TRANSMISSION OF INFORMATION ACROSS INTERNATIONAL STOCK MARKETS

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Submitted for the degree of Doctor of Philosophy

Heriot-Watt University

School of Management and Languages

May 2013

ABSTRACT

This thesis aims to contribute to the existing literature about return and volatility spillovers. First, this study examines the direct transmission of information contained in returns, volatility and trading volume across the world's eight biggest stock markets by market capitalisation using the ARCH-type models. The empirical results highlight the complexity of the information transmission mechanisms *via* different channels. Second, this study investigates the transmission of information in stock market index returns after considering the interactive effect between trading volume and returns. A new approach to analyse this joint-dynamic relation has been proposed and the findings are interpreted in the light of economic theory. The obtained results provide evidence that liquidity-based price movements, which are normally related to high trading volume, can also be transmitted across borders and have a global impact on market performance in other countries. Last but not least, this study explores the economic significance of international information spillovers and presents evidence showing that active investment strategies which apply trading rules based on the signals from the forecasts of the meteor shower models are profitable even after considering transaction costs. In addition, the information about the interactive relation between trading volume and returns is found to be an exploitable phenomenon which investors can use to trade profitably.

DECLARATION STATEMENT

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ACKNOWLEDGEMENTS

I am very grateful to my supervisors Dr Janusz Brzeszczynski and Dr Boulis Ibrahim for their valuable help and encouragement at every stage of my PhD. I would like to thank them for comments on earlier drafts and for offering me excellent training.

I would also like to thank Professor Andrew Adams and Professor Brian Lucey for their constructive suggestions and positive inputs in the review of my thesis.

I wish to thank the participants at the conferences and workshops held by the Scottish Graduate Programme in Economics and the Scottish Doctoral Programme in Accounting and Finance for their comments and discussions.

I am grateful to Dr Julian Fennema and members of the PhD studentship selection committee for offering me a full scholarship, without which this work would not have been started.

I owe the deepest gratitude to my family for their tremendous love and support.

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CHAPTER 1 – INTRODUCTION

1.1 Research Background

The phenomenon known as the comovements of equity prices across international stock markets has attracted attention of financial academics, media and practitioners over the past four decades. A good understanding of cross-market linkages not only contributes to the pool of academic knowledge in finance but can also be beneficial to financial market practitioners: their investment strategies in international markets can be more profitable if the nature of market interactions is better understood.

Early research in the 1970s used mainly weekly or monthly frequency data and found low correlations of returns among national markets (e.g. Levy and Sarnat, 1970; Solnik, 1974).[1] This finding encourages international diversification investment strategies where diversification benefits can be achieved by expanding the investment portfolio to include securities from other international stock exchanges. Investing in a well diversified global market portfolio enables investors to achieve a higher rate of return or lower level of risk compared to investing only in a domestic market portfolio.

However, the surge in international portfolio investment activity, along with the growth of global capital flows, the increased level of financial market deregulation (e.g. the opening-up of the stock market to foreign investors) and the improvements in communication and information technology, has translated into stronger financial linkages between otherwise seemingly unrelated economies. This has led to increased interactions between countries which have real linkages created by international trade and foreign direct investments (Gagnon and Karolyi, 2006). An important consequence of this force of globalization is the increased interdependence of equity prices across international stock markets.

[1] A number of papers reports low levels of international stock market integration using cointegration measures. However, other studies present evidence of increased degree of long-run relations of national stock market prices over time. An excellent review of the literature is provided by Kearney and Lucey (2004).

Over the last two decades, the literature has reported strong evidence about high correlations of stock returns in the world's equity markets in the short run, using relatively high frequency data. The main stream of literature focuses on examining the dynamic return and volatility spillovers across international stock markets (e.g. Hamao, Masulis and Ng, 1990; 1991; Lin, Engle and Ito, 1994). Meanwhile, some studies have attempted to associate these spillovers with economic fundamental variables, such as inflation rate, interest rate, GNP, money supply, etc., but with limited success (e.g. Karolyi and Stulz, 1996; Ng, 2000; Connolly and Wang, 2003). Other studies have found that the phenomenon of closer market comovements between countries is beyond what can be explained by connections through their economic fundamentals, and that investors may infer information from other markets by simply focusing on price movements in other countries (e.g. King and Wadhwani, 1990; Lin, et al., 1994). More recently, some other studies have showed that trading volume can explain the time-varying nature of international return spillovers (e.g. Gagnon and Karolyi, 2003; 2009).

Motivated by recent developments in this field, this thesis examines the information transmission mechanisms across the world's eight largest stock markets over the short term and investigates the dynamics of international return spillovers in relation to trading volume.[2] It further explores the economic significance of international stock market information in domestic stock market trading. The active investment trading strategies which use the price and trading volume information from domestic and foreign stock markets are designed and their performance results are discussed after consideration of transaction costs and adjustment for risk.

[2] The markets included in this study are the New York, Toronto, London, Frankfurt, Paris, Tokyo, Hong Kong and Shanghai stock exchanges. They are the world's eight largest stock markets in terms of capitalisation value at the end of 2008 according to the world federation of exchanges (WFE). A further discussion of the selection criteria is included in Chapter 3.

1.2 Motivation, Research Questions and Contribution

Motivation, Research Questions and Contribution of Chapter 4

The international stock markets located in different geographic time zones open and close sequentially around the globe. A review of the existing literature suggests that the issue of non-synchronous trading periods for different stock exchanges deserves more attention in the analysis of market interdependence (e.g. Hamao et al. 1990; Cheung and Ng, 1996; Martens and Poon, 2001). Numerous studies have employed intradaily data to examine the comovements in the returns and volatility among international stock markets over the short time horizon and have documented much evidence in favour of the existence of dynamic return and volatility spillover effects. [3] However, the information transmission mechanism in trading volume among international stock markets has not received much attention in the literature so far, and only a small number of studies have investigated the causality in the trading volume between markets (e.g. Lee and Rui, 2002; Gebka, 2012).

The main objective of Chapter 4 is to investigate the direct information transmission mechanisms in returns, volatility and trading volume across international stock markets using the ARCH-type models.

More specifically, this chapter answers the following research questions:

- Is the ARCH framework the appropriate methodology to investigate the information spillover effects across international stock markets?

- Is there new evidence supporting the previous findings from the existing return and volatility spillover literature?

- Can trading volume in one market be useful in providing additional information to investors in other international stock markets and affecting their decisions to trade (i.e. does trading volume spill over across countries)?

[3] See a review of the relevant literature in Chapter 2.

This chapter contributes to the existing literature in three ways:

First, it presents an examination of the information transmission mechanisms in returns and volatility using open-to-close market index price returns from the world's eight largest international stock markets.

Second, it investigates the dynamic spillovers in trading volume and offers economic interpretations to the results obtained. The findings suggest that the changes of liquidity investors' sentiments (e.g. the shifts of investors' risk aversion) have a contagious effect and can be transmitted across countries.

Third, it distinguishes the spillovers from markets located in the same region (intra-regional effects) and in different geographical regions (inter-regional effects). It investigates whether the inter-regional spillover effects are stronger than the intra-regional ones. In addition, this study investigates the dynamic spillover effects between mature markets and emerging markets.

Motivation, Research Questions, and Contribution of Chapter 5

The existing studies on international stock market comovements have mainly focused on the transmission of returns and volatility across national market indices and have found strong evidence of spillovers in the first and second moments of stock returns. Gagnon and Karolyi (2006) attribute this phenomenon to the gradual increase of real and financial linkages among the world's economies. However, there is little evidence in the literature that has succeeded in explaining the driving forces behind these international spillover effects using macroeconomic information variables. It is not until recently that the literature (see e.g. Gagnon and Karolyi, 2003; 2009) reported the usefulness of trading volume in explaining the return spillover effects across international stock markets.

The main objective of this chapter is to investigate the interactive effect between stock returns and trading volume in both domestic and international contexts.

More specifically, this chapter answers the following research questions:

- Does trading volume provide information that can help in explaining the time-varying nature of stock market price movements and cross-market comovements?

- Is the pattern of the international return spillover effect in relation to trading volume consistent among markets?

- Is the pattern of the first-order returns autocorrelations in relation to trading volume consistent across markets?

- In both international and domestic markets contexts, how can the interactions between returns and trading volume be interpreted in light of economic theory?

This research is distinguishable from the existing studies (i.e. Gagnon and Karolyi, 2003; 2009) in the following important aspects.

First, Gagnon and Karolyi (2003; 2009) hypothesise that the price movements associated with heavy trading volume (i.e. liquidity trades, according to the heterogeneous-agent trading model developed by Campbell, Grossman and Wang (1993)) are less likely to be transmitted across countries because they do not reflect a fundamental revaluation of stock prices by the market. However, this study argues that, even if price changes caused by liquidity trades do not reflect changes of fundamental value of underlying assets, they can still spill over to other countries. Fads and herd instinct may occur on the world-wide scale. The analysis presented in this thesis aims to find out whether the price movements driven by liquidity trades can be transmitted across borders.

Second, an econometric model, which allows one to explicitly investigate the magnitude and significance of the return spillover effect depending on different levels of the foreign market trading volume, is proposed in this study. This approach provides better insights about the dynamics of international return spillovers in relation to trading volume, which is a new contribution to the existing spillover literature.

Third, the joint dynamics between stock returns and trading volume are also examined with and without controlling for the international return spillover effect. It provides an investigation of interactive effects between returns and trading volume on the aggregate market level in both domestic and international stock market contexts.

Motivation, Research Questions and Contribution of Chapter 6

Technical analysts usually use the past domestic stock market information (such as historical stock prices and trading volume) in their predictions of stock price movements and in the design of trading strategies. However, the existing literature has shown that international stock market information exerts a great influence on the price movements in the domestic market and that asset prices are increasingly determined globally. The phenomenon of the statistically significant international information spillover effect motivates one to explore further its economic significance. This leads to the following research question in Chapter 6: can profitable trading strategies be constructed by exploring stock market information from abroad? With the availability of intradaily data (e.g. open-to-close returns of world major indices), the profitability of simulated trading strategies, in which market index day traders open and close their trading positions according to the forecasts from the econometric models incorporating the price information from the previously opened foreign market, can be tested.

The main objective of Chapter 6 is to investigate the economic significance of international return spillovers and to design trading strategies which take into account the interactive effect between stock returns and trading volume.

More specifically, this chapter answers the following research questions:

- Are the trading rules based on forecasts from the econometric model of return spillovers profitable?

- Is the information about interactive relation between trading volume and returns an exploitable phenomenon which traders can use to trade profitably?

The key features of analysis in this chapter are as follows:

First, trading strategies designed to examine the economic significance of international return spillovers are based on the data from the world's three largest stock markets (the US, UK and Japan).

Second, the constructed trading rules incorporate the information about trading volume in both domestic and foreign markets.

Third, the performance of forecasts in the out-of-sample period from the econometric model is investigated using the direction quality measures.

Fourth, the performance of regression-based trading strategies is compared to the passive buy-and-hold (B&H) investment strategy.

Last but not least, the profitability of trading rules is examined with and without inclusion of transaction costs and with adjustment for risk.

1.3 Research Methodology

In this thesis, the autoregressive conditional heteroskedasticity (ARCH) framework is used to investigate the information transmission mechanisms across international stock markets. Earlier studies on cross-market interdependence rely on the vector autoregression (VAR) models (e.g. see Eun and Shim, 1989; Von Furstenberg and Joen, 1989; Huang, Yang and Hu, 2000; Sheng and Tu, 2000; Masih and Masih, 2001; Climent and Meneu, 2003). However, the VAR methodology, which assumes time invariant conditional variance, fails to capture the autoregressive conditional heteroskedasticity effect that is inherent in the volatility of stock returns. Hamao et al. (1990) are the first model explicitly the dynamics of the conditional variance by employing a generalised ARCH model (GARCH) while studying the stock market interdependence in the short run. A new strand of literature has emerged since then, using the ARCH framework to uncover the information transmission mechanisms across international stock markets.

The ARCH-type models have been traditionally applied by empirical financial economists to study the second moment (i.e. volatility) of the financial time series. As a result, they are normally regarded as the volatility models which have little relevance to the description of the first moment (i.e. returns) of time series. However, Hamilton (2010) stresses that even if it is of primary interest to estimate the conditional mean rather than the conditional variance, it is still important to take into account the observed ARCH effect in the estimation of the relevant models. Hamilton (2010) shows that White (1980) or Newey-West (1987) robust standard errors may not be the best possible solution to avoid the inference problems related to ARCH. Furthermore, Hamilton (2010) points out that if one is indeed interested in measuring the magnitude of the coefficients, not only the standard errors but also the parameter estimates themselves should be corrected in light of the ARCH effect displayed in the data.

1.4 Outline of the Study

Chapter 2 presents a review of literature on short-term international stock market comovements and describes the most commonly used econometric methods that have been employed in the literature so far. Chapter 3 presents the description of trading hours of the world's eight largest stock exchanges, discussion about statistical properties of data and preliminary analysis of cross-market correlations. Chapters 4, 5, and 6 are the empirical chapters which contain analysis of international information spillovers. The first empirical chapter (Chapter 4) examines the direct information transmission mechanisms in returns, volatility and trading volume among international stock markets. The second one (Chapter 5) investigates the transmission of information after considering the interactive effect between trading volume and returns. The last empirical chapter (Chapter 6) explores the economic significance of international information spillovers. Finally, Chapter 7 provides a summary of the results and findings for each empirical chapter. It presents also the limitations of this study and recommendations for future research.

CHAPTER 2 – REVIEW OF LITERATURE AND METHODOLOGY

2.1 Introduction

Using weekly or monthly frequency data, early research on the comovements of international stock markets reported in the literature since the 1970s has demonstrated little evidence of interdependence of stock prices between markets. However, the issue of inter-market transmission of returns and volatilities over short horizons has later attracted the attention of financial academics, the media and practitioners, especially in the wake of the 1987 stock market crash and the 1997 Asian financial crisis.[4]

Numerous studies have reported strong evidence for high correlations of returns across international stock markets by taking advantage of the advances in econometric theory and availability of high frequency data (e.g. Eun and Shim, 1989; Von Furstenberg and Joen, 1989; Hamao, Masulis and Ng, 1990; 1991; Engle, Ito and Lin, 1990; Lin, Engle, and Ito, 1994; Koutmos and Booth, 1995; Koutmos, 1996; Christofi and Pericli, 1999; Niarchos, Tse, Wu and Yang 1999; Huang, Yang and Hu, 2000; Climent and Meneu, 2003; Connolly and Wang, 2003; Masih and Masih, 2001; Hsin, 2004; Lee, Rui and Wang, 2004; Ibrahim and Brzeszczynski, 2009; Mukherjee and Mishra, 2010). Gagnon and Karolyi (2006) attribute this phenomenon to the gradual increase of real and financial linkages among the world's economies, which can be caused by a number of factors, such as the growth of international trade and foreign direct investment, the surge in international portfolio investment activities and global capital flows, the increased level of financial market deregulation and the improvements in communication and information technology.

Meanwhile few studies have succeeded in associating variations of daily (or intradaily) stock return comovements with the impact of economic fundamental variables (e.g.

[4] On 19th October 1987, the major stock markets around the globe crashed. For example, the S&P 500 index in the US lost 20.47%, the FTSE100 index in the UK dropped 10.84%, the TOPIX index in Japan declined 12.00%, and the Hang Seng index in Hong Kong fell 11.12%. On 27th October 1997, international stock markets experienced another major crash following the collapse of currency markets in Asia in July 1997.

inflation rate, interest rate, GDP, money supply, and so on). King and Wadhwani (1990) show that changes in correlations between market index returns are primarily not driven by those "observable" macroeconomic variables. As a result, King and Wadhwani (1990) introduce a "contagion model" where investors infer information from other markets by simply focusing on price movements in these markets, especially in the US. This provides a channel through which price shocks from one market can be transmitted to another.[5] Lin, Engle and Ito (1994) suggest that closer market comovements between countries are beyond what can be explained by connections through their economic fundamentals. Lin et al. (1994) postulate that information contained in price information revealed during trading hours of one market can have a global impact on the returns and volatilities of other markets. Lin et al. (1994) find supporting evidence of this contagion hypothesis by studying the information transmission mechanisms between the Tokyo and New York stock markets. Connolly and Wang (2003) investigate the market comovements between the domestic daytime returns and preceding foreign daytime returns in the US, UK and Japanese markets after controlling for the effects of macroeconomic news announcements in both domestic and foreign markets. Connolly and Wang (2003) find evidence in favour of the market contagion hypothesis, indicating that foreign returns exert a significant and positive impact on the following domestic returns and that news announcements about macroeconomic fundamentals exhibit little power in explaining domestic returns.

Although a large body of literature has investigated the information transmission mechanisms across international stock markets, few studies provide a thorough review of the relevant literature. The objective of this chapter is to present a review of the existing literature and methodology and to provide the theoretical support and methodological background for the investigation of international stock market comovements in this thesis. In addition to the coverage of some important studies that

[5] There is not yet a uniform definition for contagion. A number of notations of contagion are surveyed by Karolyi (2003). Contagion study (e.g. correlation coefficient measures of market contagion in financial crisis period) is related but not the main objective of this research. Hsin (2004) points out that correlation coefficient measures are limited in terms of capture asymmetric transmission effect. Karolyi and Stulz (1996) suggest that the issue of imperfect synchronous trading periods for different national stock markets around the globe should be a concern when investigating the covariance between the returns of indices in these markets. Since the objective of this research is an examination of the nature of return and volatility transmission mechanisms across international stock markets using intraday data, the emphasis is placed on the regression coefficient measures.

were not reviewed by Gagnon and Karolyi (2006), this chapter outlines the development of the original ARCH techniques through to more recent findings in this field.

In this chapter, the review of literature follows the classification of Gagnon and Karolyi (2006), who categorised relevant papers into different groups according to methodologies employed in them. Therefore, this chapter is organised as follows. Section 2.2 provides a brief review of early literature on cross-market interdependence, focused on the Vector Autoregressive Model (VAR) methodology. Section 2.3 presents a detailed review of the strand of literature, which uses the Autoregressive Conditional Heteroscedastic (ARCH) family of models to investigate the transmissions of return and volatility across international stock markets. Section 2.4 provides a survey of papers that employ the time-varying parameters models to explore the nature of comovements of international stock market returns. Finally, Section 2.5 concludes.

2.2 The Vector Autoregressive (VAR) Model

2.2.1 The VAR Model

Eun and Shim (1989) are among the first to investigate the international transmission mechanisms of stock market comovements over short horizons. By using the vector autoregression (VAR) model, Eun and Shim (1989) estimate the close-to-close price returns of market indices in nine national stock exchanges in a dynamic simultaneous equation system. The VAR(*p*) model employed is specified as follows:

$$R_t = \mu + \sum_{p=1}^{p} A_p R_{t-p} + \varepsilon_t \ , \qquad (2.2.1)$$

where *p* represents the lag length; R_t is a 9×1 column vector of close-to-close price returns of stock market indices in the US, UK, Canada, France, Germany, Switzerland, Australia, Japan and Hong Kong on day *t*; ε_t is the 9×1 column vector of errors; μ and A_p are 9×1 and 9×9 matrices of coefficients; the *i, j* (where *i* = 1, 2, …, 9; *j* = 1, 2,…, 9) component of A_p measures the direct effect that a change in the return in the market *j* would have on the market *i* on day (*t*-*p*). Eun and Shim (1989) find evidence that a substantial amount of interdependence exists across national stock markets.

2.2.2 The Granger Causality Test

Huang, Yang and Hu (2000) explore the causality relations between the stock markets in the US, Japan, Hong Kong, Taiwan and mainland China. A short-term analysis of Granger causality can be carried out through the following bivariate VAR model:

$$R_{1t} = \mu_1 + \sum_{i=1}^{k} \alpha_{1,i} R_{1,t-i} + \sum_{i=1}^{k} \alpha_{2,i} R_{2,t-i} + \epsilon_{1,t}, \qquad (2.2.3)$$

$$R_{2t} = \mu_2 + \sum_{i=1}^{k} \beta_{1,i} R_{1,t-i} + \sum_{i=1}^{k} \beta_{2,i} R_{2,t-i} + \epsilon_{2,t}, \qquad (2.2.4)$$

where R_{1t} and R_{2t} represent close-close price returns of two stock markets under investigation; the coefficients α and β measure the direct effects of independent variables on dependent variables, and k is the lag length. If the null hypothesis H_0: $\alpha_{2,1} = \alpha_{2,2} = \alpha_{2,3} = \cdots \alpha_{2,k} = 0$ is rejected, it implies that R_{2t} does Granger cause R_{1t}. Conversely, if H_0: $\beta_{1,1} = \beta_{1,2} = \beta_{1,3} = \cdots = \beta_{1,k} = 0$ is rejected, it indicates that R_{1t} is the cause of R_{2t}, in the sense of Granger.[6] It is noteworthy that the Granger test statistics may be sensitive to the presence of autoregressive conditional heteroskedasticity.

Huang et al. (2000) report a strong Granger causality in market index returns from the US to Hong Kong and Taiwan, but not *vice versa*. The US returns can be used to predict subsequent daily price changes in the Hong Kong and Taiwan stock markets. However, no significant Granger causality can be indentified between the Shanghai market and any of the other markets during the sample period from 2 October 1992 to 30 June 1997.

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[6] The definition of causality in the Granger sense is based on the statistical test that examines whether movements in one variable precede movements in another variable. Granger causality is determined by discovering whether including the past values of a variable in the information set can improve the forecast of another variable. In a regression context this means running a regression of one variable on the past values of itself and the past values of any potentially casual variable, and testing the significance of coefficient estimates associated with the potentially causal variable.

Sheng and Tu (2000) also use the Granger causality analysis to examine the linkages between the US and the Asian stock markets during the 1997 Asian financial crisis. Their results show that the market index returns in the US Grange cause returns in China, Hong Kong, Indonesia, Japan and South Korea, but play the second dominant role (behind market index returns in South Korea) during the crisis sample period (1 July 1997 – 30 June 1998). On the other hand, the price movements in the Chinese, Hong Kong and South Korean markets cause the US stock market price changes in the same period.

Masih and Masih (2001) examine the dynamic causal inference in the sense of Granger across the four major OECD stock markets (the US, UK, Germany and Japan) and the Asian-Pacific markets (South Korea, Taiwan, Australia, Singapore and Hong Kong). Their results present further evidence of significant interdependence between these markets.

Climent and Meneu (2003) study how the effects of the 1997 Asian Financial crisis change the relations of the Southeast Asian stock markets (Thailand, Philippines, Indonesia, Malaysia, South Korea, Hong Kong and Japan) with the stock markets in three other geographical regions (Europe, North America and Latin America) by also using the Granger causality analysis. They test the existence of short-term causality in both pre-crash and post-crash subsample periods. Their results provide strong evidence for greater dependence of the Asian countries on flows of information from the main international stock markets in the post-crash period. Granger causality analysis shows that the price information in the US market plays a central role in predicting returns in the Asian markets and this role also extends to the European markets after the crisis period.

2.3 The ARCH-type Models

2.3.1 Theoretical Background

Although a large number of studies use the VAR models to investigate cross-market interdependence, a strand of literature has emerged since the 1990s using the Autoregressive Conditional Heteroskedasticity (ARCH) family of models to investigate the information transmission mechanisms across international stock markets. This methodology has become increasingly popular because it enables one to model the first and second moments of stock returns at the same time and to take into account the ARCH effect inherent in many financial time series (see e.g. Gagnon and Karolyi (2006) for a good review of relevant literature).

It is a stylised fact that the distributions of financial time series, such as stock returns, exchange rates and interest rates, have fat tails relative to the normal distributions. The volatilities of these series are also time-varying and display volatility clustering effects, where large daily price changes tend to be followed by large daily changes of positive or negative sign. Thus, large outliers and persistent volatility are the common features of the financial time series. Given these statistical properties, the application of the VAR methodology which assumes time invariant conditional variance is not efficient and does not allow the study of all aspects of the transmission of price movements (Kim and Rogers, 1995). It is also known that statistical inferences of the OLS regression can be seriously affected by the presence of ARCH effects and the hypothesis tests about the mean in a model where variance is misspecified are invalid. As pointed out by Engle (1982), in the presence of heteroskedasticity, the OLS estimator is still an unbiased and consistent linear estimator. However, it is no longer the best linear unbiased estimator (BLUE). The maximum likelihood estimator under the ARCH framework is nonlinear and is more efficient. It is a consistent nonlinear estimator that is more efficient than the OLS estimator. The gain in efficiency from using the maximum likelihood estimation in the ARCH models rather than the OLS estimation with robust standard errors could be substantial. In other words, more efficient use of the data can be achieved by the models that take the ARCH error structure into account. More importantly, the ARCH framework recognises the temporary dependence in the second moment of stock returns. Engle (1982) states that many statistical procedures have been designed to be robust to large errors, but none has made use of the fact that temporal clustering of outliers can be used to predict their occurrence and minimize the effects of large outliers, which is exactly the approach taken by the ARCH models.

Furthermore, Hamilton (2010) stresses the point that, even if the primary interest of econometric analysis is in the first moment rather than the second moment of the time series data, it is important to model the time variant conditional variance in the estimation of the relevant models when the ARCH effect has been detected. Hamilton

(2010) indicates that the White's (1980) or Newey-West's (1987) robust standard errors may not be the best possible practice of avoiding the inference problems introduced by ARCH. Substantially more efficient estimates of the first moment could be obtained by taking the observed features of the ARCH effect into account. Furthermore, it is preferable to use maximum likelihood estimators in ARCH-type models rather than OLS estimators with heteroskedasticity correction for standard errors if the research interest is in obtaining accurate estimates of model's parameters.

2.3.2 The GARCH Framework

In order to capture the effect of volatility clustering in the financial time series, Engle (1982) develops the Autoregressive Conditional Heteroskedasticity (ARCH) model. The simple ARCH(p) model is expressed as:

$$R_t = \mu + \epsilon_t, \tag{2.3.1}$$

$$h_t = a + \sum_{s=1}^{p} b_s \epsilon_{t-s}^2, \tag{2.3.2}$$

where the error term (ϵ_t) in Equation (2.3.1) has the time varying conditional variance (h_t). h_t is a positive linear function of the squared error terms in the past p periods that is defined in Equation (2.3.2). The ARCH parameters $b_1, b_2, \dots, b_p \geq 0$, so that the large past squared shocks imply a large conditional variance h_t at time t.

Bollerslev (1986) generalises the ARCH(p) to Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by allowing the conditional variances h_t to be a positive function not only of the squared error terms in q lagged periods but also of conditional variances in q lagged periods. The GARCH(p,q) model is specified as:

$$h_t = a + \sum_{s=1}^{p} b_s \epsilon_{t-s}^2 + \sum_{s=1}^{q} c_s h_{t-s}^2, \tag{2.3.3}$$

Engle, Lilien and Robins (1987) extend the GARCH model by allowing the conditional mean to depend on conditional variance at time t. The mean equation of GARCH-M model is defined as:

$$R_t = \mu + \alpha h_t + \epsilon_t \, , \tag{2.3.4}$$

where the coefficient α measures the volatility feedback effect, which is the impact that higher variability of ϵ_t has on the level of R_t. The conditional variance is assumed to follow the GARCH process. In specification of the GARCH-M model the time-varying conditional variance is modelled into the mean equation. According to finance theory, the mean return should be positively related to the variance of the return (i.e. an asset with a higher perceived risk is expected to have a higher expected return on average). In other words, investors require higher expected returns as compensation for holding riskier assets.

2.3.3 The Meteor Shower and Heat Wave Hypothesis of Engle, Ito and Lin (1990)

The ARCH approach to study the market interdependence has been focused on analysing how the first and second moments of returns in one market influence those of returns in other markets, to which return and volatility spillovers occur. Engle et al. (1990) are the first to apply this approach when investigating market interdependence in terms of volatility spillovers in foreign exchange markets. The study of Engle et al. (1990) introduces the meteor shower hypothesis which postulates the positive volatility spillover effect across markets, i.e. a volatile day in one market is likely to be followed by a volatile day in another market. [7] This phenomenon resembles the actual astronomical phenomenon of meteor showers. The alternative meteorological analogy corresponding to the meteor shower effect proposed by Engle et al. (1990) is the heat wave effect. The heat wave hypothesis assumes that the conditional variance in one market depends solely on the past shocks within this market. One large country-specific shock increases the conditional volatility of its own market in the future. This process is similar to meteorological phenomenon of a heat wave where a hot day in one country is likely to be followed by another hot day in the same place, but typically not by another hot day in other countries in different geographical locations. Engle et al. (1990) suggest that the heat wave hypothesis should be consistent with a view that major sources of

[7] Although the term of meteor showers effect is commonly used to describe the positive spillover effect in volatility, Brzeszczynski and Ibrahim (2009) associate it also with the return spillover effect in their analysis of transmission of returns across international stock markets. This research generalises this concept as the positive spillover effect between markets regardless of the underlying financial variables.

shocks are the changes in country-specific fundamentals. Accordingly, it suggests that one large shock in a specific market should increase the conditional volatility but only in that market. On the contrary, the meteor shower hypothesis suggests that this shock should also increase the conditional volatility in other foreign markets in the sequence in which they trade.

In order to test both hypotheses, Engle et al. (1990) develop two models, named the heat wave model and the meteor shower model, using the framework of the ARCH methodology. The heat wave model is specified as:

$$\epsilon_{i,t}|\Omega(i,t) \sim N\big(0, h_{i,t}\big), \tag{2.3.5}$$

$$h_{i,t} = a + b\big(\epsilon_{i,t-1}\big)^2 + c\, h_{i,t-1} + d\epsilon_{Ni,t-1}^2, \tag{2.3.6}$$

where $\epsilon_{i,t}$ equals the daily exchange rate returns divided by the square root of the number of business hours in the market i on date t; $\Omega(i,t)$ is the information set for market *i* on date *t*, which includes all the past information before the market is opened. The per-hour squared changes between the opening and closing prices are a reflection of daytime volatility in the domestic market. The overnight volatility $\epsilon_{Ni,t-1}^2$, which is the per-hour squared change between the closing price on preceding day *t-1* and opening price on day *t*, measures the aggregated effect of foreign news on domestic market *i*. The test for the heat wave hypothesis is equivalent to the test of zero coefficient of *d*.

The meteor shower model disaggregates the overnight changes into three different segments:

$$h_{i,t} = a + b\big(\epsilon_{i,t-1}\big)^2 + c\, h_{i,t-1} + \sum_{j\neq i}^{3} d_{i,j}\epsilon_{j,t-1}^2, \tag{2.3.7}$$

where $\epsilon_{j,t-1}^2$, (for $j \neq i$) is per-hour volatility from three previously opened foreign markets (e.g. if the Japanese market is assumed to be domestic market segment *i* on date *t*, $\epsilon_{j,t-1}^2$, (for $j \neq i$) denotes per-hour volatility from Pacific, New York and Europe segments on date *t-1*); $\epsilon_{i,t}$ and $\epsilon_{j,t}$ are assumed to be uncorrelated for *i*≠*j*; the coefficient $d_{i,j}$ measures the impact of news from foreign market *j* on the per-hour volatility of domestic market *i*.

Using the ARCH-type models, Engle et al. (1990) find that empirical evidence in hourly yen/dollar exchange rate generally supports the meteor showers hypothesis (i.e. the volatility in the New York market can predict volatility in Tokyo market several hours later). Their results show that the spillover effect from foreign market plays an important role in determining intraday volatility in the domestic market, and the null hypothesis of heat wave is soundly rejected (i.e. the coefficient d is significantly different from zero at the 1% significance level).

2.3.4 GARCH-M Model of Hamao, Masulis and Ng (1990; 1991)

Hamao, Masulis and Ng (1990) study the return and volatility spillover effects across three major international stock markets (the US, UK and Japan) using the GARCH-M model.

Hamao et al. (1990) employ the MA(1)-GARCH(1,1)-in-Mean model to evaluate the appropriateness of the GARCH-M specification for open-to-close stock index returns.[8] The model is defined as:

$$R_t = \mu + \alpha h_t + \beta D_t + \gamma \epsilon_{t-1} + \epsilon_t, \tag{2.3.8}$$

$$h_t = a + b h_{t-1} + c\, \epsilon_{t-1}^2 + d\, D_t\ , \tag{2.3.9}$$

where R_t represents the open-to-close price returns in the domestic market, μ is the constant, h_t is the conditional variance of the stock index return at time *t*; D_t represents the dummy variable of day of the week effects which equals 1 on a day following a weekend or holidays and 0 otherwise, the coefficient α measures the volatility feedback effect, and a MA(1) process is included in the conditional mean equation to extract the serial correlation from the stock index return's first moment.[9]

[8] The validity of the univariate GARCH-in-Mean model in describing the return time series is assessed by likelihood ratio (LR) statistics and the appropriate model specifications were determined.

[9] French (1980) and Gibbons and Hess (1981) document negative mean returns for US stocks on Mondays, while Fama (1965) and Godfrey, Granger and Morgenstern (1964) document higher return

The results indicate the existence of strong ARCH effects in return series of all three stock markets. The likelihood ratio (LR) statistics reject the null hypothesis that the returns are normally distributed against the alternative that they are generated by the MA(1)-GARCH(1,1)-M model at the 1% significance level.[10] There are no serious indications against model misspecification except a relatively high value of Kurtosis.[11] However, the volatility feedback effects are only observed in the pre-crash sub-period and only in the Tokyo and London stock markets.

Hamao et al. (1990) incorporate the foreign information into the model in order to examine the significance of potential volatility spillovers from the most previously opened foreign stock exchange to the domestic market. The proposed model is:

$$R_t = \mu + \alpha h_t + \beta D_t + \gamma \epsilon_{t-1} + \epsilon_t, \tag{2.3.10}$$

$$h_t = a + b h_{t-1} + c\, \epsilon_{t-1}^2 + d\, D_t + f X_t^2\ , \tag{2.3.11}$$

where X_t^2 are the squared residuals derived from the MA(1)-GARCH(1,1)-M model estimation using open-to-close returns in the foreign market that traded most recently. For example, if the UK stock market is assumed as the domestic market, the Japanese stock market is the foreign market that trades earlier in the sequence. If the Japanese stock market is assumed to be the domestic market, the US stock market is then considered to be the most recently active foreign market. In this GARCH specification, X_t^2 can be interpreted as the most recent volatility surprise that was observed in foreign markets.

The results show that the impact of volatility surprises from the most recent foreign markets on the conditional volatility of the domestic markets, is positive and statistically

variances for US stocks on Mondays (Hamao et al.,1990). Hamao et al. (1990) take these potential day of the week effects into account in both the conditional mean and variance equations.

[10] Nested specification tests using LR statistics are employed to examine the descriptive validity of the GARCH-M model. LR (6) for null hypothesis: $\alpha = \beta = \gamma = b = c = d = 0$.

[11] Ljung-Box statistic is used to test for H_o: the time series has no serial correlation. Ljung-Box values for the model residuals and the squared residuals are all insignificant at the 5% and 1% levels which are the indications that the models are properly specified. The skewness and kurtosis coefficients for the model residuals are expected to close to zero and three, respectively, in a properly specified model.

significant for all three stock exchanges in the full samples. But the volatility spillovers from Japan to the UK and from the UK to the US are insignificant for the pre-crash period. These results are unaffected when X_t^2 is replaced with the most recent h_t from the previously opened foreign market.

The volatility surprises from both foreign markets that complete the trading cycle while the domestic market is closed are also introduced into the conditional variance equation:

$$R_t = \mu + \alpha h_t + \beta D_t + \gamma \epsilon_{t-1} + \epsilon_t, \tag{2.3.12}$$

$$h_t = a + b h_{t-1} + c\, \epsilon_{t-1}^2 + d\, D_t + f_1 X_{1t}^2 + f_2 X_{2t}^2, \tag{2.3.13}$$

where X_{1t}^2 and X_{2t}^2 denote the most recent volatility surprises from foreign markets *1* and *2*, respectively. The estimation results indicate that the inclusion of the second foreign market does not appear to diminish the volatility spillover effect of the first market and the observed relations appear unlikely to be influenced by a common economic effect manifesting itself in all three markets.

Hamao et al. (1990) expand the model further by considering the possibility of the return spillover effect on the conditional mean equation (as captured by coefficient γ) and the volatility spillover effect on the conditional variance equation (as captured by coefficient *f*). The model is of the following form:

$$R_t = \mu_. + \alpha h_t + \beta DM_t + \gamma R_{F,t} + \delta \epsilon_t + \epsilon_{t-1}, \tag{2.3.14}$$

$$h_t = a + b h_{t-1} + c\, \epsilon_{t-1}^2 + d DM_t + f {X_t}^2, \tag{2.3.15}$$

where DM_t represents a dummy variable that takes on a value of 1 on days following weekends and holidays (and takes on 0 otherwise) in both the conditional mean and variance equations to capture potential day of the week effect; R_t is daytime return from the domestic market; $R_{F,t}$ represents the open-to-close return from the most recently active foreign stock market. The coefficient γ measures the daytime return spillovers from the previous foreign stock market to the domestic market. ${X_t}^2$ are the squared residuals obtained from the first stage GARCH model estimation of foreign daytime returns. In this GARCH specification, ${X_t}^2$ can be interpreted as the most recent "volatility surprise" observed in foreign markets. The coefficient f measures the impact of shocks from foreign market on the conditional variance of daytime returns in the home market. It captures the potential volatility spillover effect from previously open foreign market into the domestic stock market.

Hamao et al. (1990) find evidence showing that the conditional mean returns exhibit a positive spillover effect from prior markets (e.g. positive and statistically significant return spillovers from the US to Japan). The parameter estimates in variance equations do not change dramatically from the estimates obtained in previous models. The results indicate that the spillover patterns are very similar to previous findings.

To eliminate the effect caused by the one hour overlapping trading activity between the UK and the US stock markets, Hamao et al. (1990) re-estimate the model using the noon-to-close returns from the US market. They find that the return spillovers from the UK market to the US market are no longer significant, while the volatility spillovers remain significant and become stronger.[12]

Hamao et al. (1990) also investigate the contemporaneous return spillover effects between daytime returns in the foreign markets and overnight returns in the domestic market. This allows the study of the impact of "overnight information" obtained from the trading in foreign markets on the opening price of the domestic market. The model is defined as follows:

$$NR_t = \mu + \alpha h_t + \beta D_t + \gamma_1 R_{F1,t} + \gamma_2 R_{F2,t} + \delta \epsilon_{t-1} + \epsilon_t \qquad (2.3.16)$$

$$h_t = a + b h_{t-1} + c\,\epsilon_{t-1}^2 + d\,D_t + f_1 X_{1,t}^2 + f_2 X_{2,t}^2, \qquad (2.3.17)$$

[12] This is the evidence showing that dynamic spillovers from Europe to North America are significantly affected by the overlapping trading hours of the markets. The return and volatility spillover literature normally excludes or does not report results for this sequence. Ibrahim and Brzeszczynski (2009) indicate that investigating non-overlapping markets is more relevant to answering questions such as whether or not a particular market leads another.

where NR_t denotes close-to-open returns from the domestic market; $R_{F1,t}$ and $R_{F2,t}$ represent the most recent open-to-close returns from foreign markets; X_{1t}^2 and X_{2t}^2 are volatility surprises from both foreign markets.

In summary, Hamao et al. (1990) find evidence of positive and statistically significant daytime volatility spillover effects from one stock market to the next in the full sample period from 1 April 1985 to 30 March 1988, but the volatility spillovers from the Tokyo market to London market and from the London market to the New York market are insignificant in the subsample period prior to the worldwide stock market crash of October 1987 (from 1 April 1985 to 30 September 1987). More importantly, Hamao et al. (1990) observe the existence of the daytime return spillover effect from the US market to the Japanese market and from the UK market to the US market in both sample periods. However, no such return spillovers are observed from Japan to the UK. They also find that the price changes in foreign market indices affect the opening price in the domestic market and are related to the subsequent daytime return and volatility spillovers after the opening of trading.

The effect of the 1987 Stock Crash on international financial integration in the context of the volatility spillover effect across the Tokyo, New York and London stock exchanges is also studied by Hamao, Masulis and Ng (1991). Hamao et al. (1991) extend further the univariate GARCH-M model of Hamao et al. (1990) to estimate the potential structural shifts in the volatility spillover relations among these three markets during and after the 1987 stock crash.[13]

The model is defined as follows:

$$R_t = \mu + \alpha h_t + \beta DM_t + \gamma \epsilon_{t-1} + \epsilon_t, \tag{2.3.18}$$

$$h_t = \alpha + b h_{t-1} + c\, \epsilon_{t-1}^2 + d DM_t + (f + g\, D_t + k\, A_t) X_{1,t}^2 + (p + q D_t + r A_t) X_{2,t}^2, \tag{2.3.19}$$

where DM_t is a dummy variable for weekend or post-holiday effects. D_t and A_t are dummy variables for structure shifts. D_t equals 1 if t is in October 1987 (during the

[13] Structural shifts here refer to the discrete change in the magnitude of volatility spillover effects across the Tokyo, New York and London stock markets during and after the 1987 stock crash.

crash month) and 0 otherwise, and A_t equals 1 if t is in the post-Crash period (November 1987 - February 1990) and 0 otherwise. The parameters of the dummy variables *g*, *k*, *q* and *r* allow Hamao et al. (1991) to investigate the extent of shifts in the levels of volatility spillovers from foreign market *1* and foreign market *2* across the three subperiods (i.e. the sum of parameters *f* and *d* captures the volatility spillovers from foreign market *1* to the domestic market during the crash month while the sum of parameters *f* and *k* measures the effect in the period after the October 1987 crash).

Hamao et al. (1991) report evidence that the volatility spillovers between the US and Japan exhibit significant shift after the 1987 crash. The volatility spillover effect from the US to Japan is statistically significant before the crash, but it does not change markedly during the crash month or afterwards. On the contrary, Japan has an insignificant influence before and during the crash, but it exerts a statistically significant and positive effect after the 1987 crash. As for the volatility spillovers between the UK and Japan, Hamao et al. (1991) find that the spillovers from Japan to the UK are positive and statistically significant before the crash and remain unchanged during the crash month or thereafter. However, the volatility spillover effect from the UK to the Japanese market is statistically significant before 1987 crash, remains unchanged during the crash month, but shows a decrease in spillover level to the 1/3 of its pre-crash level afterwards. For the volatility spillovers between the UK and the US, the estimation results show that there is no significant volatility spillover effect from the US to the UK in the analysed sample periods. The results also indicate that the volatility spillover effect from the UK to the US market is statistically significant in the pre-crash period, increases remarkably during crash month and remains unchanged after the crash.

