which is not guaranteed using standard optimization techniques. During optimization, the possibility of the routine choosing a local maximum as opposed to a global maximum might pose a problem. Hence the literature in which BEKK model is used to test volatility spillovers is sparse. Though the diagonal BEKK might be a better computationally feasible option it is too restrictive and does not offer flexibility that might make empirical studies on volatility spillovers more interesting.

2.2.3. FGARCH Model

The Factor-GARCH (FGARCH) model can be viewed as a particular case of BEKK (1, 1, K) model. The conditional variance for the FGARCH model is given as below.

$$H_t = \Omega + \sum_{k=1}^{K} \alpha_k^2 \lambda_k \omega_k^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} \omega_k \lambda_k^{'} + \sum_{k=1}^{K} \beta_k^2 \lambda_k \omega_k^{'} H_{t-1} \omega_k \lambda_k^{'} \tag{2.34}$$

where $\Omega = C^{*}{}'C^{*}$. A_k^{*} and G_k^{*} are replaced by unit rank matrices that are proportional to each other. The N×1 vectors λ_k and ω_k are subject to the restrictions listed below.

$$\omega_k^{'} \lambda_i = \begin{cases} 0 \, for; k \neq i \\ 1 \, for; k = i \end{cases} \text{ and } \sum_{n=1}^{N} \omega_{kn} = 1 \tag{2.35}$$

By substituting K =1, the model can be simplified and written as below.

$$H_t = \Omega^{*} + \lambda \lambda^{'} h_t \text{ where} \tag{2.36}$$

$$h_t = \omega + \alpha^2 f_{t-1}^2 + \beta^2 h_{t-1} \tag{2.37}$$

is the GARCH (1, 1) conditional variance of the factor $f_t = \omega^{'} \varepsilon_t$.

The conditional variance for a bivariate FGARCH (1, 1, 1) model can be expressed as below.

$$\left.\begin{aligned} h_{11t} &= \omega_{11}^{*} + \lambda_1^2 h_t \\ h_{21t} &= \omega_{21}^{*} + \lambda_1 \lambda_2 h_t \\ h_{22t} &= \omega_{22}^{*} + \lambda_2^2 h_t \end{aligned}\right\} \tag{2.38}$$

The literature on volatility spillovers using a full factor MVGARCH is fairly sparse. Vrontos, Dellaportas, and Politis (2003) in their paper use a FGARCH model. They use Bayesian techniques and maximum likelihood method for estimation of their results. They show the necessity for Markow Chain Monte Carlo (MCMC) algorithms in estimating the results. They find evidence of positive volatility spillovers in their study for the equity asset class. Lanne and Saikkonen (2007) study the volatility spillovers in foreign exchange markets using the FGARCH model and weekly frequency data. They look at foreign exchange for French Franc, Dutch Guilder, German Mark, Swiss Franc and U.S. Dollar. They show evidence that a single factor works best in explaining volatility spillovers which are mostly positive. Also the spillovers generally seem to occur from one market to the other and not vice versa, e.g. from German Mark to Dutch Guilder and not vice versa. The inference that could be made from these results is that certain markets affect others significantly in a unidirectional sense.

Study of contagion in the international bond markets during certain crises was done by Martin et.al (2006) using an integrated FGARCH model. The specific crises they have used are the Russian bond default crisis in August 1998 and the long-term-capital-management (LTCM) recapitalization announcement. While the results show clear evidence of contagion or spillovers in the bond markets due to the Russian crises, the evidence of contagion due to LTCM crises seems smaller. The contagion due to the Russian debt crises was significant with spillovers to the Netherlands, Bulgaria, Thailand and Brazil ranging from 7.784 to 17.191 percent of total volatility. Identifying the factors that affect the FGARCH model may be difficult and can be attributed as the reason for the sparse literature using this model.

2.2.4. CCC Model

In all the MVGARCH models that I have discussed above, the conditional covariances have to be specified in addition to the variances. The CCC (constant conditional correlation) model developed by Bollerslev (1990) is a nonlinear combination of univariate GARCH models and instead of specifying the conditional variance, the conditional correlations in addition to the variance is specified. This allows for some flexibility in the specification of the variances. They need not be the same for each component. For this model the conditional covariance can generally be written as below.

$$H_t = D_t R \ D_t \text{ where} \tag{2.39}$$

$$D_t = diag(h_{11t}^{1/2}, h_{22t}^{1/2}, ...h_{NNt}^{1/2}) \text{ and} \tag{2.40}$$

$$R = D_T^{-1} H \ D_T^{-1} = \rho_{ij} \text{ with } \rho_{ii} = 1 \tag{2.41}$$

R is the N×N matrix of conditional correlations and h_{iit} is defined as a univariate GARCH model. D_t is a diagonal matrix of time varying standard deviations. Hence,

$$h_{ijt} = \rho_{ij} \sqrt{h_{iit} h_{jjt}} \text{ for all } i \neq j. \tag{2.42}$$

This results in representing the conditional covariance as $H_t = D_t R D_t$. The positive definiteness of H_t, follows from the positivity of R and each of ρ_{ij}. The correlations do not vary over time and thus the dynamics of the covariance is determined only by the dynamics of the conditional variances.

Bollerslev (1990), Longin and Solnik (1995), Fong and Chng (2000), Schleicher (2001) and Bera and Kim (2002)[3] use constant conditional correlation (CCC) type models in their studies involving volatility spillovers. They find that the international covariance and correlation

[3] Bollerslev (1990), Schleicher (2001) and Bera and Kim (2002) all use CCC(1, 1) model for their variance equation and estimate their results using a maximum likelihood (ML) and Berndt, Hall, Hall, and Hausman (BHHH -1974) type procedure. Longin and Solnik (1995) and Fong and Chng (2000) use a CCC (1, 1) model for their variance equation but use a quasi-maximum likelihood estimation for their results.

matrices are unstable over time and the CCC-GARCH model helps capture some of the evolution in the conditional covariance structure. Fong and Chng (2000) look at conditional variance of dual listed stocks on the Singapore stock exchange for the period 1991 to 1996. They use an ARMA (1, 1) process to model the returns of the series. Using a likelihood-ratio test on the coefficient for conditional variance, they test spillovers and find positive spillover evidence. Scheicher (2001) looks at stock markets in Hungary, Poland and Czech Republic for the years 1995 to October 1997. He models returns as an AR (1) process. He shows evidence of positive spillovers in five cases out of the nine that he examines.

Nakatani and Terasvirta (2009) test volatility spillovers or interaction using an extended constant conditional correlation (CCC) GARCH model. The ECCC-GARCH model can be defined as below.

$$h_t = [h_{1,t},....,h_{N,t}]' = a_0 + \sum_{i=1}^{q} A_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} B_j h_{t-j} \tag{2.43}$$

where, A_i and B_j are diagonal for all 'i' and 'j'. If $B_j = 0$, then this model collapses into a CCC-GARCH model. The significance and magnitude for coefficients of B_j, is used to test for volatility spillovers. The magnitude of the volatility spillovers they find is small; nevertheless they find evidence to support the existence of positive spillovers. The pertinence of their study lies in their demonstration of how the conditional variance term can be extended to include not only lagged variance of the residuals but also factors from other equations. I draw inference primarily from their study and extend the conditional variance equation to include thresholds in this study. Karanasos and Conrad (2010) show the formulation for an unrestricted extended constant conditional correlation (ECCC) GARCH model that allows for negative volatility spillovers. They employ a fairly complex model that allows for asymmetry in the time varying correlations and find evidence of negative volatility spillovers.

Bera and Kim (2002) look at equity returns for six markets namely U.S., Japan, Germany, the U.K., France and Italy. They use White (1982), information matrix (IM) test, to test the parameter variation. Under the assumption of constant conditional correlation, the cross product terms in the conditional variance should be serially uncorrelated. The empirical results in all these studies that have been examined support the uncorrelated evidence of cross products of residuals. This evidence suggests constant conditional correlations. These studies also find evidence of predominantly positive direct volatility spillovers. The limitation in these papers is that the dynamics of conditional covariance is determined solely by the dynamics of the conditional variances. CCC reduces the model complexity and the number of parameters greatly, but this feature might be restrictive and not as interesting for an empirical study as the correlations are not allowed to change dynamically over time.

2.2.5. DCC Model

Engle (2002) developed the dynamic conditional correlation (DCC-MGARCH) model, which is a generalization of the CCC model introduced by Bollerslev (1990). The DCC model is a fairly new model that can be used for examining and measuring volatility spillovers as it models the volatilities and correlations. The DCC calculates current correlation between variables as a function of both past variances and correlations. Another important point to note is that the DCC model can be extended to allow for conditional variance of other series to affect the series being examined. Nakatani and Terasvirta (2009) show that this can be done and that it is meaningful and more relevant for financial markets.

The main difference between the CCC and DCC is how R_t (assumed to be conditionally multivariate normal) is specified. In the DCC, R_t, has time varying correlations. The statistical specification for R_t is as

$$R_t = (diag Q_t)^{-1/2} Q_t (diag Q_t)^{-1/2} \tag{2.44}$$

where Q_t, is an N×N symmetric matrix and $Q_t > 0$. Q_t can be specified as

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha \varepsilon_{t-1} \varepsilon_{t-1}^{'} + \beta Q_{t-1} \tag{2.45}$$

α and β are the key scalar parameters that are estimated. If α = β = 0, then R_t is simply $\overline{R}$ and the constant conditional correlation model is derived. Also, α and β are positive parameters satisfying the condition α + β < 1. For this model the conditional variance-covariance matrix can generally be written as

$$H_t = D_t R_t D_t \tag{2.46}$$

D_t, which is obtained from a univariate GARCH specification, can be represented as below.

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & . & . & . & 0 \\ 0 & \sqrt{h_{22t}} & 0 & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & . & . & . & . & \sqrt{h_{NNt}} \end{bmatrix} \tag{2.47}$$

The DCC extends the CCC model but with few extra parameters and hence it is computationally feasible. An important thing to pay attention to is the choice of starting parameter values. Based on the choice of these starting parameter values the log-likelihood of the DCC can behave poorly, resulting in non-convergence or computational complexities. Carol Alexander in her book “Market Risk Analysis: Practical Financial Econometrics” and Kuper and Lestano (2007), suggest that it is a good practice to assume that the starting parameters are generated from a GARCH model and estimate those parameters.

Perez-Rodriguez (2006) uses DCC-GARCH model and use daily exchange rate data to discuss the interdependent effects of volatility spillover. He finds significant volatility spillovers between exchange rate markets. He also finds a short run effect where the impulse responses of volatility gradually diminish and disappear after ten days for new member states of the European Union. Chiang et. al. (2007) in their analysis of volatility spillovers between nine Asian equity markets, use a DCC-MVGARCH model. They find evidence of contagion effect contrary to the findings of Forbes and Rigobon (2002). They also show that the Asian financial crisis has a two phase nature. In the first phase, they find an increase in contagion effect and in the second phase they find the continuance of the contagion effect.

Chou, Liu and Wu (2009) compare six different models and also use the S&P500 stock index and ten year Treasury bond futures data in their study. They use a new estimator to estimate the volatility spillovers (Chou (2005)'s CARR model focusses on the price range directly instead of using the log of price range). Their estimator puts together the conditional autoregressive range (CARR) model along with the DCC model to test range based volatility spillovers. Specifically, their range based volatility model uses the price ranges to replace the GARCH volatilities in the first step of the DCC model. The second stage of the DCC where the transformed standardized residuals from the first step are used remains the same. Their model produces more consistent and better results than MA100, EWMA, CCC, return based DCC model and diagonal BEKK because of the gains in efficiency from using range data.

In a recent paper, Savva (2009) uses an extension of the general asymmetric dynamic covariance (GADC) model proposed by Kroner and Ng (1998). His model uses the GADC model that nests the important multivariate GARCH models like VECH, Constant Conditional Correlation (CCC), Baba-Engle-Kraft-Kroner (BEKK) and Factor-ARCH (F-ARCH). Prior to this paper the GADC model had not been used to investigate volatility spillovers. The conditional variance-covariance matrix of the general asymmetric dynamic covariance model which is a variation of the DCC model can be defined as below.

$$H_t = D_t R_t D_t + \Phi \otimes \Theta_t \tag{2.48}$$

where, $\otimes$ denotes the element by element matrix multiplicator (Hadamard product operator). Savva (2009) defines the model in greater detail. His paper focuses on the spillovers within the equity asset class, where he measures the spillovers from US to European stock markets. He finds significant positive spillovers between these markets. He also shows that the conditional correlations increase between returns across markets. In employing synchronous data, he finds that the model that best captures the relationships for over half of the bivariate combinations examined is the DCC model. For the remainder of the bivariate relationships examined, the DCC model does not capture the volatility spillovers as per expectations, owing to asymmetries. This highlights the need for extending the DCC to allow for asymmetries. Roumpis and Syriopoulos (2009) analyze volatility spillovers from major Balkan equity markets to other mature equity markets. They find the absence of constant correlation between equity markets and find evidence of the asymmetric nature of the dynamic conditional correlation between equity markets. They also suggest other models that need to be employed to gain a deeper understanding of the asymmetric nature of the spillovers.

Recent research in the area of volatility spillovers emphasize the inherent asymmetry and hence the need for examining volatility spillovers allowing for asymmetric effects in conditional variance. Long and Lee (2009) use a copula based MVGARCH (C-MVGARCH) model to model non-normally distributed financial returns. The C-MVGARCH model specifies the dependence structure and the conditional correlation separately and simultaneously. The dependence structure is controlled by a copula function and the conditional variance-covariance is modeled by an MVGARCH model (BEKK, DCC, etc.). Long and Lee describe the model in greater detail. They use the fact that uncorrelated errors are not necessarily independent and find that the copula based MVGARCH model performs better than the DCC model.

Other research has been oriented towards specifying more flexible dynamic correlations without much restriction. Billio et al. (2003) extended the DCC model to a block structure of DCC model. Billio and Caporin (2006) extended the DCC model to impose a BEKK structure on the conditional correlations. They called their model the Quadratic Flexible DCC GARCH model. Hafner and Franses (2003) extended the DCC model to a generalized DCC model. Yang and Lien (2008) analyze the effect on future hedging when asymmetries are allowed for in the spot return volatility within the commodity market. Their analysis also contrasts the performance of future hedging allowing for asymmetries with that of not allowing for asymmetries or enforcing symmetry. They find evidence of better hedging and hence benefits for diversification are stronger when asymmetries are allowed in their model. Loudon et.al (2010) employ data from 1992 to 2006 and find evidence of asymmetry in volatility spillover between equity and bond markets in Australia. Their results strengthen evidence supporting benefits for diversification.

2.2.6. Regime Switching Models

There are various specifications for regime switching models. For a simplistic case of spillovers between two series, the model can be defined as below.

$$R_t = \mu[\theta_\mu(s_t), I_{t-1}] \text{ where,} \tag{2.49}$$

$$R_t = \begin{bmatrix} R_t^1 \\ R_t^2 \end{bmatrix} \text{ is the vector of two series returns} \tag{2.50}$$

$$\mu[\theta_\mu(s_t), I_{t-1}] \text{ is the vector of conditional means} \tag{2.51}$$

and θ_μ is the set of parameters of vector of conditional means.

Also,

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, H_t(s_t)\right) \text{ with,} \tag{2.52}$$

$$H_t(s_t) = H_t[\theta_H(s_t), I_{t-1}] \tag{2.53}$$

where θ_H, is the set of parameters of the conditional covariance matrix specification, I_{t-1}, is the information filtration and s_t, is the regime at time 't' which is not observed. Denoting 'vech' as the operator defined earlier in equation 2.25, a bivariate-GARCH (1, 1) model with regime-switch can be defined similar to the VEC model representation in section 2.2.1 but allowing for regime to change. This can be represented as below in matrix form.

$$H_{t,S_t} = \Gamma_{S_t}\Gamma_{S_t}^{'} + A_{S_t}E_{t-1}A_{S_t}^{'} + B_{S_t}H_{t-1}B_{S_t}^{'} \tag{2.54}$$

Quantifying volatility spillovers from collective European Union (EU) and US to 13 local European equity markets, Baele (2005) finds that during the 1980's and 1990's the volatility spillovers increased both economically and statistically. He uses thirteen European Union (EU) countries (Austria, Belgium, Denmark, France, Germany, Ireland, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland and the U.K.) and two regional markets (the aggregate European market and the U.S.). Employing a regime switching methodology, he finds an increase in market integration which is established by the statistical evidence that 8% of the country specific variance was explained by the collective EU volatility. This country specific variance increased to 23% in the late 1990's. Similarly US volatility explained 15% of the country specific variance. This increased to 27% in the late 1990's.

Otranto (2010) proposes a new model with flexible dynamic correlation that allows for regime switching. He uses a hypothetical portfolio comprised of indices relative to the two main sectors of the Italian Mibtel general index. The portfolios are for banks, insurance and finance holdings relative to the finance sector; minerals, metals, chemicals and textiles relative to the industrial sector. He finds evidence of positive volatility spillover when allowing for regime switches. The fundamental reason in allowing for the inclusion of regime switches is to highlight and consider the abrupt changes in correlation that affect assets in various ways. Though he allows for the flexibility of regime switches, the basic model is the DCC-GARCH model I have discussed earlier.

2.3. Summary of Section

Summarizing this section, there is a sufficient body of literature on volatility spillovers in equity, bond and foreign exchange markets. An entire range of univariate and multivariate GARCH models are typically used for studies involving volatility spillovers. The inadequacy of some of these models is constantly giving rise to new methods of testing spillovers. Most of the literature assumes a linear relationship in spillovers and includes only lagged innovations from other markets or other assets in the conditional variance specification. The lagged conditional variance of other assets or other markets is not used in all the studies that I have examined as part of literature review. When certain assumptions in the methods used are relaxed, for example, asymmetry in return volatility, then the findings of negative spillover are possible. There are multiple explanations for these negative spillovers. First is the market over reaction. The basis of this over reaction is rooted in irrationality and I do not want to place emphasis on this point. The second is that the market risk does not increase as much as the country specific risk and hence other markets are not as affected by the increase in country specific risk of another market. The final reasons that are attributed for the negative spillovers are hedging and diversification of investments by investors in other markets. Investors in one country know that holding financial assets in another country has higher returns and is associated with higher risks. So the investor tries to reduce the exposure of his position by hedging using derivative instruments. When risk in one market increases and causes an adverse reaction in prices, the investor is not affected as his position is already hedged.

In an overall survey of most of the literature on volatility spillovers, univariate GARCH, BEKK and DCC models are employed frequently in estimating the volatility spillover relationships. Engle et.al. (1990, 1992, 1994), Hamao et.al. (1990), Cheung and Ng (1996), Pyun et.al. (2000), Alaganar and Bhar (2002), Gray and Treepongkaruna (2009) and Skintzi and Refenes (2006) all use univariate GARCH type models in their volatility spillover studies. Darbar and Deb (1997), Kearney and Patton (2000), Caporale et. al. (2002), Ewing et. al. (2002) and Worthington and Higgs (2004) all use BEKK model in their studies. Perez-Rodriguez (2006), Chiang et. al (2007), Chou, Liu and Wu (2009), Savva (2009), Roumpis and Syriopoulos (2009), Billio et. al. (2003), Billio and Caporin (2006), Hafner and Frances (2003), Yang and Lien (2008) and Loudon et. al. (2010) all use DCC model in their studies. So in my consideration of choosing to model the conditional variance equation using univariate GARCH or BEKK or DCC, I choose univariate GARCH and DCC.

Though the BEKK model has positive definiteness constraints, it has issues of dimensionality and the interpretation of the basic parameters in the conditional variance equation is not obvious. The dimensionality issue makes it more difficult to estimate the BEKK parameters. The DCC or the univariate GARCH does not have these issues and is much easier to interpret as compared to the BEKK model. Caporin and McAleer (2010) compare the use of BEKK versus DCC. The DCC focuses on modeling conditional variances and conditional correlations separately and allows for it to be time varying. A reasonable assumption to be made is that correlations of asset returns are time varying. Hence the DCC model will be needed to estimate the conditional variance for this study. Alternately, if the correlations of asset returns are assumed to be not time varying then the univariate GARCH or an extended univariate GARCH specification can be used as a tool to estimate the conditional variance in this study.

CHAPTER 3

METHODOLOGY

The relevance and importance of modeling and studying spillovers in volatility or transmission of volatility during financial turmoil has increased significantly due to the emphasis on risk management. Volatility within the asset classes have been measured traditionally using absolute deviation or variance or standard deviation or moving average models. As emphasized in the previous section, in extending the measurements of volatility to capture spillovers in volatility, previous literature (Engle et al. (1990, 1992), Hamao et al. (1990), Cheung and Ng (1996), Pyun et al. (2000), Darbar and Deb (1997), Kearney and Patton (2000), Caporale et al. (2002), Ewing et al. (2002), Worthington and Higgs (2004), Bollerslev (1990), Fong and Chng (2000), Schleicher (2001), Bera and Kim (2002), etc.), has commonly implemented volatility spillovers using a univariate or multivariate GARCH model.

Regardless of whether these studies model volatility spillovers as a univariate or multivariate model, the conditional variance specification of asset returns in most of the studies examined in the previous section does not allow the conditional variance of other assets return to enter into the specifications of the first assets conditional variance. This has been one of the limitations of the studies that were analyzed in the previous section. The various studies include innovations from a second asset but not the conditional variance of a second asset. I include this conditional variance from a second asset as well as an indicator function that captures the conditional variance from the second asset at levels of risk exceeding a threshold. This has never been done before in any of the models that I have considered in the literature review section.

Modeling volatility as conditional variance of the assets return, I use a two-stage estimation procedure to measure the effect of direct volatility spillovers and indirect thresholds effects. E.g., In the case of two markets A and B, volatility in market A is a function of its own lagged innovations and conditional variance. I use one lag for both the innovations and the conditional variance. I also allow for lagged conditional variance of market B to enter into the specification of volatility for market A and the nonlinear or threshold variable through an indicator function that takes on a value of one when the volatility exceeds a threshold and zero otherwise. Drawing from the literature by Nakatani and Terasvirta (2009), Steeley (2006), Karanasos and Conrad (2010), etc., I extend the conditional variance equation of one market by allowing factors from other equations to affect it.

In order to explain the two stage procedure, I begin this section by describing how the conditional variance is estimated in the first stage. The conditional variance is estimated as a univariate GARCH model in the first stage and then this estimated value in the first stage is treated as observed in the second stage and used in the extended conditional variance specification in the second stage. The recent advancements in terms of extending the conditional variance specification were discussed in the literature review section to put in perspective the methods used in this study. I also extend the conditional variance equation to allow for threshold effects. Additionally, I estimate the conditional variance in the first stage using a DCC model as well, which allows for time varying correlations. This is followed by an explanation on how I compute the threshold parameter that is used in this study. A section on the need for simulated critical values to interpret research results in this study is detailed. These simulated critical values add strength to the robust results of this analysis. I conclude this section listing the various hypotheses being tested and summarize the entire methodology section at last.

3.1. Conditional Variance Estimation

The conditional variance of each series used in this study, is estimated using either a univariate GARCH (1, 1) or a DCC (1, 1) model. Both the models have been described in the previous chapter. As a re-cap from the previous chapter, the conditional variance estimated by a univariate GARCH model is a function of one lag of its own innovations and one lag of its own conditional variance. This can be represented as follows.

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3.1}$$

Similar to section 2.2.5, the DCC model can be represented as follows.

$$R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2} \tag{3.2}$$

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha \varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \tag{3.3}$$

$$H_t = D_t R_t D_t \tag{3.4}$$

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & . & . & . & 0 \\ 0 & \sqrt{h_{22t}} & 0 & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & . & . & . & . & \sqrt{h_{NNt}} \end{bmatrix} \tag{3.5}$$

R_t, has time varying correlations and D_t, is made up of a system of univariate GARCH specifications along its diagonal.

Engle (2002), under the assumption of normality, shows the likelihood of the DCC estimator, which can be written as follows:

$$L = -0.5\sum_{t=1}^{T}(N\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \varepsilon_t^{'} R_t^{-1}\varepsilon_t) \tag{3.6}$$

then, the likelihood of the DCC estimator can be re-written as below.

$$L = -0.5\sum_{t=1}^{T}(N\log(2\pi) + 2\log(|D_t|) + r_t^{'} D_t^{-1} D_t^{-1} r_t - \varepsilon_t^{'}\varepsilon_t + \log(|R_t|) + \varepsilon_t^{'} R_t^{-1}\varepsilon_t) \tag{3.7}$$

The two components in the likelihood function that are allowed to vary are the volatility component containing D_t and the correlation component containing R_t. Having two components in the likelihood function allows the estimation to be separated into two parts. In the first part, estimation of the volatility term is performed and in the second part, estimation of the correlation term occurs. The contribution of the volatility term from the estimation to the likelihood function can be expressed as follows.

$$L_V = -0.5\sum_{t=1}^{T}(\log(2\pi) + 2\log(|D_t|^2) + r_t^{'}D_t^{-2}r_t) \tag{3.8}$$

The next step involves maximization of the likelihood function for the correlation term. The contribution of the correlation term to the likelihood function can be written as below.

$$L_C = -0.5\sum_{t=1}^{T}(\log(|R_t|) + \varepsilon_t^{'}R_t^{-1}\varepsilon_t - \varepsilon_t^{'}\varepsilon_t) \tag{3.9}$$

The DCC model parameters are estimated by using the original likelihood function, conditional on the first stage univariate parameters. The conditional variance of a return series is thus computed either using a univariate GARCH or a DCC model.

3.2. Extending the GARCH and DCC Framework

Nakatani and Terasvirta (2009) show that volatility or conditional variance of returns, which was modeled as a linear combination of the asset's own lagged squared innovations and own lagged conditional variance, can be extended further. They extended volatility to include factors from other equations. As the standard DCC model does not allow for asymmetries and other asset specific parameters, Cappiello et al. (2006) incorporate the GJR-MGARCH model with the DCC model to account for asymmetric effects. Most of the studies that allow for asymmetries (Audrino and Trojani (2006), Otranto (2010), Long and Lee (2009), etc.) show that the conditional variance equation can be extended to allow for factors from other equations to affect it. It could be either conditional variance of another asset or any information variable.

Zivot (2008) discusses some of the problems or practical issues in using a univariate GARCH framework and how it can be extended to address those issues. Following the suggestions from Zivot (2008), Nakatani and Terasvirta (2009) and various other studies that allow for asymmetries, I extend the volatility (conditional variance) specification in this study.

In this study, I consider a simple bivariate case. Considering only two markets within a particular asset class makes this study computationally feasible. The extended model can now be represented as below.

$$h_{11t} = \kappa_1 + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1} \tag{3.10}$$

$$\left.\begin{array}{l} Note, when, h_{22t-1} < \lambda \\ \dfrac{\partial h_{11t}}{\partial h_{22t-1}} = \delta_{12} \\ \\ and, when, h_{22t-1} \geq \lambda \\ \dfrac{\partial h_{11t}}{\partial h_{22t-1}} = \delta_{12} + \omega_{12} \end{array}\right\} \quad \text{where, } \lambda \text{ is the threshold value.} \tag{3.11}$$

δ_{12}, is the coefficient on the volatility spillover term and ω_{12}, is the coefficient on the threshold effect term. The interesting question now becomes how to compute the threshold parameter? Even before answering the question on how to compute the threshold parameter, what is important is to know why this threshold parameter is of importance? Reverting back to some of the studies that I have examined in the previous chapter, Audrino and Trojani (2006), Harris and Pisedtasalasai (2006), Chang et al. (2009), Persand et al. (2002), Savva (2009), Zivot (2008) and Loudon et al. (2010) have all shown evidence endorsing the fact that nonlinearities in conditional variance exist. The only limitation in all these studies is that they restrict the nonlinearities to the innovation terms and do not allow for nonlinearities in the conditional variance term. Adding to this, Nakatani and Terasvirta (2009) show that the conditional variance specification can be extended to include nonlinearities and dynamics from other equations. Drawing mainly from these studies, I justify the importance of the threshold parameter in the conditional variance specification as depicted in equation 3.10. Also none of the past literature has delved into these thresholds in volatility spillovers and the one or two studies that do focus on it, estimate the threshold at a single point. They do not address the issue of whether the estimated threshold is a local maxima or global maxima. Hence, clearly laying out the method used for estimating these threshold parameters is very important.

3.3. Threshold Grid Search

The consistent estimate of the threshold value that I use in this study is endogenously determined through a sequential grid search method. The two step approach I use in estimating the threshold is very similar to Caporin (2011) and Bauwens et al. (2006). Caporin (2011) employs a sequential grid search for a DCC type model. The important assumption in that study is that the conditional variances are correlated over time. GARCH (1, 1) model does not place any constraint on the correlations and it is the weighted average of past squared residuals, but it also has declining weights that never go completely to zero. It gives a parsimonious model that is easy to estimate and is successful in predicting conditional variances. If I assume that I do not know about the existence or nature of any multivariate type effects and the time varying conditional variances, it makes sense to perform the sequential grid search on the conditional variances generated by using a GARCH (1, 1) type model. This assumption makes the estimation of parameters computationally feasible and inference of the parameters is easier. Allowing for the correlations to be time varying and some form of multivariate effects, I expect the results to be more significant.

First, I assume that the underlying data generating process for the volatility of asset returns or the conditional variance of asset returns follows a GARCH (1, 1) type process and estimate the conditional variance of each series as a univariate GARCH model in the first stage. So analyzing two markets for a particular asset, the range of the estimated conditional variance of returns of the second market is divided by 100 to get the step size and starting from the smallest value of conditional variance, each increment of step size is stored as a potential threshold value in a 100×1 vector. Ideally I would want to use each and every value of conditional variance to estimate the threshold parameters. Due to computational complexities I restrict it to a 100×1 vector. I then arrange the threshold values, in descending order and exclude the smallest 10 percent of values to avoid the potential of multi-co-linearity. Without loss of generality, I can do this as the smallest values of conditional variance do not affect the relationship as much as high levels of volatility and I also address the potential issue of multicolinearity as I am using the estimated conditional variance values. For all values of the threshold, I maximize the log likelihood function described below.

$$\arg\max_{\lambda \in \mathrm{A}} L = \frac{1}{2}(-\frac{t}{2}\log(2\pi) + \sum_{t=1}^{T} \ln | h_{11t} | + \frac{\varepsilon_{11t}^2}{h_{11t}}) \text{ where,} \tag{3.12}$$

$$h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1} \tag{3.13}$$

I repeat this step by step process with the next value of threshold from the 100×1 vector to find the λ that maximizes the likelihood function. If the calculated log likelihood is greater than the value calculated for the previous value of threshold then the threshold value is changed to the most current estimated value and left unchanged otherwise. I repeat this procedure for each value of the potential threshold (90 times) and choose the value of λ (threshold) from the set of threshold values Λ, that overall maximizes the log likelihood funtion. The consistent estimate of λ (threshold) is the parameter that yields the largest log likelihood over the set of all possible values of λ. These estimated values for the conditional variance are then used to analyze the relationship of volatility spillover and threshold effects from one market to the other within a particular asset class.

Second, I assume that the underlying data generating process has some sort of multivariate type effects and time varying conditional variances. So I use the DCC model to estimate the conditional variance of the return series in the first stage. Once the conditional variances are generated using a DCC (1,1) model, I compute the consistent estimate of the λ (threshold) parameter that yields the largest log likelihood as explained for the GARCH (1, 1) scenario. These estimated values for conditional variance and threshold are then used to analyze the relationship of volatility spillover and threshold effects from one market to the other within a particular asset class.

3.4. Hypothesis Tested

This study tests the following hypothesis for different asset classes (equity, bonds and foreign exchange).

Hypothesis 1: There are no volatility spillovers and no threshold effects.

Given the model

$$h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^{2} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1} \tag{3.14}$$

Statistically this can be represented as below.

$$\begin{aligned} &H_0 : \delta_{12} = \omega_{12} = 0 \\ &H_A : \delta_{12} \neq 0 \ \ or \ \ \omega_{12} \neq 0 \end{aligned} \tag{3.15}$$

Hypothesis 2: There is no volatility spillover effect conditional on no threshold effect.

Statistically this can be represented as below.

$$\begin{aligned} &H_0 : \delta_{12} = 0 \,|\, \omega_{12} = 0 \\ &H_A : \delta_{12} \neq 0 \end{aligned} \tag{3.16}$$

Hypothesis 3: There is no threshold effect conditional on no volatility spillovers.

Statistically this can be represented as below.

$$\begin{aligned} &H_0 : \omega_{12} = 0 \,|\, \delta_{12} = 0 \\ &H_A : \omega_{12} \neq 0 \end{aligned} \tag{3.17}$$

The hypothesis is tested using simulated p-values rather than conventional p-values, associated with likelihood ratio statistics.

3.5. Monte Carlo Simulation

In this study, I do not know the underlying distribution of the conditional variance for each series being examined. In fact the modeling of the underlying conditional variance for each series is challenging and employing some advanced techniques is replete with its own pitfalls. Hence there is a need for a way to justify the inference. According to the hypothesis that I have set up, the nuisance parameter or λ (threshold) parameter is not identified under the null hypothesis. Davies (1987) discusses the need for simulations to generate critical values when a nuisance parameter very similar to λ is absent under the null hypothesis or rather present only under the alternative hypothesis. Hence running Monte Carlo simulations that can generate the critical values for the likelihood ratio test statistic will address the issue of spurious inference.

To obtain finite sample critical values for the various test statistics, I run Monte Carlo simulations. In step one, I assume the conditional variance is generated by a GARCH (1, 1) type model without any type of spillover; I initialize a random seed to reset the computational processing. I simulate two data sequences which are independent GARCH (1, 1) processes of length 3000 observations. I apply the estimation procedure allowing for threshold effects as described in the previous section. The starting values for the data sequences are different from each other but satisfy the conditions of a GARCH (1, 1) model. I use the conditional variances of these data series to compute the threshold parameter, run a two-step analysis and compute likelihood ratio statistic values. The threshold parameter in these Monte Carlo simulations is generated mimicking the procedure explained in the previous section. I repeat this process 30,000 times to generate a large enough sample of simulated critical values. If the test statistic for likelihood ratio generated in the actual analysis exceeds these simulated critical values, the coefficients are significant. Similarly I run 20,000 simulations for the DCC type model as well and compute the critical values that help in interpreting the results.

3.6. Summary of Section

Modeling volatility as conditional variance of asset returns, the preferred approach would be to use an extended multivariate GARCH model that allows for spillovers and threshold effects. The conditional variances in the extended MVGARCH model would be estimated as a system of equations. Estimating the conditional variances as a system of equations in a single step would potentially have gains in efficiency. Equations 3.1 through 3.5 describe the DCC model. In looking at the DCC model for the preferred approach, equation 3.1 would be modified to an extended version specified in equation 3.11. Spillovers in this model could be tested by a joint hypothesis test for the significance of the coefficients for δ_{12} and ω_{12}. Significant values for δ_{12} and ω_{12} indicate the existence of spillovers and threshold effects respectively. Due to the problem of non-convergence of parameter estimates, I use an alternative approach.

The methodology used in this study employs a two-step approach. In the first step I estimate the conditional variances of asset returns in different markets using either a GARCH or a DCC model. First, the assumption in using a GARCH model to generate the conditional variance is that the correlations are not time varying and there is no multivariate type effects. Secondly, I use the DCC model assuming that there is some multivariate type of effects or there are time varying correlations. The conditional variances generated in the first step are used to compute the threshold value, using a sequential grid search that maximizes the log likelihood function as described in section 3.3. The conditional variance estimation and threshold computation form the first step.

The conditional variance and threshold estimates generated in the first step are used to estimate the extended conditional variance specification in the second step. For a simple bivariate case, the second step where the conditional variance of one country is estimated; the conditional variance and threshold of the second country from which the direct and indirect spillover effects are measured, are allowed to affect the first countries conditional variance. There might be loss of some efficiency due to the two step procedure I employ, nevertheless the results are robust. There is a need for simulating critical values as the λ (threshold) parameter is unidentified under the specification of the null hypothesis. So I use Monte Carlo simulations to generate these critical values and employ them to test the significance of my likelihood ratio statistics. This adds potency to the methodology used in this study and the interpretation of results.

CHAPTER 4

DATA

I use daily time series data for the three markets (equity, bond, and foreign exchange) in this analysis of volatility spillover and threshold effects within each market. Equity data used ranges from 8/16/1995 to 11/12/2010. Bond data ranges from 3/31/1999 to 12/16/2010 with average maturity of 5 years. Foreign exchange data ranges from 1/4/1994 to 12/9/2010. In order to compute returns for each series, closing prices stated in local currency is used for various countries within each asset class and returns are calculated as

$$R_t = 100 \text{ x } (\log(P_t) \; - \; \log(P_{t-1})) \qquad (4.1)$$

where, P_t denotes the closing price of the index at time 't'. All the data are taken from DataStream International.

A frequently asked question in empirical research when it comes to data is, "why were the specific countries chosen?" or "why the specific time period?" or "why the particular periodicity?" The decisions made by the researchers in country selection, time period or periodicity selection has had little formal explanations. The existing explanations are mostly ad hoc, ranging from availability of data to funding for data to the hypotheses in question, etc. A helpful analysis by Kohn (1989) details four distinct approaches to country selection in studies involving cross country effects. The explanations he provides are as follows. First, based on the object of study, comparing fairly similar countries is useful. Second, based on the context of study, selecting countries to maximize diversity expands the scope or universality of inference. Third, he suggests selecting countries to capture diversity within a particular framework and fourth as part of a larger system, choose countries to maximize the range of the transnational system studied.

Based on the understanding from Kohn's approaches and the hypothesis being tested or questions being addressed in this study, I have selected countries fairly similar, making the study more useful, particularly to find regionally-based and within asset class findings. The time period selected is based on availability of data for a common time period for all countries. Daily data used in this study was done deliberately as opposed to using weekly or monthly data. The common criticism of using daily data is the noise associated with it. My deliberate effort to use daily data is because increased investments in multiple asset classes globally by active investors are likely to result in increased daily trading, price changes and volatility dynamics. Capturing these volatility dynamics is critical to this study and the strengths of using daily data outweigh the possible problems or short comings with them. The sections below discuss the data and statistics for each asset class.

4.1. Equity Market

For equity data, I have 3977 observations and there are a total of nine Asian country indices that have been used along with the US equity index. Figure 4.1 plots the prices of each equity index over time and Figure 4.2 plots the returns of each series over time. Returns on the Singapore and Malaysian equity market index have comparatively less fluctuation. Thailand, China, Hong Kong and India have greater fluctuation in returns as compared to the others. Table 4.1 shows the descriptive statistics of the equity index return data and Table 4.2 shows the correlation between the returns of various equity markets. The various markets and the specific indices that I have used are US (S&P 500 composite), China (SSE composite), India (BSE 100 National), Japan (TSE TOPIX Core 30), Singapore (SGX Titan 30 composite), Malaysia (Bursa KLCI Benchmark), Thailand (Bangkok SET 50 Benchmark), Taiwan (TSEC Benchmark), Hong Kong (Hang Seng HKEx composite) and Philippines (SE I PSEi Benchmark).

Table 4.1 shows that the average return over the entire time period for China was the highest (5.56%) in this sample, followed by India (4.83%). Japan has the lowest (-2.01%) average return. Japan (-2.01%) and Thailand (-0.87%), on average, have negative returns over this time period. All other countries examined have positive average returns. The median returns on seven of the nine Asian countries examined were 0.00%. India (3.27%) has a higher median return than China (1.48%). Interestingly, the highest return over the period of study was produced by Malaysia (20.82%) followed by Hong Kong (17.25%) and Philippines (16.18%) given the strong growth of the respective markets over the last decade. The lowest return as well was from Malaysia (-24.15%) followed by Thailand (-17.23%) and Hong Kong (-14.73%). Four of the nine countries examined have negative values for skewness, meaning the distribution of the return series have longer left tails whereas five of the nine series have distributions with longer right tails.

The Jarque-Bera test of normality results for each series shows values that are significant at the 1% level and rejection of the normality hypothesis. Each series used in this analysis has a non-normal distribution. Instead of using a likelihood function with a t-distribution, I use a likelihood function with Chi-Square distribution to mitigate this issue. The correlogram of the actual return series is shown in Table 4.1 as Q-statistics at lag 2 and 10. Except Hong Kong the Q-statistics of all other countries show no evidence of correlation over time. Taking the first difference of the series instead of using the level returns could solve this issue. The sample size of 3977 observations is fairly large to capture the volatility dynamics of each of these series. Table 4.2 shows the correlation between the returns from various equity markets. All the correlations in Table 4.2 are positive. Hong Kong and Singapore have the highest correlation (0.6645), while US and China have the lowest correlation (0.0066). The correlation of US with other Asian equity market seems to be lower than within the Asian markets indicating stronger regional relationships and moderate relationship with the US equity market. Most of the return correlations are greater than 0.2251. The predominant lower correlation values indicate the possibility of benefits to diversification across these markets. Singapore and Japan seem to have stronger correlation with other Asian countries in comparison to China or India which have had higher average growth rates in the last decade.

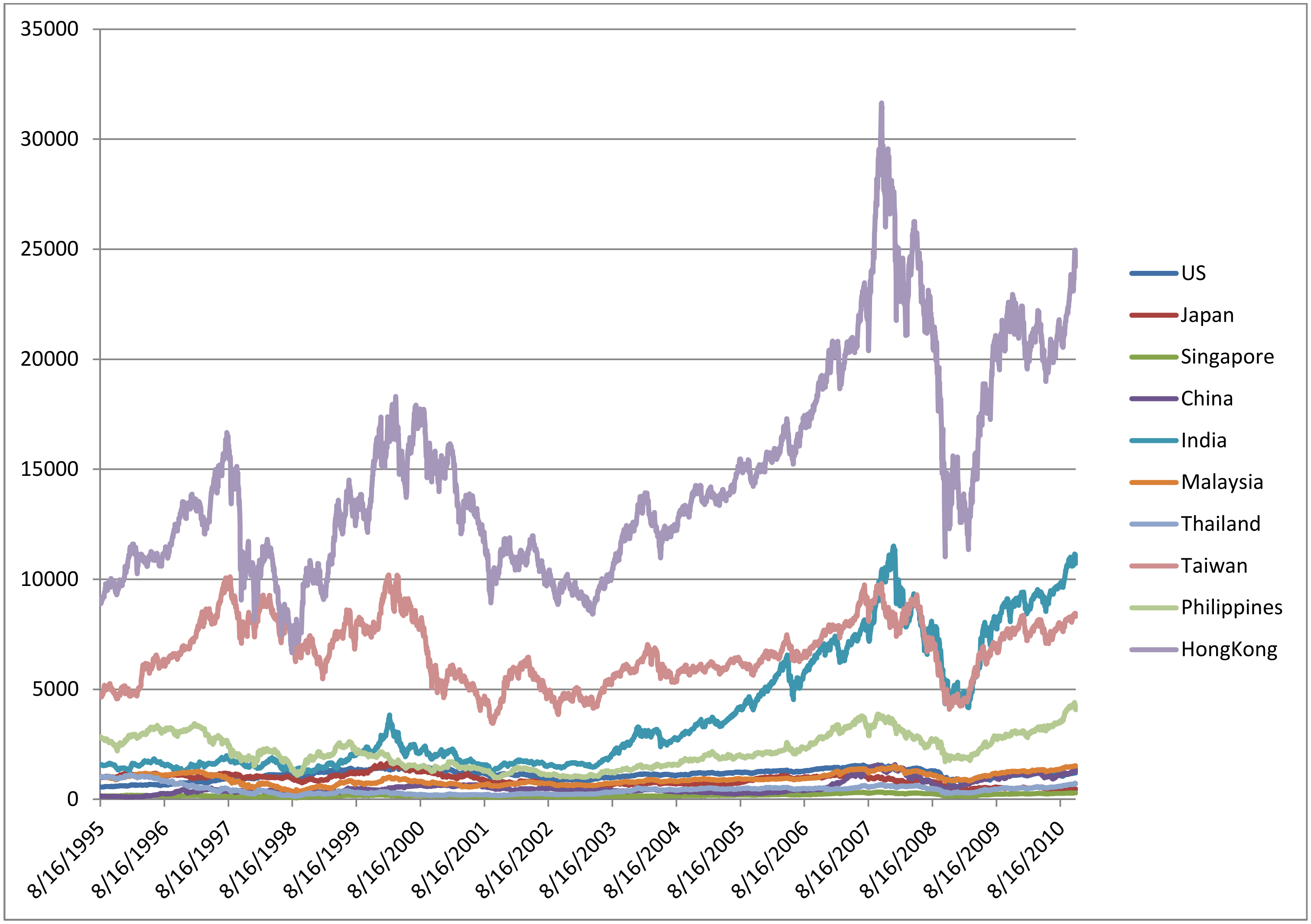

Figure 4.1 Prices of Equity Indices for Different Markets

The figure above displays equity index prices over time for different countries. The graphs use daily prices from 16 August, 1995 to 12 November, 2010.

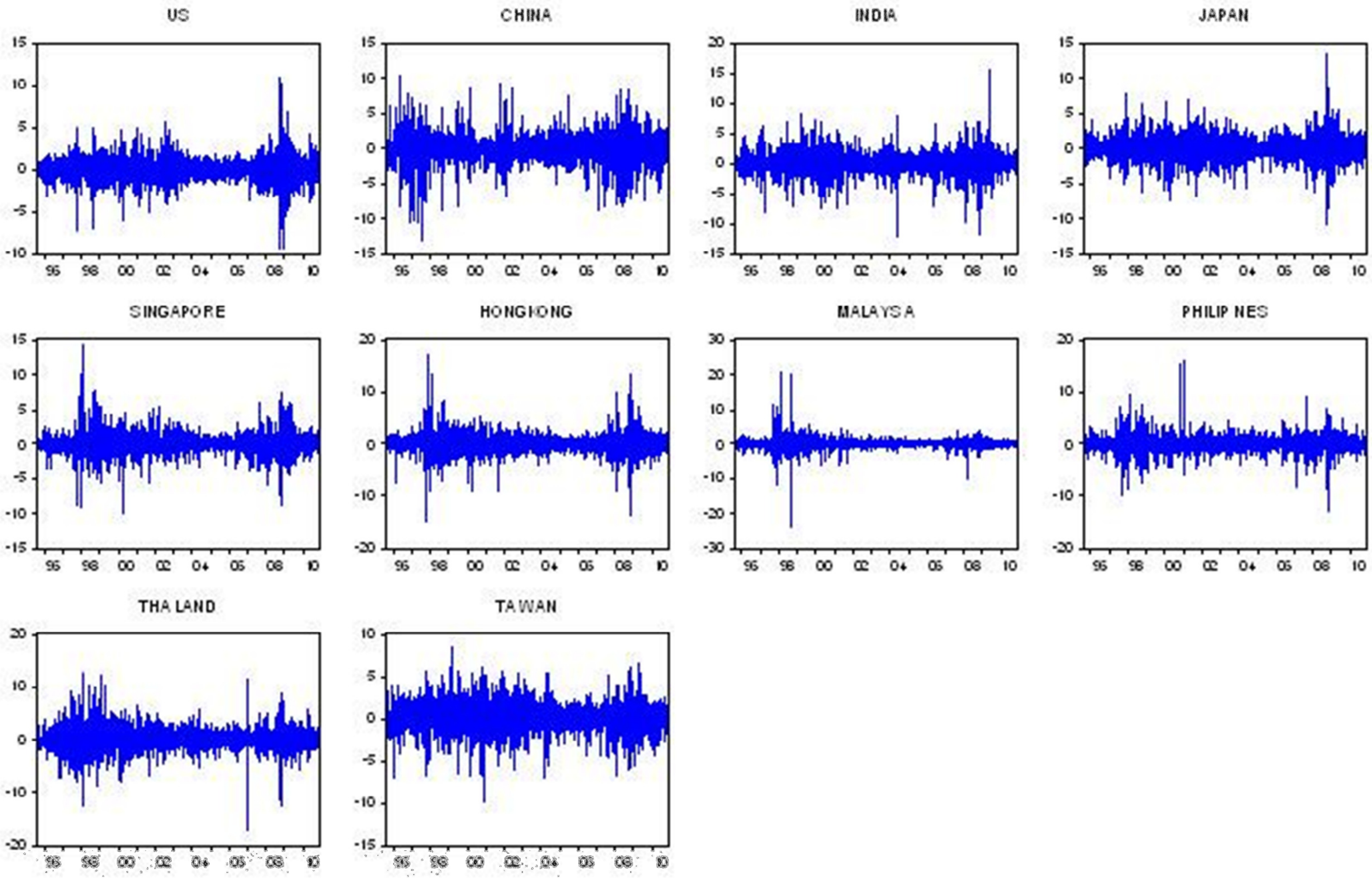

Figure 4.2 Returns of Equity Indices for Different Markets

The ten figures above display asset returns over time for different countries. The graphs use daily return data from 16 August, 1995 to 12 November, 2010.

Table 4.1 Descriptive Statistics for Equity Market Index Returns

	US	CHINA	INDIA	JAPAN	SINGAPORE	HONGKONG	MALAYSIA	PHILIPPINES	THAILAND	TAIWAN
Mean	0.0192	0.0556	0.0483	-0.0201	0.0176	0.0249	0.0095	0.0090	-0.0087	0.0139
Median	0.0286	0.0148	0.0327	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	10.9572	10.4742	15.4901	13.5290	14.4202	17.2471	20.8174	16.1776	12.5889	8.5198
Minimum	-9.4695	-13.0394	-11.9364	-10.7863	-10.0183	-14.7347	-24.1534	-13.0887	-17.2309	-9.9360
Std. Dev.	1.2761	1.8848	1.6966	1.5499	1.4258	1.7428	1.4530	1.4933	1.9581	1.5435
Skewness	-0.1916	-0.4893	-0.2387	-0.0868	0.1596	0.1079	0.4720	0.3219	0.2403	-0.1573
Kurtosis	10.9797	7.6348	8.5019	7.7005	10.8614	13.2744	54.5170	14.5358	9.7769	5.7101
Jarque-Bera	10575.78	3718.33	5053.87	3666.19	10257.79	17500.36	439937.50	22120.31	7648.55	1233.49
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	76.1580	221.0082	192.0946	-80.0082	69.8307	99.1716	37.7411	35.9624	-34.7083	55.1164
Sum Sq. Dev.	6474.90	14124.86	11445.01	9550.96	8082.44	12076.78	8394.03	8866.56	15244.31	9472.41
Q(2)	30.7750	6.3183	27.2260	13.5410	25.2250	2.9001	16.7260	103.7800	33.6980	9.0073
Probability	0.0000	0.0420	0.0000	0.0010	0.0000	0.2350	0.0000	0.0000	0.0000	0.0110
Q(10)	47.3760	46.6420	76.2180	34.0310	33.2670	15.2370	83.4330	120.6200	62.8280	35.3260
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.1240	0.0000	0.0000	0.0000	0.0000
Observations	3977	3977	3977	3977	3977	3977	3977	3977	3977	3977

The table above presents summary statistics on daily returns for the ten countries included in the empirical analysis: US represented by S&P 500 composite index, China represented by SSE composite index, India represented by BSE 100 National index, Japan represented by TSE TOPIX Core 30 index, Singapore represented by SGX Titan 30 composite index, Malaysia represented by Bursa KLCI Benchmark index, Thailand represented by Bangkok SET 50 Benchmark index, Taiwan represented by TSEC Benchmark index, Hong Kong represented by Hang Seng HKEx composite index and Philippines represented by SE I PSEi Benchmark index. The empirical analysis uses data for the period 16 August, 1995 – 12 November, 2010.