2.3.5 The Aggregate-Shock Model of Lin, Ito and Engle (1994)

Lin et al. (1994) investigate further how the price shocks such as the 1987 stock market crash transmit from one market to another. They study the information transmission mechanisms between the Tokyo and New York stock markets through the aggregate-shock (AS) model. This methodology is related closely to the GARCH-M model of Hamao et al. (1990). Lin et al. (1994) investigate contemporaneous correlations between the unexpected daytime return in the foreign stock market and the concurrent overnight return in the domestic market (e.g. the cotemporaneous correlation between the US overnight return and the Japanese daytime return can be investigated due to the US market is closed when the Japanese market is open). Using the same notation as in previous models, let R_t and NR_t denote daytime returns and overnight returns, respectively. Suffix H and F represent the returns from the domestic and foreign markets.

The foreign daytime return $R_{F,t}$ can be defined as a linear function of its current overnight return ($NR_{F,t}$) and the Monday or post-holiday dummy (DM_t):

$$R_{F,t} = \mu + aNR_{F,t} + \beta DM_t + \epsilon_{F,t}, \tag{2.3.20}$$

$$h_{F,t} = \mathrm{a} + b(\epsilon_{F,t-1})^2 + c\, h_{F,t-1} + dDM_t. \tag{2.3.21}$$

where ϵ_t represents the unexpected returns (daytime return shocks) of the foreign market that cannot be predicted based on foreign overnight returns, and it is serially uncorrelated and follows GARCH(1,1) process. DM_t is a dummy variable which captures Monday or post-holiday effect.

The overnight return in the domestic market is specified as a linear function of the preceding domestic market daytime return, the Monday or post-holiday dummy variable, and the unexpected daytime return from the previously opened foreign market.

$$NR_{H,t} = \mu + \alpha R_{H,t-1} + \beta DM_t + \gamma\epsilon_{F,t-1} + \nu_{H,t}, \tag{2.3.23}$$

$$k_{H,t} = a + b(\nu_{H,t-1})^2 + ck_{H,t-1} + dDM_t\,, \tag{2.3.24}$$

where $\gamma\epsilon_{t-1}$ represents the influence of unexpected returns in the foreign market on the overnight returns in the domestic market; $\nu_{H,t}$ represents the overnight return shocks in the domestic market revealed after the close of the foreign market but before the opening of the domestic market; ν_t is serially uncorrelated and follows the GARCH(1,1) process.

Estimation of the parameters of the AS model reveals evidence of contemporaneous correlation between the unexpected daytime return in foreign stock market and the following overnight return in the domestic market, which holds both for the Tokyo and the New York stock exchanges. The daytime return shocks from foreign markets are positively and statistically significantly related to the overnight domestic market return and affect the opening price in the domestic market in the full sample period (29 September 1985 – 29 December 1989) and two subsample periods (29 September 1985 – 30 September 1997 and 1 January 1988 – 29 December 1989). In addition, Lin et al. (1994) compare the estimation results from the AS model with those obtained from the GARCH-M model of Hamao et al. (1990). It is noteworthy that the results reported from both models are qualitatively the same.

Lin et al. (1994) also report the results for the effects of daytime return and volatility spillovers between the US and Japanese stock markets (i.e. lagged spillovers). The model is specified as:

$$R_t = \mu + \alpha NR_{t-1} + \beta DM_t + \delta R_{F,t-1} + \epsilon_t, \qquad (2.3.25)$$

$$h_t = a + bh_{t-1} + c\,\epsilon_{t-1}^2 + dDM_t + f(R_{F,t-1})^2. \qquad (2.3.26)$$

If there are no overlapping hours between the foreign and domestic stock exchanges, the above model can also be used to test Granger causality between the two markets (Lin et al., 1994). The means and variances in home market are assumed to be conditional on its past information as well as information generated from abroad. The statistical inferences of δ are regarded as a causality test of whether daytime returns from most previously traded foreign stock exchange carry any information in addition to previous domestic daytime returns in predicting the following day's domestic daytime returns.

The results from Lin et al. (1994) are generally consistent with the findings in Hamao et al. (1990). Significant and positive daytime return spillovers from the Tokyo to New York markets are observed in the full sample period. The main difference between the AS model of Lin et al. (1994) and GARCH-M model of Hamao et al. (1990) is the specification of the mean equations: (1) MA process is not incorporated into the AS model to extract the short-lived serial correlation from the stock return's first moment; (2) Lin et al. (1994) use return shocks instead of raw open-to-close returns when computing the contemporaneous correlations between the foreign daytime returns and domestic overnight returns; (3) the volatility feedback effect is not included in the AS model. In addition, the square of foreign market returns rather than "volatility surprises" from Hamao et al. (1990) are modelled into the second equation in the AS model while Lin et al. (1994) investigate the lagged spillover between the US and Japan. Although there are several differences in their model specifications of both mean equation and conditional variance equation, it is important to point out that the estimation results for contemporaneous correlations and lagged spillovers from Lin et al. (1994) are consistent with the findings from Hamao et al. (1990).

2.3.6 The Asymmetric GARCH-type Models

The standard GARCH models are symmetric in terms of their responses to past shocks. Their conditional variances are specified as a linear function of the past conditional variances and squared shocks to capture autoregressive heteroskedasticity. As a result, the sign of return shocks plays no role in affecting the size of volatility. However, in addition to the leptokurtic distribution of stock return time series, leverage effects can also be present in such data (Black, 1976; Christie, 1982). The leverage effect means that a reduction in the equity value raises the debt-to-equity ratio, hence increasing the riskiness of firm as manifested by an increase in future volatility of its stock price. This implies that negative current return shocks may have more influence on the magnitude of future volatility. In order to capture the asymmetric effect in the conditional volatility, alternative model specifications of GARCH models have been proposed.

The GJR-GARCH model by Glosten, Jagannathan and Runkle (1993) is one of the most popular specifications of GARCH models designed to capture asymmetry in the GARCH process. The conditional variance in GJR-GARCH model is specified as:

$$h_t = a + b\,\epsilon_{t-1}^2 + c(I_{t-1}\epsilon_{t-1}^2) + bh_{t-1}\,, \tag{2.3.27}$$

where I_{t-1} is a dummy variable that takes on 1 if $\epsilon_{t-1} < 0$ (and takes on 0 otherwise). I_{t-1} allows the effect of the squared residuals on conditional volatility to be different when the sign of lagged return shocks is different. The sign of coefficient c is expected to be significant and positive if negative return shocks (interpreted as bad news) induce the increase of future volatility by a larger amount than positive return shocks (interpreted as good news) of the same magnitude do, if the leverage effect exists.

The exponential GARCH (EGARCH) model introduced by Nelson (1991) also models the asymmetric effect of positive and negative shocks on future volatility. The EGARCH (1, 1) model is as follows:

$$h_t = exp\{a + b|z_{t-1}| + c\,z_{t-1} + d\,log(h_{t-1})\}, \tag{2.3.28}$$

or,

$$log(h_t) = a + b|z_{t-1}| + c\,z_{t-1} + d\,log(h_{t-1}) \tag{2.3.29}$$

where the conditional variance follows an exponential GARCH process, which implies that the leverage effect is exponential. The conditional variance is the exponential function of its own lagged log standardised shocks and conditional variance. The standardised shock is defined as $z_t = \varepsilon_t/\sigma_t$, where z_t is negative if ε_t represents a negative shock. The asymmetric impact on the volatility of market is exerted by *c*. The asymmetric effect of shock on volatility is present if c is statistically significant and negative. As a consequence, the product of c and a negative z_{t-1} is positive, which reinforces the size effect of bad news.

2.3.7 Other Relevant Literature

Apart from the literature reviewed in previous sections, there exist many other studies which also use the GARCH-family models to investigate the interdependence across the worlds' stock markets.

Theodossiou and Lee (1993) use the GARCH(1,1)-M model when examining the transmission mechanisms of stock return and volatility across the US, UK, Japanese, Canadian and German markets during the period from 11 January 1980 to 27 December 1991. Their study finds positive and statistically significant return and volatility spillovers from the US to the remaining markets (except for the insignificant return spillovers from the US to Japan). Theodossiou and Lee (1993) also find that the conditional volatility has no statistically significant effect on the conditional mean of stock returns in any of the five markets under investigation.

Kim and Rogers (1995) employ the GARCH(1,1) model to quantify volatility spillovers from Japan and the US on the mean and variance of Korean returns over the sample period ranged from 2 October 1985 to 23 March 1992. They find that the information about stock returns in the major foreign markets has become more important for open-to-close returns in the Korean stock market since its market liberalization in January 1992.

Koutmos and Booth (1995) investigate the possible changes in the nature of return and volatility spillovers across the US, UK and Japanese markets by estimating the EGARCH(1,1) model in two subsamples which cover the pre- and post-1987 crash periods (from 3 September 1986 to 3 September 1987 and from 2 November 1987 to 1 December 1993). Their research shows that the international stock markets have grown more interdependent in the sense that information affecting asset prices has become more global in nature. In particular, the stock markets in the US and UK have become more sensitive to the information originating from Japan after the 1987 crash. The existence of the price and volatility spillovers across the three major international stock markets found in Koutmos and Booth (1995) supports Engle's meteor shower hypothesis.

Koutmos (1996) examines the first and second moment interdependence among four major European stock markets (the UK, Germany, France and Italy). Koutmos (1996) contributes to methodology by extending a single equation ARCH model into a multivariate VAR-EGARCH framework. The conditional variances of the individual return series and the conditional covariance between series are estimated in one system so that the dynamics of the conditional variance and covariance in these markets can be captured simultaneously. The estimation results show that no market plays a major role as an information producer due to the multidirectional nature of the cross-market-lead/lag relationships. The UK market is the only market in which lagged returns significantly influence the conditional means of the other three markets.

Using the VAR-EGARCH model of Koutmos (1996), some other studies examine the information transmission mechanisms across the financial markets that have perfectly synchronous trading hours (i.e. the financial markets within the same geographical zone). For instance, Booth, Martikainen and Tse (1997) study the price and volatility spillovers in the Scandinavian stock markets, including the Danish, Norwegian, Swedish and Finnish stock exchanges. Christofi and Pericli (1999) investigate the correlations in price changes and volatility of major Latin American stock markets. Within the context of the Asian financial crisis, In, Kim, Yoon and Viney (2001) consider the statistical evidence relating to the dynamic interdependence of the Asian stock markets. The study investigates evidence of lead-lag relationships and volatility interactions among three Asian stock markets (Hong Kong, Korea and Thailand).

However, it should be pointed out that one major shortcoming of multivariate GARCH-type models (e.g. VAR-EGARCH model) is that the system requires the estimation of large numbers of parameters, even in the case of very small systems of equations. Harris and Sollis (2003) suggest that estimating a large number of parameters should not be in theory a problem as long as there is a large enough sample size. However, efficient estimation of parameters in GARCH models by maximum likelihood involves the numerical maximization of the likelihood function. Obtaining convergence of the typical optimization algorithms employed can in practice be very difficult when a large number of parameters are involved (Harris and Sollis, 2003). Koutmos (1996) estimates the model by imposing the assumption of constant conditional correlation over time so that the number of parameters to be estimated in the VAR-EGARCH model could be reduced. Booth, Martikainen and Tse (1997) note that this is a strong economic assumption in rapidly changing markets.

An analysis of volatility spillovers across three largest European markets (London, Frankfurt and Paris) for the pre-crash (1 January 1984 – 15 September 1987) and post-crash (15 November 1987 – 7 December 1993) periods (2590 observations in total) is conducted by Kanas (1998). The EGARCH model, which captures the potential asymmetric effect of return shocks on volatility according to the leverage effect, is employed in this study. Kanas (1998) shows that: (1) a comparison of results obtained from both methodologies indicates that results are generally very similar; (2) more spillovers and spillovers with higher intensity exist during the post-crash period, indicating that those three European markets became more interdependent after the stock crash of October 1987; (3) the coefficients of the leverage effect are statistically significant for all three markets, suggesting the existence of the asymmetric effect between negative return shocks and positive return shocks on the magnitude of their future volatilities.

Niarchos, Tse and Wu (1999) employ the EGARCH(1,1)-MA(1) model to examine the return and volatility spillover mechanisms between the US and Greek stock markets by using daily data from January 1993, when electronic trading on the Athens Stock Exchange (ASE) began, through September 1997. Their research shows that neither the mean nor the volatility of the Greek market returns are influenced by the past US market returns and return shocks over the sample period. However, results in general support the heat wave hypothesis for both markets.

Following the AS model of Lin et al. (1994), Hsin (2004) uses the AR(1)-GARCH(1,1)-M model to describe return generating process of world equity indices. Hsin (2004) presents evidence of the existence of significant international transmission of information, in terms of returns and volatility spillovers, across major international stock markets (the US, UK, Australia, Canada, France, Germany, Hong Kong, Italy, Japan and Singapore) during the daily sample period from January 1990 to December 2002.

Wang and Firth (2004) use the GJR-GARCH(1,1) model to investigate the contemporaneous interdependence of returns and volatility and the daytime return and volatility spillovers across three major developed international stock markets in New York, Tokyo and London, and Greater China’s four emerging stock markets in Shanghai, Shenzheng, Hong Kong and Taiwan. In order to examine the impact of the 1997 Asian crisis on the structural change of the information transmission mechanisms between the developed markets and emerging markets in that region, Wang and Firth (2004) split the full sample period (25 November 1994 – 28 September 2001) into pre-crash subsample period (25 November 1994 – 22 October 1997) and post-crash subsample period (29 October 1997 – 28 September 2001), so the changes on pattern of contemporaneous returns and volatility interdependence between the two subsample periods could be investigated.

Wang and Firth (2004) find that daytime returns in Japanese stock market spill over to the Hong Kong, Shanghai and Shenzhen overnight returns in the whole sample period. The overnight return in Hong Kong is also influenced by the daytime return shock from the US market. The return shocks from the US and the UK markets have a significant and positive impact on the overnight returns of Taiwan market. Except for the post-crisis daytime return spillover from Taiwan to London and New York and daytime return spillovers from Hong Kong to London, the shocks of daytime returns in the Greater China’ stock markets have little effects on the overnight returns in any developed markets. Thus, return spillovers are mainly unidirectional from the developed markets to the emerging markets. However, Wang and Firth (2004) observe generally significant interdependence of volatility between three major international stock markets and the Greater China’s four stock markets in both subsample periods with no clear patterns. They suggest that the US is the most influential market.

Wang and Firth (2004) find little evidence of lagged return spillovers from three major developed stock markets to Greater China’s four stock markets in both pre- and post-crisis periods. On the other hand, there are strong bi-directional return spillovers between Hong Kong stock market and mainland China’s two stock markets in the post crisis period indicating that the above three markets became closer after the 1997 Asian crisis. Another interesting finding from the results is that significant and positive volatility spillovers from the New York market to the above markets emerged after the 1997 Asian crisis, although there is no significant return spillover effect from the New York market to the Shanghai and Shenzhen markets in both sample periods.

It is noteworthy that the three major international stock markets are characterised by the statistically significant asymmetric effects. On the contrary, the asymmetric effects in Greater China's stock markets, apart from the Hong Kong market, are not statistically significant, which indicate that the delayed "bad news" do not have a bigger impact on the conditional volatility.

Lee, Rui and Wang (2004) examine the information transmission mechanisms between the NASDAQ stock market and those of the Asian stock exchanges in which the majority of companies listed have similar characteristics to the NASDAQ stock exchange, such as a large share of high-tech companies, small capitalization, high risks and high growth companies, and so on.

Lee et al. (2004) employ a simple EGARCH(1,1) model to investigate spillover effects among NASDAQ in the US and Asian stock markets (Japan, Hong Kong, Singapore, South Korea and Taiwan). The results show strong evidence of the substantial meteor shower effect and the heat wave effect in stock return and volatility from the US to the Asian stock markets. Lee et al. (2004) find that the NASDAQ exerts significant spillover effects on Asian markets during their sample periods which include the 1997 Asian financial crisis.

Following Lin, Engle and Ito (1994), Baur and Jung (2006) employ the aggregate-shock model to investigate the short-term information transmission mechanisms between the US and German stock markets based on a sample of intradaily data ranging from 2 January 1998 to 29 December 2000. Baur and Jung (2006) find strong evidence of a contemporaneous relation between the two markets showing that foreign daytime returns can significantly affect the domestic overnight returns, which is consistent with the findings from Lin et al. (1994). However, they find little evidence about the interdependence of volatility between the US daytime returns and the German overnight returns.

Nam, Yuhn and Kim (2008) study how the 1997 Asian financial crisis has changed financial markets in Asia by focusing on price and volatility spillovers from the US market to five Pacific-Basin emerging markets (Hong Kong, Singapore, South Korea, Malaysia and Taiwan). They break down the full sample (from 3 January 1995 to 24 April 2001) into three subsamples to compare the spillover effects between the prior-and post-crisis periods by employing the EGARCH(1,1) model. Nam et al. (2008) find that the influence of US return shocks on the stock returns in the region increased after the 1997 financial crisis (only with the exception of the Malaysian market), but the influence of US shocks on market volatility decreased substantially after the crisis (only with the exception of the Korean market).

Mukherjee and Mishra (2010) use the simple GARCH(1,1) model to investigate the return and volatility spillover effects between India and other 12 Asian stock markets (China, Hong Kong, Japan, Hong Kong, Korea, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka, Taiwan and Thailand) based on intradaily (both opening and closing) price index data sample ranging from November 1997 to April 2008. Mukherjee and Mishra (2010) find that the contemporaneous daytime return spillovers between India and its counterparts are positive and statistically significant, indicating that most of the information is transmitted between the markets without much delay. In addition, they find evidence of overnight spillover effects from the previously opened foreign stock market daytime returns to the overnight (close-to-open) returns in the domestic market, implying that some information in the foreign market still remains uncounted and can be reflected in the opening price of the market index as soon as the domestic stock exchange opens on the following day.

2.4 Time-varying Parameters Models

2.4.1 The Latent Variable Regression Model of Karolyi and Stulz (1996)

The existing empirical studies (e.g. Longin and Solnik, 1995; Karolyi and Stulz, 1996) demonstrate strong evidence of time-varying correlations across world's stock markets, so it is reasonable to assume that the parameters that measure return and volatility spillovers can be time-varying and may depend on by other information variables which capture the time-variation in the correlations between the index returns.

Karolyi and Stulz (1996) use a latent variable regression model to investigate the effects of macroeconomic information variables on the intraday return correlations between the US and Japan. They study the time-varying nature of the return correlations using a two-step regression model. Instead of focusing on the returns of market indices, they construct an equally-weighted portfolio of Japanese stocks traded in the New York stock market in the form of American Depositary Receipts (ADR) and an equally-weighted portfolio of the matching US companies of comparable size.[14]

In the first step, the regression model conditions the US and Japanese intradaily portfolio returns $R_{i,t}$ on a set of information variables Ω_{t-1}:

$$R_{i,t} = E\ (R_{i,t}|\Omega_{t-1}) + \epsilon_{i,t}. \qquad (2.4.1)$$

where the expected return of $R_{i,t}$ is conditioned on a set of information variables available at time *t-1* (Ω_{t-1}), such as the lagged returns on Yen/Dollar exchange rate futures, the US Treasury bill futures, value-weighed US stock index from Centre for Research on Security Prices (CRSP), news announcement dummy, a Monday dummy and preceding returns on the S&P and Nikkei indices.

$R_{i,t}$ is defined by:

$$E(R_{i,t}|\Omega_{t-1}) = \mu_i + \sum_{k=1}^{k} \omega_{i,k} X_{k,t-1}, \qquad (2.4.2)$$

where μ_i is the constant term, the coefficients $\omega_{i,k}$ measure the direct effects from each individual information variable $X_{k,t-1}$ on the return of the US portfolio and the Japanese portfolio.

The second step is extraction of the residuals series $\epsilon_{i,t}$ from Equation (2.4.1) and estimation of:

$$\epsilon_{JA,t} = \alpha_t + \beta_t \epsilon_{us,t} + v_{\ t}, \qquad (2.4.3)$$

[14] This approach aims to circumvent the problem caused by non-synchronous trading between the Japanese stock market and the US stock market and to investigate the covariance between these returns without concerns about the imperfect synchronous trading hours. The intradaily returns of market indices may only reflect information revealed over different time intervals due to these two markets not operating at the same time, which leads to failure in to capturing an impact of macroeconomic announcements on the daytime return comovements across the international stock markets. (Karolyi and Stulz,1996; Von Furstenberg and Joen, 1989)

where

$$\alpha_t = \alpha_0 + \alpha_k X_{k,t-1},$$

$$\beta_t = \beta_0 + \beta_k X_{k,t-1}.$$

The coefficient β_0 can be interpreted as the average "normalised" conditional correlation coefficient between the Japanese and the US portfolios and β_k are the response coefficients of the conditional correlation with respect to the level of information variables $X_{k,t-1}$. The coefficient β_k measures how information variable influences the slope of the relationship between return residuals in the US portfolio and return residuals in Japanese portfolio. Moreover, α_t is also expressed as a linear function of the instrumental variables and can be interpreted as the impact of information variables on the Japanese portfolio return residuals. It measures the level of the relationship between the Japanese portfolio return residuals and the US portfolio residuals.

Karolyi and Stulz (1996) also introduce the absolute value of the information variable into the model:

$$\epsilon_{JA,t} = \alpha_t + \beta_t \epsilon_{us,t} + v_t, \tag{2.4.4}$$

where

$$\alpha_t = \alpha_0 + \alpha_{1,k} X_{k,t-1} + \alpha_{2,k} |X_{k,t-1}|,$$

$$\beta_t = \beta_0 + \beta_{1,k} X_{k,t-1} + \beta_{2,k} |X_{k,t-1}|.$$

Let α_t and β_t be linear functions of an instrumental variable levels $X_{k,t-1}$ and their absolute terms $|X_{k,t-1}|$. The coefficient $\beta_{2,k}$ measures the impact of the absolute value of information variables on an increase in comovements between the Japanese portfolio return residuals and the US portfolio residuals. The model's parameters are obtained by the OLS regression and the Newey and West (1987) robust standard errors are reported.

Karolyi and Stulz (1996) find that the most important explanatory variables for the US and Japanese portfolio returns are the preceding returns of the Nikkei and S&P indices. They find that the daytime comovements between the US portfolio and the Japanese portfolio are significantly positively related to the previous night absolute returns on the S&P 500 index and preceding daytime absolute returns on the Nikkei 225 index. However, the macroeconomic information variables such as the lagged returns on Yen/Dollar exchange rate futures and the US Treasury bill futures and macroeconomic news announcements have little power in explaining the conditional correlations.

2.4.2 The Time-varying Volatility Spillover Model of Ng (2000)

Ng (2000) uses weekly equity indices to investigate time-varying spillover effects from the US and Japanese stock markets to six Pacific-Basin stock markets (Hong Kong, South Korea, Malaysia, Singapore Taiwan and Thailand). Ng (2000) relaxes the assumption of constant spillover effects from foreign market and models the mean equation as:

$$R_{i,t} = \mu_i + \alpha_i R_{i,t-1} + \beta_{i,JA.t-1} R_{JA,t-1} + \beta_{i,US,t-1} R_{US,t-1} + \gamma_{i,JA,t-1}\epsilon_{JA,t} + \gamma_{i,US,t-1}\epsilon_{US,t} + \epsilon_{i,t}, \quad (2.4.5)$$

where

$$\beta_{i,JA.t-1} = v_{i,JA}^{'} X_{i,JA,t-1},$$

$$\beta_{i,US,t-1} = w_{i,US}^{'} X_{i,US,t-1},$$

$$\gamma_{i,JA,t-1} = p_{i,JA}^{'} X_{i,JA,t-1},$$

$$\gamma_{i,US,t-1} = q_{i,US}^{'} X_{i,US,t-1}.$$

The vectors of parameters ($v_{i,JA}^{'}$, $w_{i,US}^{'}$, $p_{i,JA}^{'}$ and $q_{i,US}^{'}$) measure the impact of the local information variables in market *i* on the spillover effect from Japan and the US. The local information variables $X_{i,JA,t-1}$ (and $X_{i,US,t-1}$) contain the economic fundamental variables in market i, such as the exchange rate of Yen against the US dollar, the total trade with the Japan (the US) as a ratio to GDP, the number of depositary receipt listings that are cross-listed in various markets, plus a constant. $R_{i,t}$ denotes weekly return from one of the six Pacific-Basin stock markets denoted as "i" during the week t; $R_{JA,t-1}$ and $R_{US,t-1}$ are the weekly returns from the Tokyo Stock Price Index (TOPIX index) in the Japanese market and the S&P 500 index in the US market; $\epsilon_{US,t}$ and $\epsilon_{JA,t}$ are the return shocks from the US and Japanese markets, which are obtained from the estimated return residuals after fitting the GARCH (1,1) model.

The variance ($h_{i,t}$) of the return shock of market i ($\epsilon_{i,t}$), given the information set available at time *t-1* (Ω_{t-1}), is specified as the GJR-GARCH process with the asymmetric effect in conditional variance:

$$\epsilon_{i,t}|\Omega_{t-1} \sim N\ (0, h_{i,t})$$

$$h_{i,t} = a_i + b_i h_{i,t-1} + c_i \epsilon_{i,t}^2 + d_i \eta_{i,t}^2, \qquad (2.4.6)$$

where $\eta_{i,t}$ represents the negative return shock of country *i*.

The estimation results from the above model indicate that both regional (Japanese) and world (US) market factors are important for the Pacific-Basin market spillover effects. The relative importance of the regional and world market factors is influenced by fluctuations in currency returns, number of depositary receipt listings, and the size of trade. This is the evidence that longer horizon returns might be more closely related to the economic fundamentals in contrast to the existing findings for the short horizon returns (such as daily returns or intradaily returns) where little evidence indicates that macroeconomic information plays an important role in affecting the spillover effect across international equity markets (Connolly and Wang, 2003; Karolyi and Stulz 1996).

2.4.3 The Linear and Nonlinear News Model of Connolly and Wang (2003)

Connolly and Wang (2003) use the linear and nonlinear news model to investigate whether macroeconomic news announcements from both domestic and foreign markets can be used to explain the return comovements across international stock markets in the US, UK and Japan. They distinguish the role of economic fundamentals *versus* contagion effects in understanding the determinants of the international stock markets comovements. According to the contagion hypothesis, international investors purely infer information from the price movements of the preceding foreign markets regardless of the economic fundamentals. As a result, the returns from foreign markets should have a separate and significant impact on the returns of the subsequent domestic market after controlling for the macroeconomic news announcements. The impact of foreign markets on the domestic market is expected to be primarily caused by the foreign returns, in the short run, not by macroeconomic fundamentals.

In order to test this hypothesis, Connolly and Wang (2003) first construct the linear news models for daytime returns in the domestic market:

$$R_t = \mu + \alpha\, NR_t + \beta_1\, R_{F1,t} + \beta_2\, R_{F2,t} + \sum_{i=1}^{2} \gamma_i\, FNews_{i,t} + \sum_{i=3}^{5} \gamma_i\, News_{i,t} + \delta\, DM_t + \epsilon_t, \tag{2.4.7}$$

and for overnight returns in the domestic market:

$$NR_t = \mu' + \alpha'\, R_{t-1} + \beta_1'\, R_{F1,t} + \beta_2' R_{F2,t} + \sum_{i=1}^{2} \gamma_i'\, FNews_{i,t} + \sum_{i=3}^{5} \gamma_i'\, News_{i,t} + \delta'\, DM_t + \epsilon_t, \tag{2.4.8}$$

where the domestic daytime (overnight) returns are a linear function of previous domestic returns (NR_t or R_{t-1}), foreign daytime returns ($R_{F1,t}$ and $R_{F2,t}$), and macroeconomic news shocks (*News* and *FNews*). For a selected domestic market, $R_{F1,t}$ represents the daytime returns from the immediately preceding foreign market, while $R_{F2,t}$ denotes the daily open-to-close returns from more distant foreign markets. $FNews_{i,t}$ (for $i = 1, 2$) represents the unexpected components of macroeconomic news announcements from foreign market *i* (for $i = 1, 2$). $News_{i,t}$ (for $i = 3, 4, 5$) represents the unexpected components of macroeconomic news announcements made before the domestic market opens (for i = *3*), during the domestic intraday trading (for i = *4*) and after the domestic market closes (for i = *5*). DM_t is the dummy variable to capture Monday or post-holiday effects.

The unexpected components of macroeconomic news announcements are defined as the percentage difference between the actual announcement values and the median expected values. The median expected values in the US market are obtained from the survey from the Money Market Services (MMS international). As in the case of the UK and Japanese markets, residuals from an ARIMA model for actual news announcements series were used as the proxies of unexpected percentage changes in the news since no similar expected values on announcements were available. A comprehensive data set of real economic news announcements (such as money supply, consumer price inflation, industrial production, unemployment rate, and so on) made in the US, UK and Japan from 1985 to 1996 was included in the analysis.

The estimation results from the linear news model indicate that: (1) immediately prior domestic overnight (daytime) returns affect domestic daytime (overnight) returns. The only exception is in the model of US overnight market returns where the previous domestic daytime returns have little influence on the following domestic overnight returns. The null hypothesis that $\alpha = 0$ ($\alpha' = 0$) is rejected at the 1% significance level; (2) previous foreign daytime returns affect the current domestic daytime returns in all three markets. The null hypothesis that $\beta_1 = \beta_2 = 0$ ($\beta_1' = \beta_2' = 0$) is soundly rejected at the 1% significance level; (3) foreign market returns seem to have a greater impact on the domestic market than previous own domestic market returns have (i.e. the size of coefficient β is larger than α); (4) foreign returns in the immediately preceding markets tend to have a greater impact on the domestic market than more distant foreign markets do (i.e. $\beta_1 > \beta_2$ or $\beta_1' > \beta_2'$); (5) incremental explanatory power of the macroeconomic news announcements diminishes sharply in the presence of the foreign market returns. This means that the foreign returns play a dominant role in affecting the following domestic returns over the real economic announcements.

Connolly and Wang (2003) also use a nonlinear news model to investigate the volatility effect of macro news announcements. For daytime returns in the domestic market, they define the model as:

$$R_t = \mu + (\alpha + \sum_{i=3}^{5} \gamma_i \, |News_i|) NR_t + (\beta_1 + \gamma_1 |FNews_1|) R_{F1,t} + (\beta_2 + \gamma_2 |FNews_2|) \, R_{F2,t} + \delta \, DM_t + \epsilon_t \, , \tag{2.4.9}$$

and for overnight returns in the domestic market, the model has the following form:

$$NR_t = \mu' + (\alpha' + \sum_{i=3}^{5} \gamma_i' |News_i|) \, R_{t-1} + (\beta_1' + \gamma_1' |FNews_1|) \, R_{F1,t} + (\beta_2' + \gamma_2' |FNews_2|) R_{F2,t} + \delta' \, DM_t + \epsilon_t, \tag{2.4.10}$$

where the absolute value of the unexpected macro news announcements is a proxy for volatility due to public information flow. The coefficients γ_i (for $i = 3, 4, 5$) and $\gamma_i^{'}$ (for $i = 3, 4, 5$) measure how the volatility of domestic unexpected macro news announcements affects the own-market correlations between the daytime and overnight stock returns. The coefficients γ_1 and γ_2 ($\gamma_1^{'}$ and $\gamma_2^{'}$) measure how the volatility of the foreign unexpected macro news announcements affect the cross-market lead-lag relationships. If the return comovements coefficients α, β_1 and β_2 ($\alpha^{'}$, $\beta_1^{'}$ and $\beta_2^{'}$) drop substantially after controlling for the volatility of macro news shocks, then the shift in return correlation between markets may simply reflect common economic fundamentals. Connolly and Wang (2003) conclude that the macro news effect is too small to account for an economically sizeable part of the return comovements among the three national equity markets and suggest that further investigations on market comovements should focus on the distinction between contagion and trading on private information.

In order to account for the asymmetric volatility clustering effect, Connolly and Wang (2003) use the GJR-GARCH model to describe the residual terms (ϵ_t) of the daytime and overnight returns.

$$h_t = a + bh_{t-1} + c \, \epsilon_{t-1}^2 + d \, (I_{t-1}\epsilon_{t-1}^2) + eDM_t + f \, Int_t \, . \tag{2.4.11}$$

The conditional volatility equation considers the interest rate effect (Glosten et al., 1993) by including domestic interest rate of respective countries (Int_t) and Monday or post-holiday effects by including a dummy variable DM_t.

2.4.4 The Time-varying Return Spillover Model of Gagnon and Karolyi (2003; 2009)

Gagnon and Karolyi (2003) test whether trading volume plays an important role in affecting returns transmission between the US and Japanese stock markets. Gagnon and Karolyi (2003) are the first to extend the study of the informational role of trading volume and its relation with return dynamics of stock market into an international context. The model is expressed as follows:

$$R_{i,t} = \mu + \left(\alpha_0 + \alpha_1 V_{i,t-1} + \alpha_2 V_{i,t-1}^2 + \alpha_3 h_{i,t-1}^{1/2}\right) R_{i,t-1} + \left(\beta_0 + \beta_1 V_{j,t-1} + \beta_2 V_{j,t-1}^2 + \right.$$
$$\beta 3hj,t-11/2Rj,t-1+\gamma 1HOLi,t+\gamma 2WKDi,t+\epsilon t, \qquad (2.4.12)$$

where $R_{i,t}$ is the current daily returns of the S&P500 index (Nikkei 225 index); $R_{j,t-1}$ is the preceding daily returns of the Nikkei 225 index (S&P500 index); $HOL_{i,t}$ and $WKD_{i,t}$ are the holiday and weekend dummy variables controlling for holiday and weekend effects in market *i*; $h_{i,t-1}^{1/2}$ and $h_{j,t-1}^{1/2}$ are the square roots of the conditional volatility series from the GARCH models. $V_{i,t-1}$ and $V_{j,t-1}$ represent the de-trended trading volumes which are the residual terms obtained by running the following OLS regression in market *i* and market *j* in the previous trading day:

$$log(Trading\ volume_t) = \gamma_0 + \gamma_1 t + v_t, \qquad (2.4.13)$$

where the trading volume series is the raw volume in the form of the number of stocks traded during the day; *t* is the time trend; γ_0 is the constant term.

The coefficients α_1, α_2 and α_3 capture the interaction effects between returns and lagged trading volume, lagged trading volume squared and conditional volatility, respectively. α_1 measures the impact of the domestic volume in previous trading days on today's return autocorrelation. α_2 captures the potential nonlinearity in the return autocorrelation and lagged volume interaction. α_3 measures the influence of the conditional volatility of the returns from preceding day in domestic market *i* on today's return autocorrelation.

The coefficients β_1, β_2 and β_3 share the similar interpretations as α_1, α_2 and α_3, with the extension to an international context. β_1 measures the informational role of foreign trading volume in affecting the cross return correlations between the previous day's trading in foreign market *j* and domestic market *i*. β_2 captures the potential nonlinearity in the cross return correlations and foreign volume interaction. β_3 measures the impact of conditional volatility of foreign returns on the magnitude of return spillover effects from foreign market *j* to domestic market *i*.

The most important finding from Gagnon and Karolyi (2003) is that daytime returns in the Japanese market spill over to the US market and this relation is sensitive to the trading volume in the Japanese market. The volume interaction is statistically significant and negative (β_1 equals -0.046 with t-statistic of -1.709). This result implies that the returns accompanied with heavy trading volume in the Japanese market have a smaller impact on the US market than those returns with normal volume in the Japanese stock market. Gagnon and Karolyi (2003) suggest that a negative β_1 is consistent with the direct interpretations of the CGW model for the international setting, i.e. liquidity-motivated price movements in the foreign market are likely to be less informative for investors in the domestic market.

Gagnon and Karolyi (2009) use a sample of cross-listed stocks that are listed in both the US stock market and their respective domestic markets to investigate the joint dynamics of return spillovers and trading volume on the firm-specific level.

The model of the US cross-listed stocks is specified as follows:

$$R_{i,t}^{US} = \mu_i + \left(\alpha_0 + \alpha_1 V_{i,t-1}^{US}\right) R_{i,t-1}^{US} + \left(\beta_0 + \beta_1 V_{i,t-1}^{H}\right) R_{i,t-1}^{H} + \gamma_1 R_{H,t-1} + \gamma_2 R_{US,t-1} + \gamma_3 R_{FX,t-1} + \epsilon_t. \tag{2.4.14}$$

The model of the home market stock is defined as follows:

$$R_{i,t}^{H} = \mu_i' + \left(\alpha_0' + \alpha_1' V_{i,t-1}^{H}\right) R_{i,t-1}^{H} + \left(\beta_0' + \beta_1' V_{i,t-1}^{US}\right) R_{i,t-1}^{US} + \gamma_1' R_{US,t-1} + \gamma_2' R_{H,t-1} + \gamma_3' R_{FX,t-1} + \epsilon_t. \tag{2.4.15}$$

In Equation (2.4.20) and Equation (2.4.21), $R_{i,t}^{US}$ are the daily returns of firm *i*'s stocks which are traded in the US market on day *t*; $R_{i,t-1}^{H}$ are the daily returns of firm *i*'s stocks which are traded in their home market on the preceding day *t-1*; $R_{US,t-1}$ and $R_{H,t-1}$ are the market index returns in the US market and the home market; $R_{FX,t-1}$ is the foreign exchange rate between the US dollars and home currency on the day *t-1*; $V_{i,t-1}^{US}$ and $V_{i,t-1}^{H}$ are the trading volume of stock i in the US market and the home market. The models control for the market-wide sources of corss-correlations such as the movements from the US stock market index, home stock market index and currency market.

The parameters α_0 and α_0' measure firm *i*'s return autocorrelation in the US market and home market, respectively. α_1 and α_1' are the coefficients associated with the lagged-volume-return interaction, which measure the informational role of trading volume for stock *i* in affecting the return autocorrelation in the US market and the home market. β_0 (β_0') captures the return spillovers from the stock *i* in the home (US) market to the returns of the US cross-listed (home) stocks. β_1 (β_1') measures the interaction between the return spillovers from home (the US cross-listed) stocks to the US cross-listed (home) stocks and trading volume of stock *i* in the home (US) market.

In the home-to-US market spillover test, Gagnon and Karolyi (2009) find a negative mean of β_1 across entire sample that is categorized according to the firms' size, geographical locations of home firms and US institutional ownerships. It means that, on average, stocks' returns associated with positive volume shocks in the home market have less influence on the returns of the US cross-listed counterpart in all categories. In the US-to-home market spillover test, the results show a negative mean of β_1' in all categories except for the category of Asia. This implies that there is a tendency where liquidity-induced price changes originating in the US cross-listed stocks have a smaller impact on their home stocks; however, this is not a tendency for those firms whose home stocks are based on the Asian market. In other words, liquidity trades are also informative for the Asian investors.

2.4.5 The Foreign Information Transmission (FIT) Model of Ibrahim and Brzeszczynski (2009)

Ibrahim and Brzeszczynski (2009) introduce a Foreign Information Transmission (FIT) model to examine the role of foreign information on heat-wave-like and meteor-shower-like transmission of returns within and between major international stock markets in the

USA, Europe and Asia. The FIT model of Ibrahim and Brzeszczynski (2009) is defined as follows:

$$R_t = \alpha_t + \beta_t R_{F1,t} + \epsilon_t, \tag{2.4.16}$$

$$(\alpha_{t+1} - \bar{\alpha}) = \left[a + b \left(R_{F2,t} - \bar{R}_{F2} \right) \right](\alpha_t - \bar{\alpha}) + v_{\alpha,t+1}, \tag{2.4.17}$$

$$(\beta_{t+1} - \bar{\beta}) = [c + d \left(R_{F2,t} - \bar{R}_{F2} \right)](\beta_t - \bar{\beta}) + v_{\beta,t+1}, \tag{2.4.18}$$

where α_t and β_t are time-varying coefficients which have steady-state values of $\bar{\alpha}$ and $\bar{\beta}$, respectively. R_t are the open-to-close (daytime) returns in the domestic market on day *t*. $R_{F1,t}$ and $R_{F2,t}$ are the daytime returns from the previously opened foreign market *1* and foreign market *2*. $\bar{R}_{F2}$ stands for average value of daytime returns in foreign market *2*. $(R_{F2,t} - \bar{R}_{F2})$ is the daytime return deviation of the foreign market *2* from its mean level, which represents the "non-average" information from this foreign market. $v_{\alpha,t+1}$ and $v_{\beta,t+1}$ are the error terms following a normal distribution.

The time-varying coefficient α_t can be interpreted as the level of the relationship between the daytime returns from the domestic market and foreign market *2*, while the slope parameter β_t measures the intensity of this relationship. β_t captures the direct return spillover effects from foreign market *1* to the domestic market. $(\alpha_{t+1} - \bar{\alpha})$ is the deviation of the level from its steady-state value, and $(\beta_{t+1} - \bar{\beta})$ is the deviation of the intensity from its steady-state value. The constant parameters *a* and *c* capture the autocorrelations of these deviation over time, and parameters *b* and *d* measure covariance of these deviations with the return deviations of the third market from its mean level. If the constant parameters *b* and *d* are significant and positive, it means that the deviations of daytime returns from foreign market *2* have a substantial influence on the level and intensity of return spillovers from foreign market *1* to the domestic market (the meteor shower effect). Thus, the daytime returns from foreign market *2* have an indirect effect on the domestic market.

The FIT model can also be applied to test heat wave hypothesis in returns where the model is specified as follows:

$$R_t = \alpha_t + \beta_t R_{t-1} + \epsilon_t, \tag{2.4.19}$$

$$(\alpha_{t+1} - \bar{\alpha}) = \left[a + b \left(R_{F,t} - \bar{R}_F \right)\right](\alpha_t - \bar{\alpha}) + v_{\alpha,t+1}, \tag{2.4.20}$$

$$(\beta_{t+1} - \bar{\beta}) = [c + d \left(R_{F,t} - \bar{R}_F \right)](\beta_t - \bar{\beta}) + v_{\beta,t+1}. \tag{2.4.21}$$

The parameters *b* and *d* measure the impact of the return deviations from foreign market $\left(R_{F,t} - \bar{R}_F\right)$ on the level and intensity of the relationship between two consecutive daytime returns in the domestic market. A positive and significant coefficient β_t indicates that there exists a direct return transmission effect from day *t-1* to *t* in a market.