Table 4.2 Correlation Between Equity Market Index Returns

	US	CHINA	INDIA	JAPAN	SINGAPORE	HONGKONG	MALAYSIA	PHILIPPINES	THAILAND	TAIWAN
US	1									
CHINA	0.0066	1								
INDIA	0.1510	0.1021	1							
JAPAN	0.0973	0.1143	0.2417	1						
SINGAPORE	0.1786	0.1147	0.3666	0.4344	1					
HONGKONG	0.1754	0.1985	0.3652	0.4911	0.6645	1				
MALAYSIA	0.0181	0.0801	0.1651	0.2436	0.4122	0.3526	1			
PHILIPINES	0.0398	0.0778	0.1785	0.2868	0.3704	0.3649	0.2458	1		
THAILAND	0.1126	0.0982	0.2556	0.2699	0.4567	0.4120	0.3252	0.2931	1	
TAIWAN	0.0824	0.1094	0.2334	0.3412	0.3826	0.3784	0.2251	0.2412	0.2447	1

The table above presents coefficients of correlation in daily returns among the ten country equity indices during the period of the empirical analysis, 16 August, 1995 – 12 November, 2010.

4.2. Bond Market

Bond market data consists of 3056 observations, and there are a total of fourteen European country indices that have been used along with the US bond index. My focus on the European countries stems from the recent interest generated by the European debt crisis. Following studies done on volatility in bond indices (Christiansen 2007, Skintzi et al. 2006, and Dungey et al. 2006), the maturity of the bond indices chosen in this study is 5 years. Figure 4.3 shows the plot of bond index prices over time and Figure 4.4 shows the plots for the various return series over time. Returns generated from Switzerland, the Netherlands, Sweden, Italy, and Belgium bond market indices have comparatively less fluctuation in returns compared to Greece, Ireland, Spain, France, and Germany. Table 4.3 shows the descriptive statistics of the bond index return data and Table 4.4 shows the correlation between the returns. The European markets that I have used are Austria, Belgium, Denmark, France, Germany, Greece, Italy, Ireland, the Netherlands, Norway, Spain, Sweden, Switzerland and the UK. The set of European countries I have chosen are very similar to the one chosen by Baele (2005). DataStream International has its own benchmark index for each of these countries government bonds of five year maturity. Due to the unavailability of data for the 5 year maturity bond index for Portugal, I do not include it in the bond analysis.

Table 4.3 clearly shows that the average return over the entire time period for France to have the highest (0.35%) return followed by Germany (0.32%) and Greece to have the lowest (-1.28%) average return. Greece (-1.28%) is followed by Switzerland (-0.33%) with average returns being negative over this time period. The US on the other hand has a positive average return of 0.63% over this time period. Six of the fourteen European countries analyzed in this study have negative returns on average. The median returns on thirteen of the fourteen European countries examined were 0.00%. The US has a median 0.00% return and the only country with a positive median return is Italy (0.20%). Strikingly, the highest daily return over the period of study was produced by Greece (2716.57%), followed by Ireland (456.92%), and Spain (346.61%) as opposed to other countries, which have their highest daily return greater than 80%. This statistic of maximum return over the entire time period is interesting to note as Greece, Ireland, and Spain have been in the news recently about the possibility of default and requiring funds from the

European Monetary Union (EMU) and International Monetary Fund (IMF) to bail them out from the situation. Eight of the fourteen countries examined have produced daily returns greater than 100%. The lowest daily return was from Greece (-1237.71%), followed by Ireland (-252.08%), and Denmark (-138.19%). Eight of the fourteen countries examined have negative values for skewness meaning the distribution of the return series has longer left tails. The distribution of returns from Netherlands (-0.3003) is most skewed towards the left tail. Six of the fourteen series have distributions with longer right tails. The distribution of returns from Greece (19.2950) is most skewed towards the right tail.

The Jarque-Bera test of normality results for each series shows values that are significant at the 1% level and rejection of the normality hypothesis. Each series used in this analysis has a non-normal distribution. One way to deal with this is to use likelihood function with a Chi-Square distribution. Q-statistics are reported at the 2nd and 10th lags in Table 4.3. The Netherlands, France, Denmark and Austria have returns with correlation over time. Table 4.4 shows the correlation between the returns from various bond markets. All correlations in Table 4.4 are positive. The Netherlands and France have the highest correlation (0.9599) over the time period examined, while Greece and Norway have the lowest correlation (0.0030). Investors from French or the Netherlands markets looking to diversify in their respective countries might not have much benefit to diversification versus investors in Greece and Norway, who may have the maximum benefits to diversification by investing in each other's markets. The correlation between the US and European bond market is lower than within the European markets, indicating significantly stronger regional relationships and only a moderate relationship with the US bond market. The highest correlation the US bond market has with the European country bond markets are with the Netherlands (0.5246), France (0.5127), and Germany (0.5028). Most of the return correlations are greater than 0.2223. The Netherlands seems to be having the strongest correlation with other European country bond markets and its least correlation is with Greece (0.1552).

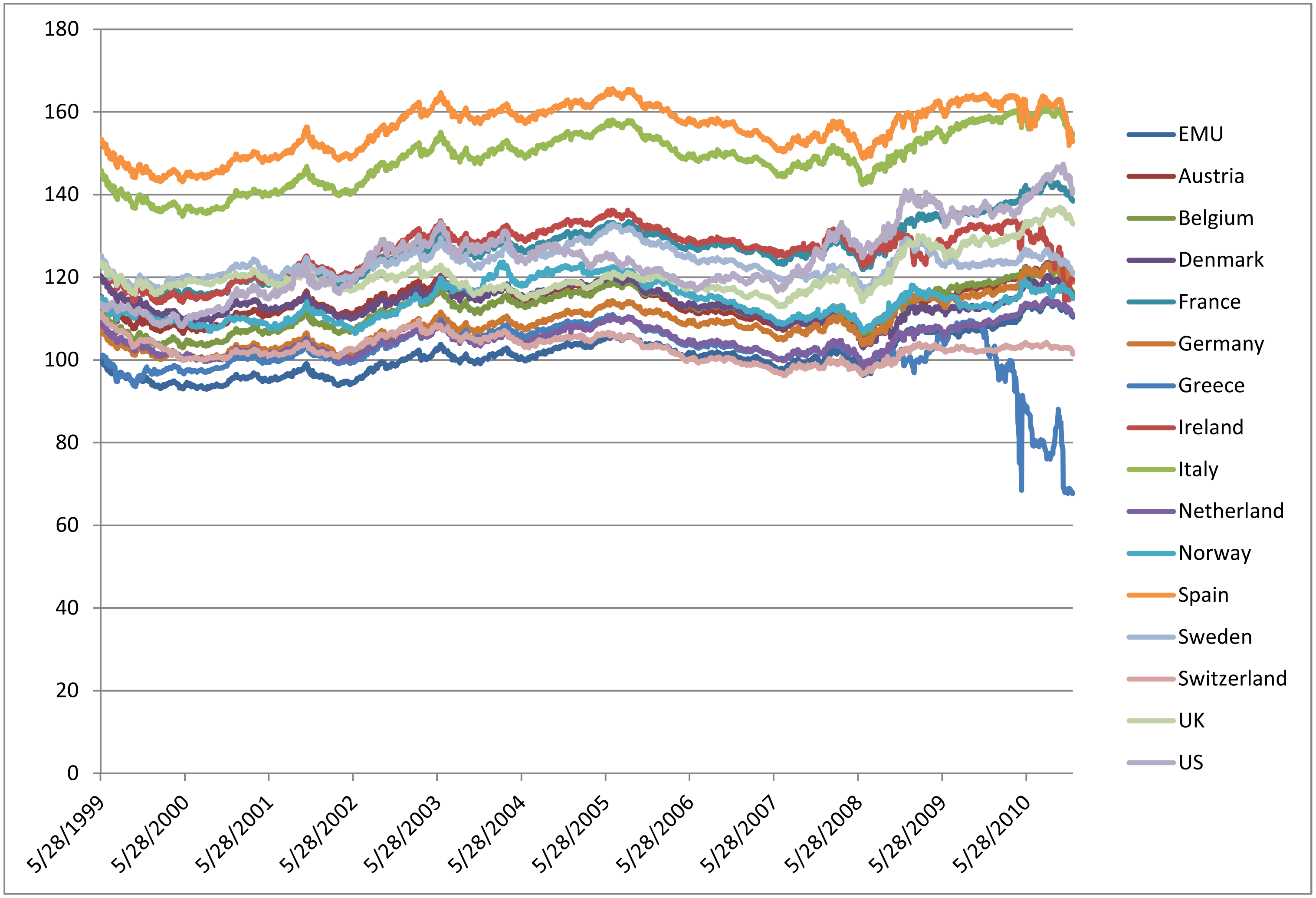

Figure 4.3 Prices of Bond Indices for Different Markets

The figure above displays bond index prices over time for different countries. The graphs use daily price data from 28 May, 1999 to 16 December, 2010.

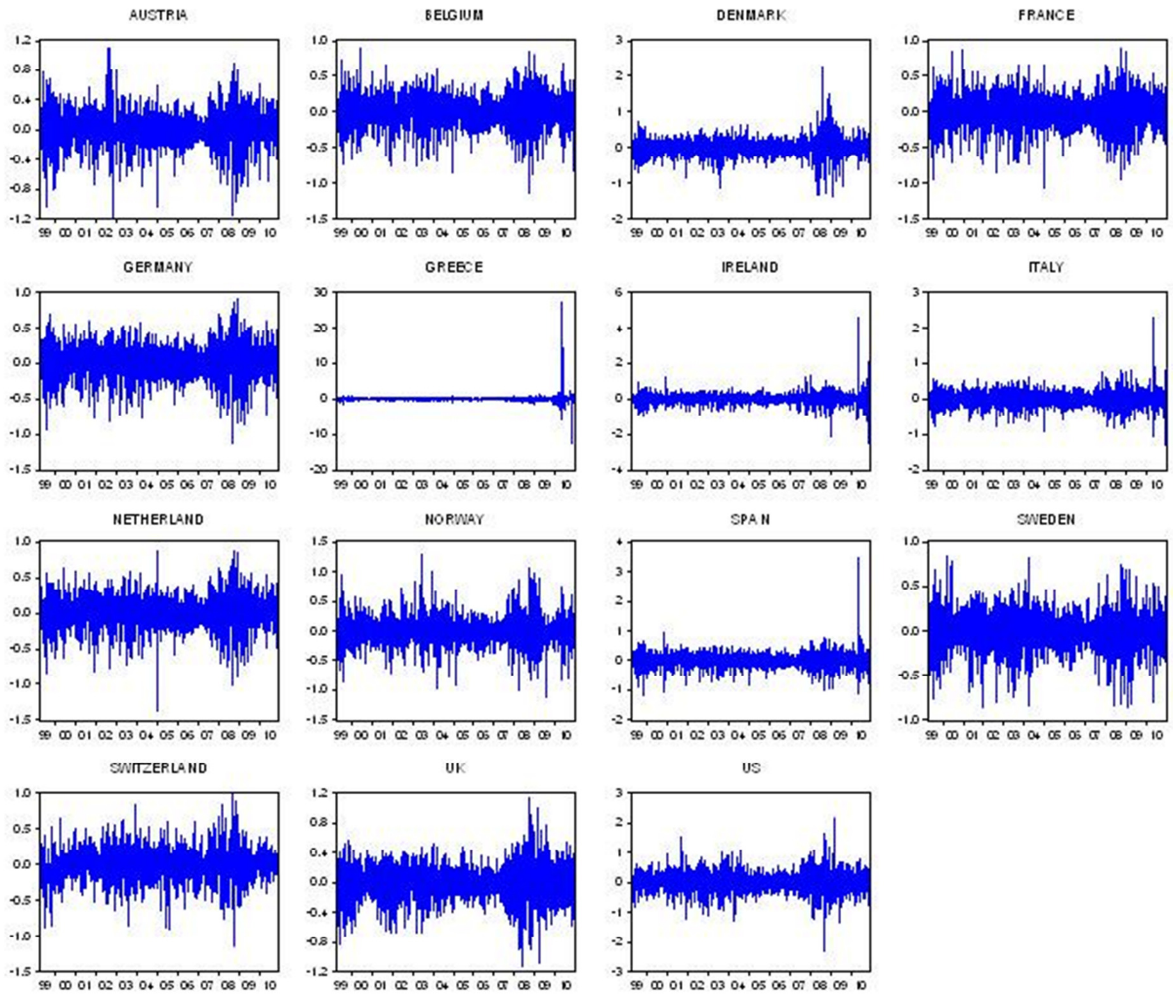

Figure 4.4 Returns of Bond Indices for Different Markets

The fifteen figures above display asset returns over time for different countries. The graphs use daily return data from 31 May, 1999 to 16 December, 2010.

Table 4.3 Descriptive Statistics for Bond Index Returns

	AUSTRIA	BELGIUM	DENMARK	FRANCE	GERMANY	GREECE	IRELAND	ITALY	NETHERLAND	NORWAY	SPAIN	SWEDEN	SWITZERLAND	UK	US
Mean	0.0009	0.0011	-0.0016	0.0035	0.0032	-0.0128	-0.0012	0.0019	0.0004	-0.0008	0.0001	-0.0017	-0.0033	0.0017	0.0063
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	1.0893	0.8922	2.2382	0.8886	0.9042	27.1657	4.5692	2.3032	0.8833	1.2789	3.4661	0.8319	0.9799	1.1270	2.1668
Minimum	-1.1681	-1.1415	-1.3819	-1.0621	-1.1364	-12.3771	-2.5208	-1.2920	-1.3731	-1.1173	-1.1966	-0.8568	-1.1398	-1.1363	-2.2966
Std. Dev.	0.2046	0.1990	0.2109	0.2039	0.2079	0.6681	0.2703	0.1999	0.1981	0.2022	0.2208	0.1930	0.1798	0.2044	0.3039
Skewness	-0.2515	-0.2916	0.0910	-0.2331	-0.2530	19.2950	1.2048	0.2136	-0.3003	0.1585	0.9499	-0.2004	-0.1207	-0.2497	-0.1093
Kurtosis	6.1931	4.9387	13.3881	4.8194	4.6740	943.8419	37.3182	10.7339	5.4031	6.9274	24.8885	4.8510	6.6517	5.3020	6.6098
Jarque-Bera	1330.51	521.92	13745.20	449.18	389.43	113000000.00	150704.80	7639.43	781.27	1976.86	61466.02	456.76	1705.38	706.50	1665.33
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	2.8792	3.3681	-4.9562	10.8069	9.7309	-39.0271	-3.5995	5.6557	1.2604	-2.5119	0.1924	-5.1782	-10.1147	5.0416	19.1727
Sum Sq. Dev.	127.89	121.04	135.87	126.99	132.09	1363.63	223.19	122.13	119.92	124.94	148.99	113.77	98.76	127.64	282.09
Q(2)	2.2318	9.4543	0.1626	3.0805	8.4323	10.5980	26.9610	22.7250	5.1872	27.5670	18.6500	27.0090	21.0060	15.4710	18.4470
Probability	0.3280	0.0090	0.9220	0.2140	0.0150	0.0050	0.0000	0.0000	0.0750	0.0000	0.0040	0.0000	0.0000	0.0000	0.0000
Q(10)	10.0200	18.1600	11.3350	7.6583	13.9630	205.1500	29.2280	34.8030	8.7148	42.0470	23.4220	33.7620	33.2500	23.0530	29.9780
Probability	0.4390	0.0520	0.3320	0.6620	0.1750	0.0000	0.0010	0.0000	0.5590	0.0000	0.0090	0.0000	0.0000	0.0110	0.0010
Observations	3056	3056	3056	3056	3056	3056	3056	3056	3056	3056	3056	3056	3056	3056	3056

The table above presents summary statistics on daily returns for the fifteen countries included in the empirical analysis. The bond indices chosen for this study are from DataStream International Benchmark indices and have average maturity of five years. The empirical analysis uses data for the period 31 March, 1999 – 16 December, 2010.

Table 4.4 Correlation Between Bond Index Returns

	AUSTRIA	BELGIUM	DENMARK	FRANCE	GERMANY	GREECE	IRELAND	ITALY	NETHERLAND	NORWAY	SPAIN	SWEDEN	SWITZERLAND	UK	US
AUSTRIA	1														
BELGIUM	0.8555	1													
DENMARK	0.4553	0.4455	1												
FRANCE	0.8305	0.8958	0.4593	1											
GERMANY	0.8844	0.8708	0.5188	0.8865	1										
GREECE	0.1920	0.2808	0.0386	0.1685	0.1319	1									
IRELAND	0.4683	0.5859	0.2416	0.5447	0.4510	0.4970	1								
ITALY	0.7296	0.8179	0.3985	0.7436	0.7268	0.4426	0.6248	1							
NETHERLAND	0.8448	0.9019	0.4513	0.9599	0.8872	0.1552	0.5475	0.7427	1						
NORWAY	0.4173	0.4323	0.4234	0.4862	0.4830	0.0030	0.2644	0.3638	0.4730	1					
SPAIN	0.7281	0.8185	0.3444	0.7211	0.7199	0.5033	0.6406	0.8411	0.7151	0.3105	1				
SWEDEN	0.6306	0.6616	0.5185	0.7171	0.7131	0.0600	0.3902	0.5445	0.7101	0.5097	0.5173	1			
SWITZERLAND	0.3424	0.3479	0.2947	0.3781	0.3972	0.0425	0.2260	0.3054	0.3686	0.2770	0.2732	0.3714	1		
UK	0.6197	0.6657	0.4156	0.7185	0.6956	0.1113	0.4347	0.5544	0.7230	0.4220	0.5391	0.5990	0.3509	1	
US	0.4560	0.4795	0.2481	0.5127	0.5028	0.0751	0.2744	0.3709	0.5246	0.2321	0.3758	0.4211	0.2223	0.4715	1

The table above presents coefficients of correlation in daily returns among the fifteen country bond indices during the period of the empirical analysis, 31 March, 1999 – 16 December, 2010.

4.3. Foreign Exchange Market

Foreign exchange market consists of 4417 observations and there are a total of eleven Asian country foreign exchange indices that have been used along with the US foreign exchange index. Figure 4.5 plots the prices of each series over time and Figure 4.6 plots returns of each series over time. Daily returns from the foreign exchange indices of Indonesia, Korea, Japan, Thailand, Philippines, and Malaysia are more volatile. Hong Kong, Singapore, China, and Taiwan have lower fluctuation in returns as evident from Figure 4.6. Table 4.5 shows the descriptive statistics of the foreign exchange index return data, and Table 4.6 shows the correlation between the returns. The Asian markets used in this study along with the US are China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand. The closing prices of the nominal trade weighted JP Morgan currency indices are used to compute returns for each series.

Table 4.5 shows that the average daily return over the entire time period is highest for Japan (0.85%), followed by China (0.73%), and Singapore (0.0048%). Indonesia (-3.36%) has the lowest average daily return followed by Philippines (-1.06%), and Korea (-0.76%). Eight of the eleven Asian foreign exchange markets examined have negative average daily return. The median daily returns on all the Asian countries examined were 0.00%. The US foreign exchange market also has a median 0.00% return. The highest daily return over the period of study was produced by Indonesia (2186.47%), followed by Korea (1972.57%), and the Philippines (1104.92%) as opposed to Hong Kong (92.95%), and China (143.97%). The lowest daily return was from Indonesia (-3242.67%), followed by Thailand (-1935.29%), and Korea (-1371.14%). Six of the eleven countries examined have negative values for skewness along with US, meaning the distribution of the return series have longer left tails versus five of the eleven series have distributions with longer right tails.

The Jarque-Bera test of normality results for each series shows values that are significant at the 1% level and rejection of the normality hypothesis. Each series used in our analysis has a non-normal distribution. I use a likelihood function with Chi-Square distribution to address this issue of non-normality. The Q-statistics at 2nd and 10th lags are shown in Table 4.5. The US and Japan have correlogram statistics that show evidence of correlation of returns over time. Table 4.6 shows the correlation between the returns from various exchange rate markets. Some of the correlations in Table 4.6 are negative, indicating potential for diversification benefits. The correlation between China and Hong Kong (0.9005) is the highest. The correlation of the US foreign exchange market with China (0.8260), and Hong Kong (0.8133) seem to be fairly strong in comparison to other Asian foreign exchange markets indicating the strong integration (most of the period, Hong Kong and China pegged their currencies to the US dollar) between US, China, and Hong Kong foreign exchange markets. The US market is negatively correlated with Japan (-0.1949), Korea (-0.1301), Indonesia (-0.0384), and Singapore (-0.0077). Nineteen of the correlation pairs have negative correlations. Japan has a negative correlation with every other country in this study over the time period under analysis. Given the negative correlations, investment risk could be significantly reduced by diversifying or hedging in these markets for this asset class. Japan and China have the most negative correlation (-0.4954), followed by Japan and Hong Kong (-0.4681). The correlation between the US and Asian foreign exchange market seems to be fairly strong.

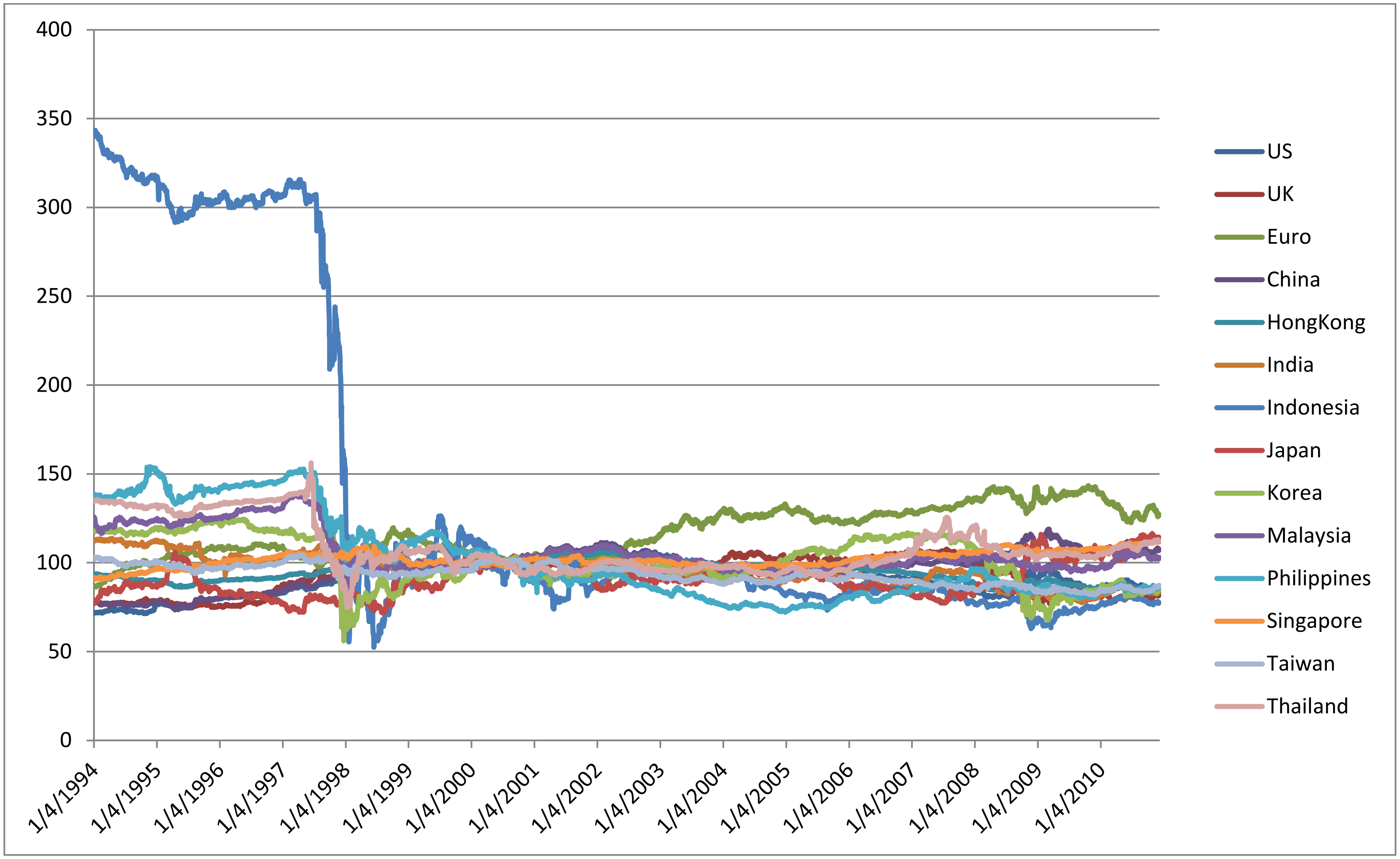

Figure 4.5 Prices of Foreign Exchange Indices for Different Markets

The figure above displays asset prices over time for different countries. The graphs use daily price data from 4 January, 1994 to 9 December, 2010.