Ibrahim and Brzeszczynski (2009) provide empirical evidence indicating that the meteor shower effect is stronger than the heat wave effect in returns transmission mechanism and thus inter-regional returns transmission is more relevant in predicting next-day's returns than region-specific transmission. It is found that daytime returns can spillover directly from some international stock markets to others. Information about the index returns from foreign markets plays an important role in predicting the price movements in the following domestic market returns. Moreover, Ibrahim and Brzeszczynski (2009) show that this foreign information is economically beneficial for traders who study overnight signals from international markets before they start trading for the new day in their domestic markets. It is shown that trading strategies based on out-of-sample forecast for the FIT model are profitable over various out-of-sample horizons under even relatively high transaction costs.

2.5 Summary

The literature on the information transmission mechanisms among international stock markets is extensive. The main stream in the field of transmission of signals focuses on how the lagged information contained in the price movements of one stock market may influence investors and prices in other markets to which the spillovers occur. The availability of intraday data allows one to investigate the international stock markets comovements over short horizons by careful consideration of the chronological sequence of the trading times at which markets located in different time zones are open.

A review of the literature in Section 2.2 shows that earlier research on market interdependence often employs the VAR methodology. However, standard econometric techniques, suffer from problems caused by ARCH effects. The new developments of econometric methods in the 1980s (e.g. the GARCH methodology) provided a solution to these problems. Moreover, as pointed out by Hamilton (2010), if one is indeed interested in measuring the magnitude of the coefficients, not only the standard errors but also the parameter estimates themselves should be corrected in light of the dramatic ARCH displayed in the data. The maximum-likelihood estimates under the ARCH framework are more appropriate than the OLS estimates if ARCH is present in the financial time series. Hamilton's work justifies the GARCH technique employed in this research.

The review of the literature in Section 2.3 shows strong evidence about the presence of the meteor shower effects in both return and volatility among international stock markets especially in the wake of the 1987 stock market crash and 1997 Asian financial crisis. The existence of positive return and volatility spillovers across markers implies that the first and second moments of equity prices in one stock market help to predict the future price movements in other markets. The information transmission mechanisms in returns and volatilities operate largely in the same direction.

The literature discussed in Section 2.4 shows that variations of macroeconomic variables have little power in explaining the time-varying nature of the return correlations across international stock markets (e.g.; Karolyi and Stulz, 1996; Connolly and Wang, 2003). On the other hand, Gagnon and Karolyi (2003; 2009) provide evidence that trading volume plays an important informational role in affecting the transmission of returns between international stock markets. In addition, Ibrahim and Brzeszczynski (2009) find that the information about return deviations in the third market can be used to describe the time-varying relations of returns between the markets in two countries.

CHAPTER 3 – DATA AND PRELIMINARY ANALYSIS

3.1 Data

The stock markets selected for the empirical analysis in this study are the New York, Toronto, London, Frankfurt, Paris, Tokyo, Hong Kong and Shanghai markets. They are the world's eight largest stock markets in terms of capitalisation value.[15] The market indices chosen to represent these markets are the S&P 500 index (the US), S&P/TSX index (Canada), FTSE100 index (the UK), DAX 30 index (Germany), CAC 40 index (France), TOPIX index (Japan), Shanghai A Share index (China) and Hang Seng index (Hong Kong). The daily opening price, closing price and trading volume of market indices are employed over an eight-year period from 1 August 2003 to 29 July 2011, with a total of 2086 observations. The full sample period is separated into a seven-year in-sample estimation period (1 August 2003 – 30 July 2010) and a one-year out-of-sample period (2 August 2010 – 29 July 2011). All indices are market capitalisation weighted and are denominated in local currency. The data are obtained from the DATASTREAM database.

3.2 Description of International Trading Hours

Given that international stock markets are open at different times around the globe, it is necessary first to describe their sequences and the timeframes for the opening and closing hours of stock markets selected for this study.

As can be seen in Table 3.1, the Tokyo stock exchange (TSE) opens at 09:00 and closes at 15:00 by Japan Standard Time (JST) and it has a lunch break from 11:00 to 13:00. JST is nine hours ahead of Greenwich Mean Time (GMT), i.e. GMT + 9:00. The trading

[15] The ranking is based on the market capitalisation at the end of 2008 according to the World Federation of Exchanges (WFE). See the last column in Table 3.1 for details. The criterion for selection of international stock markets is that the market capitalisation should be above 1,000 billion US dollars.

time in Shanghai stock exchange is 09:30 - 11:30 and 13:00 - 15:00, local time (GMT + 8:00). In the Hong Kong stock exchange, morning session is from 10:00 to 12:30, and the afternoon session is from 14:30 to 16:00. Hong Kong and Shanghai markets are located in the same geographical time zone which one hour behind JST. The three Asian stock markets do not observe Daylight Saving Time.

The trading session in the UK stock market lasts from 08:00 to 16:30 in local time (GMT + 0:00; GMT + 1:00 during Daylight Saving Time).[16] Trading hours in France and Germany are 09:00 to 17:30 in European Central Time (GMT + 1:00; GMT + 2:00 during Daylight Saving Time). Since ECT is one hour ahead of GMT, the three stock markets in Europe are open and closed concurrently.

The trading time in the US and Canadian stock markets is from 09:30 to 16:00 by New York time (Eastern Standard Time, or EST). The trading time corresponds to GMT time from 14:30 to 21:00 (GMT- 5:00; GMT - 4:00 during Daylight Saving Time). Both markets are the last to open for the day according to the GMT time scale. The stock markets in North America (i.e. Toronto and New York) and in Europe (i.e. London, Frankfurt and Paris) are open concurrently for two hours until European markets close at 16:30 in London time. The three European stock markets close two hours after the Toronto and New York stock markets have opened.

During the trading hours of the stock markets in Europe and North America, stock markets in Asia such as Hong Kong, Shanghai and Tokyo stock exchanges have already finished their activity on the same calendar day. Thus, investors in the western hemisphere will have full information on price movements of stock markets in Asia before the commencement of trading in their own market. On the other hand, information on price changes of stocks traded in the west on the previous trading day is also available to investors in the Asian stock markets before they trade on the new day.

A problem in studying the spillover effect across international stock markets is the existence of nonsynchronous holidays among these markets. There are three possible methods that are commonly used in the literature to tackle this problem (Yong, 1992). One approach is to assign zero return for the market with no trading activities. The

[16] Daylight Saving Time (DST) is also called summer time. Typically clocks are adjusted forward one hour during DST adding daylight to evenings.

second one is to exclude the nonsynchronous holidays from the data set. The third alternative approach is to construct a linear model to estimate the returns of the days with no trading. In the database in this dissertation, the prices on non-trading days are represented as the same prices of prior trading days and zero return is assigned to the markets that are closed for holidays. The reasons for this choice are: (1) it is not appropriate to simply ignore the days with no trading activity since non-trading is a character of thin markets; (2) the linear model generating observations in the third alternative approach are not actual returns; (3) the zero returns reflect the actual returns on the non-trading days; (4) when measuring the spillover effect from one market in periods during which another market is closed, no returns from the market can spill over to returns of another market that is closed for holidays.

3.3 Descriptive Statistics on Returns

Basic statistics of open-to-close (daytime) returns during the in-sample period are summarised in Table 3.2. Open-to-close returns (denoted by R_t) are calculated as logarithmic returns, i.e. as the difference between natural logarithms of closing and opening prices.

As shown in Table 3.2, the kurtosis and skewness measures for all the series suggest a higher frequency of extreme values for stock returns. In order to test whether returns in each market have a normal distribution, the Jarque-Bera test is conducted. It shows that the null hypothesis that daytime returns are normally distributed is rejected for all eight markets. This finding is broadly consistent with most previous studies that have tested the normality of daily stock returns (e.g. Niarchos, Tse, Wu and Young, 1999; Nam, Yuhn and Kim, 2008).

Table 3.3 and Table 3.4 present the Ljung-Box Q-statistics for testing serial correlations in the returns (R_t) and the squared returns (R_t^2) series. In this study the autocorrelations of $R_{i,t}$ and R_t^2 are investigated for 8, 16 and 24 lags.[17]

[17] The Ljung-Box Q-statistic is often used for testing whether the series exhibit white noise processes. The Q-statistic at lag *k* is the test statistic for the null hypothesis that there is no autocorrelation up to order *k*. The practical problem is the choice of the order of lag *k* for the test. The test may not detect serial

The Ljung-Box Q-statistics, calculated for the returns and the squared returns series, suggest the presence of linear and nonlinear dependence of stock returns in each investigated market. The null hypothesis of no autocorrelation is rejected at the 1% level regardless of the length of lags selected. The results in Table 3.3 show that the stock returns are serially correlated. The Q-statistics for the squared return series reported in Table 3.4 are statistically significant for all the markets, suggesting the presence of the autoregressive conditional heteroskedasticity in the volatility of returns in those markets (i.e. once the volatility of returns becomes larger, a larger volatility is persistent for a certain period of time, and a large shock tends to be followed by another large shock). However, the nonlinear dependence can be captured by the GARCH-type models which are applied in this study. It is noteworthy that the Q-statistic for the squared returns is several times greater than that calculated for returns themselves. This is an indication that the second moment (nonlinear) dependence is far more significant than the first moment dependence. The pattern of large volatility clustering is evident. As a result, the GARCH-type models discussed in Chapter 2 are chosen for modelling such phenomena.

3.4 Descriptive Statistics on Trading Volume

The existing literature finds empirical evidence for both linear and non-linear time trends in trading volume (e.g. Gallant, Rossi and Tauchen, 1992; Lee and Rui, 2002). Following Lee and Rui (2002), this study replaces trading volume with the de-trended trading volume. It is obtained from the OLS estimated residuals of the following model:

$$Trading\ Volume_{i,t} = \mu_i + \alpha t + \beta t^2 + \epsilon_{i,t}, \tag{3.1}$$

where μ_i is the constant term; t and t^2 represent linear and non-linear time trends, respectively. $Trading\ Volume_{i,t}$ is the number of stocks traded for market index i on day t. The residual term $\epsilon_{i,t}$ obtained in the OLS estimation of Equation (3.1) is the de-trended trading volume, which is controlled for the linear and non-linear time trends.

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correlation at high-order lags if k is too small. However, the test may have low power as the significant correlation at one lag may be diluted by insignificant correlations at other lags if a large k is chosen (Ljung and Box, 1978; Harvey, 1990; 1993).

Tables 3.5-3.7 show that the de-trended trading volume time series for all the markets exhibit characteristics that are common in the high frequency financial time series: the leptokurtic distribution and statistically significant serial correlations in the first and second moments of the series.[18] The summary statistics suggest the appropriateness of using GARCH-type models to investigate the trading volume spillovers across international stock markets.

3.5 Testing for ARCH Effects

ARCH effects are tested using the Lagrange Multiplier (LM) test which has been proposed by Engle (1982). As suggested by Bollerslev, Engle and Nelson (1994), the intuition behind the ARCH test of Engle (1982) is as follows: if the data are homoskedastic, then the variance cannot be predicted and variations in squared residuals of the model will be purely random. However, if ARCH effects are present, large values of squared residuals will be predicted by large values of the past squared residuals.[19] Under the null hypothesis that there is no ARCH up to order q in the residuals, it is assumed that the model can be specified as:

$$y_t = \mu + \alpha y_{t-1} + \epsilon_t, \tag{3.2}$$

where ϵ_t is a Gaussian white noise process. The alternative hypothesis is that the errors follow the ARCH(q) process. The LM test of ARCH(q) can be carried out by computing the LM test statistic (TR^2) in the regression of $\hat{\epsilon}_t^2$ on a constant and q lagged values:

$$\hat{\epsilon}_t^2 = \mu + \left(\sum_{s=1}^{q} \beta_s \hat{\epsilon}_{t-s}^2\right) + v_t, \tag{3.3}$$

[18] The de-trended trading volume can be standardised by dividing the residual term in Equation (3.1) over the standard deviation of residual term. The statistic values in the tables are unchanged in the standardisation except that the standard deviation of the time series has been normalised to one.

[19] It is noteworthy that this particular specification of heteroskedasticity (i.e. ARCH) was motivated by the observation that in many financial time series (Engle, 2004).

under the null hypothesis that $\beta_1 = \beta_2 = \cdots = \beta_q = 0$ (i.e. there is no ARCH up to order q), the LM test statistic is asymptotically distributed as $\chi^2(q)$ and can be computed as the number of observations (T) times the R^2 from the regression. The statistically significant LM values give evidence of the presence of ARCH (or GARCH) effects.

The results reported in Table 3.8 indicate that LM test statistics using both returns and trading volume data are statistically significant at the 1% level for all the markets, suggesting that ARCH effects are strong.

3.6 Unit-root Tests

In order to avoid the spurious regression problem, tests for the stationarity of the open-to-close returns and trading volume series are also conducted.[20] The most common stationarity tests are the Phillips-Perron (P-P) and Augmented Dickey-Fuller (ADF) tests for unit roots.

The P-P method relies on the following regression:

$$\Delta Y_t = \mu + \alpha t + (\rho - 1)Y_{t-1} + \epsilon_t, \tag{3.4}$$

where μ is a constant, t is a time trend and ϵ_t are assumed to be white noise.

The P-P method tests H_0: $\rho - 1 = 0$ against H_1: $\rho - 1 < 0$. If H_0 can not be rejected then Y_t has a unit root. If H_0 is rejected, then Y_t is stationary.

The ADF test estimates:

$$\Delta Y_t = \mu + \alpha t + \psi^* Y_{t-1} + \psi_1 \Delta Y_{t-1} + \psi_2 \Delta Y_{t-2} + \cdots \psi_{p-1} \Delta Y_{t-p+1} + \epsilon_t \tag{3.5}$$

where $\psi^* = (\psi_1 + \psi_2 + \cdots + \psi_{p-1}) - 1$.

[20] If the variables are nonstationary, the spurious regressions problem may arise. The regression estimates are invalid in a spurious regression.

The ADF test assumes that the variable Y_t follows an AR (p) process. It adds lagged difference terms of the variable to the right hand side of the test regression. If the $H_0: \psi^* = 0$ against $H_1: \psi^* < 0$ cannot be rejected, then Y_t contains a unit root and Y_t is nonstationary.

The results from both the ADF and P-P tests in Tables 3.9 -3.10 show that the null hypothesis that the stock returns and standardised de-trended trading volume series are nonstationary (i.e. have a unit root) is rejected in all the international stock markets, suggesting that all variables under investigation are stationary.

3.7 Correlation Coefficient (Pearson's r) Analysis

The simplest method of describing market comovements adopted by many studies is to report the unconditional correlation coefficient (Pearson's r) matrix in returns across markets of interest. Its aim is to show the direction and intensity of return comovements without necessarily investigating the drivers (causal relations) of such linear dependence. Ideally, this requires the holding periods for comparison to be contemporaneous. Given that the international stock markets operate in different time zones, the daytime returns at the same time period are not synchronised. Cheng and Ng (1996) suggest that any significant correlation coefficient between inter-regional markets on the same calendar day should be interpreted as evidence of the market that operates earlier causing the one that operates later. For example, the significant correlation coefficient between the TOPIX index and the S&P 500 (FTSE100) index implies that the Tokyo market is leading the New York (London) market.

Table 3.11 reports the cross-correlation coefficients of daytime stock market returns in a matrix. Since the correlation coefficient matrix is symmetric around the diagonal, only results in the lower half of the table are reported. All elements on the diagonal of the matrix are equal to 1, implying that one market is perfectly positively correlated with itself. The correlation coefficients are positive and statistically significant in all cases between intra-regional markets, indicating that when one market moves, either up or down, the others in the same region are more likely to move in the same direction. The top three pairs in terms of the size of correlation coefficient are Germany-France (Pearson’s r of 0.8607), Germany-UK (Pearson’s r of 0.7702) and UK-France (Pearson’s r of 0.7140), which are all located in the European region. The three stock markets in Asia are less correlated compared to those markets in Europe and North America. The correlation coefficients are not statistically significant from zero between some inter-regional markets, including China-France, China-Germany, China-Canada, Japan-France and Japan-Canada, which can be interpreted as evidence showing that the Shanghai market has little influence on the Paris, Frankfurt and Toronto stock markets, and the Tokyo stock exchange does not lead the Paris and Toronto markets.[21] In summary, the results show that cross-correlations are more pronounced and frequent between markets located in one region (intra-regional relations) than between markets from different regions (inter-regional relations).[22] It is not a surprising pattern given the high contemporaneous price comovements of the markets within the same region (e.g. due to synchronous trading hours, shorter geographical distances, closer economic policy coordinations as well as tighter economic and financial linkages etc.).

3.8 Summary

This chapter discusses the data employed in this thesis, describes trading hours of the investigated international stock exchanges and provides preliminary analysis of cross-market correlations in terms of open-to-close market index returns.

Section 3.1 describes the selection criterion of international stock markets for this study. The New York, Toronto, London, Frankfurt, Paris, Tokyo, Hong Kong and Shanghai

[21] The results are consistent with those suggested by the OLS estimates of a model in which daytime return in the domestic market is a linear function of its preceding daytime return, one-day lagged foreign market daytime return and a constant. The OLS estimates of return spillover coefficients are reported in the next chapter.

[22] The observed pattern is consistent with findings from Gebka and Serwa (2007), who study the market linkages between emerging markets in Central and Eastern Europe, Latin America, and South-East Asia after controlling for information originating at home and on developed markets. Their research shows that intra-regional interdependence is more pronounced and frequent than inter-regional one.

stock exchanges are chosen as they are the world's eight largest equity trading centres in terms of market capitalisation. An eight-year sample period (1 August 2003 – 29 July 2011) is selected as the whole sample period during which data for these markets are all available in the DATASTREAM database.

Section 3.2 explains the non-synchronous nature of international stock market trading times. It is due to the different geographical locations in which the world's stock markets operate. The international stock exchanges located in the Asian, European and North American regions open and close sequentially during the day as the globe turns. This feature has attracted attention of financial practitioners and academics in the analysis of market interdependence of stock prices.

Section 3.3 and 3.4 discuss statistical properties of the daytime stock returns and trading volume. The tests show that these data display some characteristics that are common in most financial high frequency data, i.e. the non-normal distribution and serial correlations in the first and second moments of time series. The Lagrange Multiplier (LM) test in Section 3.5 confirms that ARCH effects exist in both returns and trading volume series for all the investigated markets, and the unit root tests in Section 3.6 suggest that all returns and volume series are stationary.

Section 3.7 discusses the unconditional correlation coefficient (Pearson's r) matrix in returns. Following Cheng and Ng (1996), the results are interpreted after accounting for the non-synchronous nature of trading hours among the eight international stock markets under investigation. The results show that the contemporaneous cross-market correlations are more pronounced and frequent between markets located in one region (intra-regional relations) than between markets from different regions (inter-regional relations). Although the cross-correlation coefficient analysis of stock market returns shows an interesting pattern regarding the extent of market linkages between international stock exchanges, it does not reveal the direction of the causality in the sense of Granger. The question of how much stock return in one market helps to predict future price movements in another stock market is thus explored in the next chapter of this thesis. Chapter 4 turns to investigation of the direct information transmission mechanisms across international stock markets in the sequence in which they trade in the context of dynamic spillovers in return, volatility and trading volume.[23]

[23] The cross-correlation coefficient matrixes of return volatility and trading volume are reported in Table 3.12 and 3.13 without further interpretations, since there is a more appropriate methodology to investigate the market linkages across international stock markets, and more detailed discussions are presented in Chapter 4.

Table 3.1: International Timeframe of Regular Stock Market Trading Session

Stock Exchanges	Regime	Local Time	Greenwich Mean Time	Difference	Market Cap (in billion of US dollars)
Tokyo	Asia	09:00 -11:00 12:30 -15:00	00:00 -02:00 03:30 -06:00	GMT + 09:00	3115.8037
Shanghai	Asia	09:30 -11:30 13:00 -15:00	01:30 -03:30 05:00 -07:00	GMT + 08:00	1425.3540
Hong Kong	Asia	10:00 -12:30 14:30 -16:00	02:00 -04:30 06:30 -08:00	GMT + 08:00	1328.7685
Paris	Europe	09:00 -17:30	08:00 -16:30	GMT + 01:00	2101.7459
Frankfurt	Europe	09:00 -17:30	08:00 -16:30	GMT + 01:00	1110.5796
London	Europe	08:00 -16:30	08:00 -16:30	GMT	1868.1530
New York	North America	09:30 -16:00	14:30 -21:00	GMT - 05:00	9208.9341
Toronto	North America	09:30 -16:00	14:30 -21:00	GMT - 05:00	1033.4485

Notes:

1. The markets tabulated are the world's eight biggest international stock markets in terms of market capitalisation at the end of year 2008 according to the World Federation of Exchanges (WFE).
2. Euronext Paris is France's stock market, formerly known as the Paris Bourse, which merged with the Amsterdam, Lisbon and Brussels exchanges in September 2000.
3. Clocks are adjusted forward one hour in Daylight Saving Time for the European and North American stock markets.

Table 3.2: Basic Statistics for Open-to-close Daily Returns

Stock Markets	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Jarque-Bera statistics
UK	0.0105	1.2518	-0.1450	13.0906	7753.2170*** (0.0000)
France	- 0.0350	1.1314	-0.3749	8.2599	2147.7380*** (0.0000)
Germany	0.0148	1.2385	0.3786	12.5346	6960.2660*** (0.0000)
US	0.0040	1.2735	-0.3380	15.0368	11058.0200*** (0.0000)
Canada	- 0.0346	1.0518	-0.8747	13.3088	8318.3600*** (0.0000)
Japan	0.0526	1.1212	-0.1446	15.536	11962.8700*** (0.0000)
Hong Kong	- 0.0139	1.1972	0.2985	18.3711	18003.4100*** (0.0000)
China	0.0861	1.6667	-0.2877	5.7354	594.4801*** (0.0000)

Table 3.3: Ljung-Box Q-statistics for Returns

Stock Markets	Q-statistics (8 lags)	Q-statistics (16 lags)	Q-statistics (24 lags)
UK	59.1050*** (0.0000)	78.1490*** (0.0000)	86.0660*** (0.0000)
France	28.1780*** (0.0000)	45.4280*** (0.0000)	53.3050*** (0.0010)
Germany	15.4410*** (0.0050)	42.5980*** (0.0000)	51.9800*** (0.0010)
US	58.2840*** (0.0000)	76.9920*** (0.0000)	99.7210*** (0.0000)
Canada	16.9080*** (0.0310)	36.3890*** (0.0030)	57.2220*** (0.0000)
Japan	23.4500*** (0.0030)	44.3620*** (0.0000)	55.9930*** (0.0000)
Hong Kong	57.1900*** (0.0000)	95.7880*** (0.0000)	119.8000*** (0.0000)
China	25.3530*** (0.0010)	35.9590*** (0.0030)	54.3500*** (0.0000)

Notes: *** denotes statistic is significant at the 1% level. The figures in parentheses are the p-values.

Table 3.4: Ljung-Box Q-statistics for the Squared Returns

Stock Markets	Q-statistics (8 lags)	Q-statistics (16 lags)	Q-statistics (24 lags)
UK	1121.3000*** (0.0000)	691.5600*** (0.0000)	822.5200*** (0.0000)
France	748.6000*** (0.0000)	1148.9000*** (0.0000)	1360.2000*** (0.0000)
Germany	466.7300*** (0.0000)	1053.8000*** (0.0000)	1381.1000*** (0.0000)
US	1342.2000*** (0.0000)	2541.5000*** (0.0000)	3397.5000*** (0.0000)
Canada	1452.3000*** (0.0000)	2389.0000*** (0.0000)	3070.1000*** (0.0000)
Japan	1650.2000*** (0.0000)	2367.9000*** (0.0000)	2534.9000*** (0.0000)
Hong Kong	839.2900*** (0.0000)	1256.2000*** (0.0000)	1629.1000*** (0.0000)
China	176.1200*** (0.0000)	312.6600*** (0.0000)	398.4600*** (0.0000)

Table 3.5: Basic Statistics for De-trended Trading Volume

Markets	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Jarque-Bera statistics
UK	0.0000	486150.9438	-0.2413	6.1991	796.3730*** (0.0000)
France	0.0000	47341.6121	1.2110	10.7018	4959.3557*** (0.0000)
Germany	0.0000	50127.4371	1.6201	11.5861	6407.6630*** (0.0000)
US	0.0000	1007499.2971	-0.0890	8.5023	2305.9280*** (0.0000)
Canada	0.0000	62793.6897	-0.0748	7.2148	1353.2654*** (0.0000)
Japan	0.0000	624281.8395	-0.7429	6.0775	888.5510*** (0.0000)
Hong Kong	0.0000	804997.6020	1.2385	7.9285	2314.8728*** (0.0000)
China	0.0000	36389457.5801	0.4651	4.5225	242.1888*** (0.0000)

Table 3.6: Ljung-Box Q-statistics for De-trended Trading Volume

Stock Markets	Q-statistics (8 lags)	Q-statistics (16 lags)	Q-statistics (24 lags)
UK	1481.2374*** (0.0000)	1704.6049*** (0.0000)	1749.2277*** (0.0000)
France	2177.1724*** (0.0000)	2751.9552*** (0.0000)	2820.7208*** (0.0000)
Germany	2109.9177*** (0.0050)	2711.4914*** (0.0000)	2829.3275*** (0.0010)
US	2342.5232*** (0.0000)	3244.7365*** (0.0000)	3664.5876*** (0.0000)
Canada	1300.7133*** (0.0310)	1781.2097*** (0.0030)	2125.5949*** (0.0000)
Japan	1176.6472*** (0.0000)	1402.7732*** (0.0000)	1558.7975*** (0.0000)
Hong Kong	2293.2103*** (0.0000)	3280.6878*** (0.0000)	4108.9311*** (0.0000)
China	5939.5099*** (0.0000)	8849.8348*** (0.0000)	10910.7671*** (0.0000)

Table 3.7: Ljung-Box Q-statistics for De-trended Trading Volume Squared

Stock Markets	Q-statistics (8 lags)	Q-statistics (16 lags)	Q-statistics (24 lags)
UK	423.9744*** (0.0000)	444.6537*** (0.0000)	456.0603*** (0.0000)
France	718.9320*** (0.0000)	904.5667*** (0.0000)	1001.9362*** (0.0000)
Germany	657.0651*** (0.0050)	952.5185*** (0.0000)	1023.3161*** (0.0010)
US	757.3395*** (0.0000)	1109.6997*** (0.0000)	1486.5621*** (0.0000)
Canada	364.4052*** (0.0310)	445.5890*** (0.0030)	516.7965*** (0.0000)
Japan	503.2677*** (0.0000)	556.5252*** (0.0000)	587.4894*** (0.0000)
Hong Kong	679.6890*** (0.0000)	871.2436*** (0.0000)	954.8976*** (0.0000)
China	3489.7016*** (0.0000)	4827.3582 *** (0.0000)	5474.6412*** (0.0000)

Table 3.8: Testing for ARCH Effects

Markets	LM test statistics: Returns	LM test statistics: Trading Volume
UK	111.0571*** (0.0000)	61.1576*** (0.0000)
France	131.7618*** (0.0000)	375.9904*** (0.0000)
Germany	109.6424*** (0.0000)	116.6952*** (0.0000)
US	54.4251*** (0.0000)	178.6312*** (0.0000)
Canada	193.3624*** (0.0000)	255.8806*** (0.0000)
Japan	47.6396*** (0.0000)	149.6401*** (0.0000)
Hong Kong	337.5975*** (0.0000)	72.0527*** (0.0000)
China	41.6507*** (0.0000)	92.3608*** (0.0000)

Table 3.9: Unit Root Tests for Stock Returns

Stock market	ADF test statistics	H_0: nonstationary	P-P test statistics	H_0: nonstationary
Tokyo	-33.0503*** (0.0000)	rejected	-44.1683*** (0.0000)	rejected
Shanghai	-46.7668*** (0.0000)	rejected	-46.6884*** (0.0000)	rejected
Hong Kong	-48.2694*** (0.0000)	rejected	-50.4855*** (0.0000)	rejected
Paris	-47.7750*** (0.0000)	rejected	-47.6507*** (0.0000)	rejected
Frankfurt	-41.9402*** (0.0000)	rejected	-42.0069*** (0.0000)	rejected
London	-21.0788*** (0.0000)	rejected	-46.0670*** (0.0000)	rejected
New York	-35.3399*** (0.0000)	rejected	-48.5848*** (0.0000)	rejected
Toronto	-44.5843*** (0.0000)	rejected	-44.5576*** (0.0000)	rejected

Table 3.10: Unit Root Tests for De-trended Trading Volume

Stock markets	ADF test statistics	H_0: nonstationary	P-P test statistics	H_0: nonstationary
Tokyo	-10.2559*** (0.0000)	rejected	-34.9768*** (0.0000)	rejected
Shanghai	-7.0725*** (0.0000)	rejected	-12.4760*** (0.0000)	rejected
Hong Kong	-9.0505*** (0.0000)	rejected	-32.1095*** (0.0000)	rejected
Paris	-10.2550*** (0.0000)	rejected	-27.1105*** (0.0000)	rejected
Frankfurt	-10.2996*** (0.0000)	rejected	-28.0857*** (0.0000)	rejected
London	-10.2996*** (0.0000)	rejected	-27.8172*** (0.0000)	rejected
New York	-9.7830*** (0.0000)	rejected	-27.7065*** (0.0000)	rejected
Toronto	-10.2559*** (0.0000)	rejected	-34.9768*** (0.0000)	rejected

Table 3.11: Correlation Coefficient Matrix for Returns

Pearson's r (market returns)	Tokyo	Hong Kong	Shanghai	London	Paris	Frankfurt	New York	Toronto
Tokyo	**1.0000** **---**							
Hong Kong	**0.3186*** (0.0000)**	**1.0000** **---**						
Shanghai	**0.1460*** (0.0000)**	**0.3399*** (0.0000)**	**1.0000** **---**					
London	0.3290*** (0.0000)	0.2746*** (0.0000)	0.0787*** (0.0008)	**1.0000** **---**				
Paris	0.0191 (0.4155)	0.1198*** (0.0000)	-0.0172 (0.4627)	**0.7140*** (0.0000)**	**1.0000** **---**			
Frankfurt	0.1617*** (0.0000)	0.2056*** (0.0000)	0.0213 (0.3627)	**0.7702*** (0.0000)**	**0.8607*** (0.0000)**	**1.0000** **---**		
New York	0.1293*** (0.0000)	0.3144*** (0.0000)	0.0643*** (0.0060)	0.5006*** (0.0000)	0.5678*** (0.0000)	0.5730*** (0.0000)	**1.0000** **---**	
Toronto	0.0125 (0.5926)	0.1258*** (0.0000)	0.0306 (0.1910)	0.3081*** (0.0000)	0.4104*** (0.0000)	0.3374*** (0.0000)	**0.6575*** (0.0000)**	**1.0000** **---**

Notes: Correlation coefficients between intra-regional markets are in bold and surrounded by thick lines. Values in the upper half of table are not reported due to symmetry of the correlation coefficient matrix. The p-values reported in parentheses are for testing the null hypothesis that correlation coefficient is equal to zero. The *t*-statistic is computed as $t = \text{r}\sqrt{(n-2)/(1-r)^2}$, where *n* is sample size and *r* is correlation coefficient (Pearson's r). The p-values are obtained from a *t*-distribution with *n*-2 degrees-of-freedom.

Table 3.12: Correlation Coefficient Matrix for De-trended Trading Volume

Pearson's r (trading volume)	Tokyo	Hong Kong	Shanghai	London	Paris	Frankfurt	New York	Toronto
Tokyo	**1.0000** **---**							
Hong Kong	**0.1592***** **(0.0000)**	**1.0000** **---**						
Shanghai	**0.0816***** **(0.0005)**	**0.1964***** **(0.0000)**	**1.0000** **---**					
London	0.2704*** (0.0000)	0.2937*** (0.0000)	0.0892*** (0.0001)	**1.0000** **---**				
Paris	0.2305*** (0.0000)	0.4505*** (0.0000)	-0.0045 (0.8479)	**0.6925***** **(0.0000)**	**1.0000** **---**			
Frankfurt	0.2231*** (0.0000)	0.4405*** (0.0000)	-0.0081 (0.7299)	**0.6768***** **(0.0000)**	**0.8533***** **(0.0000)**	**1.0000** **---**		
New York	0.1938*** (0.0000)	0.4061*** (0.0000)	0.1045*** (0.0000)	0.4947*** (0.0000)	0.6412*** (0.0000)	0.6061*** (0.0000)	**1.0000** **---**	
Toronto	0.1926*** (0.0000)	0.4273*** (0.0000)	0.0703*** (0.0027)	0.5500*** (0.0000)	0.6041*** (0.0000)	0.6128*** (0.0000)	**0.6708***** **(0.0000)**	**1.0000** **---**

Table 3.13: Correlation Coefficient Matrix for Squared Returns

Pearson's r (squared returns)	Tokyo	Hong Kong	Shanghai	London	Paris	Frankfurt	New York	Toronto
Tokyo	**1.0000** **---**							
Hong Kong	**0.3858***** **(0.0000)**	**1.0000** **---**						
Shanghai	**0.1425***** **(0.0000)**	**0.1901***** **(0.0000)**	**1.0000** **---**					
London	0.3211*** (0.0000)	0.2065*** (0.0000)	0.1215*** (0.0000)	**1.0000** **---**				
Paris	0.1123*** (0.0000)	0.1988*** (0.0000)	0.1264*** (0.0000)	**0.5677***** **(0.0000)**	**1.0000** **---**			
Frankfurt	0.2107*** (0.0000)	0.5182*** (0.0000)	0.1873*** (0.0000)	**0.6045***** **(0.0000)**	**0.6452***** **(0.0000)**	**1.0000** **---**		
New York	0.1877*** (0.0000)	0.4639*** (0.0000)	0.1474*** (0.0000)	0.4637*** (0.0000)	0.5477*** (0.0000)	0.6539*** (0.0000)	**1.0000** **---**	
Toronto	0.5089*** (0.0000)	0.3171*** (0.0000)	0.1311*** (0.0000)	0.2525*** (0.0000)	0.2952*** (0.0000)	0.2026*** (0.0000)	0.4803*** (0.0000)	**1.0000** **---**

CHAPTER 4 – INTERNATIONAL SPILLOVER EFFECTS IN STOCK RETURNS, VOLATILITY AND TRADING VOLUME

4.1 Introduction

A review of the literature on short-term comovements of international stock market prices reported in Chapter 2 leads to the conclusion that traditionally the main stream of research has focused on the direct transmission of information in returns and volatility across national stock markets (e.g. Hamao, Masulis, and Ng, 1990; 1991; Theodossiou and Lee, 1993; Lin, Engle and Ito, 1994; Kim and Rogers, 1995; Koutmos and Booth, 1995; Koutmos, 1996; Kanas, 1998; Christofi and Pericli, 1999; Niarchos, Tse and Wu, 1999; Huang, Yang and Hu, 2000; Masih and Climent and Meneu, 2003; Masih, 2001; Hsin, 2004; Lee, Rui and Wang, 2004; Wang and Firth, 2004; Baur and Jung, 2006; Nam, Yuhn and Kim, 2008; Mukherjee and Mishra, 2010). The general findings that emerge from these studies can be summarised as follows: (1) returns and volatility spillovers observed across international stock markets are usually positive in sign; (2) strong autoregressive conditional heteroskedasticity (ARCH) effects and the asymmetric effects exist in the second moment of stock returns (i.e. the volatility); (3) the conditional volatility usually has little impact on expected returns; (4) the US market is a major information producer and it has an influential role in affecting price movements of other international stock markets.[24]

The main research objectives of this chapter are twofold. First, by using intraday market index return data, this study examines the direct information transmission mechanisms in returns and volatility among the world's eight largest stock markets. It intends to provide new evidence supporting the general findings in the previous literature on return and volatility spillovers. This study aims to document empirical evidence in

[24] Engle et al. (1990) use the meteor shower effect to describe the positive volatility spillover effect across foreign exchange markets, i.e. a volatile day in one market is likely to be followed by a volatile day in another market. However, this can be generalised to describe the positive spillover effect across markets regardless of the underlying financial variables. The statistically significant causality in price returns and variance of returns between market indices is interpreted as empirical evidence of the return and volatility spillover effects between international stock markets in the literature.

favour of the findings of Hamilton (2010), showing that the maximum-likelihood estimates under the ARCH framework are more appropriate than the OLS estimates if ARCH is present in the financial time series.

Following Hamao et al. (1990) and Lin et al. (1994), the ARCH-type models are employed to study the dynamic return and volatility spillovers between selected markets. Given that the analysed stock exchanges operate in different time zones, disaggregating close-to-close (daily) return into close-to-open (overnight) return and open-to-close (daytime) return offers better insights into the information transmission mechanism across markets as it allows the investigation of contemporaneous spillovers and dynamic (inter-temporal) spillovers. This study also distinguishes between spillovers from markets located in one region (the intra-regional spillover effect) and in different regions (the inter-regional spillover effect). For example, considering trading centres in three main geographic regions, Asia (Tokyo, Hong Kong and Shanghai), Europe (London, Paris and Frankfurt) and North America (New York and Toronto), and the time sequence in which they trade, the stock exchanges in the Asian region are open before markets in the other two regions. As a result, the dynamic daytime spillovers from Asian markets to those other markets (inter-regional spillovers) occur on the same calendar day. On the contrary, the dynamic spillovers within Asian markets (intra-regional spillovers) measure the one-day lagged influence of one market on another, and thus do not occur on the same calendar day according to the GMT time scale. Furthermore, contemporaneous spillovers are examined by using overlapping returns between markets. For example, the daytime returns in the preceding day’s European and North American markets are contemporaneous with the current overnight returns in Asian markets because the Tokyo, Hong Kong and Shanghai stock exchanges are closed when the London, Paris, Frankfurt, New York and Toronto markets are open.

In addition, the study in this chapter investigates the spillover effect between developed and emerging markets. Previous literature shows that emerging stock markets have become more integrated with global markets over time (e.g. Kim and Rogers, 1995; Liu and Pan, 1997; Niarchos, et al., 1999; Huang et al., 2000; Sheng and Tu, 2000; Masih and Masih, 2001; Climent and Meneu, 2003; Hsin, 2004, Wang and Firth, 2004, Lee et al., 2004; Nam et al., 2008). However, few studies (see e.g. Wang and Firth, 2004) consider the Chinese stock market when investigating the information transmission mechanisms between mature markets and emerging markets, despite the fact that the

Shanghai stock exchange is one of the world's largest stock trading centres as measured by market capitalisation. Given the growing influence of the Chinese economy and increasing liberalization of the domestic stock market, it is interesting to investigate how the Shanghai stock market is related to other international stock markets.

Second, this study explores the direct information transmission mechanism of trading volume across international stock exchanges. The issue of international trading volume spillovers has not attracted great attention in the literature so far and only few studies have investigated the causality in the trading volume between markets. Notable exceptions are Lee and Rui (2002), who investigate the causal relation in the sense of Granger among trading volume for the US, UK and Japanese stock markets, and Gebka (2012), who reports the results of five-day cumulative causality between trading volume for the US stock market and Asian markets. However, it is important to point out that both studies employ the VAR methodology, which assumes the time invariant conditional variances of the models. Since the analysis of data in Chapter 3 indicates the existence of autoregressive conditional heteroskedasticity in the trading volume series, this study employs the ARCH methodology when modelling the trading volume processes.

The information content of trading volume in stock markets has been discussed in the literature before (e.g. Clark, 1973; Karpoff, 1987; Lamoureux and Lastrapes, 1990; Campbell, Grossman, and Wang, 1993; Bohl and Henke, 2003; Connolly and Stivers, 2003; Brian, 2005; Gebka, 2012). The informational role of trading volume in one market could potentially prove useful in providing additional information for investors in other international stock markets and thus influence their trading behaviour. As a result, the trading volume in foreign markets may help in the prediction of future trading volume in the domestic market, and trading volume can spill over across borders. The empirical investigation in this study intends to seek evidence supporting this volume spillover hypothesis. More importantly, the results of cross-county causal relations are interpreted in light of the economic theory, which is an important contribution to the existing literature.[25]

[25] Lee and Rui (2002) present evidence of positive Granger causality in trading volume between the US, UK and Japanese stock markets. However, Lee and Rui (2002) describe these cross-country causal relations without interpreting them in light of economic theoretical models. Gebka (2012) presents good discussion about the informational role of trading volume.

The remainder of this chapter is organised as follows. Section 4.2 analyses international returns and volatility spillover effects. Section 4.3 discusses the informational role of trading volume and the spillover effects in trading volume across international stock markets. Section 4.4 offers a summary of findings and concluding remarks.

4.2 International Return and Volatility Spillover Effects

4.2.1 Estimation Results of the GARCH-M Model

Following Hamao et al. (1990) and Lin et al. (1994), an AR(1)-GARCH(1,1)-in-Mean model is first employed to evaluate the appropriateness of the model's specification for daytime returns in the world's eight biggest stock trading centres.[26] The model is specified as follows:

$$R_t = \mu + \alpha R_{t-1} + \beta h_t + \epsilon_t, \tag{4.1}$$

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}, \tag{4.2}$$

where parameter μ is a constant term; R_t and R_{t-1} are the open-to-close daytime returns at time *t* and *t-1*, respectively. The mean equation includes the lagged dependent variable.[27] The conditional variance h_t has a GARCH(1,1) specification. It is defined as

[26] Dowling and Lucey (2008) indicate that studies that employ only one GARCH specification over a large number of equity indices may run the risk of not optimally specifying all of their stock return series. However, a large number of studies have employed the GARCH(1,1) model, following the parsimonious principle (e.g. Lamoureux and Lastrapes, 1990; Hamao et al., 1990; 1991; King, Sentana, and Wadhwani, 1994; Lin et al., 1994; Abhyankar, 1995; Ng, 2000; Bohl and Henke, 2003; Hsin, 2004; Lucey, 2005; Mukherjee and Mishra, 2010). Hamao et al. (1990) find that the simpler specification is more strongly supported by data. Engle (2004) indicates that a slightly better model can be found among variations of the GARCH-type models in some cases, but the GARCH(1,1) specification is always the work-horse of financial application and can be used to properly describe the volatility dynamics of most financial return series.

[27] Hamao et al. (1990) employ the MA(1) process to extract the serial autocorrelation in stock returns. It is noteworthy that the AR(1) process employed in Equation (4.1) can be expressed in terms of the MA(∞) process by doing the substitution iteratively and it allows for the possible influence of high-order MA

a positive linear function of the squared error term and conditional variance in the last period. The coefficient β measures the volatility feedback effect. According to Hamilton (1994), the volatility feedback effect is the influence that higher perceived variability of ϵ_t has on the level of R_t. It captures the impact of the conditional variance on stock returns. Finance theory suggests that there is a trade-off between risk and return, and a higher risk is normally associated with higher returns.

Table 4.1 shows parameter estimates of the AR(1)-GARCH(1,1)-M model for the daytime returns in the London, Paris, Frankfurt, New York, Toronto, Tokyo, Hong Kong and Shanghai stock markets.

In the mean equations, the volatility feedback effect coefficients (denoted by β) are statistically insignificant for all eight stock markets under investigation. The results imply that the conditional variance has little influence on the conditional mean. The findings are congruent with the evidence reported by a number of other studies, including Hamao et al. (1990), Theodossiou and Lee (1993) and Hsin (2004).[28] Engle (2004) explains that the volatility feedback effect is normally difficult to detect as it is disguised by other dominating effects, and obscured by the reliance on relatively low frequency data. In the variance equations, the parameter estimates are all positive and significant at the 1% level, indicating the presence of the autoregressive conditional heteroskedasticity (ARCH) in stock returns for all the markets and a widespread phenomenon of volatility clustering.

Following the model diagnostics procedure in Lin et al. (1994), nested specification tests using likelihood ratio (LR) statistics are employed to examine the descriptive validity of the model. The LR(6) statistics, which allow for testing of H_0 that returns are normally distributed against the alternative that they are generated by an AR(1)-

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terms. It can also be interpreted in an economic context which assumes that all past information has been fully reflected in the stock daytime returns before the market is closed at time *t-1*.

[28] Hamao et al. (1990) find little evidence in favour of the volatility feedback effect in the US, UK and Japanese stock markets during the period from 1 April 1985 to 31 March 1988; Theodossiou and Lee (1993) report the absence of the volatility feedback effect in the US, UK, Japanese, German and Canadian markets in the period from 11 January 1980 to 27 December 1991. Hsin (2004) finds that the volatility feedback effect coefficient is statistically insignificant in the US, UK, Canada, Germany, Hong Kong and Singapore and only significant at the 10% level in Japan, France and Italy from January 1990 to December 2002.

GARCH(1,1)-M model, are soundly rejected at the 1% level in all eight markets.[29] The Ljung-Box Q-statistics calculated for normalized residuals show no evidence of significant linear dependence in the error terms up to 12 lags.[30] The Ljung-Box Q-statistics calculated for squared residuals show little evidence of significant nonlinear dependence. The specification of the model appears to be complete in the sense that diagnostics tests based on the standardised residuals show no serious evidence against the model specification.

The initial estimation results in this section indicate that the AR(1)-GARCH(1,1) model fits the data well and is an appropriate specification for the eight market return time series. The AR(1)-GARCH(1,1) model is thus employed to examine the statistical significance of cross-market returns and volatility spillovers in the subsequent sections, where exogenous variables such as foreign returns and volatility are introduced in the model.

4.2.2 Estimation Results of the Dynamic Return Spillover Model

In order to investigate the dynamic spillovers across international stock markets, the models considered in this section follow the approach employed by Hamao et al. (1990) and Lin et al. (1994). The return spillover model is first formulated by including an exogenous variable (the preceding foreign market return) in the mean equation of the AR(1)-GARCH(1,1) model. However, the conditional variance is excluded from the mean equation specified in Equation (4.1) as the volatility feedback effect is not statistically significant in daytime returns in all investigated markets.

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[29] The test measures how close the unrestricted estimates of the model come to satisfying the restrictions in the null hypothesis. Under H_0: $\mu = \alpha = \beta = a = b = c = 0$, likelihood ratio (LR) statistic has a chi squared distribution with 6 degrees of freedom.

[30] In a dynamically complete model, enough lags of explanatory variables have been included so that further lags do not matter for explaining explained variable. Specifying a dynamically complete model means that there is no serial correlation in the disturbance terms. In other words, if the goal is to estimate a model with complete dynamics, one should re-specify the model in the presence of serial correlations in the error terms. Wooldridge (2003) points out that for forecasting purposes all models should be dynamically complete.

The proposed model defines the daytime return in the domestic market as a linear function of its preceding daytime return and one-day lagged foreign daytime return. The information contained in the preceding foreign return is included in the model so that the direct impact of the potential dynamic return spillover effect from the previously active foreign stock exchange can be examined. The dynamic return spillover model is as follows:

$$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t, \tag{4.3}$$

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}, \tag{4.4}$$

where $R_{H,t-1}$ is the domestic market daytime return at time *t-1*. It is assumed that all past information has been fully reflected in the stock prices prior to the close of the domestic market at time *t-1*. $R_{F,t-1}$ is the previous daytime return in the foreign market. It represents the new information revealed after the domestic market's close at time *t-1*, but before its open at time *t*. The potential impact of the new information on the current domestic market daytime return is captured by the parameter β which is called the dynamic return spillover coefficient. It measures the direct impact of daytime return in the preceding foreign market on the domestic market. β captures the dynamic return spillover effect from the previously opened foreign market to the domestic one. The conditional variance (h_t) is assumed to follow the GARCH (1,1) process.

As suggested by Lin et al. (1994), the return spillover model can also be used to test Granger causality in returns between foreign and domestic markets, which have non-overlapping trading hours between day *t* and *t-1*. The question of whether foreign market returns (R_F) Granger-cause domestic market returns (R_H) is to examine if the current domestic market return ($R_{H,t}$) can be explained by past foreign market returns (e.g. $R_{F,t-1}$). R_H is said to be Granger-caused by R_F, if R_F occurs before R_H, and R_F helps in the prediction of R_H (i.e. if the parameter estimates on past foreign market returns (e.g. $R_{F,t-1}$) are statistically significant).

It is important to note that the statement "R_F Granger causes R_H" does not necessarily mean that R_F is the real cause of R_H. Granger causality measures the precedence and causal direction of information content. The statistical inferences of β can be regarded as a causality test of whether daytime returns in the previously opened foreign stock markets contain any information (in addition to the preceding daytime return in the domestic market) that helps in the prediction of the domestic market daytime return.

Table 4.2 presents parameter estimates of β in the dynamic return spillover model described by Equations (4.3) and (4.4). The table also summarises the results of the OLS estimates of β for Equation (4.3).[31]

Of particular interest is the pattern that the magnitude of β estimated by the return spillover model (under the ARCH framework) is normally much smaller than that obtained by the OLS estimation. For example, as shown in Panel D in Table 4.2, the return spillover coefficients from the US to the UK and Japan estimated under the ARCH framework are 0.3489 and 0.0874, respectively. However, their OLS estimates counterparts are 0.4413 and 0.2544, respectively. It shows that the magnitude of the return spillover effect appears to be considerably smaller than one would infer on the basis of the OLS estimates. This pattern is consistent with the findings of Hamilton (2010), who suggest that, since ARCH estimation is allowed the possibility of serial dependence in the squared residuals (nonlinearity in the volatility equation), the maximum likelihood estimation of ARCH model would give less weight to the observations during which periods are more volatile, resulting in a flatter slope estimate relative to OLS estimation.

In addition, the interference of β is also affected in a substantial way when the ARCH structure is considered in the model. For example, under the GARCH framework, return spillovers from Japan to France and Canada are significant at the 1% level and the 5% level, respectively (as indicated in Panel F in Table 4.2). On the contrary, the OLS estimates suggest insignificant results for both spillovers.

[31] In the presence of heteroskedasticity, the usual OLS standard errors will be invalid and should not be used for inference. White (1980) has derived statistical procedure which provides heteroskedasticity-consistent standard errors. After fitting the ARCH model, the study also reports the skewness and the kurtosis of standardised residuals in Table 4.1. These statistics are still too large to accept that residuals are conditionally normally distributed. Therefore, the robust standard errors calculated by Bollerslev-Wooldridge (1992) are used to carry out statistical inferences.

The observed pattern provides strong empirical evidence in favour of Hamilton's (2010) findings, which indicate that in the presence of autoregressive conditional heteroskedasticity (ARCH) in time series (i.e. large outliers and persistent volatility clustering), it is more appropriate to use maximum likelihood estimation in the ARCH-type models rather than the OLS estimation with heteroskedasticity corrections if the research interest is in obtaining accurate estimates of the parameters. This is also consistent with Engle's (1982) observation that many statistical procedures (e.g. White's (1980) heteroskedasticity-consistent estimate) have been designed to be robust to large errors, but none has made use of the fact that temporal clustering of outliers can be used to predict their occurrence and minimize the effects of large outliers. This is the exact approach offered by the ARCH-type models.

Before interpreting the estimated β coefficients which capture the dynamic return spillover effect across the investigated stock markets, the robustness of the estimated β with respect to different specifications of the variance equation under the ARCH framework is first examined. The aim is to investigate if there are substantial changes in the return spillover coefficient β when some well documented phenomena such as the asymmetric effect and the volatility spillover effect are introduced in the model.[32]

4.2.3 Estimation Results of the GJR-GARCH and EGARCH Models

In the previous section, Table 4.2 presents the estimated β of the dynamic return spillover model where the variance equation has a GARCH(1,1) specification. However, the standard GARCH(1,1) model is symmetric in terms of its response to past shocks. Black (1976) and Christie (1982) show that negative stock return shocks have more influence on the magnitude of future volatility. The study in this section investigates the existence of the asymmetric effect in the conditional volatility and examines its impact on the estimation results of β in the mean equation. The GJR-GARCH model and the EGARCH model are employed for the investigation.

[32] It is the joint-estimates of parameters in the mean and variance equations using the ARCH methodology. Cheung and Ng (1996) and Gebka and Serwa (2007) suggest that omitting the return spillover effect might cause biased inference in the volatility-spillover tests. Following the same logic, this study intends to test if there are substantial changes in estimated parameters of the mean equation when applying different specifications of the variance equation.

The GJR-GARCH model developed by Glosten, Jagannathan and Runkle (1993) captures the asymmetric effect of positive and negative shocks on the conditional volatility. The GJR-GARCH(1,1) model is specified as:

$$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t, \tag{4.5}$$

$$h_t = a + b\,\epsilon_{t-1}^2 + c(I_{t-1}\epsilon_{t-1}^2) + d\,h_{t-1}, \tag{4.6}$$

where error term ϵ_t can be explained as the unexpected return in the domestic market that cannot be predicted based on the information contained in the preceding returns in the domestic and foreign markets. I_{t-1} is a dummy variable that equals 1 if $\epsilon_{t-1}< 0$ (and 0 otherwise). I_{t-1} allows the effect of the squared residuals on conditional volatility to be different when the sign of unexpected return is different. The coefficient c captures the asymmetric effect of the lagged squared residual (ϵ_{t-1}^2) on the conational variance (h_t). The sign of coefficient c is expected to be significant and positive if a unit of negative return shock (interpreted as bad news) induces the increases of future volatility by a larger amount than a unit of positive return shock (interpreted as good news).

The exponential GARCH (EGARCH) model introduced by Nelson (1991) is another specification of the GARCH model designed to capture the asymmetric effect in the GARCH process. The EGARCH(1,1) model is defined as:

$$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t, \tag{4.7}$$

$$log(h_t) = a + b|z_{t-1}| + c\,z_{t-1} + d\,log(h_{t-1}), \tag{4.8}$$

where the conditional variance follows an exponential GARCH process. The standardised shock is defined as $z_t = \varepsilon_t/\sigma_t$, where z_t is negative if ε_t represents a negative shock. The asymmetric impact on the volatility is exerted by c. The asymmetric effect of shock on volatility is present if c is statistically significant and negative. As a consequence, the product of c and a negative z_{t-1} is positive which reinforces the size effect of bad news.

Table 4.3 reports the estimation results of return spillover coefficients (denoted by β) and asymmetric coefficients (denoted by c) in the GJR-GARCH(1,1) model and the EGARCH(1,1) model. The results show that there are no substantial changes in the estimated β coefficients in the mean equation when the asymmetric effect is modelled in the variance equation under the ARCH framework. The significance and magnitude of estimated coefficients β reported in Table 4.2 do not differ remarkably from the ones in Table 4.3. For instance, the return spillover effect coefficient β from the US to the UK (Japan) is 0.3489 (0.0874) when the model has the standard GARCH(1,1) specification. As a comparison, the estimated β equals 0.3343 (0.0783) when the model follows the GJR-GARCH(1,1) process, and 0.3222 (0.0871) when the EGARCH(1,1) process is specified. All cases are significant at the 1% level.

The estimated parameter c in the GJR-GARCH model is statistically significant and positive for the London, Paris, Frankfurt, New York, Toronto and Tokyo stock markets, indicating that a negative shock exerts more influence on the conditional variance of index returns in these markets. On the other hand, c is not statistically significant though still positive for the Hong Kong and Shanghai markets. It is an interesting pattern since Hong Kong and Shanghai are the only two emerging markets among the world’s eight largest stock markets. The estimated results for the asymmetric effect coefficient c using the EGARCH model indicate a consistent pattern (e.g. c is statistically significant and negative for the six developed markets under investigation, confirming the existence of the asymmetric effect in these cases). The results from the GJR-GARCH and EGARCH models both suggest that the six developed stock markets respond more strongly to bad news than to positive ones in terms that negative shocks increase conditional volatility considerably more than positive shocks.

It is also noteworthy that the results of estimated asymmetric coefficient (denoted by c) in the variance equation are not substantially affected by the influence of return spillovers from different international stock markets (i.e. there are not substantial differences in the size and significance of the coefficient c when return spillovers from different international stock markets are introduced in the mean equation). For example, the estimated c (reported in Table 4.3) in the GJR-GARCH model that captures the asymmetric effect of the conditional variance in the FTSE100 index returns is equal to 0.1431, 0.1427, 0.1251, 0.1397, 0.1264, 0.1451 and 0.1436, when the mean equation controls for the return spillover effects from Paris, Frankfurt, New York, Toronto, Tokyo, Hong Kong and Shanghai, respectively. The estimated *c* is significant at the 1% level for all cases.

4.2.4 Estimation Results of the Dynamic Return and Volatility Spillover Model

The existing literature shows extensive evidence of volatility spillovers across international stock markets. However, the dynamic return spillover model discussed in Section 4.2.2 does not capture this volatility spillover effect in the conditional variance equation. The model described in this section thus considers both return and volatility spillover effects in one system and investigates the dynamic transmission of returns and volatility at the same time. In addition, this study tests whether there are substantial changes in the estimated return spillover coefficient when the volatility spillover effect is included in the variance equation. The dynamic return and volatility spillover model is therefore specified as:

$$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t, \tag{4.9}$$

$$h_t = \mathrm{a} + b\epsilon_{t-1}^2 + ch_{t-1} + dR_{F,t-1}^2, \tag{4.10}$$

where $R_{F,t-1}^2$ is the squared return from the foreign market, which can be used as a raw measure of volatility in the foreign market at time *t-1*.[33] The parameter *d* captures the volatility spillover effect from the previously active foreign stock market.

The results indicate that there are no substantial changes in the estimated β when the international volatility spillover effect is considered in the conditional variance equation. The significance and magnitude of estimated β reported in Table 4.4 do not differ markedly from the ones reported in Table 4.2. For example, the estimated return spillover coefficient β from the US to UK (Japan) is 0.3375 (0.0904) when the US volatility spillover effect is considered in the conditional variance equation (reported in Panel D in Table 4.4). This compares to the estimated return spillover coefficient β of 0.3489 (0.0874) when the model has the standard GARCH(1,1) specification, of 0.3343

[33] Clark (1973), Lin et al. (1994), Lee and Rui (2002) and Gebka (2012) all use squared returns as a proxy for realised volatility. See Gebka (2012) for a more detailed discussion why squared returns are chosen as a proxy for volatility.

(0.0783) when the model follows the GJR-GARCH(1,1) process, and of 0.3222 (0.0871) when the EGARCH(1,1) process is specified in the model.

Furthermore, the estimation results reported in Table 4.4 suggest that return spillovers can exist with or without the presence of volatility spillovers and *vice versa*. On the one hand, there is a lack of statistically significant return spillovers and at the same time significant volatility spillovers for some pairs of markets. For example, the volatility spillovers are positive and statistically significant from the UK to France and China, compared to the insignificant results of return spillovers from the UK to both countries. The same pattern can be observed in the spillover effects from France to the UK and China, from the US to France, and between Hong Kong and Chinese stock markets. On the other hand, the opposite pattern is evident too, where the return spillovers are statistically significant, but not the volatility spillovers. This pattern is obvious when the Japanese stock market is regarded as the signalling market. The return spillovers from Japan to the US, UK and Canada are positive and statistically significant. The Japanese returns help in the prediction of returns in the US, UK and Canadian markets, which are opened after the Tokyo stock market has completed its trading for the day. However, no such spillovers are observed in the volatility transmission mechanism from Japan to these markets. In general, the reported results indicate the complexity of the information transmission mechanisms *via* different channels.

The results reported in Panel D in Table 4.4 show that the previous day's daytime return in the New York stock exchange has a statistically significant impact on current open-to-close returns in the London, Frankfurt, Tokyo and Hong Kong markets. The return spillover coefficient β which captures this effect is statistically significant at the 1% level, suggesting that the US market plays an important role in affecting the daytime returns in these markets. The US daytime returns have a positive and significant impact on the following day's daytime returns in the UK, German and Japanese markets, implying that a positive daytime return in the US tends to be followed by positive daytime returns in these markets.

The results also demonstrate that the Shanghai stock exchange is the least integrated market among the international stock markets under investigation. The dynamic daytime return spillover effects to the Chinese stock market from other stock markets are statistically insignificant even at the 10% level, indicating that the daytime returns in these markets cannot predict the following day's daytime return in the Shanghai stock market. In addition, the daytime volatility in China can be explained only by the preceding day's volatility in the UK, French and Hong Kong markets. It is interesting to note that the dynamic volatility effect from the US to China is statistically insignificant, and the preceding US volatility can spill over to all the remaining markets except for the Chinese market. On the other hand, the estimated volatility spillover coefficients (denoted by *d*) in Panel H in Table 4.4 show that the volatility spillovers from China to the US, UK, France, Germany and Canada are positive and statistically significant at the 1% level. The positive and statistically significant return spillovers from China to the US, UK, Germany and Canada are also reported. However, it is noteworthy that the size of the spillover effect is markedly smaller compared to the effects from other markets. For example, the estimated parameters for return and volatility spillovers from China to the UK are 0.0433 and 0.0045, respectively. In contrast, the estimated parameters for return and volatility spillover effects from the US to UK are 0.3375 and 0.0551, respectively. The return spillover coefficient from the US to UK is 7.7945 times larger than that from China, and the volatility spillover coefficient is 12.4444 times larger.

The unidirectional dynamic return and volatility transmission from China to the other countries is not surprising due to the lack of openness and tight financial regulations and controls of capital flows in China. The findings are consistent with the results of Wang and Firth (2004) indicating little evidence of the dynamic return and volatility spillovers from the developed markets (Tokyo, New York and London) to the Shanghai stock exchange during the period from 25 November 1994 to 28 September 2001. It is reasonable to argue that a country with greater restrictions on its financial markets would be less influenced by the dynamic return and volatility spillover effects from foreign countries. On the other hand, the statistically significant dynamic return and volatility spillovers from China provide evidence showing that the foreign market investors respond on the next trading day to the information contained in the price movements (i.e. price return and volatility) in the Shanghai stock exchange. However, the spillover effects from China are much less influential than those from the US.

The analysis next focuses on an interesting pattern which appears in the dynamic daytime return spillovers from countries located in one region (intra-regional effects) and in different regions (inter-regional effects).[34]

This study finds that intra-regional meteor shower effects in daytime returns are less frequent and weaker than inter-regional ones. This is not a surprising pattern since stock daytime returns are more likely to transmit fully and quickly across intra-regional markets on the same day, due to factors such as synchronous trading hours, tight economic and financial linkages, and so on.[35] The statistically insignificant meteor shower effect between intra-regional markets can be interpreted as evidence implying that stock daytime returns transmit across borders between these markets in an efficient way and without too much delay to the next trading day.

On the contrary, due to the non-synchronous trading hours, the inter-regional stock markets open sequentially on the same calendar day. In an efficient market, market opening price should fully and rapidly reflect any information revealed overnight (e.g. information about stock daytime returns in the foreign markets that operate earlier). In other words, the stock daytime returns from the previously opened foreign markets should fully and quickly transmit into the overnight returns in the subsequently opened markets. The contemporaneous return spillover effect between inter-regional markets, which essentially accounts for the impact of overnight foreign information on the opening price of the domestic market, is normally positive and statistically significant. However, it is often the case that the market takes time to incorporate fully such information into the stock prices after market opening. There are subsequent spillover effects in the domestic market after the opening of trade. Furthermore, the market that operates later often replicates the behaviour of the market that operates earlier (Gebka and Serwa, 2007). The results show that stock daytime returns transmitting across inter-regional markets are more likely to be in an inefficient manner, and the lagged daytime returns in foreign markets have a positive influence on the current daytime return in the domestic market, which generates the meteor shower effect in daytime returns.

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[34] It is noteworthy that no such pattern is observed in the dynamic volatility spillovers across international stock markets.

[35] This is confirmed by the positive and high contemporaneous correlation coefficients between intra-regional markets in the preliminary analysis of data in Chapter 3.

The estimation results show that there exist negative and statistically significant dynamic return spillover effects from the UK and France to Germany, and from the UK, France, Germany, US and Japan to Hong Kong. This can be interpreted as evidence that investors in the domestic market have over-reacted to the foreign market information in the current time period, which causes the positive contemporaneous return spillovers and the negative dynamic return spillovers from the foreign to domestic markets. [36]

However, it is also possible that the negative dynamic return spillovers can be caused by investors in the domestic market responding negatively to the good news from foreign markets, probably due to competing relations between countries. In this case, the contemporaneous return spillovers are expected to be negative as well. As a result, the study in the next section investigates the contemporaneous return spillover effects between these markets.

4.2.5 Estimation of the Contemporaneous Return Spillover Model

For markets located in the same region, it is obvious that contemporaneous return spillovers are positive and statistically significant. The positive and statistically significant correlations between daytime returns in these markets have been confirmed by the preliminary analysis in Chapter 3. In this section, the study investigates the contemporaneous spillover effect of concurrent daytime return in the US, UK, France and Germany on overnight return in the Hong Kong market. The close-to-open (overnight) returns in Hong Kong are synchronised with the previous open-to-close (daytime) returns in Europe and North America due to non-synchronous trading hours of international stock exchanges. By investigating inter-regional contemporaneous return spillovers, the impact of "overnight information" obtained from the trading in foreign markets on the opening price of the Hang Seng index on the next trading day can be examined.

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[36] In contrast, if the domestic market has not fully reacted to the new information from foreign markets in the contemporaneous time period, especially when the domestic market is located in the different regions and the information cannot be fully incorporated into the opening price, the positive contemporaneous return spillovers and dynamic return spillovers are both expected.

The current overnight return ($NR_{HK,t}$) in the Hong Kong stock market is specified as a linear function of its preceding day's daytime return ($R_{HK,t-1}$) and the daytime return from the foreign markets which are opened after the Hong Kong stock exchange has closed for the day($R_{F,t-1}$). The model that is used to investigate the inter-regional contemporaneous return spillovers can be expressed as:

$$NR_{HK,t} = \mu + \alpha R_{HK,t-1} + \beta R_{F,t-1} + \epsilon_t, \tag{4.11}$$

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}, \tag{4.12}$$

where β represents the influence of the previous day's open-to-close (daytime) return in the foreign market on the close-to-open (overnight) return in the Hong Kong market; the error term ϵ_t follows GARCH(1,1) process.

The estimation results in Table 4.5 show that the daytime returns in all inter-regional markets under investigation are positively and statistically significantly related to the overnight returns in the Hong Kong stock exchange, implying that investors in the Hong Kong market react positively to the overnight information revealed in these markets at the market opening. The positive and statistically significant contemporaneous return spillovers from the foreign to Hong Kong markets provide evidence that Hong Kong investors respond positively to the good news abroad. As a result, the hypothesis that the negative return spillovers from the preceding foreign markets to the Hong Kong market are due to Hong Kong investors respond negatively to the good news in foreign markets can be rejected.

4.3 International Trading Volume Spillover Effects

4.3.1 The Informational Role of Trading Volume

The informational role of trading volume is an important aspect of information transmission mechanisms in the financial markets. For example, Clark (1973) uses trading volume to measure the varying impact of new information on stock prices. Clark (1973) introduces the mixture of distribution hypothesis (MDH), which explains the possible contemporaneous correlation between trading volume and volatility. On days when new information is uncertain and creates disagreement among traders about the fundamental value of securities, large price changes will be coincident with high trading volume. Clark (1973) further points out that on days when new information is more certain and cannot create a dispersion of beliefs among traders, large price changes will be accompanied by low trading volume because all traders would revise their expectations in the same direction, and the price changes would be accompanied relatively low volume. According to the MDH of Clark (1973), Lamoureux and Lastrapes (1990) propose trading volume as a measure of the amount of information flows into the market, which generates stronger volatility clustering and explains the presence of GARCH effects in stock returns.[37]

Campbell, Grossman and Wang (1993) associate trading volume with the shifts of risk aversion of investors in a heterogeneous-agent trading model. The changes of risk attitude cause changes in the optimal holdings of stocks between type A investors - who have a constant risk aversion parameter and type B investors - who have a time-varying risk aversion parameter. The changes in optimal holdings of stock between these two types of investors generate liquidity trading in the market. The heavy trading volume is normally associated with the high demand for liquidity trades. Trading volume is positively related to the changes of risk aversion of type B investors.[38] Wang (1994) and Llorer et al. (2002) generalise the CGW (1993) model by allowing information asymmetry among the investors. They offer theoretical models which can also explain the return continuations accompanying high trading volume. In their models, returns generated by non-informational trading tend to exhibit negative first-order return autocorrelation following periods associated with high trading volume, while returns induced by speculative (informational) trading lead to the positive first-order return autocorrelation. Connolly and Stivers (2003) suggest that trading volume can be used as a proxy for dispersion in beliefs across traders. A higher disagreement about new information is likely to be associated with both higher trading volume and stronger

[37] Thus, one strand of literature (e.g. Lamoureux and Lastrapes, 1990; Bohl and Henke, 2003; Lucey, 2005) has used this approach and has investigated if these GARCH effects tend to decrease (or even to vanish) when trading volume is included as an explanatory variable in the conditional variance equation of the GARCH-type models for stock returns (i.e. the test of MDH).

[38] Campbell et al. (1993) treats type B investors' attitudes to risk as exogenous and may depend on other variables. As a result, it is reasonable to assume that type B investors become more risk-averse when information is less certain and the dispersion of beliefs among investors is higher.

volatility clustering in returns. Greater uncertainty may also lead to higher trading volume and volatility clustering which reflect more trading activities with frequent portfolio re-allocation. In general, higher trading volume is interpreted as a sign of wider investor disagreement and greater market uncertainty, which apparently are more likely to increase the risk aversion of traders. Trading volume is regarded as a proxy for traders' attitudes to risk and reflects their sentiments in the stock market.

4.3.2 The First-order Autocorrelation of Trading Volume

This section first reports the first-order autocorrelation of trading volume under the ARCH framework. Since the analysis of data in Chapter 3 suggests the presence of autoregressive conditional heteroskedasticity (ARCH) effects in volume, the ARCH methodology is thus employed in this study. The model is specified as:

$$V_{H,t} = \mu + \alpha_H V_{H,t-1} + v_{i,t} \tag{4.13}$$

$$h_t = a + bv_{t-1}^2 + ch_{t-1}, \tag{4.14}$$

where $V_{H,t}$ and $V_{H,t-1}$ are the standardised de-trended trading volumes in the domestic market at time t and t-1, respectively.[39] The coefficient α_H is the first-order autocorrelation coefficient in trading volume. The conditional variance (h_t) of domestic market trading volume is assumed to follow the GARCH (1,1) process.

The results reported in Table 4.6 indicate that the estimates of α_H are statistically significant and positive for all the markets.[40] A positive α_H suggests that the trading volume between adjacent days in a market is positively correlated (i.e. a day with high trading volume tends to be followed by another day with heavy trading volume). It is interesting that the Chinese trading volume has a very high first-order autocorrelation

[39] The de-trended trading volume is standardised by dividing the residual term obtained from the OLS regression of Equation (3.1) over the standard deviation of the residual term. In Equation (3.1), trading volume time series is a linear function of the constant, time trend and squared time trend.

[40] After fitting the ARCH model, the H_0 that residuals are conditionally normally distributed is rejected. Therefore, the robust standard errors calculated by Bollerslev-Wooldridge (1992) are used to carry out statistical inferences.

coefficient (α_H is equal to 0.9082), while the first-order correlations in other markets range from 0.5008 to 0.6609. Furthermore, it is shown that the absolute value of α_H is smaller than one for all markets ($|\alpha_H|$ <1), which is a crucial assumption for weak dependence of an AR(1) process.

4.3.3 The Meteor Shower Effect in Trading Volume

Numerous studies have documented evidence about the existence of the meteor shower effects by studying the return and volatility spillovers across international stock markets. However, only few studies have investigated the volume spillovers between markets (see e.g. Lee and Rui, 2002; Gebka, 2012). The presence of cross-market dependence in trading volume implies that the information contained in foreign trading volume may change the domestic investors' incentive to trade. The main research objective in this section is to test whether the meteor shower effect exists in the financial time series of trading volume. The positive and statistically significant volume spillovers can provide evidence suggesting that the changes of liquidity investors' sentiments could be transmitted across countries.[41] In order to investigate the meteor shower effect in trading volume across international stock markets, the trading volume spillover model is specified as:

$$V_{H,t} = \mu + \alpha_H V_{H,t-1} + \beta_F V_{F,t-1} + v_{,t}, \tag{4.15}$$

$$h_t = a + b v_{t-1}^2 + c h_{t-1}, \tag{4.16}$$

where $v_{H,t}$ is the residual term, $V_{H,t-1}$ and $V_{F,t-1}$ are the one-day lagged standardised de-trended trading volumes in the domestic market and foreign market, respectively. The AR (1) process is included in the model to control for the serial autocorrelation in trading volume (captured by the first-order autocorrelation coefficient α_H). The

[41] According to the MDH of Clark (1973), trading volume is generally regarded as a proxy of information flows. The positive and statistically significant volume spillovers can also be evidence indicating that these information flows can spill over across borders. However, this study interprets trading volume as a proxy of traders' risk aversion according to the theoretical model proposed by Campbell et al. (1993).

parameter β_F measures the spillover effect in trading volume from foreign to domestic markets.

The estimated foreign trading volume spillover coefficients (denoted by β_F) in Table 4.7 show strong evidence that trading volume in one market can spill over to other stock markets which open subsequently. According to Campbell et al. (1993), heavy trading volume can be caused by shifts in the risk attitude of liquidity traders. The statistically significant β_F implies that domestic investors may respond to the shifts in risk attitudes of foreign investors. When the dispersion of beliefs among investors is high, especially during the period of greater economic uncertainty, some traders in the foreign market may become more risk-averse and increase their needs for liquidity trades. Liquidity investors in the domestic market can observe this piece of information *via* heavy trading volume in the previously opened foreign market, which may subsequently induce the changes of their risk attitudes, and increase their incentives to trade in their own market for liquidity needs.[42] They may respond to the shifts in sentiment regardless of the fundamentals underlying the markets. This could be due to the herd mentality where liquidity investors respond to a shock in the foreign market. In summary, this study finds evidence supporting the hypothesis that the shifts of investors' sentiments (e.g. changes of risk attitudes) can transmit across countries and cause the spillover effect in trading volume across international stock markets.

Since the results in each panel share a similar pattern, the empirical analysis only focuses on the results reported in the first table. Panel A summarises the estimates of the spillover coefficient (β_F) in the volume spillover model, where the domestic market is the UK market and the foreign markets are the stock exchanges in France, Germany, the US, Canada, Japan, Hong Kong and China. The results show that the dynamic trading volume spillovers are positive and statistically significant from the US, Japan, Hong Kong and China to the UK, implying that the increase of risk aversion among traders in these markets can influence the trading behaviour of the UK investors and increase trading volume in the London stock exchange on the following day. One unit increase of trading volume in the US (Japanese, Hong Kong and Chinese) market tends to increase the trading volume in the UK market by 0.0549 (0.1657, 0.1439 and 0.0535)

[42] The cross-border trading by large institutional traders could be another possible explanation. Since liquidity trades by those global institutions can be split across international stock markets, the comovements between trading volume in different national markets could also be induced.

units. However, the lagged trading volume in the French and German stock markets cannot predict the UK trading volume. The dynamic trading volume spillovers between intra-regional markets are more likely to be insignificant. The reason may be that the UK, French and German stock markets open and close simultaneously, and the information contained in the French and German trading volume has already been fully and rapidly reflected in the UK market in the contemporaneous period. The results also show that the estimated values of α_i are similar to those reported in Table 4.6, suggesting that the first-order autocorrelations in the UK trading volume are not remarkably affected by the influence of the meteor shower effects in trading volume from other foreign stock markets. Furthermore, the size of the AR(1) coefficient (denoted by α_i) is much larger than the magnitude of the foreign market trading volume spillover coefficient (denoted by β_i), indicating that the preceding domestic market trading volume has a stronger influence than the previous foreign market trading volume on the current domestic market trading volume.

In general, the results reveal a pattern that inter-regional meteor shower effects in trading volume are more frequent and stronger than intra-regional ones. The dynamic trading volume spillover coefficients are more likely to be positive and statistically significant between markets located in different regions than between markets from the same region. The statistically insignificant dynamic trading volume spillovers between markets located in the same region indicate that the information about lagged trading volume from intra-regional markets is of little help in the prediction of trading volume in the domestic market. The existence of the statistically significant inter-market dependence in trading volume implies that the information contained in foreign market trading volume can change investors' incentive to trade in the domestic market. These cross-country Granger-causal relations in trading volume can be interpreted in light of economic theoretical models (e.g. the CGW (1993) model) where trading volume is regarded as a proxy for traders' risk aversion. The positive and statistically significant trading volume spillovers can be treated as evidence suggesting that the changes of investors' sentiments (e.g. the shifts of their attitudes to risk) have a contagious effect and can transmit across countries.

The evidence about the presence of the meteor shower effect in trading volume is consistent with the findings of Lee and Rui (2002) who report positive Granger causality in trading volume between the US, UK and Japanese stock markets. However, it is important to note that Lee and Rui (2002) describe these cross-country causal relations in trading volume without interpreting them in the light of economic theoretical models (e.g. the CGW (1993) model). Lee and Rui (2002) find that the trading volume in one market helps to predict the trading volume in others. They conclude that the information contained in trading volume is of importance for international financial markets. On the other hand, the results in this study are somehow in contrast to Gebka (2012) findings. Gebka (2012) finds little evidence of positive causality between trading volume in the US and Asian stock markets. However, Gebka (2012) examines the cumulative causality over five days, instead of a classic Granger-causality, whereas the later tests only the shot-lived causal relationship.

4.4 Summary

This chapter investigates the spillover effects in daytime returns, volatility, and trading volume among the world's eight biggest stock trading centres, including the London, Paris, Frankfurt, New York, Toronto, Tokyo, Hong Kong and Shanghai stock markets. It confirms the general findings of the previous literature on return and volatility spillovers (e.g. the statistically significant international return and volatility spillover effects, a lack of the volatility feedback effect among the world's major stock markets, the statistically significant ARCH effect and asymmetric effect for developed markets as well as the informational role of the US market). More importantly, the study finds new evidence supporting the volume spillover hypothesis, implying that the changes of liquidity investors' sentiments (e.g. their attitudes to risk) may have a contagious effect and can transmit across borders.

More specifically, the study reports on the absence of a volatility feedback effect in the GARCH-M model for all eight markets under investigation, which means that conditional variance exerts little influence on the expected returns. The findings are consistent with the results reported by Hamao et al. (1990), Theodossiou and Lee (1993) and Hsin (2004).

Furthermore, the obtained results provide strong empirical evidence in favour of the findings of Hamilton (2010), indicating that in the presence of autoregressive conditional heteroskedasticity (ARCH) effects in time series (i.e. large outliers and persistent volatility clustering) it is more appropriate to use maximum likelihood estimation (MLE) in the ARCH framework rather than the OLS estimation as the former makes use of information about the volatility dynamics of the financial time series (i.e. ARCH effects). Such information can be exploited to construct better econometric models describing the temporary dynamics of the financial time series. The results show that the magnitude of return spillovers suggested by MLE under the ARCH-type models appears to be considerably smaller than one would infer on the basis of the OLS estimates. It is because the ARCH technique can capture the temporal clustering of outliers and can also minimize the effects of large outliers.

It is important to emphasise that the estimated return spillover coefficients are robust to different specifications of volatility equations that model some well documented phenomena, such as the asymmetric and international volatility spillover effects. The study shows that the GARCH(1,1) process is appropriate to model the ARCH effect that is inherent in the financial time series, and the AR(1)-GARCH(1,1) model fits the data well for all the eight market return time series.

The estimated asymmetric coefficients in the GJR-GARCH and EGARCH models are statistically significant for the UK, France, Germany, US, Canada and Japan, indicating that a negative shock exerts more influence on the conditional variance of index returns in these countries. On the other hand, the asymmetric effect is not significant for the Hong Kong and Chinese markets. It is an interesting pattern since the Hong Kong and Shanghai stock exchanges are the only two emerging markets among the world’s eight largest stock markets.

The estimates of the dynamic return and volatility spillover model indicate that causality in mean can exist with or without the presence of causality in variance and *vice versa*. On one hand, this study shows a lack of statistically significant return spillover effects and at the same time significant volatility spillover effects for some pairs of markets (e.g. the spillovers between the UK and France and spillovers between Hong Kong and China). On the other hand, it finds the opposite pattern, where return spillover effects are statistically significant, but not the volatility spillover effects (e.g. the spillovers from Japan to the US, UK and Canadian markets). In general, the reported results indicate the complexity of the information transmission mechanisms *via* different channels.

The results presented in this chapter show that the US stock market plays an influential role in affecting the subsequent daytime returns in the German, Japanese, UK and Hong Kong markets. They are consistent with findings from the existing literature, including Hamao et al. (1990) and Lin et al. (1994). On the contrary, the Chinese stock market is less influential than the other markets. Although positive return and volatility spillovers are observed from China to some markets (e.g. the UK, US and Germany), the size of the spillover effects nevertheless is markedly small. The unidirectional daytime return transmission from China to the other countries is reported. It is not surprising due to the lack of openness and tight financial regulations and controls of capital flows in China. These findings are in line with the results from Wang and Firth (2004).

The intra-regional meteor shower effects in daytime returns are less frequent and weaker than inter-regional ones. The insignificant dynamic return spillovers between intra-regional markets can be treated as evidence indicating that stock daytime returns transmit across these markets in an efficient way and without too much delay to the next day. However, the positive and statistically significant daytime return spillovers between inter-regional markets indicate that stock daytime returns are more likely to transmit across inter-regional markets in an inefficient manner, and the lagged daytime returns in foreign markets tend to have a positive influence on the current daytime return in the domestic market, which generates the meteor shower effect in daytime returns.

Given the fact that little literature has investigated the volume spillover effect between markets and none has employed the GARCH methodology, the research in this chapter tackles this issue by using the AR(1)-GARCH(1,1) model. This study provides new empirical evidence showing that the meteor shower effect also exists in the financial time series of trading volume. The positive and statistically significant volume spillover effects across markets are interpreted in the light of economic theory, which can be interpreted as evidence that the changes of liquidity investors' sentiments (e.g. the shifts of investors' risk attitude) have a contagious effect and can transmit across countries.

In summary, this chapter examines the direct information transmission mechanisms in returns, volatility and trading volume across the analysed eight stock markets by employing the ARCH methodology. The results provide more evidence in favour of the findings in the existing return and volatility spillovers literature. More importantly, this chapter contributes to the literature by documenting evidence showing that the meteor shower effect also exists in the trading volume time series across international stock markets. The trading volume in foreign markets can have a positive and statistically significant impact on future trading volume in the domestic market and it can spill over across borders. Therefore, the trading volume in one market can provide valuable information for investors in other international stock markets and may influence their trading behaviour.

Table 4.1: Parameter Estimates of the AR(1)-GARCH(1,1)-in-Mean Model using Daytime Returns and Model Diagnostics

The table below reports the parameter estimates of the following model:

$R_t = \mu + \alpha R_{t-1} + \beta h_t + \epsilon_t,$

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1},$

where μ is a constant; R_t and R_{t-1} denote the open-to-close (daytime) returns in the markets (UK, France, Germany, US, Canada, Japan, Hong Kong and China) at time *t* and *t-1*; h_t is the current conditional variance; ϵ_t is the current error term; α is the AR(1) coefficient; β is the volatility feedback effect coefficient; *a*, *b* and *c* are the parameters in the variance equation which has the GARCH(1,1) specification.