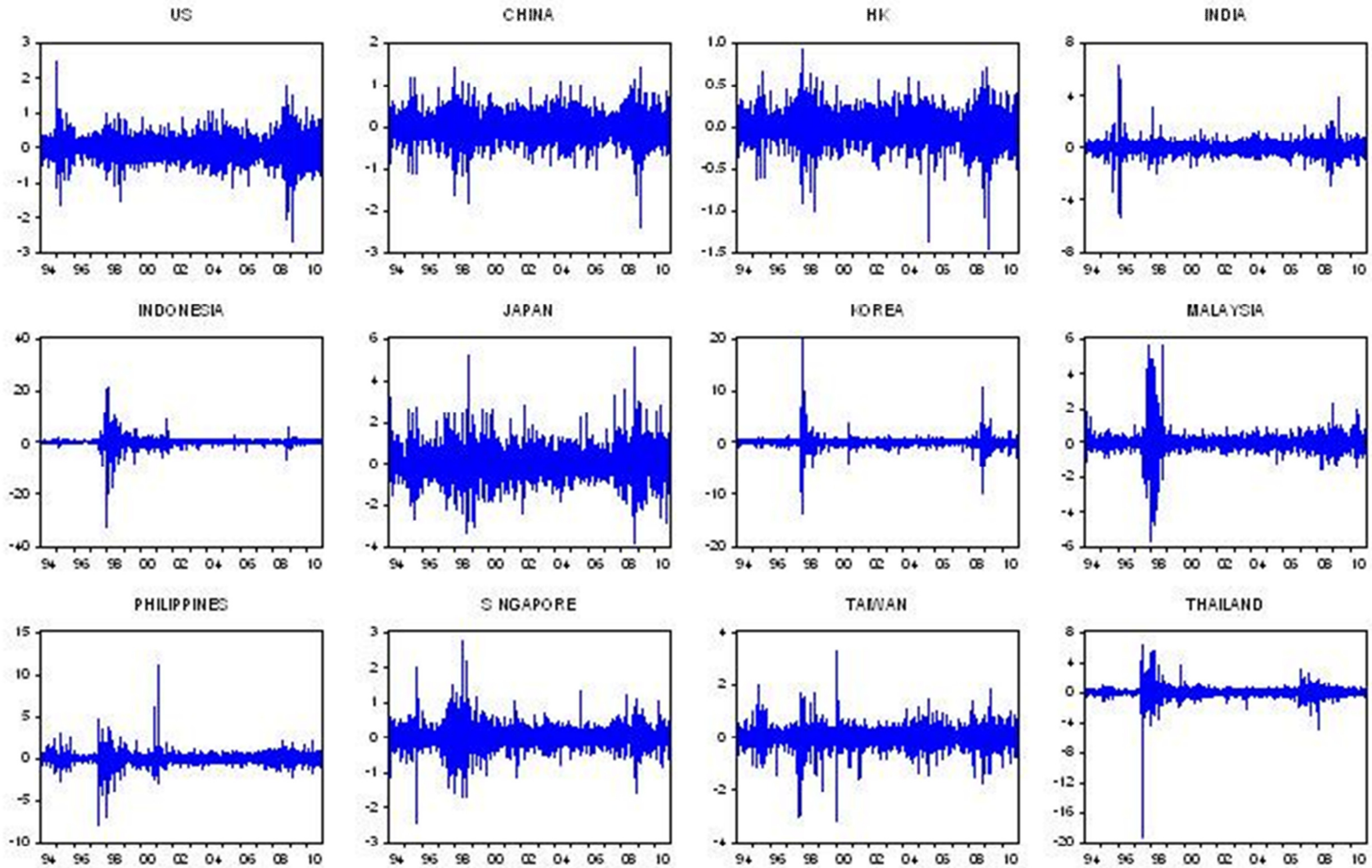

Figure 4.6 Returns of Foreign Exchange Indices for Different Markets

The twelve figures above display asset returns over time for different countries. The graphs use daily return data from 4 January, 1994 to 9 December, 2010.

Table 4.5 Descriptive Statistics for Foreign Exchange Index Returns

	US	CHINA	HONGKONG	INDIA	INDONESIA	JAPAN	KOREA	MALAYSIA	PHILIPPINES	SINGAPORE	TAIWAN	THAILAND
Mean	0.0037	0.0073	-0.0026	-0.0066	-0.0336	0.0085	-0.0076	-0.0045	-0.0106	0.0048	-0.0036	-0.0041
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	2.4958	1.4397	0.9295	6.3663	21.8641	5.6421	19.7257	5.6317	11.0492	2.7549	3.2930	6.2644
Minimum	-2.6863	-2.3754	-1.4583	-5.3422	-32.4267	-3.8211	-13.7114	-5.7109	-7.9242	-2.4734	-3.1930	-19.3529
Std. Dev.	0.3097	0.2874	0.1660	0.4389	1.5693	0.6751	0.9513	0.4867	0.5806	0.2690	0.3320	0.6438
Skewness	-0.0198	-0.2256	-0.4005	-0.0157	-2.4157	0.5472	0.6164	0.4803	0.4630	0.2231	-0.2811	-5.7325
Kurtosis	9.0059	6.4364	7.8578	36.4500	93.7170	8.1123	91.0574	37.5017	56.5439	14.4100	16.8843	201.4489
Jarque-Bera	6638.88	2210.81	4461.14	205924.60	1518882.00	5030.35	1427357.00	219247.10	527796.30	23996.44	35536.55	7272111.00
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	16.33	32.41	-11.55	-29.07	-148.41	37.68	-33.50	-19.75	-46.76	21.22	-15.93	-18.20
Sum Sq. Dev.	423.65	364.88	121.67	850.53	10875.88	2012.35	3996.58	1046.11	1488.71	319.50	486.89	1830.06
Q(2)	2.4076	12.0920	35.7200	75.0530	27.0870	0.2464	30.6080	20.2140	14.2510	68.3620	97.7900	13.5090
Probability	0.3000	0.0020	0.0000	0.0000	0.0000	0.8840	0.0000	0.0000	0.0010	0.0000	0.0000	0.0010
Q(10)	24.3400	37.1050	63.8850	96.2860	130.5600	14.3970	366.3100	89.6630	60.4420	112.2200	105.0400	68.7210
Probability	0.0070	0.0000	0.0000	0.0000	0.0000	0.1560	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	4417	4417	4417	4417	4417	4417	4417	4417	4417	4417	4417	4417

The table above presents summary statistics on daily returns for the twelve countries included in the empirical analysis. The closing prices of the nominal trade weighted JP Morgan currency indices were used to compute returns. The empirical analysis uses data for the period, 4 January, 1994 – 9 December, 2010.

Table 4.6 Correlation Between Foreign Exchange Index Returns

	US	CHINA	HONGKONG	INDIA	INDONESIA	JAPAN	KOREA	MALAYSIA	PHILIPPINES	SINGAPORE	TAIWAN	THAILAND
US	1											
CHINA	0.8260	1										
HONGKONG	0.8133	0.9005	1									
INDIA	0.3506	0.4073	0.3565	1								
INDONESIA	-0.0384	-0.0701	-0.0929	0.0019	1							
JAPAN	-0.1949	-0.4954	-0.4681	-0.2173	-0.1237	1						
KOREA	-0.1301	-0.1809	-0.1871	0.0837	0.0881	-0.3094	1					
MALAYSIA	0.1540	0.2114	0.1400	0.1718	0.3075	-0.3360	0.1062	1				
PHILIPPINES	0.1229	0.1784	0.1362	0.1842	0.1967	-0.2591	0.0586	0.2958	1			
SINGAPORE	-0.0077	0.0826	0.0082	0.0883	0.1955	-0.2018	-0.0022	0.2497	0.1249	1		
TAIWAN	0.3212	0.3711	0.3198	0.2973	0.0534	-0.4319	0.0944	0.2074	0.1918	0.1145	1	
THAILAND	0.0657	0.0914	0.0414	0.0779	0.2437	-0.1955	0.0578	0.2705	0.2167	0.1711	0.1215	1

The table above presents coefficients of correlation in daily returns among the twelve country, nominal trade weighted, foreign exchange indices during the period of the empirical analysis, 4 January, 1994 – 9 December, 2010.

4.4. Summary of Section

Data used in this study consists of 3977 observations for equity, 3056 observations for bond and 4417 observations for foreign exchange markets. The mean daily return is highest for the equity market (5.56%) returns followed by foreign exchange market (0.85%) and then the bond market (0.35%) returns. All the market returns and asset classes used have both positive and negative skewness indicating longer tails on both the right and left side. The Jarque-Bera test for normality yielded results in which the normality hypothesis was rejected in every single case. I handle this issue by using likelihood function with Chi-Square distribution. The bond market returns have the highest correlation (0.9599) between the Netherlands and France, followed by the foreign exchange market (0.9005) between China and Hong Kong, and last the equity market correlation (0.6645) between Singapore and Hong Kong. The only asset class with negative correlations for the time period examined was the foreign exchange market returns, indicating maximum potential benefits for diversification. Within the foreign exchange markets, Japan is the only country that has negative correlations with all other countries being examined. All the country pairs across all the asset classes seem to be integrated with diverse range of integration adding validity and strength to the hypothesis in this study.

CHAPTER 5

RESULTS

The purpose of this section is to provide estimation results and make inference regarding direct volatility spillover effects and indirect threshold effects within three different asset classes. A two-step estimation method is used in this study. In the first stage, conditional variances are generated using a GARCH (1, 1) model. In using the GARCH model the underlying implicit assumption is that there is no existence of time varying correlation structure in the conditional variance of returns for the various assets examined. The parameters of the model are estimated by the numerical maximization of the above discussed likelihood function in the methodology section. In the second stage of the estimation the conditional variance values from the first stage are used to verify the different hypothesis tests. The various hypotheses are stated below.

Hypothesis 1: There are no volatility spillovers and no threshold effects.

$$\begin{aligned} &H_0 : \delta_{12} = \omega_{12} = 0 \\ &H_A : \delta_{12} \neq 0 or \omega_{12} \neq 0 \end{aligned} \tag{5.1}$$

Hypothesis 2: There are no volatility spillover effects conditional on no threshold effect.

$$\begin{aligned} &H_0 : \delta_{12} = 0 \mid \omega_{12} = 0 \\ &H_A : \delta_{12} \neq 0 \end{aligned} \tag{5.2}$$

Hypothesis 3: There are no threshold effects conditional on no volatility spillovers.

$$\begin{aligned} &H_0 : \omega_{12} = 0 \mid \delta_{12} \neq 0 \\ &H_A : \omega_{12} \neq 0 \end{aligned} \tag{5.3}$$

The conditional variances of the asset returns, estimated in the first step are treated as observed data in the second step and used to estimate the parameters of the modified conditional variance specification as below.

$$h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{\hat{h}_{22t-1} \geq \lambda\}}h_{22t-1} \tag{5.4}$$

Estimation of equation 5.4 is conducted using two country pairs due to computational challenges encountered in estimating a framework with more than two countries. The modified conditional variance in the second stage allows for spillovers and threshold effects of the second country to affect the conditional variance equation of the first country. The DCC (1, 1) model is also used to generate the conditional variance in the first stage. Using the DCC in the first stage relaxes that assumption in the GARCH framework and allows for time varying correlations in the conditional variance equation. If the conditional variance in the first stage is specified as a DCC process then an extended DCC framework has to be used in the second stage as well. Using a GARCH framework in the second stage may result in model misspecification. I am aware of this and hence do not place emphasis on these results. Nevertheless the estimated results allowing for time varying correlations in the first stage are shown to verify if they alter the robustness of the GARCH (1,1) model results. This section is structured as follows; sections 5.1 and 5.4 discusses results of equity markets; section 5.2 and 5.5 discusses results of bond markets; section 5.3 and 5.6 discusses results of foreign exchange markets; and finally section 5.7 summarizes all the research findings in the various asset classes examined in this study.

5.1. Volatility Spillovers in Equity Markets – First Stage GARCH (1, 1)

Figure 5.1 shows the fluctuation of the conditional standard deviations over time for each of the countries used in this study of the equity market. On examining the plots of conditional standard deviation in figure 5.1, it can be seen that China and India show greater variation as compared to other countries. Table 5.1 shows the estimation results for the various hypotheses tested and the actual coefficient estimates for the extended conditional variance equation that is used in this study. The conventional p-values associated with the likelihood ratio test statistics as well as the simulated critical p-values are listed along with the estimation results, strengthening the inference. Panel A in Table 5.1 shows results of the hypothesis test in which the direct spillover and indirect threshold from US to the South East (SE) Asian equity markets are measured. Drawing on the existing literature by Ng (2000), Audrino and Trojani (2006), Worthington and Higgs (2004), Chiang et al. (2007), etc., the list of SE Asian countries was determined. Panels B through F similarly show results of the hypothesis test, measuring spillovers and threshold effects in conditional variance from Japan, Thailand, Singapore, China and Indian equity markets to other equity markets as depicted respectively.

The bootstrapped p-values are listed below the conventional p-values. Analyzing the results using the bootstrapped critical values is necessary since the underlying distribution of the conditional variance is not known under the null hypothesis. In fact greater trust can be placed on the results when bootstrapped p-values are used to test hypothesis. Since I use the simulated critical p-values instead of the conventional p-values, I choose a 10% significance level for analyzing the results of my estimation. Panel A in Table 5.1 shows rejection of the null hypothesis of no volatility spillovers and no threshold effects (hypothesis 1) for US-China, US-Japan, US-Philippines, US-Thailand US-Malaysia and US-Taiwan country pairs. This evidence establishes the point that including these indirect threshold effects while estimating volatility spillovers are important. Estimating the conditional variance of an assets return without including the threshold as an explanatory variable would then yield incorrect results.

The test of hypothesis 2 shows results that reject the null hypothesis of no volatility spillovers conditional on no threshold effects from US to SE Asian equity markets except for India, Hong Kong and Thailand. The test of hypothesis 3 produces results, where the null hypothesis of the existence of no threshold effects conditional on no spillover effects is rejected for US-Philippines and US-Thailand country pairs. Based on the results of hypothesis 3, for 2 of the 9 bivariate cases examined in Panel A, there seems to be some form of significant threshold effects that explain the conditional variance. Though this evidence is weak, nevertheless, there is evidence of existence of threshold effects in the conditional variance of an asset. The volatility spillover coefficients are all positive in Panel A except for US-China and US-Thailand. Though I would expect volatility spillovers as well as threshold effects to be positive, certain studies have shown the existence of negative spillovers from US to China and Thailand because of the highly segmented markets in China and the East Asian financial crisis in Thailand.

Lardy (1998) and Chan et al. (1992) show evidence in favor of market segmentation of the Asian markets. They state that when financial markets are segmented, risk does not transmit as much across markets. At high levels of volatility in US equity market, what I call exceeding the threshold; the volatility in Asian equity markets are affected negatively except for China, India, Hong Kong and Thailand. This is evident from the ω_{12} coefficients in Panel A, Table 5.1. From δ_{12} and ω_{12} for model 1 in Panel A, it can also be inferred that, when the volatility in the US market increases, volatility in Indian market increases and when volatility in US equity market increases beyond a threshold value, volatility in Indian equity market increases even greater. In the case of China and Thailand, as the US equity market volatility increases, the volatility in Chinese and Thai equity markets decrease and only when the volatility in US equity market increases beyond the threshold, the volatility in Chinese and Thai equity markets increase. The results for Hong Kong and India are not significant though and any inferences on the spillover and threshold effects for these markets are not meaningful.

An examination of Panel B in Table 5.1 shows that hypothesis 1 is rejected for all country pairs where spillovers are measured from Japan to China, Malaysia and Philippines respectively. For the country pairs examined in Panel B, since hypothesis 1 is rejected for some of the cases, if not all, it becomes important that I don't disregard this effect and can still infer that conditional variance spillovers from Japan to other equity markets studied might have both, significant volatility spillovers as well as significant threshold effects. Test of hypothesis 2 yields results where the hypothesis for existence of no spillovers given no threshold effects is rejected for five of the nine country pairs. Test of hypothesis 3 yields results in Panel B that reject the hypothesis for none of the country pairs, indicating non-existence of threshold effects. Though these results suggest that only direct volatility spillovers exist and indirect threshold effects do not affect the results, looking at the test of hypothesis 1 results, some weak evidence for threshold effects exist. It might be the case that spillovers from Japan to other SE Asian markets do not have a significant threshold component in the conditional variance of asset returns.

Panel B in Table 5.1 shows sign reversal for model 1 coefficient estimates in all country pairs. The volatility spillovers from Japan to China and Thailand are negative and their corresponding threshold effects are positive, meaning when volatility in Japanese equity market increases beyond a threshold value, the volatility in Chinese and Thai equity markets increases and otherwise it decreases. Model 2 coefficient estimates in Panel B show that volatility spillovers are mostly positive except for Japan-China and Japan-Thailand. Model 3 shows the coefficient for the threshold variable when the volatility spillover variable is omitted. So in using volatility, only when it exceeds a threshold the spillovers are positive except for Japan-Hong Kong, and Japan-US.

Hypothesis 1 results in Panel C show that rejection of the null of no spillover and no threshold effects in eight out of nine country pairs examined. Hypothesis 2 results in Panel C are rejected for five out of nine pairs examined. Strikingly hypothesis 3 results in Panel C show rejection of the null in eight country pairs examined, adding strength to the argument of the existence of threshold effects in the conditional variance specification. The only country pair where hypothesis 3 is insignificant is Thailand-China pair. The reason for this insignificance may be market segmentation as Lardy (1998) and Chan et al. (1992) state. Panel C also shows sign reversal in all cases. For the spillover from Thailand to China; coefficient ω_{12} is positive implying that, when the volatility exceeds the threshold level in Thailand market, there is positive increase in volatility of the Chinese market. Since this country pair is insignificant, it might not be meaningful to interpret these sign changes and the underlying effects on volatility. For other cases in panel C, $\omega_{12} < 0$, implies a reduction in the volatility of equities when the volatility of Thailand equities market exceeds a threshold. This is important evidence for opportunities available in Thai equities market for diversification of investment. Another reason for this negative spillover may be that investors are hedging their risk. These reasons are stated by Bhar and Nikola (2009), Persand et al. (2002) and Yang and Lien (2008).

In Panel D, where spillover and threshold effects are measured from Singapore, hypothesis 1 is rejected in eight country pairs examined and hypothesis 3 of no threshold effect conditional on no volatility spillover is rejected in six country pairs. On the other hand hypothesis 2 is rejected in five out of nine cases examined. Panel D shows positive spillover and negative threshold effect in all cases except Singapore-China and Singapore-Thailand.

Panel E results, which measure spillover and threshold effects from China, are very similar to Panel D results from Singapore. Hypothesis 1 and 3 are rejected in six and five pairs respectively, in Panel E. Hypothesis 2 is rejected three out of nine times in the same panel. The results in Panel E for the Chinese market are mixed and no clear inference can be made about them. Again the reason attributed for this is the segmentation of the Chinese market that restricts the magnitude of risk that could potentially spillover. Panel F results, which measure spillover and threshold effects from India are very similar to Panel E and D results from China and Singapore respectively. Hypothesis 1 and 3 are rejected in six and five country pairs examined respectively. Hypothesis 2 is rejected in six out of nine country pairs in Panel F. The coefficient values in Panel F show that spillover and threshold effects from Indian equity markets, has the most consistent pattern in terms of sign change. All the spillovers are positive and threshold effects are negative. Increase in volatility beyond the threshold in Indian equity markets results in a decrease in volatility on the other markets being examined. The reason for the negative coefficient is the available opportunities for diversification in other markets.

Additionally, the volatility may have two components; market component and country specific component. If the increase in volatility is due to the country specific component, then, it is less likely to affect volatility in other markets in which spillovers and threshold effects are being measured. An inference from examining all the panels in Table 5.1; hypothesis 1 and hypothesis 3 are rejected in most of the cases for panels representing US, Thailand, Singapore, China and India. This is evidence of the existence of threshold effects and that it cannot be ignored in a study of volatility spillovers. Though the spillover from regionally developed Japan financial equity market (Panel B) has the least evidence supporting the hypothesis of threshold effects, there exists some weak evidence which cannot be discarded. The lesser developed countries seem to exhibit threshold effects much stronger than the developed countries in all the cases examined. On comparing the coefficients in model 1, for most of the cases examined, there is a positive sign for δ_{12} and a negative sign for ω_{12}. This is clearer in panels representing Japan, Thailand, Singapore and India. Panel A and E, which shows the coefficients of spillover and threshold from US and Chinese equity markets, does have a sign reversal in terms of spillovers and threshold values for the most pairs, indicating a change in behavior at levels of volatility that exceed the threshold. The threshold value, though difficult to make an exact quantitative inference is listed in all the Panels of Table 5.1.

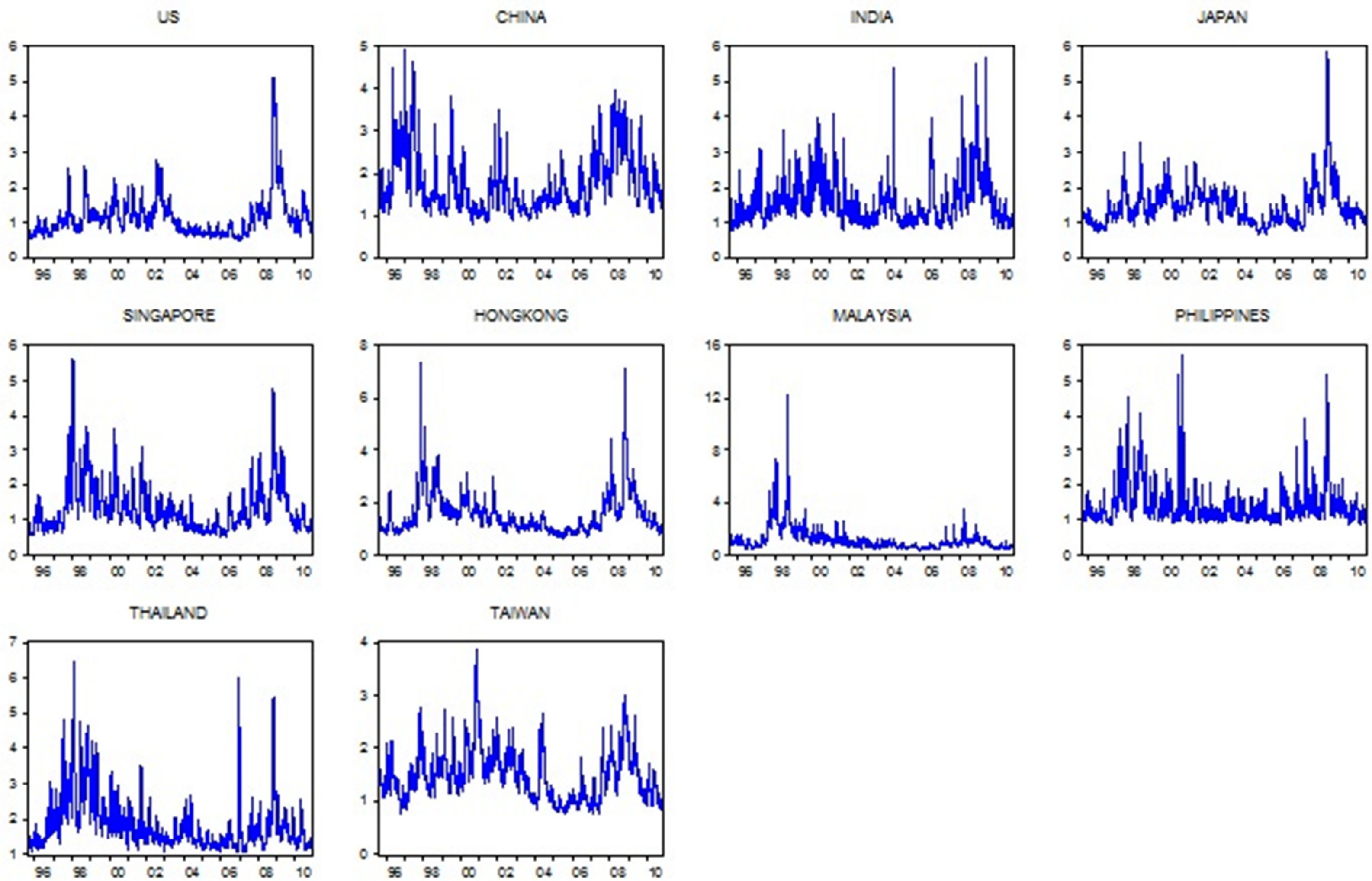

Figure 5.1 Conditional Standard Deviation of Equity Index Returns

The ten figures above display the conditional variance of asset returns over time for different countries. The graphs use daily return data from 16 August, 1995 to 12 November, 2010.

Table 5.1 Estimation Results and Coefficient Estimates of Conditional Variance Estimation for Equity Markets – GARCH (1, 1)

Panel A:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
US → China	13.17	7.85	5.33	0.0014	0.0051	0.0210	-0.0100	0.0212	15.8405	1.08	-0.0071	-0.0058
				0.0405	0.0109	0.3981						
US → Hong Kong	1.84	0.58	1.26	0.3981	0.4448	0.2620	0.0031	0.6051	23.7668	0.10	0.0034	0.6085
				0.9654	0.4962	0.9698						
US → India	4.23	3.12	1.11	0.1206	0.0771	0.2929	0.0096	0.6054	23.7668	0.10	0.0103	0.0104
				0.7166	0.1183	0.9778						
US → Japan	27.93	21.14	6.79	0.0000	0.0000	0.0092	0.0383	-0.0544	14.5195	1.16	0.0360	0.0112
				0.0002	0.0001	0.2412						
US → Malaysia	10.95	4.16	6.79	0.0042	0.0414	0.0092	0.0098	-0.0082	0.5164	81.64	0.0026	0.0011
				0.0960	0.0692	0.2421						
US → Philippines	98.92	54.75	44.17	0.0000	0.0000	0.0000	0.1236	-0.0935	0.2522	99.97	0.0578	0.0262
				0.0000	0.0000	0.0000						
US → Singapore	8.44	7.04	1.40	0.0147	0.0080	0.2360	0.0159	-0.0142	11.0848	1.48	0.0136	0.0071
				0.2339	0.0169	0.9595						
US → Thailand	18.70	0.07	18.63	0.0001	0.7949	0.0000	-0.0370	0.0418	1.0448	49.59	-0.0013	0.0360
				0.0041	0.7745	0.0015						
US → Taiwan	12.15	5.76	6.39	0.0023	0.0164	0.0115	0.0340	-0.0228	0.2522	99.97	0.0110	0.0041
				0.0610	0.0312	0.2797						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.1 - continued

Panel B:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Japan → China	12.51	3.91	8.60	0.0019	0.0479	0.0034	-0.0135	0.0147	1.4120	57.20	-0.0043	0.0102
				0.0529	0.0783	0.1213						
Japan → Hong Kong	4.36	2.30	2.05	0.1133	0.1290	0.1520	0.0065	-0.0135	1.4120	57.20	0.0059	-0.0108
				0.7003	0.1821	0.8940						
Japan → India	9.03	7.30	1.73	0.0109	0.0069	0.1884	0.0163	-0.0138	1.4120	57.20	0.0129	0.0142
				0.1912	0.0150	0.9297						
Japan → Malaysia	11.73	6.32	5.42	0.0028	0.0120	0.0200	0.0043	-0.0096	18.9903	0.70	0.0032	0.0039
				0.0700	0.0240	0.3875						
Japan →Philippines	17.68	15.19	2.49	0.0001	0.0001	0.1148	0.0276	-0.0148	0.5749	90.75	0.0197	0.0286
				0.0065	0.0004	0.8352						
Japan → Singapore	9.60	7.21	2.39	0.0082	0.0073	0.1218	0.0097	-0.1187	34.4759	0.33	0.0092	0.0136
				0.1552	0.0156	0.8485						
Japan → Thailand	3.74	0.30	3.45	0.1540	0.5862	0.0634	-0.0087	0.0221	3.5046	16.92	-0.0028	0.0174
				0.7814	0.6161	0.6802						
Japan → Taiwan	4.80	1.38	3.42	0.0906	0.2397	0.0644	0.0094	-0.0087	0.1564	99.97	0.0033	0.0053
				0.6378	0.3009	0.6836						
Japan → US	6.22	2.55	3.66	0.0447	0.1100	0.0557	0.0043	-0.0149	5.1787	7.09	0.0037	-0.0117
				0.4537	0.1583	0.6444						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.1 - continued

Panel C:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Thailand → China	4.25	0.36	3.89	0.1196	0.5513	0.0485	-0.0098	0.0083	1.1108	99.97	-0.0007	-0.0025
				0.7153	0.5858	0.6073						
Thailand → Hong Kong	15.92	5.37	10.55	0.0003	0.0204	0.0012	0.0043	-0.3647	37.9009	0.05	0.0042	-0.3467
				0.0129	0.0381	0.0540						
Thailand → India	51.05	27.93	23.12	0.0000	0.0000	0.0000	0.0263	-0.0296	11.8585	3.80	0.0150	0.0076
				0.0000	0.0000	0.0003						
Thailand → Japan	56.80	2.20	54.60	0.0000	0.1380	0.0000	0.0071	-0.0108	10.6183	4.98	0.0018	-0.0103
				0.0000	0.1922	0.0000						
Thailand → Malaysia	59.16	16.21	42.96	0.0000	0.0001	0.0000	0.0041	-0.0196	25.0864	0.48	0.0049	-0.8097
				0.0000	0.0003	0.0000						
Thailand →Philippines	101.89	57.47	44.42	0.0000	0.0000	0.0000	0.0528	-0.0598	23.0195	0.73	0.0530	0.0151
				0.0000	0.0000	0.0000						
Thailand →Singapore	46.77	6.10	40.67	0.0000	0.0135	0.0000	0.0026	-0.0207	27.5666	0.35	0.0032	-0.4603
				0.0000	0.0264	0.0000						
Thailand →Taiwan	15.35	3.15	12.20	0.0005	0.0759	0.0005	0.0076	-0.0080	7.3114	9.76	0.0021	-0.0093
				0.0161	0.1166	0.0264						
Thailand → US	43.67	0.00	43.67	0.0000	0.9646	0.0000	0.0009	-0.0061	27.1532	0.38	0.0000	-0.0037
				0.0000	0.8548	0.0000						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$

Table 5.1 - continued

Panel D:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Singapore → China	11.19	4.27	6.93	0.0037	0.0389	0.0085	-0.0013	-0.1003	28.4403	0.08	-0.0030	-0.1077
				0.0871	0.0656	0.2301						
Singapore → Hong Kong	8.82	1.37	7.45	0.0122	0.2416	0.0064	0.0151	-0.0226	2.1467	29.04	0.0089	-0.0172
				0.2058	0.3025	0.1881						
Singapore → India	74.04	27.83	46.21	0.0000	0.0000	0.0000	0.0425	-0.0607	15.1351	0.98	0.0297	0.0228
				0.0000	0.0000	0.0000						
Singapore → Japan	50.75	0.91	49.84	0.0000	0.3403	0.0000	0.0062	-0.0162	14.1847	1.08	0.0030	-0.0128
				0.0000	0.4015	0.0000						
Singapore → Malaysia	41.60	15.40	26.20	0.0000	0.0001	0.0000	0.0118	4.0147	28.4403	0.08	0.0110	2.8128
				0.0000	0.0003	0.0001						
Singapore →Philippines	159.83	140.07	19.76	0.0000	0.0000	0.0000	0.1549	-0.0887	1.1963	53.53	0.1316	0.0484
				0.0000	0.0000	0.0008						
Singapore → Thailand	20.41	16.00	4.41	0.0000	0.0001	0.0358	0.0386	1.2997	28.4403	0.08	0.0471	0.0350
				0.0019	0.0003	0.5253						
Singapore →Taiwan	11.43	0.75	10.68	0.0033	0.3858	0.0011	0.0201	-0.0187	0.2460	99.97	0.0022	-0.0379
				0.0801	0.4424	0.0512						
Singapore → US	18.73	0.01	18.72	0.0001	0.9200	0.0000	0.0113	-0.0124	2.1467	29.04	0.0001	-0.0236
				0.0041	0.8365	0.0014						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.1 - continued

Panel E:												
Country Pair	Like Ratio			P Value			Model 1				Model 2	Model 3
	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
China → Hong Kong	5.13	0.68	4.45	0.0771	0.4107	0.0349	-0.0075	0.0070	1.5963	73.85	0.0007	0.0009
				0.5941	0.4669	0.5196						
China → India	11.77	5.27	6.50	0.0028	0.0217	0.0108	0.0024	0.0998	21.6376	0.20	0.0039	0.1088
				0.0691	0.0400	0.2689						
China → Japan	4.75	0.63	4.12	0.0929	0.4271	0.0424	-0.0075	0.0069	2.0678	57.93	0.0007	0.0051
				0.6445	0.4793	0.5696						
China → Malaysia	11.81	1.92	9.90	0.0027	0.1661	0.0017	0.0024	-0.0031	7.4908	12.12	0.0007	0.0008
				0.0685	0.2238	0.0722						
China → Philippines	47.33	10.83	36.50	0.0000	0.0010	0.0000	-0.0025	-0.0190	21.6376	0.20	-0.0047	-0.0252
				0.0000	0.0032	0.0000						
China → Singapore	40.13	1.87	38.26	0.0000	0.1719	0.0000	0.0010	-0.0149	21.6376	0.20	0.0009	0.0011
				0.0000	0.2305	0.0000						
China → Thailand	13.13	0.01	13.12	0.0014	0.9269	0.0003	0.0363	-0.0303	1.3605	82.65	0.0002	0.0428
				0.0409	0.8548	0.0174						
China → Taiwan	4.49	1.44	3.05	0.1057	0.2295	0.0807	-0.0071	0.0069	1.5963	73.85	0.0010	0.0012
				0.6804	0.2899	0.7458						
China → US	18.20	5.85	12.34	0.0001	0.0155	0.0004	-0.0091	0.0086	1.1247	91.35	0.0014	0.0014
				0.0050	0.0294	0.0251						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$

Table 5.1 - continued

Panel F:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
India → China	5.39	1.11	4.28	0.0676	0.2927	0.0385	0.0116	-0.0123	0.5764	99.97	-0.0018	-0.0628
				0.5604	0.3539	0.5445						
India → Hong Kong	10.50	4.10	6.40	0.0052	0.0428	0.0114	0.0136	-0.0118	1.8930	53.33	0.0051	-0.0299
				0.1129	0.0711	0.2797						
India → Japan	25.66	7.05	18.61	0.0000	0.0079	0.0000	0.0093	-0.0311	15.0589	1.38	0.0067	-0.0668
				0.0003	0.0169	0.0015						
India → Malaysia	27.18	12.87	14.31	0.0000	0.0003	0.0002	0.0054	-0.0145	15.7171	1.18	0.0036	0.0032
				0.0002	0.0011	0.0103						
India → Philippines	100.15	42.97	57.18	0.0000	0.0000	0.0000	0.0758	-0.0589	1.5638	63.11	0.0320	0.0115
				0.0000	0.0000	0.0000						
India → Singapore	49.85	5.80	44.05	0.0000	0.0160	0.0000	0.0104	-0.0220	8.4759	5.56	0.0058	-0.0191
				0.0000	0.0301	0.0000						
India → Thailand	67.94	3.16	64.78	0.0000	0.0753	0.0000	0.1108	-0.0944	0.9056	90.47	0.0135	-0.0054
				0.0000	0.1161	0.0000						
India → Taiwan	12.51	4.75	7.77	0.0019	0.0293	0.0053	0.0154	-0.0127	0.9056	90.47	0.0040	-0.0683
				0.0528	0.0512	0.1659						
India → US	8.06	2.51	5.56	0.0177	0.1134	0.0184	0.0037	-0.0284	26.9081	0.18	0.0018	0.0012
				0.2629	0.1630	0.3708						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^{2} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^{2} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^{2} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$

5.2. Volatility Spillovers in Bond Markets – First Stage GARCH (1, 1)

Similar to the analysis of estimated results in the equity markets volatility spillover, I examine the volatility spillovers of bond markets in this section. Figure 5.2 shown below, shows the variation of the conditional standard deviation over time for each of the countries used in this section of the study. The plots of the conditional variance of returns for Greece, Ireland and Spain are comparatively different from other European bond market conditional standard deviations. Drawing from existing literature Kanas (2000), Skintzi and Refenes (2006), Porfiris et al. (2007), Christiansen (2007), Balli (2009), etc., choice of individual European countries used in this section of the study is determined. Many of the European Union countries have violated the Euro zone stability pact by having larger fiscal deficit. Also the wage and price is growing at a faster rate in some of the Euro zone countries than the rate of their productivity. These conditions indirectly signal a lower confidence or investment environment in these markets and hence eventually affect the risk in these markets. Given that these countries have been periodically in the news as well due to their debt problems, it would be interesting to see how their conditional variance affects the volatility of US bond returns and vice versa.

Table 5.2 shows the estimation results for the hypothesis tested as well as the actual coefficient estimates for the extended conditional variance equations that is used in this study of bond markets. Panel A in Table 5.2 shows results of the hypothesis test in which the spillover and threshold effects from US to the European bond markets is measured. Panel B shows results of the hypothesis test for the UK bond market spillovers; panel C shows results for Greece; panel D for Italy; panel E for Ireland and panel F for Spain respectively. Similar to section 5.1, I use a 10% significance level and bootstrapped critical values to test the various hypotheses. Panel A in Table 5.2 shows that the null hypothesis of no volatility spillovers and no threshold effects from US bond market to other European bond markets is rejected in fourteen of the fifteen country pairs examined. US-Switzerland is the only case where I fail to reject hypothesis 1.

The test of hypotheses 2 shows that the null hypothesis of no volatility spillovers conditional on no threshold effects is rejected for all the country pairs except US-Switzerland similar to hypothesis 1 results. The test of hypothesis 3 produces results, where the null hypothesis of no threshold effects conditional on no spillover effects is rejected for eight of the fifteen country pairs examined. So for all the bivariate cases examined in panel A, there seems to be some form of significant threshold effects that explain the conditional variance of European bond returns. The results of hypothesis 3, which is a joint hypothesis test for no threshold effects conditional on no spillover effects, aids in the inference that the European bond markets are consistently affected by increases in volatility of the US bond market when it exceeds a particular threshold.

On comparing the coefficients in model 1 for US bond market; for all the cases examined, there is a positive sign for δ_{12} and for thirteen out of the fifteen cases there is a negative sign for ω_{12}. At high levels of volatility in US bond returns (beyond the threshold), the volatility in European bond markets are affected negatively except for Denmark and Switzerland. So when the volatility in the US market initially increases, volatility in the European bond markets increase but when volatility in the US bond returns exceeds the estimated threshold, volatility in European bond markets generally decreases. There are three potential reasons that can be attributed to this effect. First, when volatility in US bond market increases, investors become cautious and hedge their risk in other markets. Second, the European markets offer opportunities for diversification of the unsystematic component of risk. And third, only the country specific component of risk is increasing in the US bond market and this does not affect the European bond market risk as much in terms of magnitude, hence the negative sign for the threshold component.

An examination of Panel B shows that hypothesis 1 is rejected for all country pairs except for UK-Switzerland and UK-US. Most of the country pairs examined in panel B show that conditional variance spillovers from UK to other bond markets studied might have both a direct volatility spillovers as well as threshold effects. Tests of hypothesis 2 yield results where rejection of the hypothesis (no spillovers conditional on no threshold effects) is similar to hypothesis 1 results. Test of hypothesis 3 yield results where the hypothesis is rejected for five out of fifteen country pairs. Though this is roughly one third of all the pairs examined, there is some weak evidence indicating the existence of threshold effects. Panel B has positive values for δ_{12} in twelve out of fifteen country pairs and the sign reversal exists in fourteen out of the fifteen pairs analyzed. The reasons for this reversal are similar to the explanation earlier.

Hypothesis 1 results for Greece (Panel C) shows that the null hypothesis of no spillover and no threshold effects is rejected in six out of fifteen country pairs examined. Hypothesis 2 results in panel C show rejection for five out of fifteen pairs and strikingly, hypothesis 3 results in panel C, shows rejection of the null in nine out of fifteen country pairs examined. The hypothesis results also show failure to reject spillovers from Greece to Austria, Belgium, France, and Switzerland, UK and US under hypothesis 3. From the hypothesis 3 results, it can be inferred that threshold effects exist in Bond market spillovers. In looking at the results of the hypothesis test, what becomes evident in terms of spillovers from Greece is that the threshold effects seem to be more important than the volatility spillover effects and in fact only five out of fifteen country pairs examined seem to have direct spillover effects when the estimation is conditional on no threshold effects. The inference from examining panel C shows that only Belgium, Italy, Ireland, Norway and Spain are significantly affected by direct changes in the volatility of the Greek bond returns. Panel C has positive values for δ_{12} in all the country pairs and the sign reversal exists similar to panel B with similar reasons as explained earlier. The volatility spillover and threshold coefficients for Greece-UK pair in panel C remain positive. Though these coefficients are positive, they are very small and insignificant.

In panel D, spillover and threshold effects are measured from Italy to other bond markets, hypothesis 1 is rejected in four out of the fifteen country pairs examined and hypothesis 3 of no threshold effect conditional on no volatility spillover is rejected in six out of fifteen country pairs. Based on the test statistics, hypothesis 2 is rejected in four out of fifteen cases examined. Though the evidence is weak, this potentially adds validity to the argument that the threshold effects are more important in countries that have greater financial distress. Spillovers from Italy have positive coefficient values for δ_{12} in twelve out of fifteen country pairs and the sign reversal exists in all the country pairs analyzed for reasons of potential diversification opportunities, or hedging or only country specific risk increasing and not having an impact on other markets.

Panel E results which measure spillover and threshold effects from Ireland to other bond markets show that hypothesis 1 is rejected in eight pairs examined, hypothesis 2 in ten out of fifteen pairs and hypothesis 3 in five out of fifteen pairs. Panel E has positive values for δ_{12} in all cases except the Ireland-

Switzerland pair and the sign reversal exists in all the country pairs analyzed. Among all the panels examined this far in table 5.2, Ireland has the weakest evidence supporting the hypothesis tests. Surprisingly panel F results, which measures spillover and threshold effects from Spain to other bond markets, shows that whenever volatility spillovers occur, the indirect threshold effects are more important and even when evidence of direct volatility spillovers might be weak, the indirect thresholds matter. Hypothesis 1 in panel F is rejected for seven pairs examined and hypothesis 3 is rejected in eight pairs examined. I reject only two out of fifteen times for hypothesis 2 in panel F. Panel F has positive values for δ_{12} in all cases except the Spain-Switzerland pair and the sign reversal exists in all the country pairs except Spain-Switzerland as well.

Examining panels A through F in Table 5.2, it is evident that hypothesis 1 and hypothesis 3 are rejected in some of the cases if not all. An inference from this evidence is that threshold effects could potentially exist in volatility spillovers. The European countries that have been in financial distress and in news for the wrong reasons typically labeled PIIGS, (Portugal, Ireland, Italy, Greece and Spain) seem to exhibit significant threshold effects. I am unable to show the results for spillovers from Portugal due to the unavailability of data. For all the other PIIGS countries, the threshold effects seem to be more relevant and do exist as part of the conditional variance specification that measures volatility spillover effects. In terms of the coefficient signs, first, the sign reversal seems to be occurring across all the country pairs, except a few anomalies. This indicates a change in behavior at higher levels of volatility. Second, the effect of the threshold variable seems to be negative in most cases. This implies that at high levels of volatility in one market the volatility in the other market decreases. It lends support to the theory that the hedging of assets in one market when volatility in other markets increases or opportunities for diversification of risk in one market when volatility in other markets increases. It is very difficult to draw an exact quantitative inference from the magnitude of the threshold coefficients and they are listed along with other coefficients in Table 5.2. Overall, it is evident that the hypothesis results are robust and it is not misplaced to infer that spillovers and threshold effects are important.

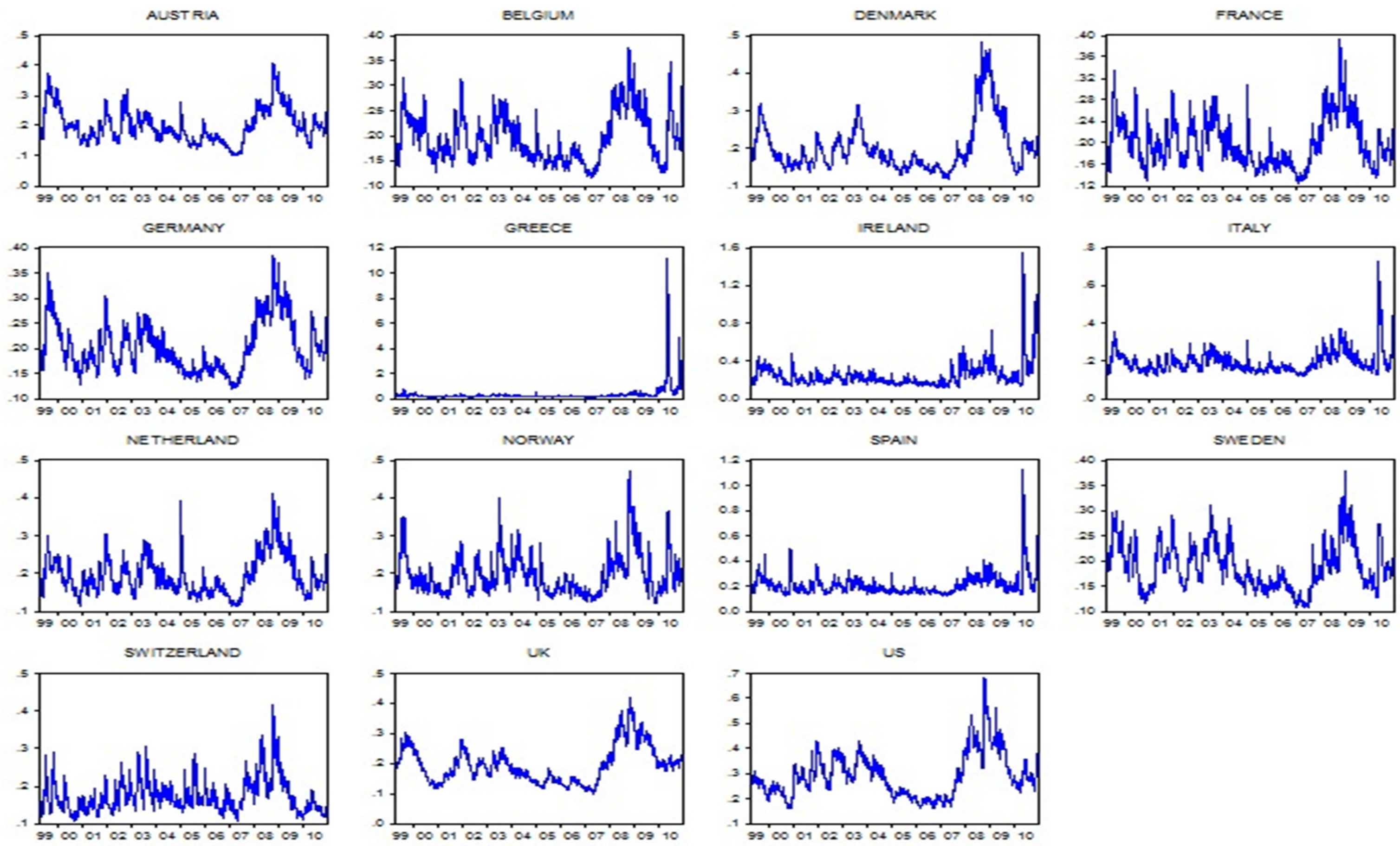

Figure 5.2 Conditional Standard Deviation of Bond Index Returns

The fifteen figures above display the conditional standard deviation of asset returns over time for different countries. The graphs use daily return data from 31 May, 1999 to 16 December, 2010.