	Parameters in the Mean Equation			Parameters in the Variance Equation			Model Diagnostics				
Markets	μ	α	β	a	b	c	Skewness of residuals	Kurtosis of residuals	Q-statistic for residuals	Q-statistic for squared residuals	LR(6) for H_0: $\mu = \alpha = \beta = a = b = c = 0$
UK	0.0004 * (0.0642)	-0.0691 *** (0.0057)	2.1334 (0.3821)	1.05E-06 *** (0.0000)	0.1052 *** (0.0000)	0.8899 *** (0.0000)	-0.3784	3.8266	5.2113	22.3740	67195.48
France	0.0005 * (0.0590)	-0.1024 *** (0.0000)	-3.3777 (0.2569)	1.14E-06 *** (0.0001)	0.0907 *** (0.0000)	0.9021 *** (0.0000)	-0.3304	4.1507	5.7752	9.9206	71179.44
Germany	0.0005 (0.1449)	-0.0359 (0.1336)	1.9352 (0.5448)	2.13E-06 *** (0.0005)	0.1066 *** (0.0000)	0.8808 *** (0.0000)	-0.4780	4.7272	8.4256	14.4113	52819.09

Table 4.1 Continued: Parameter Estimates of the AR(1)-GARCH(1,1)-in-Mean Model using Daytime Returns and Model Diagnostics

	Parameters in the Mean Equation			Parameters in the Variance Equation			Model Diagnostics				
Markets	μ	α	β	a	b	c	Skewness of residuals	Kurtosis of residuals	Q-statistic for residuals	Q-statistic for squared residuals	LR(6) for H_0: $\mu = \alpha = \beta = a = b = c = 0$
US	0.0003 (0.3010)	-0.0743 *** (0.0012)	1.4831 (0.5695)	1.06E-06 *** (0.0101)	0.0735 *** (0.0000)	0.9163 *** (0.0000)	-0.5328	4.8043	9.2545	23.8623	93660.12
Canada	0.0002 (0.3339)	0.0025 (0.9225)	-2.7099 (0.3607)	7.53E-07 *** (0.0000)	0.0780 *** (0.0000)	0.9136 *** (0.0000)	-0.3622	3.7185	7.1580	7.7182	110369.32
Japan	-0.0004 (0.2116)	-0.0429 * (0.0870)	1.9720 (0.5238)	1.49E-06 *** (0.0000)	0.1020 *** (0.0000)	0.8883 *** (0.0000)	-0.4670	4.8435	4.9228	15.1808	48487.61
Hong Kong	0.0002 (0.5312)	-0.0819 *** (0.0008)	-1.2148 (0.6508)	6.12E-07 *** (0.0000)	0.0538 *** (0.0000)	0.9407 *** (0.0000)	-0.1935	4.3393	19.3408	8.0973	182303.81
China	0.0000 (0.9681)	-0.0786 *** (0.0039)	3.6995 (0.1745)	2.62E-06 *** (0.0000)	0.0511 *** (0.0000)	0.9405 *** (0.0000)	-0.2322	4.9049	20.0304	14.7990	155931.71

Notes: The p-values are reported in the parentheses. For all tables, one asterisk (*), two asterisks (**), and three asterisks (***) represent that regression coefficients are statistically significant at the 10%, 5%, and 1% level, respectively. Ljung-Box Q-statistics, which are used to test for a lack of serial correlation in the model residuals and in the residuals squared up to 12 lags, follow the chi squared distribution. $x^2(12)$ critical value: 18.55 (10%) 21.03(5%) 26.22 (1%). Likelihood Ratio (LR) statistics, which are employed to evaluate the descriptive validity of the estimated model, are chi-square distributed. $x^2(6)$ critical value: 10.64 (10%) 12.59 (5%) 16.81 (1%).

Table 4.2: Return Spillovers from Foreign to Domestic Markets (OLS and GARCH)

The return spillover coefficient β (GARCH) is obtained by running the maximum likelihood estimation of the return spillover model:

$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t,$

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1},$

where μ is a constant; $R_{H,t}$ and $R_{H,t-1}$ denote the daytime return in the domestic market at time *t* and *t-1*, respectively; $R_{F,t-1}$ is the previous daytime return in the foreign market; the conditional variance of domestic market daytime returns has the GARCH (1,1) specification; the coefficient β captures the return spillover effect from the foreign to domestic markets. The return spillover coefficient β (OLS) is obtained by running the OLS estimation for the conditional mean equation of the return spillover model.

Panel A: Return Spillovers from the UK to other Stock Markets (OLS and GARCH)

Spillovers from the UK to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
France	0.0342 (0.3355)	0.0410 (0.4969)
Germany	-0.0865** (0.0422)	-0.1993** (0.0208)
US	N/A	N/A
Canada	N/A	N/A
Japan	0.1528*** (0.0000)	0.2806*** (0.0000)
Hong Kong	-0.0507** (0.0464)	-0.0430 (0.4133)
China	0.0132 (0.7266)	-0.0038 (0.9302)

Notes:

1. As the focus is on the size and significance of return spillover coefficients (denoted by β), the results of parameter estimates of the other coefficients in the conditional mean and conditional variance equations are not reported, for brevity.

2. The p-values are reported in the parentheses. Inferences of β under GARCH reflect standard errors computed using the inference procedures developed by Bollerslev and Wooldridge (1992), which are robust to non-normality of the residuals. Inferences of β under OLS are based on White's (1980) heteroskedasticity-consistent standard errors.

3. The open-to-close return spillovers cannot be explicitly investigated due to two hours of overlapping trading time between the late afternoon in the European stock markets and early morning in the North American markets. The study excludes this sequence and report "N/A" in tables.

Table 4.2 Continued: Return Spillovers from Foreign to Domestic Markets (OLS and GARCH)

Panel B: Return Spillovers from the French Market to other Stock Markets (OLS and GARCH)

Spillovers from France to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
Germany	-0.1737*** (0.0015)	-0.3155*** (0.0055)
UK	0.0003 (0.9942)	0.0347 (0.6600)
US	N/A	N/A
Canada	N/A	N/A
Japan	0.1635*** (0.0000)	0.2799*** (0.0000)
Hong Kong	-0.0522** (0.0188)	-0.0524 (0.1846)
China	-0.0062 (0.8720)	-0.0100 (0.8148)

Panel C: Return Spillovers from the German Market to other Stock Markets (OLS and GARCH)

Spillovers from Germany to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
France	0.0847* (0.0510)	0.1319* (0.0598)
UK	0.0146 (0.6452)	0.1636** (0.0482)
US	N/A	N/A
Canada	N/A	N/A
Japan	0.1461*** (0.0000)	0.2994*** (0.0000)
Hong Kong	-0.0452** (0.0366)	-0.0113 (0.8107)
China	-0.0066 (0.8473)	-0.0078 (0.8587)

Table 4.2 Continued: Return Spillovers from Foreign to Domestic Markets (OLS and GARCH)

Panel D: Return Spillovers from the US Market to other Stock Markets (OLS and GARCH)

Spillovers from the US to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
Germany	0.1004*** (0.0010)	0.1407** (0.0176)
France	-0.0075 (0.7908)	0.0708 (0.1310)
UK	0.3489*** (0.0000)	0.4413*** (0.0000)
Canada	-0.0176 (0.5289)	0.0279 (0.6970)
Japan	0.0874*** (0.0002)	0.2544*** (0.0000)
Hong Kong	-0.0741*** (0.0020)	-0.1012*** (0.0055)
China	-0.0090 (0.7969)	-0.0606 (0.1062)

Panel E: Return Spillovers from the Canadian Market to other Stock Markets (OLS and GARCH)

Spillovers from Canada to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
Germany	0.0372 (0.3038)	0.0488 (0.5277)
France	-0.0067 (0.8278)	0.0417 (0.4545)
UK	0.2829*** (0.0000)	0.3146*** (0.0000)
US	-0.0010 (0.9789)	-0.0944 (0.3797)
Japan	0.1027*** (0.0002)	0.1744*** (0.0026)
Hong Kong	-0.0191 (0.4894)	-0.0870 (0.2464)
China	0.0097 (0.8087)	-0.0539 (0.2406)

Table 4.2 Continued: Return Spillovers from Foreign to Domestic Markets (OLS and GARCH)

Panel F: Return Spillovers from the Japanese Market to other Stock Markets (OLS and GARCH)

Spillovers from Japan to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
Germany	0.1535*** (0.0000)	0.1915*** (0.0000)
France	0.0713*** (0.0017)	0.0547 (0.1124)
UK	0.2403*** (0.0000)	0.4199*** (0.0000)
US	0.0756*** (0.0005)	0.2010*** (0.0000)
Canada	0.0399** (0.0434)	0.0189 (0.7635)
Hong Kong	-0.0556** (0.0362)	-0.0273 (0.6564)
China	-0.0447 (0.2244)	-0.0974** (0.0254)

Panel G: Return Spillovers from the Hong Kong Market to other Stock Markets (OLS and GARCH)

Spillovers from Hong Kong to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
Germany	0.1569*** (0.0000)	0.2140*** (0.0008)
France	0.0998*** (0.0001)	0.1073*** (0.0085)
UK	0.2041*** (0.0000)	0.2837*** (0.0000)
US	0.1253*** (0.0000)	0.3234*** (0.0000)
Canada	0.0765*** (0.0002)	0.1080** (0.0157)
Japan	0.0455* (0.0752)	0.1159** (0.0392)
China	-0.0595 (0.1661)	-0.0880* (0.0729)

Table 4.2 Continued: Return Spillovers from Foreign to Domestic Markets (OLS and GARCH)

Panel H: Return Spillovers from the Chinese Market to other Stock Markets (OLS and GARCH)

Spillovers from China to:	Return Spillover Coefficient β (GARCH)	Return Spillover Coefficient β (OLS)
Germany	0.0315* (0.0730)	0.0159 (0.5506)
France	0.0128 (0.4074)	-0.0121 (0.5546)
UK	0.0454*** (0.0025)	0.0586** (0.0145)
US	0.0339* (0.0953)	0.0445* (0.0804)
Canada	0.0251** (0.0460)	0.0183 (0.3737)
Hong Kong	-0.0198 (0.1204)	-0.0460** (0.0196)
Japan	-0.0197 (0.1740)	-0.0213 (0.3429)

Table 4.3: Return Spillovers from Foreign to Domestic Markets (GJR-GARCH and EGARCH)

The table below reports the estimation results of return spillover coefficients (denoted by β) and asymmetric coefficients (denoted by c) in the GJR-GARCH(1,1) model and the EGARCH(1,1) model. The GJR-GARCH(1,1) model is specified as:

$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t,$

$h_t = a + b\,\epsilon_{t-1}^2 + c(I_{t-1}\epsilon_{t-1}^2) + d\,h_{t-1},$

where dummy variable I_{t-1} equals 1 if ϵ_{t-1}< 0 (and 0 otherwise). I_{t-1} allows the effect of the squared residuals on conditional volatility to be asymmetric when the sign of ϵ_{t-1} is different. The sign of asymmetric effect coefficient c is expected to be statistically significant and positive if negative return shocks (interpreted as bad news) induce higher future volatility than positive return shocks (interpreted as good news) do.

The EGARCH(1,1) model is defined as:

$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t,$

$log(h_t) = a + b|z_{t-1}| + c\,z_{t-1} + d\,log(h_{t-1}),$

The standardised shock is defined as $z_t = \varepsilon_t/\sigma_t$. The asymmetric effect of return shocks on volatility is present if c is statistically significant and negative. As a consequence, the product of c and a negative z_{t-1} is positive, which reinforces the size effect of bad news.

Panel A: Return Spillovers from the UK Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from the UK to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
France	0.0382 (0.2690)	0.1368*** (0.0000)	0.0425 (0.2042)	-0.1198*** (0.0000)
Germany	-0.0768* (0.0519)	0.1416*** (0.0000)	-0.0747* (0.0543)	-0.1162*** (0.0000)
US	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A
Japan	0.1311*** (0.0000)	0.1183*** (0.0931)	0.1424*** (0.0000)	-0.1055*** (0.0001)
Hong Kong	-0.0578** (0.0236)	0.0259 (0.2408)	-0.0661*** (0.0082)	-0.0247 (0.1997)
China	0.0121 (0.7503)	0.0101 (0.6100)	-0.0013 (0.9722)	-0.0266 (0.2132)

Table 4.3 Continued: Return Spillovers from Foreign to Domestic Markets (GJR-GARCH and EGARCH)

Panel B: Return Spillovers from the French Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from France to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
Germany	-0.1931*** (0.0005)	0.1474*** (0.0000)	-0.1933*** (0.0005)	-0.1217*** (0.0000)
UK	-0.0139 (0.6901)	0.1431*** (0.0000)	-0.0268 (0.4379)	-0.1126*** (0.0000)
US	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A
Japan	0.1473*** (0.0000)	0.1187*** (0.0015)	0.1571*** (0.0000)	-0.1028*** (0.0002)
Hong Kong	-0.0563** (0.0121)	0.0232 (0.2826)	-0.0642*** (0.0042)	-0.0218 (0.2439)
China	-0.0071 (0.8532)	0.0103 (0.6037)	-0.0439 (0.2674)	-0.0390 (0.1166)

Panel C: Return Spillovers from the Germany Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from Germany to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
France	0.0720* (0.0971)	0.1331*** (0.0000)	0.0872** (0.0385)	-0.1178*** (0.0000)
UK	-0.0037 (0.9098)	0.1427*** (0.0000)	-0.0107 (0.7349)	-0.1126*** (0.0000)
US	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A
Japan	0.1331*** (0.0000)	0.1213*** (0.0010)	0.1430*** (0.0000)	-0.1062*** (0.0000)
Hong Kong	-0.0492** (0.0238)	0.0232 (0.2856)	-0.0537** (0.0138)	-0.0219 (0.2466)
China	-0.0075 (0.8300)	0.0104 (0.6031)	-0.0300 (0.4013)	-0.0325 (0.1640)

Table 4.3 Continued: Return Spillovers from Foreign to Domestic Markets (GJR-GARCH and EGARCH)

Panel D: Return Spillovers from the US Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from the US to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
Germany	0.0928*** (0.0016)	0.1447*** (0.0000)	0.0901*** (0.0022)	-0.1160*** (0.0000)
France	-0.0187 (0.4990)	0.1372*** (0.0000)	-0.0144 (0.5931)	-0.1185*** (0.0000)
UK	0.3343*** (0.0000)	0.1251*** (0.0000)	0.3222*** (0.0000)	-0.1034*** (0.0000)
Canada	-0.0197 (0.4800)	0.0756*** (0.0027)	-0.0222 (0.4255)	-0.0548*** (0.0009)
Japan	0.0783*** (0.0012)	0.1324*** (0.0005)	0.0871*** (0.0004)	-0.1097*** (0.0000)
Hong Kong	-0.0761*** (0.0014)	0.0210 (0.3205)	-0.0860*** (0.0005)	-0.0221 (0.2316)
China	-0.0087 (0.8043)	0.0102 (0.6056)	-0.0323 (0.3729)	-0.0117 (0.4450)

Panel E: Return Spillovers from the Canadian Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from Canada to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
Germany	0.0382 (0.2577)	0.1452*** (0.0000)	0.0483 (0.1310)	-0.1169*** (0.0000)
France	-0.0113 (0.6924)	0.1364*** (0.0000)	0.0031 (0.9091)	-0.1189*** (0.0000)
UK	0.2741*** (0.0000)	0.1397*** (0.0000)	0.2632*** (0.0000)	-0.1129*** (0.0000)
US	0.0155 (0.6612)	0.1242*** (0.0000)	0.0189 (0.5937)	-0.0966*** (0.0000)
Japan	0.1008*** (0.0001)	0.1376*** (0.0004)	0.1231*** (0.0000)	-0.1137*** (0.0000)
Hong Kong	-0.0207 (0.4541)	0.0188 (0.3788)	-0.0178 (0.5164)	-0.0169 (0.3647)
China	0.0107 (0.7890)	0.0104 (0.6013)	-0.0188 (0.6373)	-0.0311 (0.1641)

Table 4.3 Continued: Return Spillovers from Foreign to Domestic Markets (GJR-GARCH and EGARCH)

Panel F: Return Spillovers from the Japanese Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from Japan to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
Germany	0.1383*** (0.0000)	0.1395*** (0.0001)	0.1229*** (0.0000)	-0.1119*** (0.0000)
France	0.0568*** (0.0100)	0.1337*** (0.0000)	0.0580*** (0.0079)	-0.1168*** (0.0000)
UK	0.2330*** (0.0000)	0.1264*** (0.0000)	0.2220*** (0.0000)	-0.1034*** (0.0000)
US	0.0768*** (0.0009)	0.1247*** (0.0000)	0.0769*** (0.0025)	-0.0959*** (0.0000)
Canada	0.0411** (0.0374)	0.0750*** (0.0032)	0.0422** (0.0340)	-0.0542*** (0.0012)
Hong Kong	-0.0574** (0.0303)	0.0207 (0.3606)	-0.0534** (0.0446)	-0.0188 (0.3391)
China	-0.0456 (0.2156)	0.0107 (0.5911)	-0.0464 (0.2058)	-0.0112 (0.4581)

Panel G: Return Spillovers from the Hong Kong Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from Hong Kong to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
Germany	0.1444*** (0.0000)	0.1348*** (0.0000)	0.1383*** (0.0000)	-0.1124*** (0.0000)
France	0.0924*** (0.0001)	0.1317*** (0.0000)	0.0918*** (0.0001)	-0.1186*** (0.0000)
UK	0.2080*** (0.0000)	0.1451*** (0.0000)	0.2010*** (0.0000)	-0.1178*** (0.0000)
US	0.1094*** (0.0000)	0.1186*** (0.0000)	0.1134*** (0.0000)	-0.0911*** (0.0000)
Canada	0.0763*** (0.0002)	0.0766*** (0.0025)	0.0789*** (0.0002)	-0.0555*** (0.0011)
Japan	0.0445* (0.0710)	0.1320*** (0.0006)	0.0508** (0.0477)	-0.1089*** (0.0001)
China	-0.0613 (0.1551)	0.0115 (0.5659)	-0.0724 (0.1008)	-0.0304 (0.1785)

Table 4.3 Continued: Return Spillovers from Foreign to Domestic Markets (GJR-GARCH and EGARCH)

Panel H: Return Spillovers from the Chinese Market to other Stock Markets (GJR-GARCH and EGARCH)

Spillovers from China to:	Return Spillover Coefficient β (GJR)	Asymmetric Coefficient c (GJR)	Return Spillover Coefficient β (EGARCH)	Asymmetric Coefficient c (EGARCH)
Germany	0.0325* (0.0554)	0.1468*** (0.0000)	0.0375** (0.0348)	-0.1204*** (0.0000)
France	0.0062 (0.6654)	0.1352*** (0.0000)	0.0045 (0.7441)	-0.1187*** (0.0000)
UK	0.0457*** (0.0011)	0.1436*** (0.0000)	0.0446*** (0.0011)	-0.1137*** (0.0000)
US	0.0296 (0.1429)	0.1233*** (0.0000)	0.0385* (0.1429)	-0.0953*** (0.0000)
Canada	0.0270** (0.0270)	0.0773*** (0.0020)	0.0304** (0.0111)	-0.0572*** (0.0005)
Hong Kong	-0.0198 (0.1202)	0.0181 (0.4102)	-0.0220* (0.0845)	-0.0161 (0.4043)
Japan	-0.0232 (0.1035)	0.1356*** (0.0004)	-0.0191 (0.2056)	-0.0075 (0.8589)

Table 4.4: Return and Volatility Spillover Effects from Foreign to Domestic Markets

The table below reports the estimation results of return spillover coefficients (denoted by β) and volatility spillover coefficients (denoted by d) in the dynamic return and volatility spillover model. The model is specified as follows:

$R_{H,t} = \mu + \alpha R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t$,

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1} + dR_{F,t-1}^2$,

where μ is a constant; $R_{H,t}$ and $R_{H,t-1}$ denote the daytime return in the domestic markets at time *t* and *t-1*, respectively; $R_{F,t-1}$ is the previous daytime return in the foreign market; β captures the return spillover effect from the foreign to domestic markets. In addition to the GARCH(1,1) specification, an exogenous variable $R_{F,t-1}^2$ is included in the variance equation. $R_{F,t-1}^2$ is the squared foreign market return at time *t-1*, which can be treated as a raw measure of volatility from the previously opened foreign market. The parameter *d* captures the volatility spillover effect from the preceding day's foreign stock market.

Panel A: Return and Volatility Spillovers from the UK Market to other Stock Markets

Spillovers from UK to:	Return Spillover Coefficient β (GARCH with *d*)	Volatility Spillover Coefficient *d*
France	0.0465 (0.1552)	0.0436*** (0.0000)
Germany	-0.0755** (0.0342)	0.0206*** (0.0010)
US	N/A	N/A
Canada	N/A	N/A
Japan	0.1542*** (0.0000)	0.0324*** (0.0000)
Hong Kong	-0.0574*** (0.0105)	0.0225*** (0.0000)
China	0.0159 (0.6096)	0.0086** (0.0409)

Table 4.4 Continued: Return and Volatility Spillover Effects from Foreign to Domestic Markets

Panel B: Return and Volatility Spillovers from the French Market to other Stock Markets

Spillovers from France to:	Return Spillover Coefficient β (GARCH with *d*)	Volatility Spillover Coefficient *d*
Germany	-0.1827*** (0.0003)	0.0342*** (0.0001)
UK	-7.52E-05 (0.9982)	0.0161 (0.1024)
US	N/A	N/A
Canada	N/A	N/A
Japan	0.1662*** (0.0000)	0.0185*** (0.0000)
Hong Kong	-0.0510** (0.0287)	0.0140*** (0.0001)
China	-0.0057 (0.8607)	0.0090* (0.0506)

Panel C: Return and Volatility Spillovers from the German Market to other Stock Markets

Spillover from Germany to:	Return Spillover Coefficient *β* (GARCH with *d*)	Volatility Spillover Coefficient *d*
France	0.0847** (0.0290)	5.57E-05 (0.9928)
UK	0.0146 (0.6239)	-0.0028 (0.5641)
US	N/A	N/A
Canada	N/A	N/A
Japan	0.1481*** (0.0000)	0.0181*** (0.0000)
Hong Kong	-0.0457** (0.0270)	0.0119*** (0.0001)
China	-0.0074 (0.7909)	0.0054 (0.1315)

Table 4.4 Continued: Return and Volatility Spillover Effects from Foreign to Domestic Markets

Panel D: Return and Volatility Spillovers from the US Market to other Stock Markets

Spillovers from US to	Return Spillover Coefficient β (GARCH with d)	Volatility Spillover Coefficient d
Germany	0.1039*** (0.0011)	0.0371*** (0.0000)
France	-0.0153 (0.6062)	0.0390*** (0.0000)
UK	0.3375*** (0.0000)	0.0551*** (0.0000)
Canada	-0.0137 (0.5857)	0.0139*** (0.0052)
Japan	0.0904*** (0.0001)	0.0265*** (0.0000)
Hong Kong	-0.0704*** (0.0048)	0.0208*** (0.0000)
China	-0.0049 (0.8848)	0.0057 (0.1197)

Panel E: Return and Volatility Spillovers from the Canadian Market to other Stock Markets

Spillovers from Canada to:	Return Spillover Coefficient β (GARCH with d)	Volatility Spillover Coefficient d
Germany	0.0611* (0.0571)	0.0731*** (0.0000)
France	-0.0090 (0.7601)	0.0535*** (0.0000)
UK	0.2781*** (0.0000)	0.0641*** (0.0000)
US	0.0044 (0.8881)	0.0204** (0.0181)
Japan	0.1086*** (0.0000)	0.0527*** (0.0000)
Hong Kong	-0.0165 (0.5409)	0.0259*** (0.0000)
China	0.0136 (0.7430)	0.0087 (0.1188)

Table 4.4 Continued: Return and Volatility Spillover Effects from Foreign to Domestic Markets

Panel F: Return and Volatility Spillovers from the Japanese Market to other Stock Markets

Spillovers from Japan to:	Return Spillover Coefficient β (GARCH with d)	Volatility Spillover Coefficient d
Germany	0.1486*** (0.0000)	0.0394*** (0.0000)
France	0.0720*** (0.0017)	0.0147*** (0.0041)
UK	0.2418*** (0.0000)	0.0064 (0.1455)
US	0.0767*** (0.0005)	0.0014 (0.6118)
Canada	0.0399** (0.0397)	0.0004 (0.8918)
Hong Kong	-0.0536** (0.0177)	0.0093*** (0.0024)
China	-0.0437 (0.1968)	0.0039 (0.3312)

Panel G: Return and Volatility Spillovers from the Hong Kong Market to other Stock Markets

Spillovers from Hong Kong to:	Return Spillover Coefficient β (GARCH with d)	Volatility Spillover Coefficient d
Germany	0.1531** (0.0000)	0.0412*** (0.0000)
France	0.1027*** (0.0000)	0.0380*** (0.0000)
UK	0.2097*** (0.0000)	0.0515*** (0.0000)
US	0.1281*** (0.0000)	0.0212*** (0.0001)
Canada	0.0791*** (0.0000)	0.0125*** (0.0004)
Japan	0.0489** (0.0330)	0.0360*** (0.0000)
China	-0.0520 (0.1078)	0.0104** (0.0199)

Table 4.4 Continued: Return and Volatility Spillover Effects from Foreign to Domestic Markets

Panel H: Return and Volatility Spillovers from the Chinese Market to other Stock Markets

Spillovers from China to:	Return Spillover Coefficient β (GARCH with d)	Volatility Spillover Coefficient d
Germany	0.0253* (0.0756)	0.0050*** (0.0016)
France	0.0072 (0.5678)	0.0040*** (0.0006)
UK	0.0433*** (0.0004)	0.0045*** (0.0018)
US	0.0248** (0.0431)	0.0031*** (0.0000)
Canada	0.0229** (0.0311)	0.0029*** (0.0037)
Hong Kong	-0.0205 (0.1287)	0.0012* (0.0736)
Japan	-0.0206* (0.0644)	0.0013 (0.2011)

Table 4.5: Inter-regional Contemporaneous Return Spillovers to the Hong Kong Overnight Return

The model for investigating contemporaneous return spillovers from inter-regional foreign stock markets to the Hong Kong market can be expressed as:

$NR_{HK,t} = \mu + \alpha R_{HK,t-1} + \beta R_{F,t-1} + \epsilon_t,$

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1},$

where the current overnight return ($NR_{HK,t}$) in the Hong Kong stock market is specified as a linear function of its preceding day's daytime return ($R_{HK,t-1}$) and the daytime return from the foreign markets which are opened after the Hong Kong stock exchange has closed for the day ($R_{F,t-1}$). The coefficient β represents the influence of daytime return from foreign markets on the following day's overnight return and thus the opening price of market index in the Hong Kong stock exchange. It is assumed that ϵ_t follows GARCH(1,1) process.

Spillover From the Daytime Return ($R_{F,t-1}$) in:	Spillovers to the Overnight Return ($NR_{HK,t}$) in Hong Kong
Germany	0.4132*** (0.0000)
France	0.4890*** (0.0000)
UK	0.4544*** (0.0000)
US	0.6475*** (0.0000)
Canada	0.5313*** (0.0000)

Table 4.6: The Estimated Value of AR(1) Coefficient of Trading Volume

The AR(1) coefficient is estimated from the following model:

$V_{H,t} = \mu + \alpha_H V_{H,t-1} + v_{i,t}$

$h_t = a + bv_{t-1}^2 + ch_{t-1}$,

where $V_{H,t}$ and $V_{H,t-1}$ are the standardised de-trended trading volume in domestic market at time *t* and *t-1*, respectively. The parameter α_H is the AR(1) coefficient of trading volume. The conditional variance (h_t) of domestic market trading volume is assumed to follow the GARCH (1,1) process.

Trading Volume in Domestic Markets:	First-order Autocorrelation Coefficients α_H
UK	0.5579*** (0.0000)
France	0.5713*** (0.0000)
Germany	0.5767*** (0.0000)
US	0.5924*** (0.0000)
Canada	0.6140*** (0.0000)
Japan	0.5008*** (0.0000)
Hong Kong	0.6609*** (0.0000)
China	0.9082*** (0.0000)

Table 4.7: Trading Volume Spillovers from Foreign to Domestic Markets

The trading volume spillover model is specified as:

$V_{H,t} = \mu + \alpha_H V_{H,t-1} + \beta_F V_{F,t-1} + v_{,t},$

$h_t = a + bv_{t-1}^2 + ch_{t-1},$

where $v_{H,t}$ is the residual term, $V_{H,t-1}$ and $V_{F,t-1}$ are the standardised de-trended trading volumes from the domestic and foreign markets in the last trading period. The AR (1) process has been included in the model to control for the first-order autocorrelation in domestic trading volume (as captured by parameter α_H). The parameter β_F measures the meteor shower effect in trading volume from the foreign to domestic markets.

Panel A: Volume Spillovers from Foreign Markets to the UK Market

Volume Spillovers to the UK from Foreign markets :	AR(1) Coefficient in the UK Trading Volume α_{UK}	Foreign Volume Spillover Coefficient β_F
France	0.5453*** (0.0000)	0.0178 (0.6041)
Germany	0.5567*** (0.0000)	0.0017 (0.9615)
US	0.5301*** (0.0000)	0.0549** (0.0359)
Canada	0.5468*** (0.0000)	0.0199 (0.4362)
Japan	0.5228*** (0.0000)	0.1657*** (0.0000)
Hong Kong	0.5239*** (0.0000)	0.1439*** (0.0000)
China	0.5554*** (0.0000)	0.0535** (0.0124)

Notes:

Panel A reports the parameter estimates of the trading volume spillover model, where the domestic market is the UK market. The estimated coefficient α_{UK} measures the first-order autocorrelation in the UK trading volume after controlling for the trading volume spillover effect from foreign markets (as captured by the estimated coefficient β_F)

Table 4.7 Continued: Trading Volume Spillovers from Foreign to Domestic Markets

Panel B: Volume Spillovers from Foreign Markets to the French Market

Volume Spillovers to France from Foreign markets :	AR(1) Coefficient in French Trading Volume α_{Fra}	Foreign Volume Spillover Coefficient β_F
Germany	0.5173*** (0.0000)	0.0664* (0.0636)
UK	0.5657*** (0.0000)	0.0077 (0.7412)
US	0.4943*** (0.0000)	0.1102*** (0.0007)
Canada	0.5123*** (0.0000)	0.0845*** (0.0001)
Japan	0.5584*** (0.0000)	0.0887*** (0.0000)
Hong Kong	0.4916*** (0.0000)	0.2150*** (0.0000)
China	0.5705*** (0.0000)	0.0230 (0.2256)

Panel C: Volume Spillovers from Foreign Markets to the German Market

Volume Spillovers to Germany from Foreign markets:	AR(1) Coefficient in German Trading Volume α_{Ger}	Foreign Volume Spillover Coefficient β_F
France	0.5075*** (0.0000)	0.0809** (0.0405)
UK	0.5603*** (0.0000)	0.0211 (0.4600)
US	0.5110*** (0.0000)	0.0946*** (0.0002)
Canada	0.4938*** (0.0000)	0.1159*** (0.0000)
Japan	0.5687*** (0.0000)	0.0795*** (0.0001)
Hong Kong	0.5181*** (0.0000)	0.1826*** (0.0000)
China	0.5767*** (0.0000)	-0.0002 (0.9945)

Table 4.7 Continued: Trading Volume Spillovers from Foreign to Domestic Markets

Panel D: Volume Spillovers from Foreign Markets to the US Market

Volume Spillovers to the US from Foreign markets :	AR(1) Coefficient in the US Trading Volume α_{US}	Foreign Volume Spillover Coefficient β_F
Germany	N/A	N/A
France	N/A	N/A
UK	N/A	N/A
Canada	0.6007*** (0.0000)	-0.0094 (0.7065)
Japan	0.5797*** (0.0000)	0.0514*** (0.0013)
Hong Kong	0.5299*** (0.0000)	0.1110*** (0.0000)
China	0.5891*** (0.0000)	0.0504*** (0.0038)

Panel E: Volume Spillovers from Foreign Markets to the Canadian Market

Volume Spillovers to Canada from Foreign markets :	AR(1) Coefficient in Canadian Trading Volume α_{Can}	Foreign Volume Spillover Coefficient β_F
Germany	N/A	N/A
France	N/A	N/A
UK	N/A	N/A
US	0.5697*** (0.0000)	0.0663* (0.0667)
Japan	0.5970*** (0.0000)	0.0861*** (0.0000)
Hong Kong	0.4793*** (0.0000)	0.2338*** (0.0000)
China	0.6101*** (0.0000)	0.0241 (0.2104)

Notes:

The dynamic spillover effect in trading volume cannot be explicitly investigated due to a 2-hour overlapping trading time between the late afternoon in the European stock markets and early morning in the North American markets. The study excludes this sequence and report "N/A" in tables.

Table 4.7 Continued: Trading Volume Spillovers from Foreign to Domestic Markets

Panel F: Volume Spillovers from Foreign Markets to the Japanese Market

Volume Spillovers to Japan from Foreign markets :	AR(1) Coefficient in Japanese Trading Volume α_{Jap}	Foreign Volume Spillover Coefficient β_F
Germany	0.4977*** (0.0000)	0.0105 (0.7462)
France	0.4880*** (0.0000)	0.0426 (0.2102)
UK	0.4783*** (0.0000)	0.0707*** (0.0041)
US	0.4862*** (0.0000)	0.0453 (0.1641)
Canada	0.4903*** (0.0000)	0.0392 (0.1770)
Hong Kong	0.4947*** (0.0000)	0.0261 (0.3438)
China	0.4935*** (0.0000)	0.0566** (0.0196)

Panel G: Volume Spillovers from Foreign Markets to the Hong Kong Market

Volume Spillovers to Hong Kong from Foreign markets :	AR(1) Coefficient in Hong Kong Trading Volume α_{HK}	Foreign Volume Spillover Coefficient β_F
Germany	0.5716*** (0.0000)	0.1208*** (0.0000)
France	0.6064*** (0.0000)	0.0876** (0.0109)
UK	0.6420** (0.0000)	0.0392* (0.0922)
US	0.6017*** (0.0000)	0.1179*** (0.0007)
Canada	0.6035*** (0.0000)	0.0853*** (0.0004)
Japan	0.6603*** (0.0000)	0.0260 (0.3872)
China	0.6311*** (0.0000)	0.0693*** (0.0013)

Table 4.7 Continued: Trading Volume Spillovers from Foreign to Domestic Markets

Panel H: Volume Spillovers from Foreign Markets to the Chinese Market

Volume Spillovers to China from Foreign markets :	AR(1) Coefficient in Chinese Trading Volume α_{Chn}	Foreign Volume Spillover Coefficient β_F
Germany	0.8978*** (0.0000)	0.0283*** (0.0019)
France	0.9013*** (0.0000)	0.0233** (0.0112)
UK	0.9080*** (0.0000)	0.0014 (0.7989)
US	0.9051*** (0.0000)	0.0185 (0.1358)
Canada	0.8956*** (0.0000)	0.0233*** (0.0031)
Hong Kong	0.8842*** (0.0000)	0.0325** (0.0207)
Japan	0.9082*** (0.0000)	-0.0062 (0.3675)

CHAPTER 5 – TRADING VOLUME AND INTERNATIONAL STOCK MARKET RETURNS

5.1 Introduction

When analysing international stock markets, traders often exploit the information incorporated not only in the prices but also in the trading volume data. It has been long recognised by financial practitioners that trading volume can provide valuable information about future equity price changes. The existing literature (e.g. Campbell, Grossman and Wang, 1993; Wang, 1994; Conrad, Hameed and Niden, 1994; Llorente, Michaely, Saar and Wang, 2002; Connolly and Stivers, 2003; Gebka, 2012) provides evidence about strong interactive relations between stock returns and trading volume on both aggregate stock market and individual firm-specific levels. The informational role of trading volume in understanding the behaviour of serial autocorrelation in stock returns has been investigated and confirmed. However, it is not until recently that the literature (e.g. Gagnon and Karolyi, 2003; 2009) reported the usefulness of trading volume in explaining how return spillovers change over time.[43] The findings of Gagnon and Karolyi (2003; 2009) are of great importance given the challenges that the earlier literature faced in terms of discovering the driving forces of the spillovers.[44]

Gagnon and Karolyi (2003; 2009) frame their analysis of the joint dynamics of stock return comovements and trading volume in the context of the heterogeneous-agent trading model developed by Campbell, Grossman and Wang (1993). In the CGW model, the aggregate trading volume of the market is used as an indicator that helps market agents to distinguish between price movements associated with public information and those associated with liquidity trading. Trading volume is regarded as a signal of the information content of given price changes. The price movements accompanied by heavy volume during the trading day are normally associated with

[43]The term "return spillovers" was proposed by Hamao et al. (1990) to describe the market comovements in returns across international stock markets (see Chapter 2 for the details).

[44] A number of studies have found that the return spillovers are, indeed, time-varying. However, few of them have been able to explain this time-varying nature of these spillovers. The details have been discussed in Chapter 2.

shifts in the demand of liquidity traders. Since they are not due to any changes of fundamental factors that affect a revaluation of stock prices by the market, the price movements are more likely to be reversed on the next trading day.[45]

Gagnon and Karolyi (2003) first extend the implications of the CGW model to an international setting by allowing the trading volume to explain the variations of the first-order return autocorrelations in a market and the time-varying nature of the inter-temporal cross-correlations between international stock markets. They propose two types of price movements in the stock markets: liquidity-based price movements that are typically associated with heavy trading volume and information-based price movements that are usually accompanied by low or normal trading volume.

Gagnon and Karolyi (2003) hypothesise that price movements caused by liquidity trading are less likely to be transmitted across countries because they are not due to any fundamental revaluation of the stock. They investigate the joint dynamics of the stock returns and trading volume between the US and Japanese markets, and find that the magnitude of daytime return spillovers from Japan to the US tends to decrease with the previous day's trading volume in the Japanese market.

However, it is important to emphasise that the CGW model addresses only domestic market trading. Campbell et al. (1993) show that liquidity trading is normally associated with high trading volume and tends to cause the negative first-order autocorrelation of stock returns. Gagnon and Karolyi's interpretations about the CGW model in an international context are questionable as it is arguable that liquidity-based price movements are less likely to be transmitted across borders. According to the contagion hypothesis, non-information-based price movements can also spill over to other countries (Lin et al. 1994). Fads and herd instincts may occur in an international context. In addition, Gagnon and Karolyi (2003) only consider the US and Japanese markets and provide some evidence to support their hypothesis.[46] This chapter is

[45] In the CGW model, the fundamental factors refer to risk-free interest rate, average dividend payment, expected future dividend and the signal that all investors received about future dividend shocks. These factors affect the present value of the expected future cash flows from a stock (see Section 4.2 for the detailed descriptions of the CGW model).

[46] Gagnon and Karolyi (2003) find that the stock return spillover effect from Japan to the US is sensitive to interactions with Japanese trading volume, but the result is only significant at the 10% level.

motivated by the question whether or not Gagnon and Karolyi's (2003) hypothesis can be verified for a broader set of international stock markets.

Therefore, Chapter 5 attempts to answer the question of whether liquidity-based price movements can be transmitted across borders. The return transmission mechanism across international stock markets is investigated by focusing on the interactions between intraday returns and trading volume. The objective of this chapter is to examine the informational role of trading volume in affecting the magnitude and significance of the spillover effect in the open-to-close returns across international stock markets in the US, UK, Canada, France, Germany, Japan, Hong Kong and China. This study further investigates the first-order autocorrelation behaviour of stock returns in relation to trading volume with and without controlling for the influence from the foreign market. The empirical analysis is closely related to implications of the theoretical model of trading proposed by Campbell et al. (1993).

This chapter employs an econometric model, which allows one to study explicitly whether the magnitude and significance of international return spillovers vary with trading volume. This new approach provides richer insights about the dynamics of international return spillovers in relation to trading volume, which is a new contribution to the existing spillover literature. By using the same method, the dynamic relations between stock returns and trading volume in the domestic market are also examined with and without controlling for the international return spillover effect. This study is the first such attempt to analyse explicitly the behaviour of the first-order return autocorrelations with respect to different levels of trading volume in both domestic and international contexts.

The remainder of this chapter is organised as follows. Section 5.2 presents a theoretical model and discusses the relation between trading volume and predictable patterns in stock returns. Section 5.3 describes an econometric model and investigates the international return spillover effect and its interactive effect with trading volume. Section 5.4 uses an extended version of the model to examine the dynamics of first-order return autocorrelations in relation to trading volume with considerations of the influence from foreign stock returns. Section 5.5 provides a summary and concluding remarks.

5.2 Trading Volume and Stock Returns: The Theoretical Model and Empirical Evidence

5.2.1 The Theoretical Model of Campbell, Grossman and Wang (1993)

Campbell, Grossman and Wang (1993) present a theoretical model (the CGW model) which explains the relation between trading volume and the serial autocorrelation of stock returns. In the CGW model, there are two types of investors in the economy. Type A investors have a constant risk aversion parameter a, and type B investors have a time-varying risk aversion parameter b_t. The changes in type B investors' risk aversions are treated as exogenous. Liquidity trading is caused by the shifts in the risk aversion of the type B investors in the market.[47] Liquidity traders (type B investors) create noise to the suppliers of immediacy (type A investors). When type B investors become more (or less) risk-averse and less (or more) willing to hold the stock, it leads to a decrease (increase) of current stock price and an increase (decrease) of the expected return from holding more risky asset since the type A investors require compensation for accommodating the selling (or buying) pressure from type B investors. In each period, both types of investors maximise their utility function defined as:

$$\max E_t[-\exp(-\Psi W_{t+1})], \tag{5.1}$$

subject to the following budget constrain:

$$W_{t+1} = W_t R + X_t(P_{t+1} + D_{t+1} - RP_t), \tag{5.2}$$

where E_t is the expectation operator; $\Psi = a, b_t$; the parameter a denotes the constant risk aversion of type A investors, and b_t is the time-varying risk aversion parameter of type B investors; W_{t+1} and W_t are wealth at time *t* and time *t+1*, respectively; *R=1+r*, *r* is the risk-free interest rate; X_t is the holding of stocks at time *t*; P_{t+1} and P_t are stock prices at time *t* and time *t+1*, respectively; D_{t+1} is the dividend paid in period *t+1*.

[47] Campbell et al. (1993) derive liquidity trades from shifts in the risk aversion of type B investors as they find it natural to relate changing demands to changing tastes. Investors' attitudes to risk are treated as exogenous and may depend on wealth and other variables. However, Campbell et al. (1993) suggest that the basic intuition behind their model should be valid regardless of how liquidity trades are introduced.

Campbell et al. (1993) assume that the dividend paid at time *t* is:

$$D_t = \overline{D} + \widetilde{D}_t, \tag{5.3}$$

where $\overline{D}$ is the mean dividend, and $\widetilde{D}_t$ is the zero mean stochastic component of the dividend which follows the AR(1) process:

$$\widetilde{D}_t = \alpha_D \widetilde{D}_{t-1} + u_{D,t}, \tag{5.4}$$

where $u_{D,t}$ is the current dividend shock which is i.i.d with a normal distribution.

The expected stochastic component of dividend at time *t+1* given the information available at time *t* is:

$$E\left(\widetilde{D}_{t+1} \middle| \widetilde{D}_t\right) = \alpha_D \widetilde{D}_t. \tag{5.5}$$

$\widetilde{D}_t$ causes the payoff to the stock at time *t* (D_t) to be stochastic so that a premium is demanded by investors for holding it.

Let $u_{D,t+1}$ be the future dividend shock and assume that:

$$E\left(u_{D,t+1} \middle| S_t\right) = S_t, \tag{5.6}$$

where S_t is the signal which all investors receive at time *t* about future dividend shock $u_{D,t+1}$.

In addition, let F_t be the present value of the expected future cash flows from a stock, which can be expressed as:

$$F_t \equiv E\left(\sum_{s=0}^{\infty} \frac{1}{R} D_{t+s} \middle| \widetilde{D}_t, S_t\right). \tag{5.7}$$

By substituting Equations (5.3) - (5.6) into Equation (5.7), it is shown that the fundamental value of a stock is determined by $R, \overline{D}, \widetilde{D}_t$ and S_t. Fundamental value F_t represents the equilibrium price of the stock if investors are risk neutral:

$$F_t = \frac{R\overline{D}}{r} + \frac{R}{R-\alpha_D}\widetilde{D}_t + \frac{1}{R-\alpha_D}S_t, \tag{5.8}$$

where $R=1+r$, and r is the return of risk-free asset.

However, when investors are risk-averse the equilibrium price will depend on the risk aversion of the marginal investors. Define the variable Z_t that can be interpreted as the risk aversion of the marginal investors in the market:

$$Z_t \equiv \frac{ab_t}{(1-w)a+wb_t}, \tag{5.9}$$

where w is the weight of type A investors; parameter a is a constant risk aversion of type A investor; b_t is a time-varying risk aversion parameter of type B investors.

Campbell et al. (1993) assume that:

$$Z_t = \bar{Z} + \widetilde{Z}_t, \tag{5.10}$$

where $\bar{Z}$ is the mean of Z_t, and $\widetilde{Z}_t$ is assumed to follow an AR(1) process:

$$\widetilde{Z}_t = \alpha_Z \widetilde{Z}_t + u_{z,t}, \tag{5.11}$$

$u_{z,t}$ is independent of other shocks and is i.i.d. normal with zero mean and variance σ_Z^2.

As shown in Campbell et al. (1993), there exists an equilibrium price of the stock in the economy where each type of investors maximises their utility function in Equation (5.1) given their wealth constraint that was described in Equation (5.2). The equilibrium price of the stock has the following form:

$$P_t = F_t - D_t + (p_0 + p_z Z_t), \tag{5.12}$$

where $p_0 = (1-\alpha_Z)p_Z\bar{Z}/r$ and $p_Z = -\left(\frac{R-\alpha_Z}{2\sigma_Z^2}\right)(1-\sqrt{1-(\frac{\sigma_Z^2}{(R-\alpha_Z)^2}/4\sigma_F^2})})$

and p_Z is always smaller than zero as $R > 1$ and $\alpha_Z < 1$. P_t is negatively related to Z_t.

The excess return per stock realised at time *t+1* (denoted by Q_{t+1}) can be written as:

$$Q_{t+1} \equiv P_{t+1} + D_{t+1} - RP_t. \tag{5.13}$$

Let X_t^a and X_t^b be the optimal stock holdings of type A and type B investors. Campbell et al. (1993) show that a solution to the optimization problem given the price function is:

$$X_t^a = \frac{1}{a} Z_t, \tag{5.14}$$

$$X_t^b = \frac{1}{b_t} Z_t. \tag{5.15}$$

The changes in Z_t (risk attitudes of marginal investors) cause changes in X_t^a and X_t^b, and the changes in X_t will generate the liquidity trades among investors. Thus, the trading volume provides some information about the current level of Z_t.

Equations (5.11) - (5.13) show that Z_t can be used to predict future excess returns. However, since Z_t can not be directly observed, trading volume can be used as a proxy for Z_t to help predict future excess returns.

When Z_t is high (i.e. trading volume as a proxy for Z_t is high), type B investors are highly risk-averse and less willing to hold the stock. The stock price has to decrease at time *t* in order to increase the expected future excess return at time *t+1*, so that type A investors can be included to hold more of the stock. In other words, when type B investors sell stocks for hedging reasons, the stock price must decrease to attract type A investors to enter the opposite position. Since the expectations of future stock payoff remain the same, the declining stock price leads to a low return at time *t* and a higher expected future return at time *t+1*. Thus, heavy trading volume tends to cause a negative autocorrelation of the stock return between time *t+1* and time *t*.

5.2.2 Empirical Evidence

Campbell et al. (1993) employ daily returns of the CRSP (Center for Research in Security Prices) value-weighted stock index of NYSE/NASDAQ firms and aggregate market trading volume over the period 3 July 1962 to 30 December 1988 to investigate whether the autoregressive behaviour of market index returns varies with trading volume. They find that returns associated with higher trading volume tend to exhibit stronger return reversals. In other words, the first-order daily return autocorrelation tends to decline with trading volume. On the firm-specific level, Conrad, Hameed and Niden (1994) test for the relations between trading volume and subsequent returns patterns that are suggested by Campbell et al. (1993). By studying individual stocks in the US market, they find that price changes accompanied by heavy trading volume tend to reverse in the following period, which is consistent with the prediction of the CGW model. Llorer, Michaely, Saar and Wang (2002) also test the daily volume-return dynamics of individual stocks traded in the US stock market. Llorer et al. (2002) find that stocks with a high degree of non-informational trading tend to exhibit the negative first-order return autocorrelation following the periods with high trading volume. Connolly and Stivers (2003) use weekly returns of the CRSP value-weighted stock index of NYSE/NASDAQ firms and aggregate market turnover over the period July 1962 to December 2000 to examine the dynamic pattern between stock returns and trading volume. Connolly and Stivers (2003) find that consecutive equity-index returns tend to display substantial momentum when trading volume is high and tend to display substantial reversals when trading volume is low. [48]

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[48] Wang (1994) and Llorer et al. (2002) generalise the CGW (1993) model by allowing information asymmetry among the investors. They offer theoretical models which can also explain the return continuations accompanied by high trading volume. In their models returns generated by non-informational trading tend to exhibit the negative first-order return autocorrelation in the period with high trading volume, while the returns induced by speculative (informational) trading lead to the positive first-order return autocorrelation. The analysis in this study is based on the CGW (1993) model because the negative first-order return autocorrelation following a day with heavy trading volume is observed in each country under investigation, which implies that high trading volume is more likely to be associated with liquidity trading.

5.3 Models and Results: Trading Volume and International Return Spillovers

5.3.1 Research Questions and Model Specification

By linking two strands of the literature (i.e. literature on international return spillovers and literature on interactions between return autocorrelation and trading volume), this study investigates the informational role of foreign market trading volume in affecting the magnitude and significance of daytime return spillovers among the world's eight largest stock markets.

According to the theoretical model of CGW (1993), trading volume can provide valuable information on the nature of price movements in the short run. Price movements accompanied by heavy trading volume are typically associated with liquidity trading and are likely to be reversed in the following trading period (see Section 5.2). In contrast, information-based price movements are normally associated with low or normal trading volume and are more likely to continue their momentum in the following trading period. A gradual price adjustment with low or normal trading volume is expected to reflect the gradual flow of information instead of an abrupt price adjustment with abnormal trading volume over a relatively short horizon.

As suggested by Gagnon and Karolyi (2003; 2009), the implications of CGW (1993) model can be extended to an international context. Since the liquidity-based price movements typically contain no new information that can affect the fundamental value of a stock, they are not only more likely to reverse the momentum in the following day's trading in the domestic market, but also less likely to spill over to other markets. By contrast, information-based price movements, which are normally associated with low or normal trading volume, reflect a fundamental revaluation of stock prices by the market. Thus, they are not only more likely to continue the momentum in the domestic market but also easier to spill over to other markets to a large extent.

Gagnon and Karolyi (2003; 2009) suggest that the magnitude and the size of return spillovers from foreign to domestic markets may be sensitive to foreign market trading volume. This means that the partial effect of the dependent variable (domestic return at time *t*) with respect to an explanatory variable (foreign return at time *t-1*) depends on the magnitude of another variable (foreign market trading volume at time *t-1*).

Therefore, an interaction term between the explanatory variable and another variable can be designed to capture this interactive effect (Wooldridge, 2003).

This chapter proposes a model, in which daytime returns in each market follow the AR(1)-GARCH(1,1) process with the mean equation augmented to include an interaction term with trading volume in the foreign market. It is specified as follows:

$$R_{H,t} = \mu + \alpha\, R_{H,t-1} + \beta_0 R_{F,t-1} + \beta_1 V_{F,t-1} R_{F,t-1} + \epsilon_t, \tag{5.16}$$

$$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}, \tag{5.17}$$

where $R_{H,t}$ and $R_{H,t-1}$ are the open-to-close index price returns in the domestic market at time *t* and *t-1*, respectively; $R_{F,t-1}$ is the daytime return in the foreign market at time *t-1*; $V_{F,t-1}$ is the preceding day's trading volume in the foreign market.[49] The variance equation is specified as the GARCH(1,1) process.

β_1 is the coefficient of the interaction term ($V_{F,t-1}R_{F,t-1}$) designed to measure the joint-dynamic effect between the previous day's return and trading volume in the foreign market on today's return in the domestic market. The coefficient β_0 captures the marginal (partial) effect of $R_{F,t-1}$ on $R_{H,t}$, *ceteris paribus*. It measures the impact of yesterday's foreign market return on today's domestic market return, holding all the other explanatory variables constant. However, the interaction term $V_{F,t-1}R_{F,t-1}$ can only be constant when $V_{F,t-1} = 0$. In other words, the interpretation of β_0 is subject to *ceteris paribus* conditions and β_0 measures the return spillover effect from the foreign market that is associated with zero trading volume.

In order to solve this problem, Equation (5.16) can be rewritten as:

$$R_{H,t} = \mu + \alpha R_{H,t-1} + \left(\beta_0 + \beta_1 V_{F,t-1}\right) R_{F,t-1} + \epsilon_t. \tag{5.18}$$

[49] Lo and Wang (2000) suggest that raw volume rather than the de-trended volume should be used in the empirical investigations given the situation in which the de-trending methods can have a substantial impact on the time-series properties of de-trended volume. Trading volume is defined as the number of stocks traded during the day. However, the de-trending procedure used by Lee and Rui (2002) and Gebka (2012) is employed in Section 4.5 as a robustness test and the results are qualitatively identical.

The first derivative of R_t with respect to $R_{F,t-1}$ holding other factors fixed is:

$$dR_{H,t}/\, dR_{F,t-1} = \left(\beta_0 + \beta_1 V_{F,t-1}\right), \tag{5.19}$$

where $\left(\beta_0 + \beta_1 V_{F,t-1}\right)$ is the partial effect of $R_{F,t-1}$ on R_t.

If $\beta_1 < 0$, the above equation implies that the magnitude of return spillover from the foreign to domestic markets tends to decline with yesterday's foreign market trading volume. This is consistent with the interpretations of Gagnon and Karolyi (2003; 2009) about the CGW model.

Let $\bar{V}_F$ be the mean level of foreign market trading volume between e.g. certain percentiles,

$dR_t/\, dR_{F,t-1} = (\beta_0 + \beta_1 \bar{V}_F)$ is the partial effect of $R_{F,t-1}$ on $R_{H,t}$ while $V_{F,t-1} = \bar{V}_F$.

Define

$$(\beta_0 + \beta_1 \bar{V}_F) = \bar{\theta}, \tag{5.20}$$

where $\bar{\theta}$ will measure the partial effect of $R_{F,t-1}$ on R_t at a certain value of $V_{F,t-1}$.

In order to calculate the standard error of $\bar{\theta}$ and to be able to examine the significance of the partial effect, Equation (5.18) can be re-parameterised by adding and then subtracting a $\beta_1 \bar{V}_F R_{F,t-1}$ term.

$$R_{H,t} = \mu + \alpha R_{H,t-1} + (\beta_0 + \beta_1 \bar{V}_F) R_{F,t-1} + \beta_1 R_{F,t-1}(V_{F,t-1} - \bar{V}_F) + \epsilon_t. \tag{5.21}$$

Substituting $(\beta_0 + \beta_1 \bar{V}_F) = \bar{\theta}$ into Equation (5.21) leads to:

$$R_{H,t} = \mu + \alpha R_{H,t-1} + \bar{\theta} R_{F,t-1} + \beta_1 R_{F,t-1}(V_{F,t-1} - \bar{V}_F) + \epsilon_t. \tag{5.22}$$

By running a regression for Equation (5.22), one can obtain the estimated $\bar{\theta}$ and its standard error, which allows one to find explicitly the magnitude and significance of the return spillover effect when $V_{F,t-1} = \bar{V}_F$.[50]

5.3.2 *Results and Discussion*

Tables 5.1-5.8 report the estimates of $\bar{\theta}$ and β_1 for Equation (5.22) by using daytime returns of the S&P 500 index (the US), S&P/TSX Composite Index (Canada), FTSE100 index (the UK), CAC40 index (France), DAX30 index (Germany), TOPIX index (Japan), Hang Seng index (Hong Kong) and SHANGHAI SE A SHARE index (China) during the sample period from 1 August 2003 to 30 July 2010.

The country in the top-left cell of each panel is regarded as the signalling market (foreign market) and the following are the signal receiving markets (domestic markets). The foreign market trading volume over the sample period is sorted in ascending order and divided into quartiles. $V_{F,0-25\%}$, $V_{F,25-50\%}$, $V_{F,50-75\%}$ and $V_{F,75-100\%}$ represent the foreign market trading volume that belongs to the 0-25th percentiles (i.e. trading volume is very low), 25-50th percentiles (i.e. trading volume is low), 50-75th percentiles (i.e. trading volume is high) and 75-100th percentiles (i.e. trading volume is very high), respectively. $\bar{V}_{F,50\%}$ is the mean average of foreign market trading volume (i.e. trading volume is normal). $\bar{V}_{F,0-25\%}$ denotes the mean value of the foreign market trading volume in the first quartile. $\bar{\theta}_{0-25\%}$ measures the return spillover effect from the foreign to domestic markets when $V_{F,t-1} = \bar{V}_{F,0-25\%}$ (i.e. yesterday's foreign market trading volume is very low). Similarly, parameters $\bar{\theta}_{25\%-50\%}$, $\bar{\theta}_{F,50\%}$, $\bar{\theta}_{50\%-75\%}$ and $\bar{\theta}_{75\%-100\%}$ measure return spillovers from the foreign to domestic markets when trading volume in the previously traded foreign market is low, normal, high, and very high, respectively.

For the stock markets located in the same region, a general pattern is observed where stock returns accompanied by lower trading volume are more likely to spill over to other markets on the next trading day. On the other hand, foreign returns associated

[50] Alternatively, Equation (5.22) can be obtained by rewriting β_0 in Equation (5.20) in terms of $\beta_1\bar{V}_F$ and $\bar{\theta}$ (i.e. $\beta_0 = \bar{\theta} - \beta_1\bar{V}_F$) and then substituting for β_0 in Equation (5.18).

with higher trading volume tend to have a negative impact on the next day's domestic returns.

For example, when the UK market is considered as the foreign market, the results in the last column in Table 5.1 show that the joint-dynamic coefficients $\beta_{1,Fra}$ and $\beta_{1,Ger}$ are both negative and statistically significant at the 1% level, implying that the magnitude of the return spillover effect from the UK to the French and German stock markets tends to decline with the preceding day's UK trading volume. This pattern is consistent with the findings of Gagnon and Karolyi (2003; 2009).

The parameter estimates of $\bar{\theta}$ show a clearer picture of the dynamics of the return spillovers in relation to different levels of trading volume. The estimation results of $\bar{\theta}$ reported in the first row in Table 5.1 indicate the size and significance of the return spillover effect from the UK to France when the preceding day's UK volume is very high, high, normal, low, and very low, respectively. More specifically, when the previous day's trading volume in the UK stock market is very low (i.e. $V_{UK,t-1} = \bar{V}_{UK,0-25\%}$), the return spillover coefficient $\bar{\theta}_{0-25\%}$ is equal to 0.1641 and is statistically significant at the 1% level. However, it is found that the size of the spillover effect tends to decline with the increasing level of the UK trading volume. When $V_{UK,t-1} = \bar{V}_{UK,25-50\%}$, the return spillover effect from the UK to France is still positive, but the size and significance of the spillover coefficient are reduced ($\bar{\theta}_{25-50\%}$ is equal to 0.0939 and significant at the 5% level). When the UK trading volume is increased to the average level (i.e. $\mathrm{V_{UK,t-1}} = \mathrm{\bar{V}_{UK,50\%}}$), a positive and statistically significant spillover coefficient $\bar{\theta}$ ($\bar{\theta}_{50\%}$ is equal to 0.0741 and significant at the 5% level) is still observed, but the magnitude of the return spillover effect keeps decreasing.

It is noteworthy that the return spillover effect from the UK to France becomes statistically insignificant following days associated with above-normal trading volume in the UK market. When the lagged trading volume in the UK market is high (i.e. $V_{UK,t-1} = \bar{V}_{UK,50-75\%}$), the return spillover coefficient $\bar{\theta}_{50\%-75\%}$ is positive but not significant at the 10% level, indicating a decreasing influence of the UK returns to French returns with increasing UK trading volume. When the lagged trading volume in the UK market is very high (i.e. $V_{UK,t-1} = \bar{V}_{UK,75-100\%}$), the sign of regression coefficient $\bar{\theta}$ changes from positive to negative. However, the result is not statistically significant, even at the 10% level.

The return spillover effect from the UK to France is statistically insignificant following a day associated with above-normal UK trading volume. Price movements in the French market are less likely to be in the same direction as liquidity-based price movements in the preceding day's UK market. On the other hand, the dynamic return spillovers are positive and statistically significant following days associated with low levels of trading volume, which can be interpreted as empirical evidence that information-based price movements in the UK market tend to have a positive impact on the following day's French market.

The estimation results of $\bar{\theta}$ reported in the second row in Table 5.1 show the size and significance of the return spillover effect from the UK to Germany when the preceding day's UK volume is very high, high, normal, low, and very low, respectively. There is evidence for a negative and statistically significant return spillover effect following days associated with higher trading volume in the UK market. This means that stock returns in the German market tend to move in the opposite direction from the preceding day's UK price movements when the UK trading volume is heavy. In other words, liquidity-based price movements in the UK market have a negative return spillover effect on the subsequent day's price changes in the German market.

In summary, the results show that the lagged FTSE100 index daytime returns associated with lower trading volume are more likely to spill over to the CAC40 index daytime returns on the next trading day. However, when the preceding trading volume in the UK stock market is very heavy, the positive return spillovers (i.e. the meteor shower effect in returns) are less likely to transmit to France and Germany and may even cause price reversals in the German market. It is important to point out that the pattern of the joint dynamics between return spillovers and trading volume from the UK to Germany is different from that to France, though the estimated $\beta_{1,Fra}$ and $\beta_{1,Ger}$ are both negative and statistically significant.

Furthermore, the estimated return spillover coefficient (denoted by β) from the UK to France is small and statistically insignificant in the dynamic return spillover model as suggested in Chapter 4 (estimation results are reported in Table 4.2), where the interaction between the foreign market return and trading volume is not modelled. However, the estimation results (reported in Table 5.1) in this chapter show that the return spillover effect from the UK to France is statistically significant and also large in size when the UK trading volume is not heavy. The results discussed above highlight the advantages of the model employed in this study in the analysis of return spillovers across international stock markets.

Table 5.2 and Table 5.3 report the estimation results of Equation (5.22) where the French and German stock markets are regarded as the signalling markets, respectively. The patterns of return spillovers and their interactive effects with trading volume are similar to those in Table 5.1.

For the stock markets located in different regions (inter-regional markets), mixed patterns of the joint-dynamic relations between stock returns and trading volume are observed. Tables 5.4 and 5.6 present the estimation results of Equation (5.22) where the US and Japanese stock markets are regarded as the signalling markets. Since the New York and Tokyo are two of the most important developed stock exchanges in the world, it is of particular interest to investigate how returns from these two markets can spill over to other markets.

First, the results indicate that the magnitude of return spillovers to the European markets from the US and Japanese markets is generally constant over different levels of lagged trading volume (i.e. the size of $\bar{\theta}$ does not vary a lot when $\bar{V}_{US}$ and $\bar{V}_{Jap}$ take on different values). This is confirmed by the statistically insignificant β_1 (except that $\beta_{1,UK}$ is only significant at the 10% level when the Japanese market is the signalling market) that measures the interactive effect between the return and volume from both markets to the European markets. It means that trading volume in the US and Japanese market does not provide investors with much information about the intensity of the returns spillovers from these two markets to the European markets.

Second, it appears that the return spillovers from the US (Japanese) market to the Hong Kong and Shanghai markets tend to decline with the trading volume in the US (Japanese) market. The observed pattern is similar to that found among the stock markets located in the same region and can be explained by the hypothesis of Gagnon and Karolyi (2003).

Last but not the least, there is an interesting pattern between the Japanese market and the US market. The estimation results show that the return spillovers between the US and Japan tend to increase with the trading volume in both directions. The return spillover effect from the US to Japan is larger in magnitude and significant at the 1% level when trading volume in the US market is very heavy (i.e. $V_{US,t-1} = \bar{V}_{US,75-100\%}$), but this effect becomes statistically insignificant when the US trading volume is very low (i.e. $V_{US,t-1} = \bar{V}_{US,0-25\%}$). The same pattern can also be found in the return spillovers from Japan to the US. The observed new pattern suggests that liquidity-induced price changes in the foreign market, which are typically associated with heavy trading volume, have a positive and statistically significant influence on the following day's price movements in the domestic market. In other words, liquidity-based price movements can also be transmitted across borders.

Under the CGW (1993) model, risk-averse foreign investors sell stocks for liquidity needs when they become more risk-averse. In this case, heavy trading volume is accompanied by a decrease of foreign stock prices in the current period. If this phenomenon (foreign liquidity trading) can increase the marginal investors' risk aversion in the subsequently opened domestic market and make them become more risk-averse, it will also cause the decline of stock prices in the domestic market resulting from the selling pressure of domestic liquidity traders. In consequence, the returns associated with heavy trading volume (liquidity trading) in the foreign market can spill over to the domestic market on the next trading day.

Table 5.7 and Table 5.8 report the estimation results for parameters $\bar{\theta}$ and β_1 where the Hong Kong and Shanghai markets are considered as the signalling markets. The estimation results show that return spillover effects from Hong Kong and Shanghai to the US and UK tend to become stronger when trading volume in the Hong Kong and Shanghai exchanges are higher. This provides more evidence indicating that liquidity-based price movements do transmit across borders.

5.3.3 Robustness Test Results on De-trended Trading Volume

The preliminary data analysis in Chapter 3 finds both linear and non-linear time trends in the trading volume time series. In order to examine the robustness of the results reported in the last section to the presence of time trends in trading volume, the raw trading volume series is de-trended, and the regression of model described in Section 5.3.1 is repeated. The results are reported in Tables 5.9 –5.16.

The results show that there are no substantial changes of patterns when de-trended trading volume is employed. The findings reported in Section 5.3.2 are robust to the influence of time trend on trading volume. For example, Table 5.9 reports the dynamic relation between return spillovers and de-trended trading volume from the UK market to the other international stock markets under investigation. It suggests that the estimated β_1 which captures the interactive effect of trading volume and return is still negative and statistically significant when France and Germany are regarded as signal receiving markets. The pattern of $\bar{\theta}$ is also consistent with that reported in Table 5.1 for all the countries. The return spillover effects from the UK to France are estimated at: -0.0134 (statistically insignificant at the 10% level), 0.0519 (statistically insignificant at the 10% level), 0.0741 (statistically significant at the 5% level), 0.0939 (statistically significant at the 5% level), and 0.1641 (statistically significant at the 1% level), when the preceding UK trading volume is very heavy, heavy, normal, low, and very low, respectively. These results compare with their counterparts of 0.0004 (statistically insignificant at the 10% level), 0.0523 (statistically insignificant at the 10% level), 0.0658 (statistically significant at the 10% level), 0.0789 (statistically significant at the 5% level) and 0.1317 (statistically significant at the 1% level), when the de-trended trading volume is used.

5.3.4 Robustness Test Results on Turnover by Value

Several authors advocate the usage of the turnover ratio, defined as number of stocks traded to number of stocks outstanding, instead of raw trading volume as a measure of trading activity. For instance, Lo and Wang (2000) suggest that there are sound theoretical arguments for using turnover of individual stocks in the cross-sectional studies. By using a two-asset, two-investor numerical example, they show that using the total number of shares traded normalised by the total number of shares outstanding gives the same results as turnover ratios using dollar trading volume. However, Lo and Wang (2000) also show that for portfolios, as opposed to individual stocks, turnover is questionable as a measure of trading activity: although turnover is a preferred measure of trading activity for an individual stock, there is still some ambiguity in extending it to the portfolio case. There is no neutral definition of portfolio turnover in the absence of a theory for which portfolios are traded, why they are traded and how they are traded. Furthermore, stock turnover is argued to be superior if the focus of study is on the cross-sectional properties of volume (e.g. the series are normalised, which makes them easier to compare cross-sectionally). However, this study focuses on the time-series variation in volume and its relations with market index return spillovers. Thus, the (detrended) trading volume instead of turnover is used in Section 5.3.2 and 5.3.3 to measure trading activity, following Lee and Rui (2002), Gagnon and Karolyi (2003), Gebka (2012), among others.[51]

However, in order to investigate whether the models used provide qualitatively similar results using different measures of trading volume, the study in this section employs the turnover by value (VA series) data from DataStream, which calculates aggregation of number of shares traded multiplied by the closing price of each constituent stock of market index. The available data covers the period from 22 September 2003 to 30 July 2010 on the FTSE 100, CAC40, DAX30, S&P/TSX, Hang Seng, TOPIX and Shanghai A Share Stock Indices, but not the S&P 500 index. The results are reported in Tables A1-A7 in Appendix A.

The results show that overall patterns across all models are very similar. There are no substantial changes of patterns when turnover by value is used as a measure of market activity. The findings reported in Section 5.3.2 are robust to different measures of trading volume.

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[51] Lee and Rui (2002) investigate the dynamic relations, casual relations and the sign and size of dynamic effects between stock market trading volume and returns across the US, UK and Japanese stock markets. Gagnon and Karolyi (2003) analyse short-run comovements of market returns in relation to trading volume between the New York and Tokyo stock exchanges. Gebka (2012) studies the dynamic relationship between index returns, return volatility, and trading volume for eight Asian markets (i.e. Hong Kong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand) and the US.

For example, Table A1 reports the dynamic relation between return spillovers and turnover by value from the UK market to the other international stock markets. It suggests that the estimated β_1 that captures the interactive effect of trading volume and return is still negative and statistically significant when France and Germany are regarded as signal receiving markets.

The pattern of $\bar{\theta}$ is also consistent with the one reported in Table 5.1 for all the countries. The estimation results of $\bar{\theta}$ reported in the first and second rows in Table A1 indicate the size and significance of the return spillover effect from the UK to France and Germany.

The return spillover effects ($\bar{\theta}$) from the UK to France are estimated at: -0.0134 (statistically insignificant at the 10% level), 0.0519 (statistically insignificant at the 10% level), 0.0741 (statistically significant at the 5% level), 0.0939 (statistically significant at the 5% level), and 0.1641 (statistically significant at the 1% level), when the preceding UK trading volume is very heavy, heavy, normal, low, and very low, respectively. These results compared with their counterparts of -0.0227 (statistically insignificant at the 10% level), 0.0499 (statistically insignificant at the 10% level), 0.0642 (statistically significant at the 10% level), 0.0880 (statistically significant at the 5% level) and 0.1419 (statistically significant at the 1% level) when the turnover by value data is used. The parameter estimates of $\bar{\theta}$ show a consistent pattern of the dynamics of the return spillovers using both measures of trading volume, and the size and statistical significance of parameter estimates of $\bar{\theta}$ change little when raw trading volume is replaced by turnover by value as a measure of market activities .

The return spillover effects ($\bar{\theta}$) from the UK to Germany are estimated at: -0.1201 (statistically significant at the 1% level), -0.0688 (statistically significant at the 10% level), -0.0514 statistically insignificant at the 10% level), -0.0358 (statistically insignificant at the 10% level) and 0.0914 (statistically insignificant at the 10% level), when the preceding UK trading volume is very heavy, heavy, normal, low, and very low, respectively. These results compared with their counterparts of -0.1135 (statistically significant at the 5% level), -0.0672 (statistically insignificant at the 10% level), -0.0581 (statistically insignificant at the 10% level), -0.0429 (statistically insignificant at the 10% level) and -0.0086 (statistically insignificant at the 10% level) when the turnover by value data is employed. The return spillover coefficient $\bar{\theta}$ is statistically significant at the 1% and 5% levels when the preceding UK raw trading volume is very heavy and heavy. But return spillover coefficient $\bar{\theta}$ is only statistically significant at the 5% level when the preceding UK turnover by value is very heavy. It becomes statistically insignificant at the 10% level when turnover by value in the previous UK market is heavy. Although the return spillover effects ($\bar{\theta}$) from the UK to Germany become less statistically significant when using the turnover by value data, it is important to point out these changes are not substantial. These estimates are on the borderline of statistical significance (e.g. p-value for $\bar{\theta}$ is 0.0120 and 0.1168 when the UK turnover by value is at the very heavy and heavy levels). They are slightly over the p-values of 0.01 and 0.1 for parameter estimates of $\bar{\theta}$ to be statistically significant at the 1% and 10% levels.

A similar pattern is observed across tables. For example, the estimated $\bar{\theta}$ parameters reported in the Table A2 are similar to that presented in Table 5.2, but some results are again on the borderline of statistical significance. Table A2 shows that the return spillover coefficients (as captured by $\bar{\theta}_{0-25\%}$) from France to Germany and the UK are -0.1046 with p-value of 0.0998 and 0.0704 with p-value of 0.1019, respectively, following a very heavy trading day in the Paris stock exchange (as measured by turnover by value). These compare to the estimates of $\bar{\theta}_{0-25\%}$ equal to -0.1024 with p-value of 0.1200 and 0.0752 with p-value of 0.0766 in Table 5.2. In Table A3, it is shown that $\bar{\theta}_{75\%-100\%}$ which captures the return spillover effect from the Frankfurt stock market to the Paris market is 0.0794 with p-value of 0.0986. This result is qualitatively no different from that reported in Table 5.3, which is equal to 0.0623, but statistically significant at the 10% level. There are also other results which are on the borderline of statistical significance with the p-value greater than 0.1 which further confirm the observed patterns (e.g. in Table A3, the estimate of β_1 for Hong Kong has a p-value of 0.1081, so it only marginally exceeds the 0.10 level)

The study in this section also finds positive and statistically significant β_1, implying that liquidity-based price movements can also be transmitted across borders. The estimation results of $\bar{\theta}$ in Tables A6 and A7 show that return spillover effects from Hong Kong and Shanghai to the UK become stronger when trading volume in the Hong Kong and Shanghai exchanges are higher, i.e., the magnitude and significance of return spillovers from the Hong Kong and Shanghai stock exchanges to the London stock market tend to increase with the previous day’s turnover by value in these markets. The new results are consistent with the ones using the raw trading volume (as reported in Tables 5.7 and 5.8).

Although the estimates for $\bar{\theta}$ parameters exhibit similar patterns across all tables, there are differences in the estimates of the parameters β_1. They become statistically insignificant in some cases when using the turnover by value data (see e.g. Table 5.3 *versus* Table A3). The results in Table 5.3 and Table A3 report the dynamics of return spillovers in relation to raw trading volume and turnover by value series from the German stock exchange to other markets. The joint dynamic coefficients β_1 in Table 5.3 are positive and statistically significant at the 5% and 10% levels when the Japanese and Hong Kong markets are regarded as signal receiving markets. They compare to insignificant though positive β_1 for both markets in Table A3. These results provide evidence implying that raw trading volume captures some important aspects of market activity which were not captured by turnover by value. This indicates that the daily raw trading volume that shows the aggregation of number of shares for each stock in the index traded during the day is a good measure of market activity. It is a good proxy for traders' attitudes to risk and reflects their sentiments in the stock market. Furthermore, it is noteworthy that although β_1 estimates become statistically insignificant after using the turnover by value data, the dynamic of $\bar{\theta}$ estimates remains consistent with the previous results. For example, the return spillover effect from the German stock market to the Japanese stock market tends to increase with the previous day's German trading volume regardless of the measure of volume employed.

In summary, the results of robustness tests are reported in this section using the turnover by value data obtained from DataStream as a measure of market activity. The new results from the models with turnover by value are consistent with the previous results, i.e. the estimates for $\bar{\theta}$ parameters present similar patterns as the previous ones for the raw trading volume. They provide the evidence that the models used provide qualitatively similar results using different measures of trading volume. Section 5.3.4 also discusses some differences in the estimates of β_1, i.e. they become statistically insignificant at the 10% level in some cases when the turnover by value data is used, though the estimates $\bar{\theta}$ parameters exhibit similar patterns across all tables. This finding indicates that raw trading volume captures important aspects of market activity.

5.4 Models and Results: Trading Volume, Return Autocorrelations and International Return Spillovers

5.4.1 Research Questions and Model Specifications

This section investigates the interactions between stock returns and trading volume at the aggregate market level in both domestic and international stock market contexts.

A growing body of literature has analysed the joint dynamics of stock returns and trading volume in a domestic market context (e.g. Campbell, Grossman and Wang, 1993; Wang, 1994; Conrad, Hameed and Niden, 1994; Llorente, Michaely, Saar and Wang, 2002; Connolly and Stivers, 2003). The econometric models employed in these studies share a similar structure as the one in Connolly and Stivers (2003). The proposed model is defined as follows:

$$R_{H,t} = \mu_H + \left(\alpha_0 + \alpha_{1,H} V_{H,t-1}\right) R_{H,t-1} + \epsilon_t, \tag{5.23}$$

where $V_{H,t-1}$ is the domestic market trading volume at time *t*; $R_{H,t}$ and $R_{H,t-1}$ denote the domestic market returns at time *t* and *t-1*, respectively. The joint-dynamic coefficient $\alpha_{1,H}$ captures the interactive effect between stock returns and trading volume.

Given the fact that evidence in the literature has shown the existence of strong return spillover effects across international stock markets, the study in this section controls for the impact of preceding foreign returns on domestic returns so that a clearer pattern of the first-order return autocorrelations can be investigated without the influence of foreign markets. The model used is specified as:

$$R_{H,t} = \mu_H + \left(\alpha_0 + \alpha_{1,H} V_{H,t-1}\right) R_{H,t-1} + \beta R_{F,t-1} + \epsilon_t, \tag{5.24}$$

where $R_{F,t-1}$ are the open-to-close market returns in the previously traded foreign market; the parameter $\alpha_{1,H}$ captures the dynamics of stock returns and trading volume in the domestic market after controlling for the impact of foreign market returns on the preceding day.

Let $\gamma_{H,t} = \alpha_0 + \alpha_1 V_{H,t-1}$ and $\bar{\gamma}_H = (\alpha_0 + \alpha_1 \bar{V}_H)$. In order to obtain the standard error of the estimated $\bar{\gamma}_H$, the same method as suggested in Section 5.3 is employed. Equation (5.24) can be rewritten as:

$$R_{H,t} = \mu_H + \bar{\gamma}_H R_{H,t-1} + \alpha_{1,H} R_{H,t-1}(V_{H,t-1} - \bar{V}_H) + \beta R_{F,t-1} + \epsilon_t \qquad (5.25)$$

The parameter $\bar{\gamma}_H$ measures the partial effect of $R_{H,t-1}$ on $R_{H,t}$ when $V_{H,t-1} = \bar{V}_H$. $\bar{V}_H$ is the mean value of domestic market trading volume between certain percentiles of interest. For example, $\bar{V}_{Jap,0-25\%}$ is the average level of Japanese trading volume that is within the 1st quartile (i.e. very low trading volume). $\bar{\gamma}_{Jap,0-25\%}$ measures the first-order autocorrelation of the Japanese returns between time *t* and time *t-1* when Japanese trading volume at time *t-1* is very low. In Equation (5.25), the model also controls for the international return spillover effect. It is essentially an extension of the Connolly and Stivers model in Equation (5.23), employed to investigate the behaviour of the first-order return autocorrelations with respect to different levels of trading volume.

5.4.2 Results and Discussion

This section reports the results for the first-order return autocorrelation behaviour of domestic market indices in relation to trading volume by taking into account the influence of foreign market information. The existing literature suggests that the US market plays an important role as the information producer and should be the most influential market in the world (e.g. Eun and Shim, 1989; Hsin, 2004; Wang and Firth, 2004). This study thus chooses the New York stock market as the signalling (foreign) market while investigating serial return autocorrelations in the other markets (Tokyo, Hong Kong, Shanghai, London, Frankfurt, Paris and Toronto). The estimation results of $\bar{\gamma}_H$ which capture the first-order return autocorrelations in these markets with and without considering the influence from the US are reported in Tables 5.17 and Table 5.18, respectively.

Tables 5.17 and 5.18 also report estimation results of the joint-dynamic coefficient $\alpha_{1,H}$ (the regression coefficient of the interactive term between lagged domestic market returns and trading volume). The parameter estimates of $\alpha_{1,H}$ are negative for all the investigated markets in both tables, though the results for the Tokyo, Frankfurt and New York markets are not statistically significant at the 10% level. This pattern is consistent with the specific prediction of the negative sign of $\alpha_{1,H}$ in the CGW (1993) model, suggesting that price changes accompanied by heavy trading volume tend to be reversed on the next trading day.

It is important to point out that the existing literature (e.g. Campbell et al. 1993; Connolly and Stivers, 2003) only investigates the sign and significance of the joint-dynamic coefficient $\alpha_{1,H}$ and does not explicitly explain the behaviour of the first-order autocorrelations in relation to trading volume. The discussion below provides additional information regarding the size and significance of return autocorrelations in relation to domestic market trading volume. It highlights the distinguishable advantage of the econometric model employed in this study.

The new approach of analysing joint dynamics of returns and trading volume allows one to examine the size and significance of return autocorrelations at different levels of domestic market trading volume. Using the Asian stock markets for example, the estimation results in Tables 5.17 show that the first-order return autocorrelations in Tokyo, Hong Kong and Shanghai stock markets are negative and statistically significant when their previous day's domestic market trading volume is very heavy (i.e. yesterday's domestic market trading volume is at mean average of the 4th quartile). The parameter $\bar{\gamma}_{Jap,75-100\%}$ is equal to -0.0587 and statistically significant at the 5% level. The parameters $\bar{\gamma}_{HK,75-100\%}$ and $\bar{\gamma}_{Chn,75-100\%}$ are equal to -0.1303 and -0.1251, respectively, and both statistically significant at the 1% level. The negative and statistically significant first-order return autocorrelation following days associated with heavy trading volume can also be found in the London, Paris and New York stock markets.[52] There is strong empirical evidence in favour of the prediction of the CGW

[52] The first-order return autocorrelation in the Frankfurt market is statistically insignificant regardless of the levels of domestic market trading volume when the US return spillover effect is not controlled for (as shown in Table 5.17). But the dynamics shares a similar pattern that the size and significance of the first-order return autocorrelation decrease with the domestic market trading volume. More importantly, the

model (1993), showing that the liquidity-based price changes, which are typically associated with heavy trading volume, tend to be reversed on the next trading day.

More importantly, the first-order return autocorrelations in the three Asian stock markets are not significant when the preceding day's home market trading volume is very low or low (i.e. lagged home trading volume is in the 1st or 2nd quartile), indicating that information-based price changes in the domestic market are not correlated between two consecutive days. It is because the arrival of information that can affect fundamental value of stocks is more likely to be stochastic. The market return thus cannot be predicted purely based on the past domestic market price information. The market is weak-form efficient in that all information contained in historical price movements in the domestic market has been fully reflected in current market prices. The same pattern can also be observed in the London, Paris and New York stock markets.[53]

The parameter estimates of $\bar{\gamma}_H$ for Equation (25) are shown in Table 5.18. The results report the first-order return autocorrelations in the domestic market after controlling for the return spillovers from the previously opened US market. The most striking finding is that there are remarkable differences between the estimation results of $\bar{\gamma}_H$ reported in Table 5.17 and those obtained from the regression model in Equation (25), which takes into account the return spillover effect from the US market. The results show that the negative first-order return autocorrelations in the Tokyo, London and Frankfurt stock markets become stronger in terms of the size and statistical significance when the model controls for the influence of the US. Note that it is these markets for which the positive return spillover effect (i.e. the meteor shower effect in returns) from the US market is statistically significant (as suggested by the return spillover coefficients reported in Panel D in Table 4.2 in Chapter 4). By controlling for this US effect, it is found that the negative first-order autocorrelation becomes stronger in these markets.

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negative first-order return autocorrelation becomes statistically significant at the 1% level following heavy trading volume days in the German stock market when the return spillover effect from the US market has been considered in the model (as shown in Table 5.18).

[53] This study also finds a positive first-order return coefficient following a day with light trading volume in Canada (as suggested in Table 5.18), which can be interpreted as the evidence that information-based price movements can also cause a return continuation on the following trading day. However, this result is only significant at the 10% level.

5.5 Summary

By employing the daytime returns and trading volume of equity market indices from the world's eight biggest stock exchanges, this study investigates the interactions between stock returns and trading volume on the aggregate market level in both international and domestic market contexts.

The analysis of empirical results is closely related to the economic implications of the heterogeneous-agents model of trading proposed by Campbell et al. (1993). This study investigates explicitly the joint dynamics between stock returns and trading volume using a new approach. It is believed that no similar analysis has been conducted in the literature. It also investigates the first-order autocorrelation behaviour of stock returns in relation to trading volume after controlling for the return spillover effect from the US. The findings contribute to the existing literature by documenting the new pattern of the joint dynamics between stock returns and trading volume across international stock markets.

The study presents new evidence indicating that the foreign return spillover effect is sensitive to the volume of trades in foreign markets. Trading volume provides valuable information to explain the time-varying nature of stock market comovements.

The estimation results show that regression coefficients (denoted by β_1), which capture the interactions between foreign market returns and trading volume, are more likely to be negative and statistically significant, suggesting that the positive return spillovers tend to decrease with trading volume in the foreign markets. More importantly, positive return spillovers to the domestic market are stronger following days associated with lower trading volume. On the other hand, investors in the domestic market are more likely to react negatively to the foreign price movements associated with higher trading volume. This return-volume dynamic pattern supports the hypothesis of Gagnon and Karolyi (2003), indicating that information-based price movements in one market – which are typically associated with normal or low trading volume – are less likely to be reversed and are more likely to be positively related with the price movements in other markets in the next trading period. Similarly, liquidity-based price movements – which are typically associated with heavy trading volume – are less likely to be positively related with the price movements in other markets in the next trading period because they do not necessarily reflect a fundamental revaluation of stock prices by the market.