Table 5.2 Estimation Results and Coefficient Estimates of Conditional Variance Estimation for Bond Markets – GARCH (1, 1)

Panel A:											
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
US → Austria	26.58	14.86	11.72	0.0000	0.0001	0.0006	0.0099	-0.0047	0.0516	74.31	0.0065	0.0039
				0.0002	0.0004	0.0323						
US → Belgium	11.74	6.30	5.44	0.0028	0.0121	0.0197	0.0114	-0.0060	0.0516	74.31	0.0056	0.0028
				0.0700	0.0240	0.3856						
US → Denmark	32.92	18.85	14.07	0.0000	0.0000	0.0002	0.0034	0.0113	0.1569	12.53	0.0051	0.0081
				0.0001	0.0001	0.0113						
US → EMU	15.11	6.82	8.29	0.0005	0.0090	0.0040	0.0134	-0.0065	0.0472	78.34	0.0060	0.0036
				0.0181	0.0190	0.1361						
US → France	15.78	9.75	6.03	0.0004	0.0018	0.0141	0.0220	-0.0100	0.0428	82.30	0.0087	0.0051
				0.0137	0.0047	0.3168						
US → Germany	15.05	6.65	8.40	0.0005	0.0099	0.0038	0.0133	-0.0066	0.0472	78.34	0.0059	0.0035
				0.0185	0.0206	0.1315						
US → Greece	34.82	21.08	13.74	0.0000	0.0000	0.0002	0.0305	-0.0151	0.0428	82.30	0.0172	0.0104
				0.0001	0.0001	0.0131						
US → Ireland	29.22	18.47	10.75	0.0000	0.0000	0.0010	0.0384	-0.0177	0.0428	82.30	0.0168	0.0103
				0.0002	0.0001	0.0498						
US → Italy	28.86	19.90	8.96	0.0000	0.0000	0.0028	0.0282	-0.0126	0.0516	74.31	0.0139	0.0080
				0.0002	0.0001	0.1053						
US → Netherland	21.94	9.57	12.37	0.0000	0.0020	0.0004	0.0176	-0.0087	0.0428	82.30	0.0073	0.0032
				0.0011	0.0050	0.0249						
US → Norway	39.11	28.11	11.00	0.0000	0.0000	0.0009	0.0247	-0.0117	0.0384	87.73	0.0112	0.0101
				0.0000	0.0000	0.0449						
US → Spain	22.19	14.63	7.56	0.0000	0.0001	0.0060	0.0357	-0.0170	0.0428	82.30	0.0134	0.0088
				0.0009	0.0005	0.1793						
US → Sweden	29.73	12.59	17.14	0.0000	0.0004	0.0000	0.0171	-0.0087	0.0472	78.34	0.0060	0.0041
				0.0001	0.0014	0.0028						
US → Switzerland	5.38	1.52	3.86	0.0679	0.2177	0.0494	0.0015	0.0083	0.1832	6.94	0.0019	0.0084
				0.5618	0.2788	0.6124						
US → UK	11.27	6.39	4.89	0.0036	0.0115	0.0271	0.0060	-0.0024	0.0472	78.34	0.0035	0.0021
				0.0846	0.0232	0.4573						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \ge \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \ge \lambda\}}h_{22t-1}$

Table 5.2 - continued

Panel B:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
UK → Austria	24.46	12.99	11.47	0.0000	0.0003	0.0007	0.0295	-0.0128	0.0264	65.28	0.0190	0.0084
				0.0004	0.0011	0.0365						
UK → Belgium	19.53	12.61	6.92	0.0001	0.0004	0.0085	0.0660	-0.0262	0.0183	83.44	0.0289	0.0130
				0.0029	0.0014	0.2301						
UK → Denmark	42.31	14.26	28.05	0.0000	0.0002	0.0000	0.0166	0.0435	0.0723	13.78	0.0162	0.0362
				0.0000	0.0006	0.0001						
UK → EMU	16.26	10.46	5.80	0.0003	0.0012	0.0160	0.0556	-0.0205	0.0199	79.65	0.0298	0.0133
				0.0115	0.0038	0.3405						
UK → France	20.88	13.74	7.14	0.0000	0.0002	0.0075	0.0702	-0.0302	0.0183	83.44	0.0289	0.0138
				0.0015	0.0007	0.2114						
UK → Germany	15.81	10.06	5.74	0.0004	0.0015	0.0166	0.0544	-0.0204	0.0199	79.65	0.0287	0.0129
				0.0135	0.0043	0.3476						
UK → Greece	42.72	38.88	3.84	0.0000	0.0000	0.0501	0.0689	-0.0217	0.0395	41.88	0.0582	0.0393
				0.0000	0.0000	0.6172						
UK → Ireland	32.26	28.76	3.50	0.0000	0.0000	0.0614	-0.0018	0.0380	0.0101	99.97	0.0548	0.0370
				0.0001	0.0000	0.6720						
UK → Italy	30.68	22.53	8.15	0.0000	0.0000	0.0043	0.0675	-0.0279	0.0346	50.26	0.0370	0.0229
				0.0001	0.0001	0.1436						
UK → Netherland	20.96	13.32	7.64	0.0000	0.0003	0.0057	0.0547	-0.0222	0.0183	83.44	0.0236	0.0098
				0.0014	0.0009	0.1744						
UK → Norway	38.80	18.83	19.98	0.0000	0.0000	0.0000	0.0483	-0.0278	0.0232	71.56	0.0184	0.0135
				0.0000	0.0001	0.0007						
UK → Spain	33.35	30.02	3.33	0.0000	0.0000	0.0680	0.0599	-0.0557	0.1246	2.19	0.0567	0.0368
				0.0001	0.0000	0.6982						
UK → Sweden	20.82	10.56	10.26	0.0000	0.0012	0.0014	0.0201	-0.1337	0.1459	0.56	0.0123	0.0096
				0.0016	0.0034	0.0619						
UK → Switzerland	3.51	0.00	3.51	0.1732	0.9850	0.0611	-0.0029	0.0093	0.0723	13.78	0.0000	0.0087
				0.8122	0.8548	0.6700						
UK → US	10.27	0.16	10.11	0.0059	0.6856	0.0015	-0.0525	0.0422	0.0101	99.97	0.0020	-0.2427
				0.1239	0.6942	0.0656						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$

Table 5.2 - continued

Panel C:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Greece → Austria	9.05	5.49	3.56	0.0109	0.0191	0.0593	0.0001	-0.0005	110.2811	0.03	0.0001	0.0001
				0.1899	0.0358	0.6617						
Greece → Belgium	16.87	9.49	7.39	0.0002	0.0021	0.0066	0.0003	-0.0004	22.3116	0.39	0.0001	0.0001
				0.0091	0.0051	0.1925						
Greece → Denmark	10.68	1.56	9.13	0.0048	0.2120	0.0025	0.0003	-0.0003	2.4875	1.77	0.0000	0.0000
				0.1061	0.2731	0.0981						
Greece → EMU	9.71	0.13	9.58	0.0078	0.7208	0.0020	0.0001	-0.0007	110.2811	0.03	0.0000	-0.0002
				0.1503	0.7220	0.0822						
Greece → France	4.48	0.00	4.48	0.1065	0.9725	0.0343	0.0001	-0.0005	110.2811	0.03	0.0000	-0.0001
				0.6831	0.8548	0.5150						
Greece → Germany	9.64	0.13	9.51	0.0081	0.7222	0.0020	0.0001	-0.0007	110.2811	0.03	0.0000	-0.0002
				0.1530	0.7220	0.0841						
Greece → Ireland	60.95	13.13	47.82	0.0000	0.0003	0.0000	0.0026	-0.0049	16.1166	0.52	0.0021	-0.0171
				0.0000	0.0010	0.0000						
Greece → Italy	50.11	22.51	27.60	0.0000	0.0000	0.0000	0.0013	-0.0020	22.3116	0.39	0.0008	-0.0029
				0.0000	0.0001	0.0001						
Greece → Netherland	9.26	0.05	9.21	0.0098	0.8283	0.0024	0.0001	-0.0006	110.2811	0.03	0.0000	-0.0002
				0.1767	0.7954	0.0945						
Greece → Norway	17.63	0.19	17.45	0.0001	0.6654	0.0000	0.0007	-0.0009	2.4875	1.77	0.0000	-0.0001
				0.0066	0.6809	0.0026						
Greece → Spain	57.32	27.65	29.67	0.0000	0.0000	0.0000	0.0023	-0.0037	28.5067	0.33	0.0018	-0.0084
				0.0000	0.0000	0.0001						
Greece → Sweden	9.64	0.20	9.44	0.0081	0.6558	0.0021	0.0003	-0.0004	2.4875	1.77	0.0000	0.0000
				0.1530	0.6748	0.0860						
Greece → Switzerland	2.69	1.99	0.69	0.2611	0.1581	0.4049	0.0000	-0.0001	2.4875	1.77	0.0000	0.0000
				0.9046	0.2152	0.9893						
Greece → UK	1.56	0.77	0.79	0.4583	0.3804	0.3738	0.0000	0.0001	92.9350	0.07	0.0000	0.0001
				0.9788	0.4397	0.9877						
Greece → US	4.43	0.98	3.46	0.1089	0.3228	0.0630	0.0004	-0.0004	12.3996	0.72	0.0000	0.0000
				0.6883	0.3838	0.6785						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.2 - continued

Panel D:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Italy → Austria	7.37	3.41	3.96	0.0251	0.0648	0.0467	0.0172	-0.0121	0.0237	76.05	0.0057	0.0175
				0.3257	0.1020	0.5973						
Italy → Belgium	3.88	2.25	1.63	0.1435	0.1333	0.2018	0.0219	-0.0138	0.0341	45.39	0.0074	0.0095
				0.7634	0.1873	0.9404						
Italy → Denmark	7.01	1.73	5.28	0.0300	0.1887	0.0215	0.0112	-0.0110	0.0757	7.26	0.0035	0.0064
				0.3626	0.2477	0.4033						
Italy → EMU	2.15	0.99	1.17	0.3407	0.3202	0.2804	0.0082	-0.0112	0.0549	17.02	-0.0034	-0.0039
				0.9475	0.3817	0.9751						
Italy → France	8.62	0.15	8.47	0.0134	0.6987	0.0036	0.0397	-0.0381	0.0445	27.95	-0.0012	-0.0029
				0.2194	0.7082	0.1278						
Italy → Germany	2.22	0.96	1.26	0.3297	0.3272	0.2617	0.0088	-0.0117	0.0549	17.02	-0.0033	-0.0039
				0.9430	0.3891	0.9698						
Italy → Greece	19.47	9.68	9.79	0.0001	0.0019	0.0018	0.0213	-1.1355	0.0965	3.76	0.0416	-10.0000
				0.0029	0.0048	0.0761						
Italy → Ireland	35.88	0.98	34.90	0.0000	0.3218	0.0000	-0.0018	-1.9635	0.4349	0.10	-0.0119	-3.9799
				0.0001	0.3817	0.0000						
Italy → Netherland	9.34	0.49	8.85	0.0094	0.4819	0.0029	0.0266	-0.0272	0.0445	27.95	-0.0021	-0.0038
				0.1711	0.5272	0.1097						
Italy → Norway	24.22	12.61	11.61	0.0000	0.0004	0.0007	0.0333	-0.0327	0.0705	8.51	0.0249	-0.0141
				0.0004	0.0014	0.0341						
Italy → Spain	22.68	5.94	16.74	0.0000	0.0148	0.0000	0.0518	-0.7120	0.3880	0.13	0.0485	-1.9483
				0.0007	0.0283	0.0032						
Italy → Sweden	8.32	0.06	8.27	0.0156	0.8097	0.0040	0.0193	-0.0211	0.0393	35.24	0.0011	-0.0054
				0.2414	0.7845	0.1369						
Italy → Switzerland	10.68	0.09	10.59	0.0048	0.7636	0.0011	0.0169	-0.0182	0.0237	76.05	-0.0007	-0.0043
				0.1064	0.7466	0.0529						
Italy → UK	2.75	0.01	2.74	0.2530	0.9155	0.0980	-0.0036	0.0326	0.4349	0.10	-0.0002	0.0321
				0.8997	0.8365	0.7976						
Italy → UK	2.75	0.01	2.74	0.2530	0.9155	0.0980	-0.0036	0.0326	4349.1069	0.10	-0.0002	0.0321
				0.8997	0.8365	0.7976						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\ge\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\ge\lambda\}}h_{22t-1}$

Table 5.2 - continued

Panel E:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Ireland → Austria	14.01	10.61	3.40	0.0009	0.0011	0.0650	0.0051	-0.0039	0.1098	13.06	0.0022	0.0018
				0.0284	0.0034	0.6866						
Ireland → Belgium	17.82	16.35	1.46	0.0001	0.0001	0.2263	0.0048	-0.0048	1.0913	0.33	0.0037	0.0039
				0.0060	0.0003	0.9544						
Ireland → Denmark	11.03	4.89	6.14	0.0040	0.0270	0.0132	0.0041	-0.0043	0.1338	9.23	0.0014	0.0008
				0.0929	0.0474	0.3051						
Ireland → EMU	10.14	2.37	7.78	0.0063	0.1240	0.0053	0.0039	-0.0372	2.1446	0.07	0.0015	-0.0114
				0.1294	0.1761	0.1652						
Ireland → France	4.77	0.66	4.12	0.0919	0.4174	0.0425	0.0045	-0.0050	0.1338	9.23	0.0007	-0.0062
				0.6416	0.4723	0.5711						
Ireland → Germany	10.06	2.36	7.71	0.0065	0.1248	0.0055	0.0039	-0.0371	2.1446	0.07	0.0014	-0.0113
				0.1340	0.1770	0.1696						
Ireland → Greece	68.65	6.06	62.59	0.0000	0.0139	0.0000	0.0088	-4.5630	0.9956	0.39	0.0133	-4.4152
				0.0000	0.0272	0.0000						
Ireland → Italy	37.18	26.06	11.12	0.0000	0.0000	0.0009	0.0137	-0.2010	2.1446	0.07	0.0134	0.0126
				0.0001	0.0000	0.0424						
Ireland → Netherland	10.13	0.94	9.19	0.0063	0.3324	0.0024	0.0028	-0.0281	2.1446	0.07	0.0008	-0.0119
				0.1300	0.3934	0.0951						
Ireland → Norway	22.87	4.44	18.43	0.0000	0.0351	0.0000	0.0095	-0.0143	0.5168	1.24	0.0034	-0.0040
				0.0007	0.0597	0.0017						
Ireland → Spain	37.92	19.86	18.05	0.0000	0.0000	0.0000	0.0197	-0.1545	1.8095	0.13	0.0212	0.0294
				0.0001	0.0001	0.0020						
Ireland → Sweden	11.54	3.63	7.91	0.0031	0.0567	0.0049	0.0050	-0.0059	0.3013	2.62	0.0017	-0.0015
				0.0764	0.0902	0.1578						
Ireland → Switzerland	4.27	0.13	4.14	0.1182	0.7157	0.0419	-0.0020	0.0024	0.2295	3.50	-0.0001	-0.0079
				0.7113	0.7147	0.5686						
Ireland → UK	8.87	3.94	4.93	0.0119	0.0472	0.0264	0.0039	-0.0041	0.2535	2.98	0.0013	0.0071
				0.2026	0.0777	0.4505						
Ireland → US	8.87	3.94	4.93	0.0119	0.0472	0.0264	0.0039	-0.0041	0.2535	2.98	0.0013	0.0071
				0.2026	0.0777	0.4505						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.2 - continued

Panel F:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Spain → Austria	3.54	1.74	1.81	0.1700	0.1873	0.1791	0.0108	-0.0093	0.0147	99.97	0.0017	0.0032
				0.8074	0.2465	0.9228						
Spain → Belgium	4.15	2.98	1.17	0.1256	0.0842	0.2796	0.0089	-0.0063	0.0527	25.82	0.0036	0.0045
				0.7270	0.1270	0.9751						
Spain → Denmark	16.13	1.54	14.59	0.0003	0.2152	0.0001	0.0120	-0.0124	0.0274	67.90	0.0016	-0.0005
				0.0121	0.2760	0.0091						
Spain → EMU	5.57	0.09	5.47	0.0619	0.7629	0.0193	0.0115	-0.0133	0.0274	67.90	-0.0005	-0.0020
				0.5374	0.7466	0.3809						
Spain → France	13.52	1.38	12.13	0.0012	0.2394	0.0005	0.0217	-0.0221	0.0654	16.43	0.0022	-0.0016
				0.0351	0.3009	0.0272						
Spain → Germany	5.71	0.09	5.62	0.0576	0.7688	0.0177	0.0117	-0.0135	0.0274	67.90	-0.0005	-0.0020
				0.5195	0.7556	0.3628						
Spain → Greece	53.30	4.25	49.04	0.0000	0.0392	0.0000	0.0213	-0.0311	0.0527	25.82	0.0213	-10.0000
				0.0000	0.0661	0.0000						
Spain → Ireland	42.81	4.49	38.32	0.0000	0.0341	0.0000	0.0189	-0.3203	0.5852	0.23	0.0146	-1.6564
				0.0000	0.0584	0.0000						
Spain → Italy	19.52	0.78	18.74	0.0001	0.3774	0.0000	0.0192	-0.0316	0.0400	41.33	0.0053	-0.0130
				0.0029	0.4365	0.0014						
Spain → Netherland	9.32	0.09	9.23	0.0095	0.7690	0.0024	0.0141	-0.0154	0.0147	99.97	-0.0004	-0.0223
				0.1723	0.7556	0.0939						
Spain → Norway	17.95	2.45	15.49	0.0001	0.1174	0.0001	0.0223	-0.0228	0.0147	99.97	0.0058	-0.0040
				0.0056	0.1680	0.0059						
Spain → Sweden	13.49	0.01	13.48	0.0012	0.9313	0.0002	0.0148	-0.0170	0.0147	99.97	0.0002	-0.0032
				0.0352	0.8548	0.0144						
Spain → Switzerland	2.19	0.89	1.29	0.3353	0.3453	0.2552	-0.0001	-0.0143	1.1431	0.03	-0.0011	-0.0148
				0.9454	0.4037	0.9675						
Spain → UK	1.94	0.60	1.34	0.3784	0.4368	0.2472	0.0046	-0.0046	0.0527	25.82	0.0008	0.0134
				0.9602	0.4892	0.9648						
Spain → US	1.94	0.60	1.34	0.3784	0.4368	0.2473	0.0046	-0.0046	527.0959	25.82	0.0008	0.0134
				0.9602	0.4892	0.9648						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$

5.3. Volatility Spillovers in Foreign Exchange Markets – First Stage GARCH (1, 1)

In this section volatility spillover in Foreign Exchange (forex) markets is analyzed. Figure 5.3 shown below depicts the variation of the conditional standard deviation of asset returns over time for each of the countries used. The plots of conditional standard deviation for US, China, Hong Kong and Thailand are comparatively different from other South East (S.E.) Asian foreign exchange market conditional standard deviations. Given that these countries have been periodically in news due to their emergence after the East Asian Financial Crisis and drawing from the existing literature by Forbes and Rigobon (2002), Huang and Yang (2002), Cheung and Ng (1996), Wu (2005), Mishra et al. (2007), Shamiri and Isa (2009), Chiang et al. (2007), etc., it would be interesting to see how their conditional variance affects the US and vice versa.

Table 5.3 shows the estimation results and coefficient estimates for the various hypotheses tested in this study of foreign exchange markets. Panel A in Table 5.3 shows results of the hypothesis test in which the spillover and threshold from US to other forex markets are measured, followed by panel B for Japan, panel C for Thailand, panel D for China, panel E for India and finally panel F lists the spillover and threshold effects from Euro (which has become as popular as the US dollar) to other forex markets used in this study. Using a 10% significance level and bootstrapped critical values as in section 5.1 and 5.2, panel A in Table 5.3 shows that the null hypothesis of no volatility spillovers and no threshold effects (hypothesis 1) from US forex market to other forex markets is rejected for nine out of twelve country pairs examined. The test of hypotheses 2 shows results that reject the null hypothesis of volatility spillovers conditional on no threshold effects for all the country pairs except US-Korea and US-Malaysia. The test of hypothesis 3 produces results, where the null hypothesis of existence of threshold effects conditional on no spillover effects is rejected for five out of twelve country pairs.

So for all the bivariate cases examined in Panel A, there is evidence of some form of significant threshold effects that explain conditional variance. The results of hypothesis 3 test, add validity to the inference that the forex markets in S.E. Asia are consistently affected by increases in volatility of US forex market when they exceed a particular threshold. On comparing the coefficients in model 1 for Panel A; for all the cases examined, there is a positive sign for δ_{12} coefficient except US-Japan and US-Malaysia.

There is a negative sign for ω_{12} coefficient in seven out of the twelve cases analyzed. At high levels of volatility in US forex market (beyond the threshold), the volatility in S.E Asian forex markets are affected negatively, pointing in the direction of potential opportunities for diversification and hence reduction in risk.

An examination of Panel B shows that hypothesis 1 is rejected in four out of twelve country pairs; hypothesis 2 is rejected in five out of twelve country pairs and hypothesis 3 for three out of twelve country pairs examined. Though the evidence is weak, some of the country pairs if not all examined in Panel B, indicate that conditional variance spillovers from Japan to other forex markets studied might have volatility spillovers as well as threshold effects confirming the reason for this study. Panel B has positive coefficient values for δ_{12} in six out of twelve country pairs and the sign reversal for $\omega_{12,}$ exists in eight out of the twelve pairs analyzed. It is difficult to make a general inference due to the absence of a clear pattern in terms of volatility and threshold spillovers from Japan forex market.

Hypothesis 1 and hypothesis 3 results in Panel C show that the null is rejected in ten and nine country pairs out of twelve respectively. Hypothesis 2 results in Panel C are rejected for five out of twelve pairs examined. Strikingly hypothesis 3 results in Panel C show rejection of null in more pairs than hypothesis 2 lending greater support to the argument of existence of threshold effects and in certain cases these threshold effects being more important and appropriate than the direct volatility spillover effects. Panel C has positive values for δ_{12} in all the country pairs except Thai-Euro and the sign reversal exists in ten pairs analyzed. The volatility spillover and threshold coefficients for Thailand-Indonesia and Thailand-Malaysia pair remain positive. One of the possible explanations for this positive threshold spillover from Thailand to Indonesia and Malaysian forex market is that, when volatility in Thailand forex market increases, investors in Indonesian and Malaysian markets might not be hedging their risk exposure. Alternately, Indonesian and Malaysian markets might not provide enough diversification opportunities for investors in Thailand forex market.

In panel D, hypothesis 1 is rejected in five out of twelve country pairs, hypothesis 3 of threshold effect conditional on no volatility spillover is rejected in three country pairs and hypothesis 2 in six cases out of twelve examined. Based on hypothesis 3, there is some weak evidence that the threshold effects exist and they are more important in countries that have greater growth rates or would typically be considered as emerging markets. Panel D has positive values for δ_{12} in eight country pairs and the sign reversal exists in eight pairs as well. Given the weak evidence, I would just state that threshold effects cannot be ignored.

Panel E and F results which measure spillover and threshold effects from India and Euro respectively also exhibit results similar to panel D. Hypothesis 1 is rejected in five pairs in panel E and six pairs in panel F. Panel E has positive values for δ_{12} in five out of twelve pairs examined and sign reversal occurs in every country pair examined. Panel F has positive values for δ_{12} in all except Euro-Indonesia, Euro-Japan, Euro-Singapore and Euro-US and the sign reversal exists in nine out of twelve country pairs analyzed. Without making a strong inference I would like to just state that for spillovers from India to other forex markets; certain markets have greater impact due to threshold spillovers than others.

At this juncture, the main inference from examining all the panels in Table 5.3 can be made. There are three main points that I would like to infer from analyzing Panel A through F. First, except for a few cases, the sign reversal seems to be occurring across most of the country pairs. This indicates a change in behavior at higher levels of volatility. Second, the effect of the threshold variable seems to be not clear as in some cases it is positive and in others it is negative. This implies that at high levels of volatility in one market, the volatility in the other market either increase or decrease. The inference here is that for increase in volatility in one market, investors in some markets hedge their exposure while in others investors do not hedge. Third, when volatility, only where it exceeds a threshold is used, the spillovers are mostly negative in forex markets (US, Japan, Thailand, China and Euro). Given the sign of the coefficients for δ_{12} and $\omega_{12,}$ do not have a predominant pattern; it is difficult to generalize a relationship. So, I would like to state that foreign exchange as an asset class exhibits evidence of threshold effects but in comparison to equity and bonds markets it is fairly weaker.

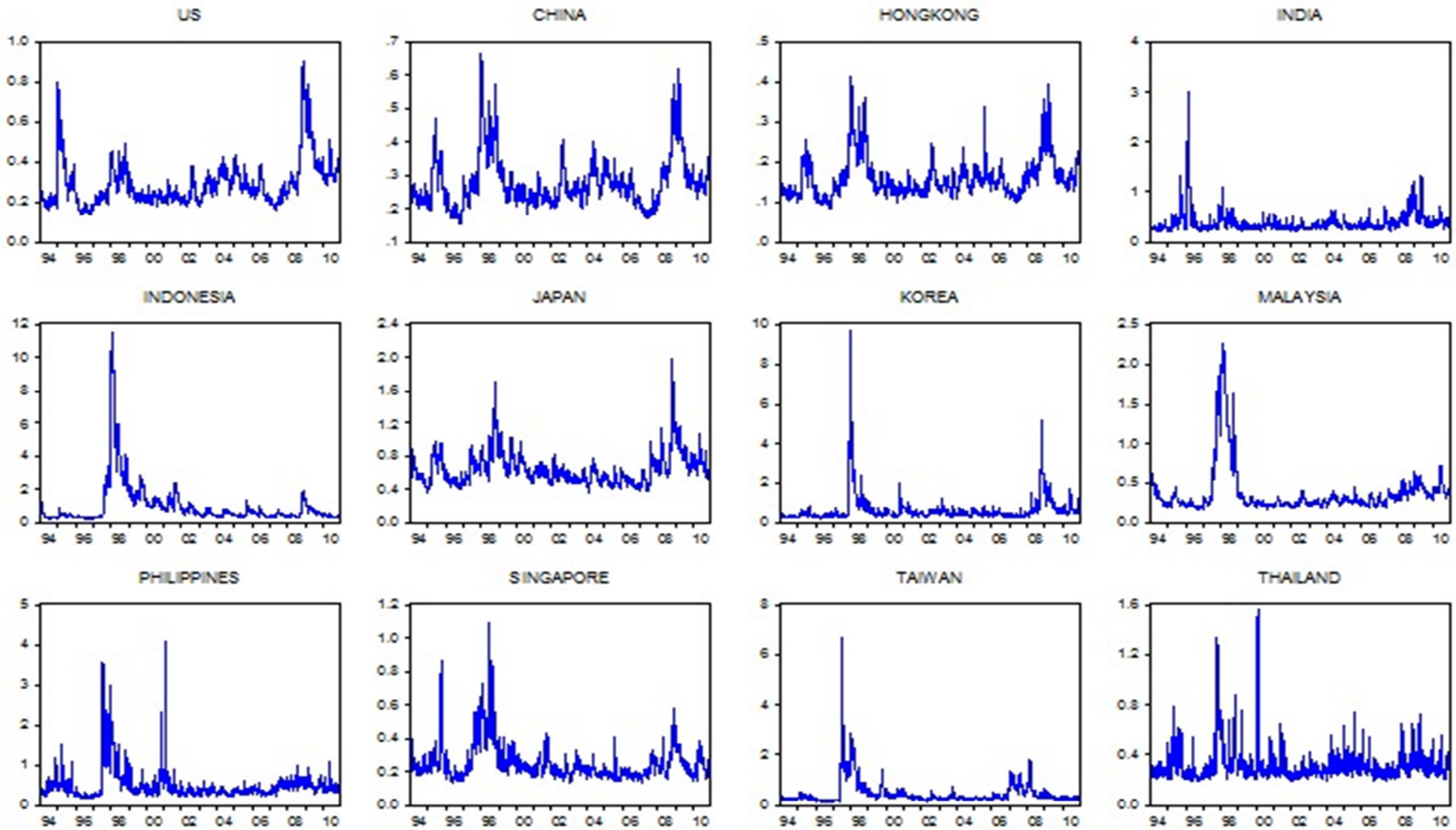

Figure 5.3 Conditional Standard Deviation of Foreign Exchange Index Returns

The twelve figures above display asset returns conditional standard deviation over time for different countries. The graphs use daily return data from 4 January, 1994 to 9 December, 2010.