This study confirms that the positive and statistically significant return spillovers exist between the US and Japanese stock markets in both directions, which is consistent with the findings from Hamao et al. (1990) and Lin et al. (1994). However, the magnitude and significance of spillovers from the Japan to the US and UK increase with the preceding trading volume in Japan, indicating that the return spillover effect is stronger following a day with higher trading volume in the Japanese stock market. This pattern is also evident in the joint dynamics of trading volume and return spillovers from Hong Kong to the US and UK, from China to the US, and from the US and Germany to Japan. The CGW (1993) model suggests that heavy trading volume at short horizons is normally associated with liquidity trades. The observed new pattern suggests that liquidity-based price changes originating in one market can transmit across the regions.

The study confirms the findings in the literature that trading volume is useful in understanding the behaviour of serial correlations in stock returns. The estimation results indicate a consistent pattern of joint dynamics between returns and trading volume in the stock market, which can be explained by the CGW (1993) model.

The estimation results show that the first-order return autocorrelations (as captured by $\bar{\gamma}_{H,0-25\%}$) are more likely to be statistically insignificant even at the 10% level when the preceding day's home trading volume is very low, indicating that the information-based price changes in the domestic market are not correlated between two consecutive days. This pattern is reasonable since the arrival of the information that can affect fundamental value of a stock is usually stochastic and this information has been fully and rapidly absorbed in the market in the contemporaneous trading period. Thus it exerts little influence in the next period. However, a positive first-order return coefficient is found when trading volume in Canada is very low, which means that information-based price movements can also cause a return continuation. But the result is statistically significant only at the 10% level.

The negative and statistically significant first-order autocorrelations of stock market returns following days associated with very heavy trading volume (as captured by

$\bar{\gamma}_{H,75-100\%}$) are observed in all the investigated markets except for Germany (i.e. $\bar{\gamma}_{Ger,75-100\%}$ is statistically insignificant at the 10% level, thought negative), implying that the liquidity-based price movements, which are normally related to high trading volume, are more likely to induce a return reversal on the following trading day. However, it is noteworthy that the negative first-order return autocorrelation becomes statistically significant at the 1% level following heavy trading volume days in the German stock market if the return spillover effect from the US is introduced in the model. The study finds that the negative first-order autocorrelations are stronger when the model controls for the meteor shower effect in returns from the US market.

In summary, this study investigates the returns-volume dynamics across the world's eight largest stock markets relying on the theoretical model of CGW (1993). In both domestic and international market contexts, the behavior of stock return autocorrelations and cross-market return spillovers and their relations with trading volume are studied. The results show that these relations are sensitive to interactions with trading volume. Trading volume provides insight into the nature of stock price movements and cross-market comovements. It does contain valuable information about future price movements and comovements across international stock markets, which can be particularly beneficial for investors in designing their trading strategies. The study in Chapter 6 thus explores the benefits of international stock market information (i.e. stock prices and trading volume) in domestic stock market trading.

Table 5.1: The Dynamics of Return Spillovers (in relation to Trading Volume) from the UK to other Countries

The tables below reports parameter estimates of $\bar{\theta}$ and β_1 for the following model:

$R_{H,t} = \mu + \alpha R_{H,t-1} + \bar{\theta} R_{F,t-1} + \beta_1 R_{F,t-1}(V_{F,t-1} - \bar{V}_F) + \epsilon_t$.

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}$,

where μ is a constant; $R_{H,t}$ and $R_{H,t-1}$ denote the daytime return in the domestic market at time *t* and *t-1*, respectively; $R_{F,t-1}$ is the previous daytime return in the foreign market; $V_{F,t-1}$ is the foreign market trading volume at time *t-1*; $\bar{V}_F$ denotes the mean level of foreign market trading volumes between certain percentiles of interest, $\bar{\theta}$ measures the partial effect of $R_{F,t-1}$ on R_t when $V_{F,t-1} = \bar{V}_F$. The parameter β_1 captures the interaction effect between trading volume and returns from the foreign market. $\bar{\theta}_{0-25\%}$, $\bar{\theta}_{25\%-50\%}$, $\bar{\theta}_{F,50\%}$, $\bar{\theta}_{50\%-75\%}$, and $\bar{\theta}_{75\%-100\%}$ measure return spillover effects from the foreign to domestic markets when the previous day's foreign market trading volume is at the mean level of the 0-25th percentiles (volume is very low), 25-50th percentiles (volume is low), 50th percentile (volume is normal), 50-75th percentiles (volume is high) and 75-100th percentiles (trading volume is very high), respectively.

UK($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
France	-0.0134 (0.7241)	0.0519 (0.1298)	0.0741 ** (0.0382)	0.0939 ** (0.0138)	0.1641 *** (0.0016)	-1.40 E-07 *** (0.0016)
Germany	-0.1201 *** (0.0087)	-0.0688 * (0.0897)	-0.0514 (0.2124)	-0.0358 (0.4028)	0.0194 (0.7220)	-1.10E-07 ** (0.0155)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1696 *** (0.0000)	0.1541 *** (0.0000)	0.1487 *** (0.0000)	0.1440 *** (0.0000)	0.1271 *** (0.0008)	3.34E-08 (0.5024)
Hong Kong	-0.0274 (0.4473)	-0.0544 ** (0.0274)	-0.0636 ** (0.0149)	-0.0717 ** (0.0155)	-0.1006 ** (0.0477)	5.77E-08 (0.3013)
China	0.0156 (0.7562)	0.0129 (0.7269)	0.0120 (0.7489)	0.0112 (0.7814)	0.0083 (0.8929)	5.75E-09 (0.9306)

Notes:

1. For all tables, asterisks *, **, and *** represent that regression coefficient is statistically significant at the 10% level (critical value: 1.64), the 5% level (critical value: 1.96), and the 1% level (critical value: 2.58), respectively. The p-values are reported in parentheses.

2. The result is written in floating-point format, and-1.40E-07 means that -1.40 times 10^{-7}.

3. The open-to-close return spillovers cannot be explicitly investigated due to two hours of overlapping trading time between the late afternoon in the European stock markets and early morning in the North American markets. The study excludes this sequence and report "N/A" in tables.

Table 5.2: The Dynamics of Return Spillovers (in relation to Trading Volume) from France to other Countries

France ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	-0.2070 *** (0.0003)	-0.1553 *** (0.0049)	-0.1495 *** (0.0074)	-0.1331 ** (0.0225)	-0.1024 (0.1200)	-8.38E-07 * (0.0544)
UK	-0.0730 (0.1025)	0.0002 (0.9962)	0.0085 (0.8104)	0.0317 (0.3837)	0.0752 * (0.0766)	-1.19E-06 *** (0.0036)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1643 *** (0.0000)	0.1631 *** (0.0000)	0.1629 *** (0.0000)	0.1626 *** (0.0000)	0.1618 *** (0.0001)	1.98E-08 (0.9637)
Hong Kong	-0.0379 (0.1688)	-0.0593 ** (0.0121)	-0.0617 ** (0.0127)	-0.0685 ** (0.0189)	-0.0812 ** (0.0441)	3.46E-07 (0.3890)
China	-0.0067 (0.8899)	-0.0059 (0.8796)	-0.0058 (0.8864)	-0.0055 (0.9074)	-0.0050 (0.9396)	-1.36E-08 (0.9841)

Table 5.3: The Dynamics of Return Spillovers (in relation to Trading Volume) from Germany to other Countries

Germany ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
France	0.0623 (0.2168)	0.0950 ** (0.0302)	0.0974 ** (0.0263)	0.1074 ** (0.0156)	0.1245 *** (0.0095)	-5.19E-07 (0.1643)
UK	0.0074 (0.8585)	0.0139 (0.6620)	0.0143 (0.6501)	0.0164 (0.6096)	0.0198 (0.5844)	-1.04E-07 (0.7788)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1793 *** (0.0000)	0.1363 *** (0.0000)	0.1332 *** (0.0000)	0.1199 *** (0.0000)	0.0973 *** (0.0027)	6.84E-07 * (0.0734)
Hong Kong	0.0009 (0.9735)	-0.0600 *** (0.0055)	-0.0646 *** (0.0036)	-0.0836 *** (0.0010)	-0.1156 *** (0.0007)	9.73E-07 ** (0.0107)
China	0.0002 (0.9964)	-0.0114 (0.7361)	-0.0122 (0.7215)	-0.0158 (0.6790)	-0.0219 (0.6605)	1.84E-07 (0.7419)

Table 5.4: The Dynamics of Return Spillovers (in relation to Trading Volume) from the US to other Countries

US ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1020 ** (0.0118)	0.0998 *** (0.0011)	0.0996 *** (0.0014)	0.0987 *** (0.0077)	0.0978 ** (0.0329)	1.20E-09 (0.9465)
France	0.0163 (0.6555)	-0.0112 (0.6929)	-0.0135 (0.6407)	-0.0243 (0.4700)	-0.0349 (0.3915)	1.46E-08 (0.3339)
UK	0.3793 *** (0.0000)	0.3468 *** (0.0000)	0.3441 *** (0.0000)	0.3314 *** (0.0000)	0.3188 *** (0.0000)	1.73E-08 (0.3523)
Canada	-0.0400 (0.2618)	-0.0010 (0.7184)	-0.0075 (0.7902)	0.0043 (0.8949)	0.0158 (0.6843)	-1.60E-08 (0.2713)
Japan	0.1317 *** (0.0000)	0.0534 ** (0.0421)	0.0469 * (0.0855)	0.0163 (0.6215)	-0.0140 (0.7266)	4.17E-08 *** (0.0005)
Hong Kong	-0.1160 *** (0.0005)	-0.0558 ** (0.0264)	-0.0508 * (0.0522)	-0.0272 (0.4159)	-0.0040 (0.9264)	-3.21E-08 * (0.0595)
China	-0.0452 (0.2297)	0.0566 (0.1571)	0.0651 (0.1186)	0.1049 ** (0.0411)	0.1441 ** (0.0214)	-5.42E-08 *** (0.0057)

Table 5.5: The Dynamics of Return Spillovers (in relation to Trading Volume) from Canada to other Countries

Canada ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	-0.0242 (0.6342)	0.0508 (0.1305)	0.0728 ** (0.0295)	0.0980 *** (0.0074)	0.1668 *** (0.0033)	-1.07E-06 ** (0.0241)
France	-0.0388 (0.4148)	-0.0055 (0.8547)	0.0043 (0.8873)	0.0155 (0.6474)	0.0460 (0.4026)	-4.76E-07 (0.3096)
UK	0.2725 *** (0.0000)	0.2815 *** (0.0000)	0.2842 *** (0.0000)	0.2872 *** (0.0000)	0.2954 *** (0.0000)	-1.29E-07 (0.7431)
US	-0.0730 (0.2175)	-0.0049 (0.8922)	0.0150 (0.6621)	0.0379 (0.2912)	0.1003* (0.0705)	-9.74E-07 * (0.0590)
Japan	0.1172 *** (0.0042)	0.0996 *** (0.0002)	0.0944 *** (0.0006)	0.0885 *** (0.0053)	0.0723 (0.1662)	2.53E-07 (0.5568)
Hong Kong	-0.0741 (0.1095)	-0.0182 (0.5080)	-0.0018 (0.9485)	0.0170 (0.5993)	0.0682 (0.2177)	-8.00E-07 * (0.0967)
China	-0.0689 (0.1087)	0.0561 (0.1778)	0.0928 ** (0.0393)	0.1348 *** (0.0075)	0.2493 *** (0.0004)	-1.79E-06 *** (0.0000)

Table 5.6: The Dynamics of Return Spillovers (in relation to Trading Volume) from Japan to other Countries

Japan ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1492 *** (0.0009)	0.1538 *** (0.0000)	0.1555 *** (0.0000)	0.1565 *** (0.0000)	0.1626 *** (0.0068)	-8.22E-09 (0.8787)
France	0.0676 ** (0.0303)	0.0715 *** (0.0016)	0.0729 *** (0.0024)	0.0738 *** (0.0046)	0.0789 * (0.0953)	-6.88E-09 (0.8587)
UK	0.2792 *** (0.0000)	0.2456 *** (0.0000)	0.2327 *** (0.0000)	0.2253 *** (0.0000)	0.1805 *** (0.0000)	6.04E-08 * (0.0971)
US	0.1182 *** (0.0003)	0.0795 *** (0.0003)	0.0646 *** (0.0042)	0.0561 ** (0.0198)	0.0045 (0.9184)	6.96E-08 * (0.0709)
Canada	0.0078 (0.8097)	0.0352 * (0.0849)	0.0458 ** (0.0168)	0.0518 *** (0.0084)	0.0883 ** (0.0128)	-4.93E-08 (0.1510)
Hong Kong	-0.0846 ** (0.0401)	-0.0525 ** (0.0462)	-0.0402 (0.1249)	-0.0331 (0.2346)	0.0097 (0.8534)	-5.78E-08 (0.2274)
China	-0.0992 * (0.0564)	-0.0319 (0.3570)	-0.0060 (0.8681)	0.0089 (0.8190)	0.0987 (0.1776)	-1.21E-07 * (0.0559)

Table 5.7: The Dynamics of Return Spillovers (in relation to Trading Volume) from Hong Kong to other Countries

HongKong ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1765 *** (0.0001)	0.1451 *** (0.0000)	0.1401 *** (0.0000)	0.1248 *** (0.0010)	0.1139 ** (0.0140)	2.48E-08 (0.3692)
France	0.0873 *** (0.0099)	0.1022 *** (0.0000)	0.1046 *** (0.0000)	0.1119 *** (0.0002)	0.1171 *** (0.0008)	-1.18E-08 (0.5272)
UK	0.2815 *** (0.0000)	0.2078 *** (0.0000)	0.1959 *** (0.0000)	0.1600 *** (0.0000)	0.1343 *** (0.0001)	5.84E-08 *** (0.0063)
US	0.1970 *** (0.0000)	0.1268 *** (0.0000)	0.1155 *** (0.0001)	0.0813 ** (0.0201)	0.0569 (0.1633)	5.56E-08 *** (0.0041)
Canada	0.0305 (0.3742)	0.0786 *** (0.0001)	0.0863 *** (0.0000)	0.1098 *** (0.0000)	0.1265 *** (0.0001)	-3.81E-08 * (0.0693)
Japan	0.0684 ** (0.0332)	0.0395 (0.1390)	0.0349 (0.2182)	0.0208 (0.5653)	0.0108 (0.8047)	2.29E-08 (0.2926)
China	-0.1032 ** (0.0206)	-0.0166 (0.6851)	-0.0027 (0.9486)	0.0395 (0.4065)	0.0696 (0.1906)	-6.85E-08 *** (0.0014)

Table 5.8: The Dynamics of Return Spillovers (in relation to Trading Volume) from China to other Countries

China ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.0613 * (0.0727)	0.0284 * (0.0643)	0.0243 (0.1023)	0.0084 (0.6627)	-0.0011 (0.9649)	5.01E-09 (0.2202)
France	0.0398 (0.2107)	0.0114 (0.4091)	0.0078 (0.5485)	-0.0059 (0.7143)	-0.0141 (0.5019)	4.34E-09 (0.2383)
UK	0.0714 ** (0.0239)	0.0436 *** (0.0031)	0.0401 *** (0.0039)	0.0267 * (0.0894)	0.0186 (0.3486)	4.24E-09 (0.2207)
US	0.0982 ** (0.0132)	0.0295 * (0.0565)	0.0209 (0.1331)	-0.0122 (0.4560)	-0.0321 (0.1540)	1.05E-08 ** (0.0196)
Canada	0.0310 (0.1809)	0.0248 ** (0.0404)	0.0240 ** (0.0426)	0.0210 (0.1426)	0.0192 (0.2771)	9.46E-10 (0.7214)
Hong Kong	-0.0485 ** (0.0121)	-0.0190 (0.1332)	-0.0153 (0.2407)	-0.0010 (0.9514)	0.0075 (0.7071)	-4.50E-09 * (0.0645)
Japan	-0.0163 (0.5071)	-0.0203 (0.1332)	-0.0208 (0.1221)	-0.0228 (0.1746)	-0.0240 (0.2439)	6.16E-10 (0.8320)

Table 5.9: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from the UK to other Countries

UK ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
France	0.0004 (0.9924)	0.0523 (0.1294)	0.0658 * (0.0660)	0.0789 ** (0.0367)	0.1317 *** (0.0094)	-1.17E-07 ** (0.0128)
Germany	-0.1051 ** (0.0185)	-0.0674 * (0.0996)	-0.0576 (0.1695)	-0.0480 (0.2705)	-0.0096 (0.8633)	-8.50E-08 * (0.0921)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1594 *** (0.0000)	0.1510 *** (0.0000)	0.1487 *** (0.0000)	0.1466 *** (0.0000)	0.1380 *** (0.0011)	1.90E-08 (0.7331)
Hong Kong	-0.0314 (0.3458)	-0.0610 ** (0.0146)	-0.0687 ** (0.0121)	-0.0762 ** (0.0145)	-0.1063 ** (0.0468)	6.67E-08 (0.2851)
China	0.0025 (0.9566)	0.0203 (0.5775)	0.0250 (0.5129)	0.0295 (0.4753)	0.0476 (0.4503)	-4.02E-08 (0.5703)

Table 5.10: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from France to other Countries

France ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	-0.2222 *** (0.0001)	-0.1534 *** (0.0047)	-0.1449 *** (0.0079)	-0.1259 ** (0.0245)	-0.0781 (0.2126)	-1.36E-06 *** (0.0051)
UK	-0.0793 * (0.0626)	0.0117 (0.7412)	0.0228 (0.5204)	0.0479 (0.1917)	0.1110 ** (0.0122)	-1.79E-06 *** (0.0002)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1616 *** (0.0000)	0.1641 *** (0.0000)	0.1645 *** (0.0000)	0.1652 *** (0.0000)	0.1669 *** (0.0000)	-5.06E-08 (0.9169)
Hong Kong	-0.0356 (0.1870)	-0.0600 ** (0.0101)	-0.0630 *** (0.0099)	-0.0696 ** (0.0123)	-0.0863 ** (0.0305)	4.73E-07 (0.3071)
China	0.0028 (0.9529)	-0.0127 (0.7415)	-0.0146 (0.7153)	-0.0189 (0.6753)	-0.0297 (0.6434)	3.05E-07 (0.6865)

Table 5.11: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from Germany to other Countries

Germany ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
France	0.0682 (0.1601)	0.1093 ** (0.0135)	0.1131 ** (0.0109)	0.1247 *** (0.0064)	0.1504 *** (0.0034)	-7.47E-07 * (0.0780)
UK	-0.0028 (0.9410)	0.0167 (0.5999)	0.0185 (0.5634)	0.0239 (0.4741)	0.0361 (0.3681)	-3.53E-07 (0.3826)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1713 *** (0.0000)	0.1381 *** (0.0000)	0.1349 *** (0.0000)	0.1256 *** (0.0000)	0.1047 *** (0.0015)	6.05E-07 (0.1337)
Hong Kong	-0.0038 (0.8853)	-0.0646 *** (0.0036)	-0.0703 *** (0.0022)	-0.0873 *** (0.0008)	-0.1255 *** (0.0005)	1.11E-06 *** (0.0071)
China	0.0010 (0.9809)	-0.0160 (0.6478)	-0.0176 (0.6261)	-0.0224 (0.5827)	-0.0331 (0.5544)	3.10E-07 (0.6215)

Table 5.12: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from the US to other Countries

US ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1169 *** (0.0007)	0.0901 *** (0.0030)	0.0857 *** (0.0066)	0.0805 ** (0.0165)	0.0553 (0.2582)	2.81E-08 (0.2768)
France	0.0037 (0.9064)	-0.0136 (0.6423)	-0.0165 (0.5914)	-0.0199 (0.5450)	-0.0362 (0.4516)	1.82E-08 (0.4558)
UK	0.3845 *** (0.0000)	0.3354 *** (0.0000)	0.3273 *** (0.0000)	0.3177 *** (0.0000)	0.2716 *** (0.0000)	5.14E-08 (0.1252)
Canada	-0.0308 (0.3499)	-0.0114 (0.6791)	-0.0082 (0.7711)	-0.0044 (0.8818)	0.0139 (0.7350)	-2.04E-08 (0.3608)
Japan	0.1241 *** (0.0000)	0.0651 ** (0.0070)	0.0554 ** (0.0290)	0.0438 (0.1063)	-0.0116 (0.7641)	6.18E-08 *** (0.0006)
Hong Kong	-0.1060 *** (0.0011)	-0.0582 ** (0.0149)	-0.0503 ** (0.0485)	-0.0409 (0.1486)	0.0040 (0.9353)	-5.01E-08 * (0.0954)
China	-0.0218 (0.5370)	0.0339 (0.3894)	0.0431 (0.2985)	0.0540 (0.2223)	0.1063 * (0.0832)	-5.84E-08 ** (0.0242)

Table 5.13: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from Canada to other Countries

Canada ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	-0.0033 (0.9493)	0.0461 (0.1749)	0.0586 * (0.0839)	0.0705 ** (0.0494)	0.1214 ** (0.0380)	-8.60E-07 (0.1510)
France	-0.0181 (0.7079)	-0.0050 (0.8669)	-0.0017 (0.9570)	0.0015 (0.9649)	0.0150 (0.8078)	-2.28E-07 (0.7192)
UK	0.2852 *** (0.0000)	0.2829 *** (0.0000)	0.2823 *** (0.0000)	0.2818 *** (0.0000)	0.2794 *** (0.0000)	3.96E-08 (0.9387)
US	-0.0498 (0.3928)	0.0010 (0.9771)	0.0140 (0.6867)	0.0261 (0.4678)	0.0785 (0.1938)	-8.85E-07 (0.1834)
Japan	0.1205 *** (0.0043)	0.1006 *** (0.0002)	0.0955 *** (0.0004)	0.0907 *** (0.0022)	0.0701 (0.1752)	3.48E-07 (0.5134)
Hong Kong	-0.0702 (0.1292)	-0.0176 (0.5204)	-0.0042 (0.8810)	0.0084 (0.7886)	0.0625 (0.2853)	-9.16E-07 (0.1366)
China	-0.0605 (0.1549)	0.0518 (0.2224)	0.0804 * (0.0780)	0.1074 ** (0.0299)	0.2231 ** (0.0019)	-1.96E-06 *** (0.0001)

Table 5.14: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from Japan to other Countries

Japan ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1743 *** (0.0001)	0.1488 *** (0.0000)	0.1420 *** (0.0000)	0.1368 *** (0.0000)	0.1082 * (0.0509)	4.70E-08 (0.4085)
France	0.0741 ** (0.0128)	0.0703 *** (0.0028)	0.0693 *** (0.0078)	0.0686 ** (0.0178)	0.0643 (0.2102)	7.00E-09 (0.8796)
UK	0.2621 *** (0.0000)	0.2355 *** (0.0000)	0.2284 *** (0.0000)	0.2230 *** (0.0000)	0.1931 *** (0.0000)	4.90E-08 (0.2535)
US	0.0973 *** (0.0008)	0.0713 *** (0.0017)	0.0644 ** (0.0114)	0.0590 ** (0.0381)	0.0298 (0.5626)	4.80E-08 (0.3025)
Canada	0.0324 (0.2656)	0.0412 ** (0.0361)	0.0436 ** (0.0373)	0.0454 ** (0.0481)	0.0553 (0.1909)	-1.62E-08 (0.6983)
Hong Kong	-0.0827 ** (0.0284)	-0.0455 * (0.0825)	-0.0356 (0.1993)	-0.0279 (0.3559)	0.0139 (0.7978)	-6.86E-08 (0.1954)
China	-0.0917 * (0.0606)	-0.0141 (0.6953)	0.0066 (0.8674)	0.0226 (0.6069)	0.1097 (0.1700)	-1.43E-07 * (0.0565)

Table 5.15: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from Hong Kong to other Countries

HongKong ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1710 *** (0.0001)	0.1443 *** (0.0000)	0.1414 *** (0.0000)	0.1327 *** (0.0003)	0.1175 ** (0.0182)	2.91E-08 (0.4319)
France	0.0847 *** (0.0051)	0.1078 *** (0.0000)	0.1104 *** (0.0001)	0.1179 *** (0.0002)	0.1311 *** (0.0013)	-2.52E-08 (0.3348)
UK	0.2320 *** (0.0000)	0.1987 *** (0.0000)	0.1950 *** (0.0000)	0.1842 *** (0.0000)	0.1651 *** (0.0001)	3.64E-08 (0.2374)
US	0.1387 *** (0.0000)	0.1220 *** (0.0000)	0.1201 *** (0.0001)	0.1147 *** (0.0018)	0.1051 ** (0.0311)	1.82E-08 (0.5421)
Canada	0.0390 (0.2069)	0.0926 *** (0.0000)	0.0985 *** (0.0000)	0.1158 *** (0.0000)	0.1466 *** (0.0004)	-5.84E-08 * (0.0676)
Japan	0.0775 ** (0.0144)	0.0344 (0.1863)	0.0296 (0.2679)	0.0157 (0.6054)	-0.0091 (0.8208)	4.70E-08 * (0.0828)
China	-0.0813 * (0.0544)	-0.0110 (-0.2552)	-0.0033 (0.9407)	0.0195 (0.6820)	0.0598 (0.2893)	-7.66E-08 *** (0.0051)

Table 5.16: The Dynamics of Return Spillovers (in relation to De-trended Trading Volume) from China to other Countries

China ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.0567 ** (0.0423)	0.0238 (0.1089)	0.0199 (0.1847)	0.0102 (0.5616)	-0.0110 (0.7012)	7.72E-09 (0.1592)
France	0.0340 (0.1883)	0.0041 (0.7491)	0.0006 (0.9659)	-0.0083 (0.5849)	-0.0276 (0.2877)	7.03E-09 (0.1729)
UK	0.0543 ** (0.0471)	0.0407 *** (0.0026)	0.0391 *** (0.0045)	0.0350 ** (0.0359)	0.0262 (0.3582)	3.21E-09 (0.5653)
US	0.0735 ** (0.0220)	0.0149 (0.2440)	0.0080 (0.5376)	-0.0094 (0.5782)	-0.0471 (0.1439)	1.38E-08 ** (0.0417)
Canada	0.0321 * (0.0968)	0.0228 * (0.0615)	0.0218 * (0.0850)	0.0190 (0.2001)	0.0131 (0.5661)	2.16E-09 (0.5819)
Hong Kong	-0.0337 ** (0.0266)	-0.0164 (0.2197)	-0.0144 (0.3041)	-0.0092 (0.5674)	0.0019 (0.9329)	-4.07E-09 (0.1943)
Japan	-0.0126 (0.5801)	-0.0226 * (0.0935)	-0.0238 * (0.0850)	-0.0268 * (0.0958)	-0.0332 (0.1842)	2.36E-09 (0.5993)

Table 5.17: The Dynamics of the First-order Return Autocorrelations in relation to Trading Volume

Table 5.17 reports parameter estimates of $\bar{\gamma}_H$ and $\alpha_{1,H}$ for the following model:

$R_{H,t} = \mu_H + \bar{\gamma}_H R_{H,t-1} + \alpha_{1,H} R_{H,t-1}(V_{H,t-1} - \bar{V}_H) + \epsilon_t$

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1},$

where $\alpha_{1,H}$ captures the interaction effect between trading volume and return in the domestic market; $\bar{V}_H$ denotes the mean average of the domestic market trading volume between certain percentiles, $\bar{\gamma}_H$ measures partial effect of $R_{H,t-1}$ on $R_{H,t}$ when $V_{H,t-1} = \bar{V}_H$.

	The first-order return autocorrelations in the UK				
$\alpha_{1,UK}$	$\bar{\gamma}_{UK,0-25\%}$	$\bar{\gamma}_{UK,25-50\%}$	$\bar{\gamma}_{UK,50\%}$	$\bar{\gamma}_{UK,50-75\%}$	$\bar{\gamma}_{UK,75-100\%}$
-1.26E-07 *** (0.0017)	0.0364 (0.4332)	-0.0269 (0.3914)	-0.0448 (0.1140)	-0.0648 ** (0.0126)	-0.1236 *** (0.0000)
	The first-order return autocorrelations in France				
$\alpha_{1,Fra}$	$\bar{\gamma}_{Fra,0-25\%}$	$\bar{\gamma}_{Fra,25-50\%}$	$\bar{\gamma}_{Fra,50\%}$	$\bar{\gamma}_{Fra,50-75\%}$	$\bar{\gamma}_{Fra,75-100\%}$
-1.17E-06 *** (0.0009)	-0.0140 (0.7271)	-0.0570 * (0.0651)	-0.0799 *** (0.0034)	-0.0881 *** (0.0008)	-0.1604 *** (0.0000)
	The first-order return autocorrelations in Germany				
$\alpha_{1,Ger}$	$\bar{\gamma}_{Ger,0-25\%}$	$\bar{\gamma}_{Ger,25-50\%}$	$\bar{\gamma}_{Ger,50\%}$	$\bar{\gamma}_{Ger,50-75\%}$	$\bar{\gamma}_{Ger,75-100\%}$
-1.33E-07 (0.6851)	-0.0267 (0.5118)	-0.0311 (0.3532)	-0.0337 (0.2660)	-0.0343 (0.2482)	-0.0427 (0.1420)
	The first-order return autocorrelations in the US				
$\alpha_{1,US}$	$\bar{\gamma}_{US,0-25\%}$	$\bar{\gamma}_{US,25-50\%}$	$\bar{\gamma}_{US,50\%}$	$\bar{\gamma}_{US,50-75\%}$	$\bar{\gamma}_{US,75-100\%}$
-1.77E-08 (0.2386)	-0.0422 (0.3231)	-0.0550 (0.1160)	-0.0680 ** (0.0205)	-0.0708 ** (0.0132)	-0.1041 *** (0.0020)
	The first-order return autocorrelations in the Canada				
α_1	$\bar{\gamma}_{Can,0-25\%}$	$\bar{\gamma}_{Can,25-50\%}$	$\bar{\gamma}_{Can,50\%}$	$\bar{\gamma}_{Can,50-75\%}$	$\bar{\gamma}_{Can,75-100\%}$
-7.75E-07 ** (0.0269)	0.0840 * (0.0726)	0.0344 (0.2492)	0.0162 (0.5307)	0.0003 (0.9902)	-0.0539 * (0.0990)

Table 5.17 Continued: The Dynamics of the First-order Return Autocorrelations in relation to Trading Volume

	The first-order return autocorrelations in Japan				
$\alpha_{1,Jap}$	$\bar{\gamma}_{Jap,0-25\%}$	$\bar{\gamma}_{Jap,25-50\%}$	$\bar{\gamma}_{Jap,50\%}$	$\bar{\gamma}_{Jap,50-75\%}$	$\bar{\gamma}_{Jap,75-100\%}$
-2.89E-08 (0.5259)	-0.0116 (0.8415)	-0.0330 (0.3015)	-0.0365 (0.2098)	-0.0427 (0.1054)	-0.0587 * (0.0876)
	The first-order return autocorrelations in Hong Kong				
$\alpha_{1,HK}$	$\bar{\gamma}_{HK,0-25\%}$	$\bar{\gamma}_{HK,25-50\%}$	$\bar{\gamma}_{HK,50\%}$	$\bar{\gamma}_{HK,50-75\%}$	$\bar{\gamma}_{HK,75-100\%}$
-4.29E-08 ** (0.0213)	-0.0221 (0.5881)	-0.0410 (0.2367)	-0.0674 ** (0.0156)	-0.0761 *** (0.0039)	-0.1303 *** (0.0001)
	The first-order return autocorrelations in China				
$\alpha_{1,Chn}$	$\bar{\gamma}_{Chn,0-25\%}$	$\bar{\gamma}_{Chn,25-50\%}$	$\bar{\gamma}_{Chn,50\%}$	$\bar{\gamma}_{Chn,50-75\%}$	$\bar{\gamma}_{Chn,75-100\%}$
-7.48E-09 * (0.0877)	-0.0321 (0.4130)	-0.0463 (0.1582)	-0.0699 *** (0.0049)	-0.0761 *** (0.0013)	-0.1251 *** (0.0001)

Table 5.18: The Dynamics of the First-order Return Autocorrelations in Relation to Trading Volume after Controlling for the US Return Spillover Effect

Table 5.18 reports parameter estimates of $\bar{\gamma}_H$ and $\alpha_{1,H}$ for the following model:
$R_{H,t} = \mu_H + \bar{\gamma}_H R_{H,t-1} + \alpha_{1,H} R_{H,t-1}(V_{H,t-1} - \bar{V}_H) + \beta R_{US,t-1} + \epsilon_t$
$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}$,
where $\bar{\gamma}_H$ measures the partial effect of $R_{H,t-1}$ on $R_{H,t}$ when $V_{H,t-1} = \bar{V}_{H,}$ after controlling for the return spillover effect from the US market.

	The first-order return autocorrelations in the UK				
$\alpha_{1,UK}$	$\bar{\gamma}_{UK,0-25\%}$	$\bar{\gamma}_{UK,25-50\%}$	$\bar{\gamma}_{UK,50\%}$	$\bar{\gamma}_{UK,50-75\%}$	$\bar{\gamma}_{UK,75-100\%}$
-7.54E-08 * (0.0760)	-0.1338 *** (0.0032)	-0.1717 *** (0.0000)	-0.1824 *** (0.0000)	-0.1944 *** (0.0000)	-0.2295 *** (0.0000)
	The first-order return autocorrelations in France				
$\alpha_{1,Fra}$	$\bar{\gamma}_{Fra,0-25\%}$	$\bar{\gamma}_{Fra,25-50\%}$	$\bar{\gamma}_{Fra,50\%}$	$\bar{\gamma}_{Fra,50-75\%}$	$\bar{\gamma}_{Fra,75-100\%}$
-1.18E-06 *** (0.0009)	-0.0146 (0.7219)	-0.0577 * (0.0746)	-0.0806 *** (0.0055)	-0.0889 *** (0.0016)	-0.1613 *** (0.0000)
	The first-order return autocorrelations in Germany				
$\alpha_{1,Ger}$	$\bar{\gamma}_{Ger,0-25\%}$	$\bar{\gamma}_{Ger,25-50\%}$	$\bar{\gamma}_{Ger,50\%}$	$\bar{\gamma}_{Ger,50-75\%}$	$\bar{\gamma}_{Ger,75-100\%}$
-2.45E-07 (0.4567)	-0.0633 (0.1262)	-0.0714 ** (0.0388)	-0.0761 ** (0.0158)	-0.0772 ** (0.0128)	-0.0926 *** (0.0026)
	The first-order return autocorrelations in Canada				
α_1	$\bar{\gamma}_{Can,0-25\%}$	$\bar{\gamma}_{Can,25-50\%}$	$\bar{\gamma}_{Can,50\%}$	$\bar{\gamma}_{Can,50-75\%}$	$\bar{\gamma}_{Can,75-100\%}$
-7.64E-07 ** (0.0294)	0.0934 * (0.0556)	0.0445 (0.1791)	0.0266 (0.3702)	0.0109 (0.6995)	-0.0425 (0.2392)
	The firs-order return autocorrelations in Japan				
α_1	$\bar{\gamma}_{Jap,0-25\%}$	$\bar{\gamma}_{Jap,25-50\%}$	$\bar{\gamma}_{Jap,50\%}$	$\bar{\gamma}_{Jap,50-75\%}$	$\bar{\gamma}_{Jap,75-100\%}$
-3.92E-08 (0.3786)	-0.0107 (0.8517)	-0.0398 (0.2115)	-0.0445 (0.1258)	-0.0529 ** (0.0451)	-0.0747 ** (0.0283)
	The first-order return autocorrelations in Hong Kong				
α_1	$\bar{\gamma}_{HK,0-25\%}$	$\bar{\gamma}_{HK,25-50\%}$	$\bar{\gamma}_{HK,50\%}$	$\bar{\gamma}_{HK,50-75\%}$	$\bar{\gamma}_{HK,75-100\%}$
-3.86E-08 ** (0.0366)	-0.0162 (0.6926)	-0.0331 (0.3430)	-0.0569 ** (0.0459)	-0.0647 ** (0.0169)	-0.1134 *** (0.0001)
	The first-order return autocorrelations in China				
α_1	$\bar{\gamma}_{Chn,0-25\%}$	$\bar{\gamma}_{Chn,25-50\%}$	$\bar{\gamma}_{Chn,50\%}$	$\bar{\gamma}_{Chn,50-75\%}$	$\bar{\gamma}_{Chn,75-100\%}$
-7.44E-09 * (0.0898)	-0.0321 (0.4151)	-0.0462 (0.1608)	-0.0697 *** (0.0053)	-0.0758 *** (0.0014)	-0.1246 *** (0.0001)

CHAPTER 6 – TRADING STRATEGY AND THE VALUE OF INTERNATIONAL STOCK MARKET INFORMATION

6.1 Introduction

The existing literature provides evidence about the presence of return and volatility spillovers across international financial markets, showing that the first and second moments of returns in one market usually have a statistically significant impact on other markets. Engle, Ito and Lin (1990) introduce the meteor shower hypothesis which postulates that the volatility spills over across markets, i.e. a volatile day in one market is likely to be followed by a volatile day in another market. Hamao, Masulis, and Ng (1990), among others, have found that this "meteor shower effect" is also evident in the return transmission mechanism across international stock markets (e.g. Hamao, Masulis, and Ng, 1990; 1991; Theodossiou and Lee, 1993; Lin, Engle and Ito, 1994; Kim and Rogers, 1995; Koutmos and Booth, 1995; Koutmos, 1996; Kanas, 1998; Christofi and Pericli, 1999; Niarchos, Tse and Wu, 1999; Huang, Yang and Hu, 2000; Masih and Climent and Meneu, 2003; Masih, 2001; Hsin, 2004; Lee, Rui and Wang, 2004; Wang and Firth, 2004; Baur and Jung, 2006; Nam, Yuhn and Kim, 2008; Mukherjee and Mishra, 2010).

Although numerous studies have found that the meteor shower effect in returns is statistically significant across international stock markets, there is not much evidence as to whether or not this effect is economically significant. A notable exception is Ibrahim and Brzeszczynski (2009; 2012), who explore the economic significance of return transmission across international stock markets using a trading rule that distinguishes the direction and strength of transmission signals from the Foreign Information Transmission (FIT) model.[54] The trading strategy is based on the statistically significant and time varying relationship between the preceding day's daytime returns in foreign markets and the current daytime return in a signal receiving market. Ibrahim and Brzeszczynski (2009; 2012) find that this relationship is sensitive to the returns from other international stock markets that operate in intermediate time. For example, the

[54] See Chapter 2 for the detailed discussions of the FIT model.

intensity of the return spillover from the Japanese stock exchange to the US stock market is affected by the returns in the UK market which is intermediate in time (the London stock exchange opens after the Tokyo stock exchange closes, but closes when the New York stock market already starts trading for the new day). As a result, a domestic US index day trader, who follows a rule of opening a trading position in the US market according to the signals from the Japanese stock market, can increase the leverage of trades when the UK returns confirm a stronger return spillover effect from the Tokyo to New York stock markets. The results of trading strategy from Ibrahim and Brzeszczynski (2009; 2012) provide supporting evidence that the meteor shower effect is economically significant because the trading rule offers profitable returns even after considering the transaction costs. In other words, the meteor shower effect in returns contains important economic value.

The study in Chapter 5 provides new evidence showing that the intensity of the meteor shower effect in returns across international stock markets varies over time. It shows that the size and significance of return spillovers are also affected by the level of trading volume in the previously opened foreign markets. The statistically significant interactive relation between trading volume and returns is interesting as one can build it into trading strategies and investigate whether or not it is an exploitable phenomenon that investors can use to trade profitably. The construction of the trading strategies in this chapter is similar to the strategies designed by Ibrahim and Brzeszczynski (2009; 2012). However, in contrast to the trading strategies which define leverage for trades based on signals generated using the information from the returns in other international stock markets that operate in intermediate time, the strategies designed in this study assign the leverage according to the information contained in the trading volume from domestic and foreign markets.

The analysis in this chapter contributes to the literature in two ways. The first, and most important, contribution is the construction of profitable trading rules that use directly the information about the trading volume from both domestic and foreign markets. Secondly, trading strategies designed to examine the economic significance of the meteor shower effect in returns are based on data from the New York, Tokyo and London stock markets. Therefore, this chapter investigates the profitability of trading rules based on the interactive relation between trading volume and returns across the world’s three largest international stock markets.

The remainder of this chapter is organized as follows. The next section introduces the methodology, the third section describes the trading strategies, the fourth section presents and discusses the results of trading rules, and the last section provides concluding remarks.

6.2 Methodology

6.2.1 Econometric Model

Following Hamao et al. (1990), this section specifies the meteor shower (MS) model in which current daytime return (denoted by R_t) in the domestic market follows the MA(1)-GARCH (1,1) process and can be explained by the preceding day's daytime return (denoted by $R_{F,t-1}$) in the foreign stock market. The model is as follows:

$$R_{H,t} = \mu + \beta R_{F,t-1} + \gamma\epsilon_{t-1} + \epsilon_t,\, \epsilon_t \sim N\,(\,0, h_t) \tag{6.1}$$

$$h_t = \, a + b\epsilon_{t-1}^2 + ch_{t-1}, \tag{6.2}$$

where μ is the constant term, $R_{H,t}$ is the open-to-close (daytime) return in the domestic stock market, ϵ_t is the error term and h_t is the conditional variance. The regression parameter β measures the dynamic return spillovers from the previously traded foreign stock markets to the domestic market. The parameter β is positive and statistically significant when the meteor shower effect exists. Equation (6.1) also contains the MA(1) term to account for any short-term serial autocorrelation in the home market returns. The conditional variance (h_t) is modelled as a function of the square of the last period's error term (ϵ_{t-1}^2) and of the last period's conditional variance (h_{t-1}). The GARCH(1,1) specification of the conditional volatility in Equation (6.2) takes into account the autoregressive conditional heteroskedasticity (ARCH) effect in stock returns. Following the return-generating process described by Equation (6.1) and Equation (6.2), the volatility is time-varying and the domestic market return is influenced by the previous day's foreign market return.