Table 5.3 Estimation Results and Coefficient Estimates of Conditional Variance Estimation for Foreign Exchange Markets – GARCH (1, 1)

Panel A:

Country Pair	Like Ratio			P Value			Model 1				Model 2	Model 3
	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
US → China	10.9838	8.2099	2.7739	0.0041	0.0042	0.0958	0.0085	-0.0068	0.3054	4.21	0.0052	0.00328
				0.0946	0.0095	0.7920						
US → Euro	7.9193	3.3766	4.5426	0.0191	0.0661	0.0331	0.0003	0.0125	0.4644	99.98	0.0032	0.01296
				0.2774	0.1035	0.5057						
US → Hong Kong	14.8806	10.2600	4.6206	0.0006	0.0014	0.0316	0.0045	-0.0036	0.2418	0.11	0.0022	0.00142
				0.0197	0.0041	0.4934						
US → India	14.6294	7.1020	7.5273	0.0007	0.0077	0.0061	0.0148	0.2321	0.6074	0.07	0.0179	0.02331
				0.0220	0.0166	0.1819						
US → Indonesia	69.9915	29.5340	40.4575	0.0000	0.0000	0.0000	0.0033	0.1259	0.4326	4.21	0.0175	0.13099
				0.0000	0.0000	0.0000						
US → Japan	6.7310	4.0175	2.7135	0.0345	0.0450	0.0995	-0.0077	0.0260	0.0669	0.29	0.0146	0.01960
				0.3935	0.0744	0.8010						
US → Korea	40.4593	3.0100	37.4492	0.0000	0.0827	0.0000	0.0267	-0.0835	0.5200	0.16	0.0140	0.64304
				0.0000	0.1248	0.0000						
US → Malaysia	7.0757	2.2634	4.8123	0.0291	0.1325	0.0283	-0.0037	0.0065	0.1384	0.05	0.0021	0.01381
				0.3554	0.1864	0.4666						
US → Philippines	17.6539	8.5832	9.0707	0.0001	0.0034	0.0026	0.0618	-0.0400	0.0192	2.04	0.0183	0.02264
				0.0066	0.0076	0.1003						
US → Singapore	41.2752	5.5142	35.7610	0.0000	0.0189	0.0000	0.0265	-0.0202	0.0271	0.11	0.0043	0.01814
				0.0000	0.0351	0.0000						
US → Thailand	19.0237	7.8830	11.1407	0.0001	0.0050	0.0008	0.0278	-0.0200	0.0192	2.04	0.0058	0.01201
				0.0033	0.0107	0.0416						
US → Taiwan	29.2270	24.7892	4.4379	0.0000	0.0000	0.0351	0.0382	-0.0328	0.5120	0.05	0.0309	0.02658
				0.0002	0.0001	0.5208						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.3 – continued

Panel B:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Japan → China	5.6747	1.8972	3.7776	0.0586	0.1684	0.0519	0.0001	0.0018	0.6621	14.67	0.0007	0.00188
				0.5235	0.2265	0.6264						
Japan → Euro	8.7435	5.6615	3.0819	0.0126	0.0173	0.0792	0.0024	-0.0014	0.2004	91.60	0.0012	0.00453
				0.2101	0.0325	0.7409						
Japan → Hong Kong	6.4863	1.0043	5.4821	0.0390	0.3163	0.0192	-0.0001	0.0008	0.6621	14.67	0.0002	0.00078
				0.4223	0.3768	0.3796						
Japan → India	11.0034	2.5058	8.4976	0.0041	0.1134	0.0036	0.0016	0.2391	3.3936	0.18	0.0024	0.24638
				0.0938	0.1630	0.1264						
Japan → Indonesia	81.9405	5.9971	75.9434	0.0000	0.0143	0.0000	-0.0018	0.0673	1.7008	1.72	0.0028	0.06537
				0.0000	0.0278	0.0000						
Japan → Korea	9.2380	0.2350	9.0030	0.0099	0.6278	0.0027	-0.0016	-2.7204	3.3936	0.18	-0.0028	-2.73979
				0.1778	0.6502	0.1034						
Japan → Malaysia	6.0094	0.0431	5.9663	0.0496	0.8355	0.0146	-0.0008	0.0022	1.3546	2.49	0.0001	0.00148
				0.4803	0.7954	0.3235						
Japan → Philippines	7.6555	5.7682	1.8872	0.0218	0.0163	0.1695	0.0053	-0.0075	2.3933	1.00	0.0040	0.00257
				0.2987	0.0311	0.9139						
Japan → Singapore	48.2890	41.7690	6.5199	0.0000	0.0000	0.0107	0.0028	0.0032	0.1620	98.60	0.0059	0.00452
				0.0000	0.0000	0.2678						
Japan → Thailand	1.8008	0.4432	1.3577	0.4064	0.5056	0.2439	-0.0006	0.0015	0.5851	19.56	0.0004	0.00103
				0.9675	0.5462	0.9633						
Japan → Taiwan	43.3354	32.8304	10.5050	0.0000	0.0000	0.0012	0.0096	-0.0147	2.6241	0.75	0.0087	0.00821
				0.0000	0.0000	0.0550						
Japan → US	2.1638	1.4923	0.6715	0.3390	0.2219	0.4125	-0.0012	0.0006	0.1620	98.60	-0.0005	-0.00059
				0.9467	0.2818	0.9896						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1} \geq \lambda\}}h_{22t-1}$

Table 5.3 - continued

Panel C:												
Country Pair	Like Ratio			P Value			Model 1				Model 2	Model 3
	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Thai → China	35.9118	0.3553	35.5565	0.0000	0.5511	0.0000	0.0002	-0.0022	39.6968	0.05	0.0000	0.00003
				0.0001	0.5858	0.0000						
Thai → Euro	9.1492	1.5807	7.5685	0.0103	0.2087	0.0059	-0.0004	0.0008	0.9089	8.26	0.0001	0.00054
				0.1836	0.2682	0.1793						
Thai → Hong Kong	39.7424	0.4341	39.3083	0.0000	0.5100	0.0000	0.0001	-0.0007	39.6968	0.05	0.0000	0.00001
				0.0000	0.5510	0.0000						
Thai → India	39.3763	0.7191	38.6572	0.0000	0.3964	0.0000	0.0006	-0.0033	39.6968	0.05	0.0002	-0.00099
				0.0000	0.4539	0.0000						
Thai → Indonesia	63.6292	49.6062	14.0231	0.0000	0.0000	0.0002	0.0000	0.0082	5.3673	1.18	0.0023	0.00815
				0.0000	0.0000	0.0115						
Thai → Japan	7.1272	1.6046	5.5226	0.0283	0.2053	0.0188	0.0020	-0.0082	32.1175	0.09	0.0006	0.00020
				0.3504	0.2645	0.3743						
Thai → Korea	38.3960	0.2255	38.1706	0.0000	0.6349	0.0000	0.0002	-0.0021	39.6968	0.05	-0.0001	-0.00153
				0.0000	0.6562	0.0000						
Thai → Malaysia	43.5048	37.1409	6.3639	0.0000	0.0000	0.0116	0.0005	0.0035	19.6341	0.20	0.0012	0.00333
				0.0000	0.0000	0.2826						
Thai → Philippines	87.2246	52.2614	34.9632	0.0000	0.0000	0.0000	0.0123	-0.0299	39.6968	0.05	0.0122	0.02510
				0.0000	0.0000	0.0000						
Thai → Singapore	52.5795	14.4830	38.0964	0.0000	0.0001	0.0000	0.0007	-0.0042	39.6968	0.05	0.0008	0.00062
				0.0000	0.0005	0.0000						
Thai → Taiwan	43.4771	5.3024	38.1747	0.0000	0.0213	0.0000	0.0010	-0.0038	39.6968	0.05	0.0008	0.00026
				0.0000	0.0392	0.0000						
Thai → US	34.8132	0.0120	34.8011	0.0000	0.9126	0.0000	0.0001	-0.0015	39.6968	0.05	0.0000	-0.00024
				0.0001	0.8365	0.0000						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.3 - continued

Panel D:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
China → Euro	4.1427	0.1128	4.0299	0.1260	0.7369	0.0447	0.0140	-0.0098	0.0360	94.34	0.0010	0.05289
				0.7283	0.7290	0.5860						
China → Hong Kong	7.8250	0.6090	7.2160	0.0200	0.4352	0.0072	0.0460	0.0232	0.0360	94.34	0.0038	-0.01029
				0.2848	0.4892	0.2055						
China → India	27.9737	5.7550	22.2187	0.0000	0.0164	0.0000	-0.0537	0.0741	0.0610	60.63	0.0220	0.27421
				0.0002	0.0312	0.0004						
China → Indonesia	19.4757	8.1203	11.3554	0.0001	0.0044	0.0008	0.0201	10.0000	0.3485	0.52	0.0205	10.00000
				0.0029	0.0099	0.0384						
China → Japan	8.9956	0.2919	8.7036	0.0111	0.5890	0.0032	-0.0602	0.0696	0.0610	60.63	0.0091	0.03356
				0.1936	0.6161	0.1159						
China → Korea	6.7515	4.0720	2.6796	0.0342	0.0436	0.1016	-0.0265	0.0374	0.0235	99.98	0.0344	0.02458
				0.3912	0.0723	0.8073						
China → Malaysia	12.5764	0.4108	12.1656	0.0019	0.5216	0.0005	-0.0003	1.9247	0.3485	0.52	-0.0026	1.93408
				0.0517	0.5591	0.0269						
China → Philippines	8.6919	4.0653	4.6266	0.0130	0.0438	0.0315	0.0455	-0.0324	0.0652	54.68	0.0221	0.02994
				0.2138	0.0727	0.4934						
China → Singapore	25.4106	17.2708	8.1398	0.0000	0.0000	0.0043	0.0202	0.7883	0.3861	0.27	0.0200	0.02102
				0.0003	0.0003	0.1442						
China → Thailand	4.3833	1.4785	2.9047	0.1117	0.2240	0.0883	0.0059	1.7956	0.3485	0.52	0.0059	1.76790
				0.6962	0.2851	0.7700						
China → Taiwan	50.2860	45.4762	4.8098	0.0000	0.0000	0.0283	0.2837	-0.0712	0.0235	99.98	0.1682	0.07765
				0.0000	0.0000	0.4683						
China → US	5.7494	0.1864	5.5630	0.0564	0.6659	0.0183	0.0080	-0.0140	0.1610	7.86	0.0017	-0.00895
				0.5145	0.6809	0.3699						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.3 - continued

Panel E:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
India → China	9.9721	9.3146	0.6576	0.0068	0.0023	0.4174	0.0002	-0.0005	0.4942	4.21	-0.0003	-0.00034
				0.1374	0.0056	0.9899						
India → Euro	6.6779	5.3446	1.3333	0.0355	0.0208	0.2482	-0.0018	0.0014	0.0453	99.98	-0.0004	-0.00044
				0.3999	0.0387	0.9648						
India → Hong Kong	9.2568	8.7400	0.5168	0.0098	0.0031	0.4722	-0.0002	0.0003	6.9589	0.11	-0.0001	-0.00010
				0.1767	0.0069	0.9909						
India → Indonesia	7.7776	0.6409	7.1368	0.0205	0.4234	0.0076	-0.0019	0.0111	7.3180	0.07	-0.0003	-0.00034
				0.2888	0.4756	0.2114						
India → Japan	6.1496	4.5143	1.6353	0.0462	0.0336	0.2010	0.0045	-0.0065	0.4942	4.21	-0.0018	-0.00205
				0.4631	0.0578	0.9397						
India → Korea	12.9749	2.6983	10.2766	0.0015	0.1005	0.0013	-0.0035	0.0060	4.7142	0.29	-0.0006	-0.00051
				0.0441	0.1479	0.0613						
India → Malaysia	3.9101	0.0404	3.8697	0.1416	0.8408	0.0492	0.0010	-0.0047	6.2406	0.16	0.0000	-0.00322
				0.7591	0.7954	0.6124						
India → Philippines	12.2101	6.0601	6.1499	0.0022	0.0138	0.0131	-0.0013	0.0069	8.0363	0.05	-0.0006	-0.00063
				0.0592	0.0271	0.3051						
India → Singapore	35.4367	0.2035	35.2332	0.0000	0.6519	0.0000	0.0066	-0.0069	0.8534	2.04	0.0004	-0.00484
				0.0001	0.6688	0.0000						
India → Thailand	5.5264	4.9812	0.5452	0.0631	0.0256	0.4603	-0.0006	0.0011	6.9589	0.11	-0.0003	-0.00033
				0.5423	0.0452	0.9907						
India → Taiwan	10.1019	1.7990	8.3029	0.0064	0.1798	0.0040	0.0064	-0.0071	0.8534	2.04	-0.0006	-0.00080
				0.1317	0.2394	0.1351						
India → US	15.0736	13.3264	1.7472	0.0005	0.0003	0.1862	-0.0005	0.0026	8.0363	0.05	-0.0003	-0.00030
				0.0182	0.0009	0.9285						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.3 - continued

Panel F:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Euro → China	10.5240	2.2719	8.2521	0.0052	0.1317	0.0041	0.0103	-0.0065	0.0843	85.31	0.0013	0.00136
				0.1122	0.1853	0.1374						
Euro → Hong Kong	6.5570	0.4823	6.0748	0.0377	0.4874	0.0137	0.0027	-0.0018	0.0843	85.31	0.0002	0.00351
				0.4136	0.5310	0.3116						
Euro → India	3.6509	0.9475	2.7035	0.1611	0.3304	0.1001	0.0180	-0.0161	0.0530	94.93	-0.0035	-0.00512
				0.7928	0.3912	0.8025						
Euro → Indonesia	55.7056	5.1229	50.5828	0.0000	0.0236	0.0000	-0.0038	0.1043	0.1911	32.42	0.0078	0.10290
				0.0000	0.0422	0.0000						
Euro → Japan	10.5653	4.9254	5.6400	0.0051	0.0265	0.0176	-0.0440	0.0465	0.0341	99.98	0.0169	0.01627
				0.1102	0.0466	0.3613						
Euro → Korea	42.0604	10.9490	31.1114	0.0000	0.0009	0.0000	0.0052	0.1927	0.2978	9.58	0.0151	0.19927
				0.0000	0.0031	0.0001						
Euro → Malaysia	5.2254	2.1139	3.1115	0.0733	0.1460	0.0777	0.0044	-0.0041	0.0906	81.89	-0.0012	-0.00101
				0.5813	0.2021	0.7354						
Euro → Philippines	30.5836	23.2761	7.3075	0.0000	0.0000	0.0069	0.0127	0.0199	0.2287	21.60	0.0179	0.01494
				0.0001	0.0001	0.1980						
Euro → Singapore	50.1293	15.0077	35.1216	0.0000	0.0001	0.0000	-0.0168	0.0159	0.0467	97.44	0.0059	0.00625
				0.0000	0.0004	0.0000						
Euro → Thailand	6.9247	4.5498	2.3749	0.0314	0.0329	0.1233	0.0049	-0.0400	0.5740	0.48	0.0045	0.00363
				0.3725	0.0570	0.8516						
Euro → Taiwan	68.3829	52.7876	15.5953	0.0000	0.0000	0.0001	0.0020	0.0269	0.1220	63.55	0.0292	0.02792
				0.0000	0.0000	0.0058						
Euro → US	13.8111	0.4134	13.3977	0.0010	0.5202	0.0003	-0.0153	0.0126	0.0341	99.98	0.0006	0.00092
				0.0305	0.5591	0.0153						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

5.4. Volatility Spillovers in Equity Markets – First Stage DCC (1, 1)

Panel A in Table 5.4 shows results of the hypothesis test in which the spillover and threshold effects are measured from US to the South East Asian equity markets followed by panel B and panel C for Japan and Thailand respectively. Using a 10% significance level and bootstrapped p-values, Panel A in Table 5.4 shows rejection of the null hypothesis of no volatility spillovers and no threshold effects (hypothesis 1) for all the country pairs examined. Test of hypotheses 2 yields results similar to hypothesis 1 results. A test of hypothesis 3 produces results, where the null hypothesis of, the existence of no threshold effects conditional on no spillover effects is rejected for all country pairs except for the US to the Philippines.

Similarly an examination of Panel B shows that hypothesis 1, hypothesis 2 and hypothesis 3 are rejected for all country pairs. Panel C shows results very similar to panel B in rejecting hypothesis 1 and hypothesis 2. Hypothesis 3 is rejected in four out of nine cases in Panel C. Panel A through C show the actual coefficient estimates for the extended conditional variance equation. The coefficient for model 3, ω_{12}, which measures the threshold effects, is insignificant for US-Philippines, Thailand-Japan, Thailand-Malaysia, Thailand-Philippines, Thailand-Singapore and Thailand-US pairs but the coefficient for model 2, δ_{12}, which measures spillover effects, is significant for all the pairs indicating the existence of spillover effects even when threshold effects may be absent in some cases. In some country pairs the threshold effects are not as significant but volatility spillovers exist and in others the threshold effects are significant even when the volatility spillovers are not.

On comparing the coefficients in model 1, except for US-India in Panel A, there is a sign reversal in every country pair examined. The volatility spillover coefficients are all positive in Panel A through C except for US-China, US-Thailand, Japan-China and Japan-Thailand. As discussed in section 5.1 where the conditional variance in the first stage is generated using a GARCH (1, 1) process, these results might be a result of segmented markets. In comparing Table 5.1 and 5.4, though the results are similar in terms of the signs on the coefficient estimates for the different country pairs, the significance of some of the country pairs have changed. Overall, in analyzing the results from both sections 5.1 and 5.4, for both the approaches, when conditional variance is generated using GARCH (1, 1) or DCC (1, 1) in the first stage, the results are very similar and robust. This similarity adds strength to our inference of the results.

Table 5.4 Estimation Results and Coefficient Estimates of Conditional Variance Estimation for Equity Markets – DCC (1, 1)

Panel A:

Country Pair	Like Ratio			P Value			Model 1				Model 2	Model 3
	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
US --> China	13.1673	7.8624	5.3049	0.0014	0.0050	0.0213	-0.0100	0.0213	15.8149	1.08	-0.0071	-0.00569
				0.0000	0.0222	0.0001						
US --> Sing	8.1251	6.7049	1.4202	0.0172	0.0096	0.2334	0.0156	-0.0142	10.8876	1.51	0.0132	0.00691
				0.0000	0.0221	0.0000						
US --> India	3.9991	2.9531	1.0459	0.1354	0.0857	0.3064	0.0094	0.0885	20.2236	0.53	0.0100	0.01064
				0.0000	0.0216	0.0000						
US --> Malaysia	10.1432	4.0273	6.1159	0.0063	0.0448	0.0134	0.0089	-0.0074	0.7737	63.52	0.0026	0.00112
				0.0000	0.0219	0.0001						
US --> Taiwan	11.4032	5.3685	6.0347	0.0033	0.0205	0.0140	0.0326	-0.0219	0.2551	99.97	0.0106	0.00406
				0.0000	0.0219	0.0001						
US --> Philippines	96.3811	53.9062	42.4748	0.0000	0.0000	0.0000	0.1219	-0.0910	0.2551	99.97	0.0579	0.02926
				0.0001	0.0245	0.1311						
US --> Hong Kong	1.7417	0.5039	1.2378	0.4186	0.4778	0.2659	0.0036	-0.0178	10.8876	1.51	0.0031	-0.01580
				0.0000	0.0215	0.0000						
US --> Jap	27.0804	20.3436	6.7367	0.0000	0.0000	0.0094	0.0379	-0.0542	14.5183	1.16	0.0355	0.01066
				0.0000	0.0226	0.0001						
US --> Thailand	18.6953	0.0686	18.6267	0.0001	0.7935	0.0000	-0.0376	0.0420	1.0330	50.16	-0.0013	0.03561
				0.0000	0.0215	0.0034						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1}$

Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

Table 5.4 - continued

Panel B:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Jap --> China	12.8275	3.9993	8.8282	0.0016	0.0455	0.0030	-0.0146	0.0167	2.1120	40.48	-0.0050	0.01182
				0.0000	0.0219	0.0002						
Jap --> India	8.9873	7.1912	1.7960	0.0112	0.0073	0.1802	0.0182	-0.0147	1.7781	50.69	0.0146	0.01119
				0.0000	0.0221	0.0000						
Jap --> Malaysia	13.8688	5.6163	8.2526	0.0010	0.0178	0.0041	0.0042	-0.0228	26.4914	0.45	0.0033	0.00496
				0.0000	0.0220	0.0002						
Jap --> Philippines	22.5269	15.4130	7.1139	0.0000	0.0001	0.0076	0.0247	-0.1708	27.4933	0.38	0.0219	0.03279
				0.0000	0.0224	0.0001						
Jap --> Hong Kong	7.8595	1.7021	6.1574	0.0196	0.1920	0.0131	0.0056	-0.2298	27.4933	0.38	0.0057	-0.95901
				0.0000	0.0216	0.0001						
Jap --> US	6.5078	1.9850	4.5228	0.0386	0.1589	0.0334	0.0040	-0.0189	4.7837	7.54	0.0037	-0.01643
				0.0000	0.0216	0.0001						
Jap --> Sing	10.6115	6.8164	3.7951	0.0050	0.0090	0.0514	0.0109	-0.1151	27.4933	0.38	0.0102	0.01346
				0.0000	0.0221	0.0001						
Jap --> Thailand	5.8904	0.1666	5.7238	0.0526	0.6832	0.0167	-0.0102	0.0325	3.7818	12.97	-0.0023	0.02421
				0.0000	0.0215	0.0001						
Jap --> Taiwan	6.5517	1.8752	4.6766	0.0378	0.1709	0.0306	0.0127	-0.0108	0.4422	99.97	0.0044	-0.00131
				0.0000	0.0216	0.0001						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1}$

Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

Table 5.4 - continued

Panel C:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Thailand → China	4.00	0.36	3.64	0.1350	0.5482	0.0563	-0.0096	0.0080	1.1220	99.97	-0.0007	-0.0026
				0.0000	0.0215	0.0001						
Thailand → Hong Kong	15.88	5.33	10.55	0.0004	0.0210	0.0012	0.0043	-0.3676	37.6195	0.50	0.0042	-0.3493
				0.0000	0.0219	0.0002						
Thailand → India	50.84	28.13	22.71	0.0000	0.0000	0.0000	0.0280	-0.0298	10.5539	4.93	0.0152	0.0076
				0.0000	0.0233	0.0080						
Thailand → Japan	51.36	2.17	49.19	0.0000	0.1408	0.0000	0.0031	-0.0073	13.4245	2.79	0.0018	-0.0104
				0.0000	0.0216	0.2352						
Thailand → Malaysia	61.72	16.11	45.61	0.0000	0.0001	0.0000	0.0052	-0.0215	24.9069	0.48	0.0049	-0.8159
				0.0000	0.0224	0.1738						
Thailand → Philippines	102.88	58.06	44.82	0.0000	0.0000	0.0000	0.0532	-0.0601	21.6262	0.83	0.0536	0.0148
				0.0004	0.0257	0.1630						
Thailand → Singapore	47.06	6.17	40.89	0.0000	0.0130	0.0000	0.0027	-0.0209	24.9069	0.48	0.0033	-0.4637
				0.0000	0.0220	0.1095						
Thailand → Taiwan	15.07	3.09	11.99	0.0005	0.0789	0.0005	0.0077	-0.0080	7.2732	9.73	0.0021	-0.0113
				0.0000	0.0216	0.0007						
Thailand → US	44.39	0.00	44.39	0.0000	0.9792	0.0000	0.0011	-0.0063	24.9069	0.48	0.0000	-0.0038
				0.0000	0.0215	0.1580						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1}$

Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

5.5. Volatility Spillovers in Bond Markets – First Stage DCC (1, 1)

Table 5.5 shows the estimation results for the various hypotheses tested in this study of bond market spillover when the conditional variance in the first stage is generated using a DCC (1, 1) type model. Using a 10% significance level and bootstrapped p-values results in rejection of all the hypotheses tested under every country pair in panels A through C. The model in this estimation might be misspecified as the conditional variance in the first stage is generated using a DCC model and in the second stage the model is estimated using an extended GARCH specification. Even though, being aware of this, I still contend that there is evidence of existence of threshold effects. Allowing for multivariate type effects in the first stage does not alter the results from section 5.2.

Using conventional p-values, Panel A shows rejection of hypotheses 1 for all European bond markets except Switzerland. Test of hypotheses 2 results using conventional p-values are similar to hypotheses 1. Hypothesis 3 results show rejection for all country pairs. These results of hypothesis 3 show that the European bond markets are consistently affected by increases in volatility of US bond markets when they exceed a particular threshold. An examination of Panel B shows that rejection of hypothesis 1 for all country pairs except for Greece-France, Greece-Switzerland, Greece-UK and Greece-US. This indicates that conditional variance spillovers from Greece to some bond markets studied might not have volatility spillovers as well as threshold effects. Test of hypothesis 2 yields results with rejection of the hypothesis in five of the fifteen country pairs examined. This means that only Austria, Belgium, Italy, Ireland and Spain might be affected by changes in volatility in the Greek bond market. The test of hypothesis 3 yields results in Panel B that reject the hypothesis for all except Greece-Austria, Greece-Switzerland, Greece-UK and Greece-US country pairs. Though the appropriate critical value is the bootstrapped critical value, for verification purpose, looking at these hypotheses tests under the conventional p-values yields similar results.

The results examined in Table 5.5 show that there is evidence of spillover and threshold effect from Greece and US to most of the European country bond markets. In some country pairs the threshold effects are not as significant but volatility spillovers exist. Panel A through C show the actual coefficient estimates for the extended conditional variance equation that is used in this study. On comparing the coefficients in model 1, Panel A through C, there is a sign reversal in every country pair examined except US-Denmark, US-Switzerland and UK-Switzerland pairs. The volatility spillover coefficients are all positive for Model 1, in Panel A, B and C except Greece-UK in Panel B. One of the possible explanations for this negative spillover from Greece to UK bond market is that, when volatility in Greek bond market increases, investors might be investing in British bonds more as compared to Greek bonds. Examining Panel A, at high levels of volatility in US bond market (beyond the threshold), the volatility in European bond markets are affected negatively except for Denmark and Switzerland. So when the volatility in the US market increases, volatility in European bond markets increase and when volatility in US bond market increases beyond a threshold value, volatility in European bond markets decrease except Swizz and Danish markets. Some of the coefficients for model 3 in panel B and C have negative coefficients indicating a decrease in volatility of one market when the volatility in another market exceeds a threshold.

Table 5.5 Estimation Results and Coefficient Estimates of Conditional Variance Estimation for Bond Markets – DCC (1, 1)

Panel A:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
US → Austria	26.5496	14.9167	11.6329	0.0000	0.0001	0.0006	0.009890	-0.004666	0.051600	74.31	0.006552	0.003951
				0.0000	0.0224	0.0007						
US → Belgium	11.9521	6.3311	5.6210	0.0025	0.0119	0.0177	0.011487	-0.006050	0.051600	74.31	0.005623	0.002855
				0.0000	0.0220	0.0001						
US → Denmark	32.9439	18.8820	14.0619	0.0000	0.0000	0.0002	0.003447	0.011312	0.156900	12.53	0.005071	0.008042
				0.0000	0.0226	0.0012						
US → EMU	15.1169	6.8555	8.2614	0.0005	0.0088	0.0040	0.013505	-0.006571	0.047300	78.27	0.006004	0.003647
				0.0000	0.0221	0.0002						
US → France	15.8097	9.7697	6.0400	0.0004	0.0018	0.0140	0.022003	-0.010052	0.042900	82.23	0.008727	0.005063
				0.0000	0.0222	0.0001						
US → Germany	15.0541	6.6894	8.3647	0.0005	0.0097	0.0038	0.013418	-0.006585	0.047300	78.27	0.005866	0.003538
				0.0000	0.0221	0.0002						
US → Greece	34.8161	21.0343	13.7818	0.0000	0.0000	0.0002	0.030477	-0.015164	0.042900	82.23	0.017163	0.010389
				0.0000	0.0226	0.0012						
US → Ireland	29.2710	18.5252	10.7458	0.0000	0.0000	0.0010	0.038399	-0.017727	0.042900	82.23	0.016795	0.010324
				0.0000	0.0226	0.0003						
US → Italy	29.5712	19.9300	9.6412	0.0000	0.0000	0.0019	0.028961	-0.013074	0.051600	74.31	0.013920	0.008026
				0.0000	0.0226	0.0002						
US → Netherland	21.9495	9.5860	12.3636	0.0000	0.0020	0.0004	0.017577	-0.008679	0.042900	82.23	0.007259	0.003158
				0.0000	0.0222	0.0008						
US → Norway	39.1766	28.1756	11.0009	0.0000	0.0000	0.0009	0.024716	-0.011749	0.038500	87.70	0.011193	0.010132
				0.0000	0.0233	0.0007						
US → Spain	22.3316	14.6840	7.6477	0.0000	0.0001	0.0057	0.035899	-0.017108	0.042900	82.23	0.013433	0.008762
				0.0000	0.0224	0.0001						
US → Sweden	29.6973	12.6060	17.0913	0.0000	0.0004	0.0000	0.017175	-0.008742	0.047300	78.27	0.005948	0.004104
				0.0000	0.0224	0.0021						
US → Switz	5.3730	1.5125	3.8605	0.0681	0.2188	0.0494	0.001456	0.008291	0.183200	6.94	0.001852	0.008419
				0.0000	0.0215	0.0001						
US → UK	11.2664	6.4029	4.8634	0.0036	0.0114	0.0274	0.006011	-0.002440	0.047300	78.27	0.003460	0.002118
				0.0000	0.0221	0.0001						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12} I_{\{h_{22t-1}\geq\lambda\}} h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12} I_{\{h_{22t-1}\geq\lambda\}} h_{22t-1}$

Table 5.5 - continued

Panel B:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Greece → Austria	9.0131	5.4799	3.5332	0.0110	0.0192	0.0602	0.000120	-0.000470	109.77	0.33	0.0000506	0.000050
				0.0000	0.0219	0.0001						
Greece → Belgium	16.8668	9.4760	7.3909	0.0002	0.0021	0.0066	0.000349	-0.000427	22.21	0.39	0.0001196	0.000096
				0.0000	0.0222	0.0001						
Greece → Denmark	10.6455	1.5469	9.0986	0.0049	0.2136	0.0026	0.000286	-0.000347	2.48	1.77	0.0000273	0.000011
				0.0000	0.0216	0.0002						
Greece → EMU	9.6011	0.1245	9.4766	0.0082	0.7242	0.0021	0.000097	-0.000749	109.77	0.33	0.0000123	-0.000222
				0.0000	0.0215	0.0002						
Greece → France	4.4498	0.0009	4.4488	0.1081	0.9755	0.0349	0.000080	-0.000529	109.77	0.33	0.0000008	-0.000122
				0.0000	0.0215	0.0001						
Greece → Germany	9.5630	0.1231	9.4398	0.0084	0.7257	0.0021	0.000097	-0.000749	109.77	0.33	0.0000122	-0.000221
				0.0000	0.0215	0.0002						
Greece → Ireland	60.7126	13.0131	47.6995	0.0000	0.0003	0.0000	0.002614	-0.004924	17.28	0.52	0.0020786	-0.017225
				0.0000	0.0224	0.2077						
Greece → Italy	48.9310	22.4415	26.4895	0.0000	0.0000	0.0000	0.001554	-0.002239	22.21	0.39	0.0008235	-0.002961
				0.0000	0.0232	0.0179						
Greece → Netherland	8.9878	0.0490	8.9388	0.0112	0.8247	0.0028	0.000066	-0.000573	109.77	0.33	-0.0000064	-0.000231
				0.0000	0.0215	0.0002						
Greece → Norway	17.6035	0.1813	17.4223	0.0002	0.6703	0.0000	0.000683	-0.000908	2.48	1.77	0.0000285	-0.000094
				0.0000	0.0215	0.0024						
Greece → Spain	56.4320	27.6092	28.8228	0.0000	0.0000	0.0000	0.002482	-0.003857	28.37	0.33	0.0018077	-0.008432
				0.0000	0.0233	0.0256						
Greece → Sweden	9.5768	0.1928	9.3840	0.0083	0.6606	0.0022	0.000314	-0.000396	2.48	1.77	0.0000159	-0.000033
				0.0000	0.0215	0.0002						
Greece → Switz	2.6812	1.9942	0.6870	0.2617	0.1579	0.4072	0.000029	-0.000060	2.48	1.77	-0.0000227	-0.000028
				0.0000	0.0216	0.0000						
Greece → UK	1.5644	0.7651	0.7993	0.4574	0.3817	0.3713	-0.000022	0.000145	92.50	0.65	0.0000163	0.000139
				0.0000	0.0215	0.0000						
Greece → US	4.3995	0.9719	3.4276	0.1108	0.3242	0.0641	0.000357	-0.000421	12.34	0.72	0.0000457	0.000042
				0.0000	0.0215	0.0001						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

Table 5.5 - continued

Panel C:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
UK → Austria	9.0100	5.4800	3.5300	0.0110	0.0192	0.0601	0.000100	-0.000500	109.77	68.55	0.0001000	0.000100
				0.0000	0.0224	0.0007						
UK → Belgium	16.8700	9.4800	7.3900	0.0002	0.0021	0.0066	0.000300	-0.000400	22.21	83.44	0.0001000	0.000100
				0.0000	0.0224	0.0001						
UK → Denmark	10.6500	1.5500	9.1000	0.0049	0.2136	0.0026	0.000300	-0.000300	2.48	13.78	0.0000000	0.000000
				0.0000	0.0224	0.0233						
UK → EMU	9.6000	0.1200	9.4800	0.0082	0.7242	0.0021	0.000100	-0.000700	109.77	79.58	0.0000000	-0.000200
				0.0000	0.0224	0.0001						
UK → France	4.4500	0.0000	4.4500	0.1081	0.9755	0.0349	0.000100	-0.000500	109.77	83.44	0.0000000	-0.000100
				0.0000	0.0224	0.0001						
UK → Germany	9.5600	0.1200	9.4400	0.0084	0.7257	0.0021	0.000100	-0.000700	109.77	79.58	0.0000000	-0.000200
				0.0000	0.0222	0.0001						
UK → Greece	60.4000	13.0100	47.3900	0.0000	0.0003	0.0000	0.002200	-0.004500	17.28	41.88	0.0021000	-0.018600
				0.0000	0.0234	0.0001						
UK → Ireland	48.9300	22.4400	26.4900	0.0000	0.0000	0.0000	0.001600	-0.002200	22.21	99.97	0.0008000	-0.003000
				0.0000	0.0233	0.0001						
UK → Italy	9.4000	0.0500	9.3500	0.0091	0.8247	0.0022	0.000100	-0.000600	109.77	50.26	0.0000000	-0.000200
				0.0000	0.0232	0.0002						
UK → Netherland	17.6000	0.1800	17.4200	0.0002	0.6703	0.0000	0.000700	-0.000900	2.48	83.44	0.0000000	-0.000100
				0.0000	0.0224	0.0001						
UK → Norway	56.4300	27.6100	28.8200	0.0000	0.0000	0.0000	0.002500	-0.003900	28.37	71.50	0.0018000	-0.008400
				0.0000	0.0226	0.0044						
UK → Spain	9.5800	0.1900	9.3800	0.0083	0.6606	0.0022	0.000300	-0.000400	2.48	2.19	0.0000000	0.000000
				0.0000	0.0233	0.0001						
UK → Sweden	2.6800	1.9900	0.6900	0.2617	0.1579	0.4072	0.000000	-0.000100	2.48	0.56	0.0000000	0.000000
				0.0000	0.0224	0.0002						
UK → Switzerland	1.5600	0.7700	0.8000	0.4574	0.3817	0.3713	0.000000	0.000100	92.50	13.78	0.0000000	0.000100
				0.0000	0.0215	0.0001						
UK → US	4.4000	0.9700	3.4300	0.1108	0.3242	0.0641	0.000400	-0.000400	12.34	99.97	0.0000000	0.000000
				0.0000	0.0215	0.0002						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{22t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{22t-1}\geq\lambda\}}h_{22t-1}$

5.6. Volatility Spillovers in Foreign Exchange Markets – First Stage DCC (1, 1)

Employing the DCC (1, 1) model to generate the conditional variance in the first stage, the estimation results for volatility spillovers and threshold effects in foreign exchange markets and the statistics used to test the various hypotheses are shown in Table 5.6. Panel A shows results of the hypothesis test for US forex markets, panel B for Japan and panel C for Thailand. Using a 10% significance level and bootstrapped p-value, hypotheses 1 and 2 are rejected in all panels A through C. Hypotheses 3 is rejected in all the country pairs in Panel C and eleven out of twelve times in panel A and B. This is considerable evidence in support of existence of threshold effects. Just for exposition purposes, looking at conventional p-values, panel A shows rejection of the null hypothesis of no volatility spillovers and no threshold effects from US forex market to other forex markets in all the country pairs. Hypothesis 3 is rejected for all the country pairs in panel A except US-Japan and hypothesis 2 is rejected in all pairs except US- Malaysia. All the coefficients in Panel A have a sign reversal except US-Euro, US-India and US-Indonesia. These results of hypothesis 3 show that the S.E. Asian forex markets are consistently affected by increases in volatility of US forex markets when they exceed a particular threshold.

Examination of Panel B and C under hypotheses 1 and using conventional p-values produces results of rejection except Japan-Thailand and Japan-US. Hypothesis 2 is rejected seven out of twelve times in both Panel B and Panel C. This means that only Euro, Indonesia, Philippines, Singapore and Taiwan might be affected by changes in volatility in the Japan forex market. The test of hypothesis 3 yields results in Panel B that reject the hypothesis for all except Japan-Philippines, Japan-Thailand and Japan-US country pairs. Analysis of panel C shows that hypothesis 1 and hypothesis 3 are rejected for all country pairs whereas, hypothesis 2 is rejected for only five of the twelve pairs examined. This indicates inference similar to other panels examined in this section. In most of the country pairs the threshold effects are significant and more important or outweigh the effects from volatility spillovers.

On comparing the coefficients in model 1, Panel A through C, there is a sign reversal in twenty eight of the thirty six country pairs examined. Twenty seven of the δ_{12} coefficients are positive and twenty of the ω_{12} coefficients are negative. At high levels of volatility in US, Japan or Thailand forex market (beyond the threshold), and the volatility in other forex markets are mostly affected negatively. The results for the foreign exchange market spillover seem to be clearer when the DCC (1, 1) model is used to generate the conditional variance in the first stage as opposed to the GARCH (1, 1) model. Given these results, it is evident that allowing for some type of multivariate effects only in the first stage of the estimation does not alter the results of this study.

Table 5.6 Estimation Results and Coefficient Estimates of Conditional Variance Estimation for Foreign Exchange Markets – DCC (1, 1)

Panel A:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
US → China	11.0140	8.2151	2.7988	0.0041	0.0042	0.0943	0.0085	-0.0068	0.3052	3.89	0.0052	0.00326
				0.0000	0.0222	0.0000						
US → Euro	7.9755	3.4121	4.5634	0.0185	0.0647	0.0327	0.0003	0.0121	0.4482	1.99	0.0032	0.01248
				0.0000	0.0219	0.0001						
US → Hong Kong	14.8191	10.2613	4.5579	0.0006	0.0014	0.0328	0.0044	-0.0035	0.2496	5.39	0.0022	0.00142
				0.0000	0.0224	0.0001						
US → India	14.5971	7.1371	7.4600	0.0007	0.0076	0.0063	0.0149	0.2099	0.6071	0.95	0.0180	0.02331
				0.0000	0.0221	0.0001						
US → Indonesia	70.6829	28.7782	41.9048	0.0000	0.0000	0.0000	0.0032	0.1184	0.4244	2.13	0.0174	0.12291
				0.0000	0.0233	0.1114						
US → Japan	6.7063	4.0625	2.6438	0.0350	0.0438	0.1040	-0.0073	0.0256	0.0669	50.31	0.0147	0.02003
				0.0000	0.0219	0.0000						
US → Korea	14.0805	2.9868	11.0937	0.0009	0.0839	0.0009	0.0714	-0.0543	0.0193	70.67	0.0139	0.64347
				0.0000	0.0216	0.0007						
US → Malaysia	7.0879	2.2528	4.8351	0.0289	0.1334	0.0279	-0.0038	0.0065	0.1384	15.76	0.0020	0.01197
				0.0000	0.0216	0.0001						
US → Philippines	17.6038	8.5531	9.0507	0.0002	0.0034	0.0026	0.0617	-0.0400	0.0193	99.98	0.0183	0.02262
				0.0000	0.0222	0.0002						
US → Singapore	41.5069	5.6009	35.9060	0.0000	0.0180	0.0000	0.0290	-0.0216	0.0193	72.77	0.0044	0.01695
				0.0000	0.0219	0.0613						
US → Thailand	19.1607	7.8709	11.2898	0.0001	0.0050	0.0008	0.0278	-0.0201	0.0193	79.98	0.0058	0.01199
				0.0000	0.0222	0.0007						
US → Taiwan	29.3113	24.8119	4.4994	0.0000	0.0000	0.0339	0.0388	-0.0351	0.5277	1.58	0.0309	0.02680
				0.0000	0.0233	0.0001						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1} + \omega_{12} I_{\{h_{12t-1}\geq\lambda\}} h_{12t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12} I_{\{h_{12t-1}\geq\lambda\}} h_{12t-1}$

Table 5.6 - continued

Panel B:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Japan → China	5.6477	1.8657	3.7819	0.0594	0.1720	0.0518	0.0001	0.0018	0.6600	14.72	0.0007	0.00187
				0.0000	0.0216	0.0001						
Japan → Euro	8.7952	5.6293	3.1659	0.0123	0.0177	0.0752	0.0024	-0.0014	0.2000	91.78	0.0012	0.00454
				0.0000	0.0220	0.0001						
Japan → Hong Kong	6.4667	0.9952	5.4716	0.0394	0.3185	0.0193	-0.0001	0.0008	0.6600	14.72	0.0002	0.00078
				0.0000	0.0215	0.0001						
Japan → India	11.0460	2.5649	8.4810	0.0040	0.1093	0.0036	0.0016	0.2397	3.4205	0.18	0.0024	0.24725
				0.0000	0.0216	0.0002						
Japan → Indonesia	81.9121	5.9316	75.9806	0.0000	0.0149	0.0000	-0.0018	0.0675	1.6952	1.72	0.0028	0.06558
				0.0001	0.0220	0.7601						
Japan → Korea	9.2416	0.2418	8.9998	0.0098	0.6229	0.0027	-0.0016	-2.7288	3.4205	0.28	-0.0028	-2.74840
				0.0000	0.0215	0.0002						
Japan → Malaysia	6.0099	0.0404	5.9694	0.0495	0.8406	0.0146	-0.0008	0.0024	1.5035	2.06	0.0001	0.00157
				0.0000	0.0215	0.0001						
Japan → Philippines	7.7051	5.8078	1.8972	0.0212	0.0160	0.1684	0.0053	-0.0075	2.3853	1.00	0.0040	0.00256
				0.0000	0.0220	0.0000						
Japan → Singapore	48.5748	42.1420	6.4328	0.0000	0.0000	0.0112	0.0028	0.0031	0.1616	90.42	0.0060	0.00450
				0.0000	0.0235	0.0001						
Japan → Thailand	1.8661	0.4373	1.4288	0.3934	0.5084	0.2320	-0.0005	0.0016	0.6600	14.72	0.0004	0.00112
				0.0000	0.0215	0.0000						
Japan → Taiwan	43.3938	32.8630	10.5307	0.0000	0.0000	0.0012	0.0093	-0.0144	2.6153	0.75	0.0087	0.00826
				0.0000	0.0234	0.0002						
Japan → US	2.2920	1.4766	0.8154	0.3179	0.2243	0.3665	-0.0012	0.0006	0.1616	98.64	-0.0005	-0.00059
				0.0000	0.0215	0.0000						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon_{1t-1}^2 + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{12t-1}\geq\lambda\}}h_{12t-1}$

Table 5.6 - continued

Panel C:												
	Like Ratio			P Value			Model 1				Model 2	Model 3
Country Pair	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	δ_{12}	ω_{12}	λ	% λ	δ_{12}	ω_{12}
Thai → China	11.4297	0.3526	11.0771	0.0033	0.5526	0.0009	0.0002	-0.0023	39.7918	0.45	0.0000	0.00003
				0.0000	0.0215	0.0510						
Thai → Euro	9.1543	1.5773	7.5771	0.0103	0.2092	0.0059	-0.0003	0.0009	5.3802	1.18	0.0001	0.00054
				0.0000	0.0216	0.0001						
Thai → Hong Kong	37.9010	0.4310	37.4700	0.0000	0.5115	0.0000	0.0001	-0.0007	39.7918	0.45	0.0000	0.00001
				0.0000	0.0215	0.0773						
Thai → India	39.2636	0.7162	38.5474	0.0000	0.3974	0.0000	0.0006	-0.0032	39.7918	0.45	0.0002	-0.00098
				0.0000	0.0215	0.0738						
Thai → Indonesia	63.6194	49.5782	14.0412	0.0000	0.0000	0.0002	0.0000	0.0082	5.3802	1.18	0.0023	0.00815
				0.0000	0.0238	0.0012						
Thai → Japan	7.1313	1.6025	5.5288	0.0283	0.2056	0.0187	0.0020	-0.0082	32.1944	0.29	0.0006	0.00020
				0.0000	0.0216	0.0001						
Thai → Korea	38.8181	0.2268	38.5913	0.0000	0.6339	0.0000	0.0002	-0.0021	39.7918	0.45	-0.0001	-0.00153
				0.0000	0.0215	0.0839						
Thai → Malaysia	43.4929	37.1219	6.3710	0.0000	0.0000	0.0116	0.0005	0.0035	19.6811	0.20	0.0012	0.00332
				0.0000	0.0234	0.0001						
Thai → Philippines	87.9596	52.2294	35.7302	0.0000	0.0000	0.0000	0.0147	-0.0346	39.7918	0.45	0.0122	0.02507
				0.0001	0.0241	0.0543						
Thai → Singapore	50.2809	14.4422	35.8387	0.0000	0.0001	0.0000	0.0006	-0.0039	39.7918	0.45	0.0008	0.00062
				0.0000	0.0224	0.0998						
Thai → Taiwan	44.7172	5.2672	39.4499	0.0000	0.0217	0.0000	0.0009	-0.0036	39.7918	0.45	0.0008	0.00026
				0.0000	0.0219	0.0812						
Thai → US	33.8359	0.0122	33.8237	0.0000	0.9121	0.0000	0.0001	-0.0015	39.7918	0.45	0.0000	-0.00024
				0.0000	0.0215	0.0472						

*Estimation results and significance for Hypothesis 1: No Volatility Spillovers and No Threshold Effects, Hypothesis 2: No Volatility Spillovers Conditional on No Threshold Effects and Hypothesis 3: No Threshold Effect conditional on No Volatility Spillover is presented in the Table above

Model 1: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1} + \omega_{12}I_{\{h_{12t-1}\ge\lambda\}}h_{12t-1}$ Model 2: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \delta_{12}h_{12t-1}$ Model 3: $h_{11t} = \kappa + \alpha_{11}\varepsilon^2_{1t-1} + \delta_{11}h_{11t-1} + \omega_{12}I_{\{h_{12t-1}\ge\lambda\}}h_{12t-1}$

5.7. Summary of Section

Summarizing this section, there are certain important implications that I would like to infer from the overall analysis of the results. The results remain robust regardless of how the conditional variance is generated in the first stage of the estimation. Generating the conditional variance in the first stage using a GARCH (1,1) model may be more appropriate as an extended GARCH specification is used in the second stage. Relaxing the model in the first stage to a DCC (1, 1) and continuing to use an extended GARCH specification in the second stage though might be misspecified, does not alter the robust results of this study. Bond market spillovers provide the strongest evidence of threshold effects followed by equity markets and then foreign exchange markets. In the case of using a GARCH (1, 1) type model to generate conditional variance, the spillover study on foreign exchange markets did not produce clear results as to generalize the results.

The DCC (1, 1) model produced results that could aid in better inference of the findings. There seems to be a clear and robust impact due to threshold effects in volatility spillovers. In certain cases, the threshold effects outweigh the regular linear volatility spillover effects. Spillovers and threshold effects within equity and bond asset class were robust, regardless of how the conditional variance is generated. The study using foreign exchange markets seems to produce a pattern when using DCC model. Using a GARCH model for foreign exchange markets produces results that cannot be used to draw much inference from. The results within the bond market spillover and threshold effects had the most consistent results on comparison to the equity and foreign exchange asset classes. The results are consistent with the initial expectations of existence of threshold effects in volatility spillovers.

CHAPTER 6

CONCLUSION

In conclusion, there is a significant importance and relevance for the understanding of dynamics and linkages of threshold effects in direct volatility spillovers and indirect threshold effects. None of the previous studies on volatility spillovers include conditional variances of the second asset or nonlinearities in the conditional variance specification and have focused primarily on spillovers in the innovations of the second asset. I model spillovers in the conditional variance of asset returns including these parameters. The return data is skewed and so, instead of using a likelihood function with a t-distribution, I use a likelihood function with Chi-Square distribution. I use a bivariate analysis to make this study computationally feasible. Following a two-step procedure for the estimation; in the first stage, I calculate the conditional variance of asset returns for second country using a GARCH (1, 1) or DCC (1, 1) model. Employing a grid search approach I sequentially compute the threshold value for the second country that uses an optimization routine to maximize the likelihood function. Treating the conditional variance of the second country and the threshold value as known, in the second stage I estimate the conditional variance of the first country with the new extended conditional variance specification. This model is a significant contribution to existing literature as it additionally incorporates the conditional variance and threshold values from the second asset.

Using likelihood ratio statistics and bootstrapped p-values, analysis of the volatility spillover and threshold effects within different asset classes of different markets, I find significant evidence for the existence of indirect threshold effects and direct volatility spillovers. While the volatility spillovers are mostly positive, the threshold effects are mostly negative. There are four potential explanations for these negative spillovers. First, investors hedge their positions, when volatility in one market exceeds the threshold. Second, these negative spillovers indicate the availability of diversification opportunities in other markets when risk in one market increases. Third, following some of the studies that show segmentation in markets, risk does not spillover as much in segmented markets and finally, when volatility in one market increases beyond a threshold, this might be country specific risk and might not affect other markets as much. The extended formulation of the conditional variance to incorporate threshold effects and the negative sign on these threshold effects are significant findings of this research. Even in the absence of volatility spillover effects, there is evidence for the existence of threshold effects in most asset class country pairs. Since I do not know the underlying distribution of the conditional variances estimated, I use bootstrap critical values to test the various hypotheses. Using the bootstrapped p-values, I still find evidence for the existence of threshold effects in volatility spillovers.

The bond market seems to exhibit the most robust set of results among the asset classes examined, followed by equity and then by foreign exchange markets. Results including some of the country pair statistics where the conditional variance in the first stage is generated using a DCC model and corresponding bootstrapped p-values are also shown. Though this model might suffer from potential misspecification, allowing for multivariate effects or the correlations to be time varying in the first stage does not alter the research findings and I find even more significant results in comparison to the model where the conditional variance in first stage was generated using GARCH model. An extension to this study could implement the second stage of the estimation to allow for multivariate effects where the correlations are time varying; allowing for regime switches; analysis of the dynamics of these threshold effects across asset classes within the domestic market or across asset classes, internationally; threshold effect implications to optimal portfolio allocation; relationship between time-varying hedge ratio and threshold effects, etc. are a study in entirety and are left as part of future research.

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