The MA(1)-GARCH(1,1) model described by Equation (6.1) and Equation (6.2) is used for forecasting stock market returns. The methodology for generating out-of-sample forecasts is based on static forecasting, which produces a series of one-step-ahead forecasts of dependent variable ($R_{H,t+1}$). If the in-sample period starts at time 0 and ends at time *t*, the first out-of-sample forecast of domestic return generated at time *t* for the time *t+1* is generated as:

$$E\ (R_{H,t+1}) = \hat{\mu} + \hat{\beta}R_{F,t} + \hat{\gamma}\epsilon_t, \tag{6.3}$$

where $\hat{\mu}$, $\hat{\beta}$, and $\hat{\gamma}$ are the parameters estimated in the in-sample period. A first-order moving average term uses the most recent error term (ϵ_t) to improve the future forecast for time *t+1*. The static forecasting method includes the actual observations of explanatory variables ($R_{F,t}$) and the most recent error term (ϵ_t) that is based upon the actual value of $R_{F,t-1}$ and $R_{H,t}$. ϵ_t is obtained according to the following equation:

$$\epsilon_t = R_{H,t} - \hat{\mu} - \hat{\beta}R_{F,t-1} + \hat{\gamma}\epsilon_{t-1}. \tag{6.4}$$

The out-of-sample forecasts of the econometric model described above produce the buying or selling signals on which the regression-based trading rules are based.

6.2.2 Direction Quality Measures

To evaluate the performance of the out-of-sample forecasts for the MS model, the direction quality measures introduced by Pesaran and Timmermann (1992) (and developed further by Dacorogna, Gauvreau, Muller, Olsen and Pictet, 1996; Dacorogna, Muller, Olsen and Pictet, 1998) can be used as indicators of predictive performance. These measures are of particular interest in situations where it is more important that the regression model captures the direction of changes in variables under consideration rather than that the model has a high value of the coefficient of determination R^2. They contrast with the traditional R^2 measure of goodness of fit which compares the variance of the model's predictions (i.e. regression sum of squares) with the total variance of the data (i.e. total sum of squares). The direction quality measures should thus be especially useful for the index day traders, who follow the trading strategies discussed in the next section, as the measures of forecasting accuracy of the models. In this analysis, the following direction quality measures are exploited:

$$Q_1 = N\{r_t r_t^* > 0\}/N\{r_t r_t^* \neq 0\}, \tag{6.5}$$

where r_t^* is the one-step-ahead forecast of returns generated by the meteor shower model, r_t is the actual return of the market on the same day, $N\{r_t r_t^* > 0\}$ is the number of days on which the directions of the forecast and the actual return are the same (i.e. the model generates signals that correctly forecast the direction of movement of the market return), and $N\{r_t r_t^* \neq 0\}$ is the number of trading days in the out-of-sample period (excluding the zero-return observations).

The next direction quality measure Q_2 is the ratio of the sum of absolute values of return when the meteor shower model generates correct signals to the sum of absolute values when it produces wrong signals. The measure Q_3 is the ratio of average absolute value of return in these two cases.

$$Q_2 = \sum_{t=1}^{T} |r_t| / \sum_{t=1}^{T} |\widetilde{r_t}|, \tag{6.6}$$

$$Q_3 = (\sum_{t=1}^{T} |r_t|)/N\{r_t r_t^* > 0\}/(\sum_{t=1}^{T} |\widetilde{r_t}|)/N\{r_t r_t^* > 0\}, \tag{6.7}$$

where

$$r_t = \begin{cases} 0 & \text{for } r_t r_t^* \leq 0 \\ r_t & \text{for } r_t r_t^* > 0 \end{cases},$$

and

$$\widetilde{r_t} = \begin{cases} 0 & \text{for } r_t r_t^* > 0 \\ r_t & \text{for } r_t r_t^* \leq 0 \end{cases},$$

and $|r_t|$ ($|\widetilde{r_t}|$) is the absolute value of market return when the forecasted return and the market return are of the same (different) sign. For the forecasts to produce the positive holding period return over a given period of time, both Q_2 and Q_3 should be greater than one.

6.3 Trading Strategies

This section describes the trading strategies based on the signals generated from the out-of-sample forecasts of the meteor shower model in Equation (6.3) and the knowledge about the interactive relation between trading volume and returns that was discussed in Chapter 5.

6.3.1 Trading Rules

Trading Rule MS (the MS model forecasts)

According to this trading rule, domestic market index traders construct trading strategies (i.e. decisions to open a long or short position) for the day based purely on the forecast signals from the MS model. Traders buy (or short-sell) their domestic market index at the market's opening price and sell (or buy back) at the market's closing price when a buying (selling) signal is forecasted by the MS model. A buying signal is generated for time *t+1* when the forecasting model predicts that the next day's domestic market return is positive ($E\left[R_{H,t+1}|F_t\right] > 0$). Conversely, a selling signal is generated when the MS model predicts a fall of the market index on the following day ($E\left[R_{H,t+1}|F_t\right] < 0$), suggesting that traders should go short next day. F_t denotes the information set about the daytime return in the signalling (foreign) market, which is available to all domestic investors at time *t*.

The daily return of a fund following this simple trading rule (Trading Rule MS) can be expressed as follows:

$$R_{MS,t} = I_{buy,t-1} \times \left(R_{Index,t}\right) + I_{sell,t-1} \times \left(-R_{Index,t}\right) - TC \qquad (6.8)$$

where $R_{MS,t}$ is the fund's daily return at time *t*; $R_{Index,t}$ is the return of the market index at time *t*; $I_{buy,t-1}$ and $I_{sell,t-1}$ are the buying and selling signals generated by the forecasting model at time *t-1*. $I_{buy,t-1}$ is the dummy variable which equals 1 if a buying signal is produced at time *t* (and 0 otherwise); $I_{sell,t-1}$ is also the dummy variable which is equal to 1 if a selling signal is forecasted by the model at time t (and 0 otherwise); TC is the roundtrip transaction cost. This study defines the trading days when selling (buying) signals are produced as the selling (buying) periods. If transaction costs are zero, the daily return of the fund in a selling period is positive when market falls (i.e. $R_{MS,t} = -R_{Index,t}$, when $I_{sell,t-1} = 1,\ TC = 0$) because trader has opened a short position for the day and would make a profit when market goes down (i.e. $R_{Index,t} < 0$).

Trading Rule FV (the MS model forecasts combined with information about foreign trading volume)

If domestic market index day traders are able to increase trading leverage when opening their trading positions based on the information about the foreign market trading volume, the daily return of the fund is defined as follows:

$$R_{FV,t} = \begin{cases} R_{MS,t}, & \text{if } DM_1 = 0 \\ R_{MS,t} \times LV_1 \times DM_1, & \text{if } DM_1 = 1, \end{cases} \tag{6.9}$$

where $R_{FV,t}$ is the fund's daily return at time *t* following Trading Rule FV; LV_1 is the multiplier that can be decided by traders based on foreign trading volume information (e.g. a multiplier of 3 means that traders use 3 times higher leverage when they open their positions, and the return, or loss, is thus magnified 3 times). DM_1 is the dummy variable which equals 1 (and 0 otherwise) if a leverage signal is generated based on the information about preceding day's foreign trading volume.[55] $R_{FV,t} = R_{MS,t}$ if $DM_1 = 0$; the traders therefore restrict from leveraged trading and receive the same daily return as in the non-leveraged simple rule.

[55] The leverage signal generating mechanism and the allocation of leverage values are discussed in more details in the next subsection.

Trading Rule DV (the MS model forecasts combined with information about home market trading volume)

Traders may also decide to leverage their positions by using the information about trading volume in the domestic market. The daily return of a fund that follows Trading Rule DV is defined as:

$$R_{DV,t} = \begin{cases} R_{MS,t}, & \text{if } DM_2 = 0 \\ R_{MS,t,} \times LV_2 \times DM_2, & \text{if } DM_2 = 1, \end{cases} \tag{6.10}$$

where $R_{DV,t}$ is the fund's daily return at time *t* following Trading Rule DV; LV_2 is the leverage factor that can be decided by traders when they open the trading position at the market open according to the previous day's trading volume information in the domestic market. DM_2 is the dummy variable which equals 1 (or 0 otherwise) if a leveraged signal is generated according to the information about the previous day's domestic market trading volume.

Trading Rule FV&DV (the MS model forecasts combined with information about trading volume in both foreign and domestic markets)

In a situation where traders consider the information from both foreign and domestic markets in deciding their leverage of trades, the daily return of the fund is defined as:

$$R_{FV\&\,DV,t} = \begin{cases} R_{MS,t,} & \text{if } (DM_1 + DM_2) = 0 \\ R_{MS,t,} \times (LV_1 \times DM_1 + LV_2 \times DM_2), & \text{if } (DM_1 + DM_2) \neq 0, \end{cases} \tag{6.11}$$

where $R_{FV\&\,DV,t}$ is the daily return of the fund that follows Trading Rule FV&DV. The leverage of trades is determined by leverage factors LV_1 and LV_2 and varies according to the information about trading volume in both foreign and domestic markets. The daily return of the fund following Trading Rule FV&DV is the same as following Trading Rule MS if information about trading volume in neither the domestic market nor foreign markets indicates that a leverage factor should be applied. However, the daily return of the fund following Trading Rule FV&DV is $(LV_1 + LV_2)$ times of that following non-leveraged Trading Rule MS when leverage signals are generated as traders can increase trading leverage based on not only the information about trading volume in the foreign market but also in the domestic market.

6.3.2 Leverage for Trades

The MS model, which captures the meteor shower effect in returns, provides market index day traders with buying or selling signals. Following Trading Rule MS, traders decide whether their domestic market index should be bought or sold for the day at the market open based only on the preceding day's forecasts of the MS model, and no leverage is applied since traders have no additional information about the strength of the meteor shower effect in returns from foreign markets.

In Chapter 5, it was demonstrated that the magnitude and significance of return spillovers are affected by the preceding day's foreign trading volume ($V_{F,t-1}$). The strength of the meteor shower effect in returns varies according to the intensity of trading activity in the signalling market on the previous day. Hence, domestic market index traders may consider increasing the leverage for trades when their conviction about the meteor shower effect that exists between the domestic market and the foreign market is strengthened (i.e. the preceding day's foreign market information is more likely to predict the direction of changes in the domestic market returns, and the price movements in the domestic market are more likely to be in the same direction as the preceding day's price changes in the foreign market). Trading Rule FV applies a leverage factor of 3 when the meteor shower effect is very strong, a factor of 2 when this effect is strong, and a factor of 1 (i.e. no leverage) when the meteor shower effect in returns is weak.[56]

For instance, the results in Table 5.4 indicate that the meteor shower effect from the US to Japanese stock market is stronger when the preceding day's US trading volume is higher. The parameter describing the return spillover effect is 0.13 (0.05) and statistically significant at the 1% (5%) level when the US trading volume is at the mean level of the 4th (and 3rd) quartile, whereas return spillovers from the US to Japanese stock market are statistically insignificant during the periods that are associated with

[56] Other values of trading leverage could also be applied as the choice of leverage values are always set arbitrarily by traders.

below-normal trading volume (e.g. the previous day's US trading volume belongs to the 1^{st} and 2^{nd} quartile). In this situation, traders following Trading Rule FV are assumed to choose a leverage multiplier of 3 when the meteor shower effect is very strong (i.e. the preceding day's US trading volume is very high and belongs to the 4^{th} quartile), a multiplier of 2 if this effect is strong (i.e. the preceding day's US trading volume is high and in the 3^{rd} quartile), and a factor of 1 when this effect is weak (i.e. the lagged trading volume in the US belongs to the 1^{st} and 2^{nd} quartiles).

In Chapter 5 it was also found that the price movements associated with low trading volume exert little influence on the next day's price changes in the domestic market. The statistically insignificant return autocorrelation at the low level of the domestic market trading volume can be perceived as the evidence of weak-form market efficiency in the sense that the current stock price has fully reflected the past price information, and price movements cannot be predicted based on the historical prices in the domestic market. The traders in the domestic market hence are more likely to be influenced by the signals received from the foreign markets when less information is available from the previous day's price movements in their domestic market. It means that the meteor shower effect is more likely to be dominant if the preceding day's domestic market trading volume is very low and low (i.e. trading volume in the domestic market belongs to the 1^{st} and 2^{nd} quartiles). Trading Rule DV hence assigns a leverage value of 3 when the previous day's trading volume in the domestic market is below the 25^{th} percentile, a multiple of 2 when the trading volume is above the 25^{th} percentile but below the 50^{th} percentile, and a multiple of 1 (i.e. no leverage) when the trading volume is above the 50^{th} percentile.

For example, when the trading volume in the Tokyo stock market at time *t* is very low (e.g. in the extreme case of non-synchronous holidays, when the Tokyo stock exchange is closed while the New York stock market is still open for the day, the trading volume in the Tokyo stock exchange is zero), the first-order return autocorrelation in Japan is statistically insignificant from zero (as shown in Table 5.17), and a domestic Japanese TOPIX index day trader cannot predict the next day's price movements of TOPIX index based on the current domestic market price information. As a result, traders in the Japanese market are more likely to look at the price movements at the New York stock exchange for the day to decide about tomorrow's strategy. The price movements in the Japanese stock market are more likely to be in the same direction as the preceding day's

US price changes and the meteor shower effect in returns from the US market tends to be dominant in the Japanese market.

Trading Rule FV&DV combines the leverages chosen in Trading Rule FV and Trading Rule DV and thus considers the additional information contained in both foreign and domestic trading volumes in assessing the impact of foreign return spillovers on the following day's returns in the domestic market. Therefore, a domestic Japanese TOPIX index trader will choose the maximum leverage value of 6 following a day when the return spillover effect from the US market is very strong (i.e. the preceding day's US trading volume is above the 75th percentile) and more likely to be dominant in the Japanese market (i.e. yesterday's Japanese trading volume is below the 25th percentile). However, if the information about trading volume in both domestic and foreign markets suggests that no leverage should be assigned for the next day's opening position, traders will restrain from leveraged trades and will simply earn the non-leveraged daily return $R_{MS,t}$.

6.4 Results

6.4.1 Data

The daily opening price, closing price and trading volume time series of the TOPIX, FTSE100 and S&P500 indices over a 7 year period from 1 August 2003 to 30 July 2010 are used for the in-sample estimation of the meteor shower (MS) model. The regression coefficients obtained from the in-sample estimation are then employed to perform out-of-sample forecasts from the first trading day in August 2010. A one year out-of-sample period is chosen to test the profitability of trading rules from 2 August 2010 to 29 July 2011. This study also uses the following interest rate data over the same period to calculate the risk free interest rate for the investigated markets: the UK 3-month interbank rate, the US 3-month commercial deposit rate, and Japan's 3-month interbank rate.[57]

[57] These are the benchmark risk-free interest rate according to DATASTREAM.

Following Gagnon and Karolyi (2009), the logarithm of trading volume is de-trended by subtracting the 50-day moving average log-volume after adding a small value (e.g. 0.00000255) to avoid problems with zero trading volume. The de-trending process is modelled as follows:

$$detrended\ volume = log(V_t + 0.00000255) - \frac{1}{50}\sum_{s=-50}^{s=-1} log\ (V_{t+s} + 0.00000255), \tag{6.12}$$

The quartiles of the US, UK and Japanese trading volume over the in-sample period are indentified and summarized in Table 6.1, which shows the filter levels for the leverage generating rule in the out-of-sample period.

6.4.2 Estimation Results of the Meteor Shower Model

Table 6.2 reports the estimation results of Equation (6.1) and Equation (6.2) for the US, UK and Japanese markets over the in-sample period. The dynamic return spillovers from the UK to US market cannot be explicitly investigated because of the overlapping trading time between the afternoon section in London and morning section in the New York stock exchange.

The estimation results from Panels A to E show that the parameter β is positive and statistically significant at the 1% level in all cases, suggesting that the meteor shower effect exists in return spillovers across the three largest international stock markets in the world. A positive (negative) return in one market tends to be followed by positive (negative) returns in the subsequently opened markets. The price changes in one market provide signals for the following day's price changes in the other markets. The return transmission mechanism across the three markets operates largely in the same direction. The estimation results also show that the variance equation well captures the volatility clustering effect since the ARCH parameter b and the GARCH parameter c are both positive and statistically significant at the 1% level.

6.4.3 Performance of Trading Strategies

Assuming that traders start with a hypothetical initial investment of 1 million units in local currency just prior to market open on the first trading day in August 2010, the holding period return (HPR), average return per trade and Sharpe ratio of the fund whose traders actively trade the domestic market index according to the investment strategies (i.e. Trading Rule MS, Trading Rule DV, Trading Rule FV and Trading Rule FV&DV) are calculated over one year out-of-sample period. A passive buy-and-hold (B&H) strategy is used as a benchmark, according to which traders buy and hold the market index over the same out-of-sample period.

Panels A to E in Table 6.3 tabulate the performance results of the trading rules. The first section of each panel reports the performance of the fund that follows the passive B&H strategy, and the second section presents the fund performance results of the active trading rules, which buying and selling signals are based on the forecasts of the meteor shower model. The same pattern is found across all panels, and hence the detailed discussion focuses only on Panel A.

Panel A in Table 6.3 reports the performance results of trading rules from the perspective of a S&P 500 market index trader. It shows that the holding period returns (HPR) for the B&H strategy, Trading Rule MS, Trading Rule FV, Trading Rule DV, and Trading Rule FV&DV are 15.96%, 41.73%, 100.99%, 85.74%, 189.97%, respectively. The active trading rules (i.e. Trading Rule MS, Trading Rule FV, Trading Rule DV and Trading Rule FV&DV) outperform the passive B&H strategy by a factor of 2.62, 6.33, 5.37 and 11.90 in one year period. A US index trader who follows the passive B&H strategy of buying the S&P 500 index and holding it for a year would achieve the price return of 15.96% over its holding period from 2 August 2010 to 29 July 2011. However, an S&P 500 index day trader, who follows an active investment strategy (Trading Rule MS) of opening a daily trading position according to the forecasts of the meteor shower model incorporating the price information from the previously opened Tokyo stock exchange, would have a higher HPR of 41.73%. Moreover, a US index day trader who can open the leveraged trading positions based on additional information about the prior trading activities in the Tokyo (Trading Rule FV), New York (Trading Rule DV), and both Tokyo and New York stock markets (Trading Rule FV&DV), would achieve even higher HPRs of 100.99%, 85.74%, 189.97%, respectively. A comparison of HPR between the non-leveraged and leveraged active trading rules reveals enhancement in returns due to leverage. Comparing to Trading Rule MS, the holding period return is magnified by a factor of 2.42 for Trading Rule FV, 2.06 for Trading Rule DV, and 4.55 for Trading Rule FV&DV.

The fund performance is also assessed by the time series behaviour of fund values and daily return throughout the out-of-sample period. Plots A in Figures 6.1 to 6.5 exhibit the graphs of fund values for both active and passive trading rules, and Plots B to E in Figures 6.1 to 6.5 show the charts of the fund's daily return following each trading rule. The analysis again focuses on Figure 6.1, but the discussion can be easily extended to Figures 6.2 to 6.5.

Time series plots of fund values in Figure 6.1A show that the passive B&H strategy steadily increases the fund value to nearly 1.2 million US dollars from the initial investment of 1 million because of an upward trend in the US stock market over the out-of-sample period; a fund following the non-leveraged active trading strategy (Trading Rule MS) grows to a higher terminal value of 1.4 million dollars. The leveraged active trading strategies that incorporate information about the trading volume in the Japanese (Trading Rule FV) and the US (Trading Rule DV) markets further improve terminal fund values to around 2 million. Trading Rule FV&DV increases the fund terminal value to nearly 3 times of the initial fund value. It is the best performing rule in terms of achieving the highest terminal value. However, it is also apparent that the fund values are more volatile following the leveraged trading strategies, especially Trading Rule FV&DV that employs a maximum leverage factor of 6 when the meteor shower effect from Japan to the US is both strong and dominant.

Figure 6.1B plots the daily returns of a domestic S&P 500 index trader that follows the non-leveraged active trading strategy (Trading Rule MS). It is evident that there are more large positive returns than large negative returns over the whole out-of-sample period, suggesting that meteor shower (MS) model provides more correct buying or selling signals than wrong signals for trading the S&P 500 index, especially on days when the price movements are extreme. This is also confirmed by the direction quality measures in Table 6.2 A. The Q_1 value of 0.5498 means that the meteor shower model produces the signals in the correct direction 54.98% of the time, and hence the active trading rules generate positive returns on 138 out of 251 days in the out-of-sample period. The direction quality measures Q_2 and Q_3 further show that the sum values and the average values of the correctly forecasted returns are higher than the respective values of incorrectly forecasted returns, so the ratios Q_2 and Q_3 are both greater than 1.

Plots C to E in Figure 6.1 provide charts of daily returns for the funds following the leveraged active trading strategies (i.e. Trading Rule FV, Trading Rule DV, and Trading Rule FV&DV). The relatively high increment of the scale of positive returns is evident. The superior performance of leveraged trading strategies is due to leverage signals produced are worth being allocating large multiple factors, i.e. high leverages are applied on those days when meteor shower model generates the correct trading signals and the absolute value of actual returns in the market is large. For instance, the remarkable increments of fund value around days on the 30 August 2010, 22 November 2010, 28 February 2011, and 9 May 2011 (as shown in Figure 6.1, Plot A) are due to the leverage generating rule that has allocated high multiple factors on the days when the meteor shower model produces the trading signals in the correct direction.

6.4.4 Risk-adjusted Performance: the Sharpe Ratio

Following Trading Rule MS, Trading Rule FV and Trading Rule FV&DV, traders apply leverage factors based on the levels of trading volume when trading market indices. It is noteworthy that a higher trading leverage implies a larger return (loss) in a day since the daily return of a fund is magnified by a higher leverage position. The leverage factor of 6 is equal to the marginal ratio of 16.67% (marginal ratio = 1/leverage factor) implying that the domestic market index has to change by 16.67% in a day against the opening position of traders in order to lose 100% of the initial investment. Higher returns of funds that use leverage may be due to the additional risk the traders bear from the high-leveraged trading. Hence, the performance of any trading strategy cannot be measured only by the increase of fund value but also by the additional risk incurred. It is therefore necessary to report the Sharpe ratio to compare the risk-adjusted performance of the funds so that the returns and risk of the trading strategies can be evaluated together. The Sharpe ratio was originally introduced by Sharpe (1966) as a measure of mutual fund performance, and has later become the industry standard in evaluating fund performance. It is the ratio of reward (risk premium) to risk (standard deviation of return) and can be expressed as:

$$\text{Original Sharpe Ratio} = (R_F - R_f)/SD, \quad (6.13)$$

where R_F is the fund's total return, R_f is the risk free interest rate, and SD is the standard deviation of return. The difference between R_F and R_f is the risk premium of the fund, which is the reward to investors for investing in risky asset over holding risk free asset. The larger value of Sharpe ratio represents a higher risk premium per unit of standard deviation (i.e. a higher excess return for the same level of risk). The fund with higher value of the Sharpe ratio is ranked above the one with lower value.

However, it is noteworthy the original Sharpe ratio assumes a constant risk free interest rate. Sharpe (1994) revised the ratio using standard deviation of excess return instead of standard deviation of return in the denominator and recognised that the risk free rate changes over time. The Shape ratio is defined as:

$$\text{Standard Sharpe Ratio} = (R_F - R_f)/SD_{Excess\ Return}, \quad (6.14)$$

where $SD_{Excess\ Return}$ is the standard deviation of the excess return. If risk free interest rate is a constant over the period, the standard deviation of excess return is equal to the standard deviation of return.

Recently, the Sharpe ratio has been challenged with regard to its reliability as a fund performance measure during evaluation periods of declining markets. With the excess returns being negative, the Shape ratio is larger when the standard deviation of excess return is high. For example, Funds A and B both have an excess return of -5%, but the standard deviation of excess return are 1% and 2%, respectively. In a two-fund world, Fund A is obviously the better choice if one accepts that lower standard deviation of excess return is better (as the lower standard deviation is associated with lower risk). However, the application of Sharpe ratio leads to the opposite ranking as the Shape ratio for Funds B is higher than that for Fund A ($\text{Sharpe Ratio}_{\text{Fund A}}$ = -5%/1% = -5, $\text{Sharpe Ratio}_{\text{Fund B}}$ = -5%/2% = -2.5, and -2.5 > -5). Fund B is assigned a higher Sharpe ratio despite being associated with higher risk. This anomaly occurs when negative excess returns are present.

Israelsen (2005) provided a solution to this problem and proposed the modified Sharpe ratio as follows:

$$\text{Modified Sharpe Ratio} = (R_F - R_f)/(SD_{Excess\ Return})^{(R_F - R_f)/|(R_F - R_f)|} \tag{6.15}$$

The exponent in the denominator is the ratio of excess return to the absolute value of excess return. If excess return is positive, the exponent equals one and the modified Sharpe ratio is identical to the standard Sharpe ratio. If excess return is negative, the exponent is equal to negative one and modified Sharp ratio assigns larger negative numbers (and thus lower rankings) to the funds associated with higher standard deviations of excess returns.

The last three columns of Panels A to E in Table 6.3 report the original Sharpe ratio, standard Sharpe ratio and modified Sharpe ratio for each trading rule. It is shown that there are no substantial differences between the original Sharpe ratio and standard Sharpe ratio, suggesting that the change of risk free interest rate exerts little influence on the risk-adjusted performance of the funds over the evaluation period. Since excess returns of the funds are positive for most trading rules (i.e. the standard Sharpe ratio and modified Sharpe ratio generate identical results), the analysis of the risk-adjusted performance of the funds focuses on the results of the modified Sharpe Ratio (hereafter referred to as the Sharpe ratio for short). As suggested by Israelsen (2005), the modified Sharpe ratio correctly ranks funds whether or not the excess return is positive or negative.

The Sharpe ratio for the funds following Trading Rule MS, Trading Rule FV, Trading Rule DV and Trading Rule FV& DV is remarkably higher than that using the buy-and-hold strategy, indicating that the active trading rules achieve higher return at the same level of risk. Moreover, for most cases, the Sharpe ratio for the funds following the leveraged active trading strategies (i.e. Trading Rule FV, Trading Rule DV and Trading Rule FV& DV) is much higher than the one following the non-leveraged trading strategy (Trading Rule MS). The fund following Trading Rule FV& DV has the highest

Sharpe ratio and thus ranks first.[58] This shows that the incrementally higher return of the active trading strategy does not come about with disproportionately increased risks. More importantly, the leveraged rule that makes use of additional information about the interactive effect between trading volume and returns is apparently improving the risk-adjusted performance of the investigated trading strategies.

6.4.5 Results after Inclusion of Transaction Costs

An important difference between the passive buy-and-hold trading strategy and regression-based trading rules is that the latter requires the active management of funds (i.e. opening a trading position when the market opens and unwinding it at the close), which in practice incurs relatively high transaction costs whereas the former does not. The comparisons of trading strategies thus need to consider the transactions costs associated with active management of funds. Pardo and Torro (2007) and Ibrahim and Brzeszczynski (2009) suggest that no more than 0.1% of contract value for transaction costs are required if the futures contracts on the market indices are used instead of the spot indices.

Therefore, in order to test whether these trading rules produce the economically significant profits, this study takes into account the round-trip transaction costs of 0.1%. The economically profitable strategies are those that have a positive holding period return (HPR) at the end of the out-of-sample forecasting period after considering transaction costs. Figure 6.6 to 6.10 are plotted to describe the time series behaviour of fund values at transaction costs of 0.1%

Figures 6.6 to 6.8 show that the active trading strategies (leveraged and non-leveraged) are still profitable in trading the S&P 500 index and the FTSE100 index at transaction costs of 0.1%. The fund values have an overall upward trend over the whole out-of-sample period and the terminal fund values are greater than the initial investment for all the active trading rules. Furthermore, the leveraged trading rules in general outperform the passive B&H trading strategy. The terminal fund values of trading the S&P500 index and the FTSE100 index following the leveraged active trading rules (i.e. Trading

[58] There is only one exception when trading the TOPIX index following Trading Rule DV based on signals from the UK.

Rule FV, Trading Rule DV, and Trading Rule FV& DV) are higher than the passive B&H trading rule. Trading Rule FV& DV remains the best in terms of achieving the highest fund value at the end of the out-of-sample forecasting period. This rule increases the fund value from initial investment of 1 million to around 1.4 million local currencies over one year period in both markets. However, Figure 6.9 and Figure 6.10 show that all the active trading strategies for trading the TOPIX index underperform the passive B&H trading strategy most of the time and fund values are lower than the initial investment at the end of the out-of-sample periods for all trading rules.

Instead of assuming the round-trip transaction costs of 0.1% per trade, this study also considers the break-even transaction costs, which completely erode the returns that the trading strategies could achieve. The average returns (per trade) for the trading rules are reported in Panels A to E in Table 6.3. Therefore, traders are left to decide whether the break-even costs are comparable to their actual transaction costs. The trades are profitable if actual transaction costs are lower than the break-even costs. For example, if traders have the actual round-trip transaction costs of 0.1%, they would make a profit following trading rules that have the break-even transaction costs higher than 0.1%. The average returns (per trade) for the active trading rules reported in Panels A to C in Table 6.3 are all above 0.1% (i.e. break-even costs are all above 0.1%), suggesting that the active trading strategies are still profitable for trading the S&P 500 index and the FTSE100 index even after consideration of transaction costs. Conversely, the average returns (per trade) for the active trading rules reported in Panel D and Panel E are smaller than 0.1%, indicating that the active trading strategies are not profitable for trading the TOPIX index at transaction costs of 0.1%. It is not surprising given the fact that the MS model produces poor forecasts for the direction of changes of the TOPIX index (as suggested by the direction quality measures). However, it is important to point out that performance results of the funds (e.g. the average returns (per trade) and the Sharpe ratio) following the leveraged active trading rules have been remarkably improved comparing to those following the non-leveraged active trading rule, indicating that the information about the interactive relation between trading volume and returns is an exploitable phenomenon and the incremental information it provides considerably improves the fund’s performance results even after adjustment for risk.

6.4 Summary

This chapter investigates the economic benefits of trading on the basis of return spillovers across the US, UK and Japanese stock markets. The profitability of regression-based trading rules implemented for market indices in these markets (S&P 500, FTSE100 and TOPIX) is examined over the out-of-sample period from 2 August 2010 to 29 July 2011. The signals for trades are generated by the forecasts of the meteor shower model, which includes the information about price changes in the previously traded foreign markets. In addition, the information about trading volume from both domestic and foreign markets is also built into trading rules because findings in Chapter 5 have shown the trading volume provides valuable information that helps to explain the time-varying nature of market price movements and cross-market comovements.

Panels A to E in Table 6.3 report the holding period return (HPR) of the funds which actively trade their domestic market index according to different trading rules. A passive buy-and-hold (B&H) strategy is used as a benchmark, according to which traders buy and hold the domestic market index over the same period. A domestic market index day trader, who follows the non-leveraged active investment strategy (Trading Rule MS) of opening and closing a daily trading position according to the forecasts of the meteor shower model incorporating the price information from the previously opened foreign market, would achieve a higher HPR than the passive B&H strategy.

Moreover, traders who can open leveraged trading positions based on additional information about the prior trading volume in the domestic market (Trading Rule DV), in the foreign market (Trading Rule FV), or in both domestic and foreign stock markets (Trading Rule FV&DV), would obtain even higher HPR. The active trading rules (i.e. Trading Rule MS, Trading Rule FV, Trading Rule DV and Trading Rule FV&DV) outperform the passive B&H strategy in every case when transaction costs are not included.

The performance of funds is also assessed by the time series behaviour of the fund values and daily returns throughout the out-of-sample period. Time series plots of the fund values illustrate that the active trading rules overall outperform the passive B&H strategy. Plots A in Figures 6.1 to 6.5 show that the leveraged active trading strategies that incorporate information about the trading volume in the domestic and foreign markets remarkably increase the fund terminal value. However, it is also apparent that the fund values are more volatile following the leveraged trading strategies.

The figures for the fund's daily return show that there are more positive returns than negative returns over the out-of-sample period, indicating that the meteor shower (MS) model produces more correct signals (than incorrect ones) and for large price movements. The relatively high increment of the size of the positive daily return for the leveraged trading rules is due to high leverage factors being applied on those days when the MS model generates the correct trading signals, especially on those days when the direction of the large price changes has been correctly predicted.

The last columns of Panels A to E in Table 6.3 report the Sharpe ratio for each trading rule. The Sharpe ratio in Trading Rule MS, Trading Rule FV, Trading Rule DV and Trading Rule FV& DV is much higher than that in the buy-and-hold strategy, indicating that the active trading rules achieve higher return at the same level of risk. Moreover, the Sharpe ratio in the leveraged active trading strategies (i.e. Trading Rule FV, Trading Rule DV and Trading Rule FV& DV) is also significantly higher than the non-leveraged trading strategy (Trading Rule MS) in most cases. These results show that the incrementally higher return of the active trading strategy does not come about with disproportionately increased risks. More importantly, the leveraged rule that makes use of additional information about the dynamics between trading volume and returns is apparently improving the risk-adjusted performance of the investigated trading strategies.

In order to test whether these trading rules produce economically significant profits, the study takes into account round-trip transaction costs of 0.1%. The economically profitable strategies are those that have a positive holding period return (HPR). Figures 6.6 to 6.8 show that the active trading strategies (leveraged and non-leveraged) are still profitable in trading the S&P 500 index and the FTSE100 index at transaction costs of 0.1%. However, the active trading strategies for trading the TOPIX index at transaction costs of 0.1% underperform the passive B&H trading strategy most of the time; and the fund values are lower than the initial investment at the end of out-of-sample periods for all trading rules.

This study also reports the results of the break-even transaction costs for all trading strategies. The break-even costs for trading the S&P 500 index and FTSE 100 index are all above 0.1% for all trading rules, indicating that the active trading strategies are profitable at transaction costs of 0.1% and the predictability of returns captured by the meteor shower model is economically significant.

Table 6.1: Quartiles of Daily Trading Volume

The panels below show the descriptive statistics about the quartiles of the daily US, UK and Japanese de-trended trading volume over a 7 year period from 1 August 2003 to 30 July 2010.

Panel A: Quartiles of Daily Trading Volume in the S&P 500 index

US trading volume	De-trended log value	Mean Average	Observations
1st quartile (0-25th percentile)	< 0.4900	-3.4963	444
2nd quartile (25-50th percentile)	[0.4900, 0.7665)	0.6166	444
3rd quartile (50-75th percentile)	[0.7665, 1.2323)	1.0192	445
4th quartile (75-100th percentile)	>= 1.2323	1.8875	444

Panel B: Quartiles of Daily Trading Volume in the FTSE00 index

UK trading volume	De-trended log value	Mean Average	Observations
1st quartile (0-25th percentile)	< 0.0957	-3.3730	444
2nd quartile (25-50th percentile)	[0.0957, 0.6887)	0.4288	444
3rd quartile (50-75th percentile)	[0.6887, 1.5420)	1.0452	445
4th quartile (75-100th percentile)	>= 1.5420	1.8776	444

Panel C: Quartiles of Daily Trading Volume in the TOPIX index

Japanese trading volume	De-trended log value	Mean Average	Observations
1st quartile (0-25th percentile)	< 0.7042	-5.82780	444
2nd quartile (25-50th percentile)	[0.7042, 1.5610)	1.1489	444
3rd quartile (50-75th percentile)	[1.5610, 2.201)	1.8752	445
4th quartile (75-100th percentile)	>= 2.201	2.8491	444

Table 6.2: Parameter Estimates of the Meteor Shower (MS) Model and Results of Direction Quality Measures

The MS model is specified as follows:

$R_{H,t} = \mu + \beta R_{F,t-1} + \gamma\epsilon_{t-1} + \epsilon_t$,

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1}$,

where μ is a constant; $R_{H,t}$ denotes open-to-close (daytime) return in the domestic market (signal receiving market); $R_{F,t-1}$ denotes preceding daytime return in the foreign market (signalling market); ϵ_t and ϵ_{t-1} are the error term at time *t* and *t-1*, respectively; β captures the return spillover effect from the foreign to domestic markets; *a*, *b*, and *c* are the parameters in the variance equation.

Panel A: the US is regarded as Domestic Market and Japan is Foreign Market

Parameters in the Mean Equation		Parameters in the Variance Equation	
μ	0.0003* (0.0521)	a	1.06E-06*** (0.0000)
β	0.0759*** (0.0004)	b	0.0727*** (0.0000)
γ	-0.0869*** (0.0018)	c	0.9169*** (0.0000)
Direction Quality Measure			
Q_1		0.5498	
Q_2		1.1493	
Q_3		1.3543	

Panel B: the UK is regarded as Domestic Market and Japan is Foreign Market

Parameters in the Mean Equation		Parameters in the Variance Equation	
μ	0.0006*** (0.0002)	a	9.67E-07*** (0.0002)
β	0.2380*** (0.0000)	b	0.1007*** (0.0000)
γ	-0.1047*** (0.0000)	c	0.8940*** (0.0000)
Direction Quality Measure			
Q_1		0.5697	
Q_2		1.2413	
Q_3		1.1457	

Notes: *, ** and *** represent that estimated parameters are statistically significant at the 10%, 5% and 1% levels, respectively. The p-values are reported in the parentheses.

Table 6.2 Continued: Parameter Estimates of the Meteor Shower (MS) Model and Results of Direction Quality Measure

Panel C: the UK is regarded as Domestic Market and the US is Foreign Market

Parameters in the Mean Equation		Parameters in the Variance Equation	
μ	0.0004*** (0.0028)	a	8.71E-07*** (0.0014)
β	0.3609*** (0.0000)	b	0.1062*** (0.0000)
γ	-0.2252*** (0.0000)	c	0.8908*** (0.0000)
Direction Quality Measure			
Q_1		0.5697	
Q_2		1.3003	
Q_3		1.2617	

Panel D: Japan is regarded as Domestic Market and the US is Foreign Market

Parameters in the Mean Equation		Parameters in the Variance Equation	
μ	-0.0002 (0.1836)	a	1.56E-06*** (0.0000)
β	0.0909*** (0.0000)	b	0.0974*** (0.0000)
γ	-0.0603** (0.0196)	c	0.8913*** (0.0000)
Direction Quality Measure			
Q_1		0.5185	
Q_2		0.9096	
Q_3		0.9422	

Panel E: Japan is regarded as Domestic Market and the UK is Foreign Market

Parameters in the Mean Equation		Parameters in the Variance Equation	
μ	-0.0003* (0.0797)	a	1.49E-06*** (0.0000)
β	0.1537*** (0.0000)	b	0.0951*** (0.0000)
γ	-0.0801*** (0.0019)	c	0.8938*** (0.0000)
Direction Quality Measure			
Q_1		0.4979	
Q_2		0.9694	
Q_3		1.1092	

Table 6.3 Performance Results of Trading Strategies

Panel A: Buy and Hold Versus Actively Trading the S&P500 Index Based on Signals from Japan

S&P 500 index	Holding Period Return	Average Return per trade	Original Sharpe Ratio	Standard Sharpe Ratio	Modified Sharpe Ratio
Passive Investment (1 trade)					
Buy & Hold	15.96%	15.96%	18.5489	18.5657	18.5657
Active Investment (based on signals from Japan, 251 trades)					
Rule MS	41.73%	0.14%	55.4067	55.4318	55.4318
Rule FV	100.99%	0.28%	67.8261	67.8176	67.8176
Rule DV	85.73%	0.25%	60.6558	60.6762	60.6762
Rule FV&DV	189.96%	0.43%	84.1233	84.1241	84.1241

Panel B: Buy and Hold Versus Actively Trading the FTSE100 index based on Signals from Japan

FTSE100 index	Holding Period Return	Average Return per trade	Original Sharpe Ratio	Standard Sharpe Ratio	Modified Sharpe Ratio
Passive Investment (1 trade)					
Buy & Hold	10.07%	10.07%	10.3006	10.2963	10.2963
Active Investment (based on signals from Japan, 251 trades)					
Rule MS	42.91%	0.14%	47.3731	47.3927	47.3927
Rule FV	90.80%	0.26%	51.0459	51.0638	51.0638
Rule DV	108.66%	0.29%	57.7821	57.8022	57.8022
Rule FV&DV	196.82%	0.43%	68.8976	68.9160	68.9160

Panel C: Buy and Hold Versus Actively Trading the FTSE100 index based on Signals from the US

FTSE100 index	Holding Period Return	Average Return per trade	Original Sharpe Ratio	Standard Sharpe Ratio	Modified Sharpe Ratio
Passive Investment (1 trade)					
Buy & Hold	10.07%	10.07%	10.3006	10.2963	10.2963
Active Investment (based on signals from US, 251 trades)					
Rule MS	55.08%	0.18%	61.4619	61.5132	61.5132
Rule FV	112.86%	0.30%	70.8839	70.8839	70.8839
Rule DV	96.31%	0.27%	51.0648	51.0833	51.0833
Rule FV&DV	181.61%	0.41%	68.1790	68.1981	68.1981

Table 6.3 Continued: Performance Results of Trading Strategies

Panel D: Buy and Hold Versus Actively Trading the TOPIX index based on Signals from the US

TOPIX index	Holding Period Return	Average Return per trade	Sharpe Ratio (1966)	Sharpe Ratio (1994)	Modified Sharpe Ratio (2005)
Passive Investment (1 trade)					
Buy & Hold	-0.96%	-0.96%	-0.9964	-0.9963	-0.0002
Active Investment (based on signals from US, 243 trades)					
Rule MS	-0.15%	-0.00%	-0.5031	-0.5029	0.0000
Rule FV	12.96%	0.05%	6.6211	6.6213	6.6213
Rule DV	12.21%	0.05%	7.5952	7.5951	7.5951
Rule FV&DV	33.59%	0.12%	13.8145	13.8152	13.8152

Panel E: Buy and Hold Versus Actively Trading the TOPIX Index based on Signals from the UK

TOPIX index	Holding Period Return	Average Return per trade	Sharpe Ratio (1966)	Sharpe Ratio (1994)	Modified Sharpe Ratio (2005)
Passive Investment (1 trade)					
Buy & Hold	-0.96%	-0.96%	-0.9964	-0.9963	-0.0002
Active Investment (based on signals from UK, 243 trades)					
Rule MS	6.21%	0.03%	5.9949	5.9947	5.9947
Rule FV	24.08%	0.09%	16.8592	16.8616	16.8616
Rule DV	0.99%	0.00%	0.4144	0.4144	0.4144
Rule FV&DV	16.80%	0.06%	8.6587	8.6593	8.6593

Figure 6.1: Fund Values for Trading the S&P 500 Index (when Japan is regarded as the Signalling Market)

Figure 6.1 A: Fund Value ($m)

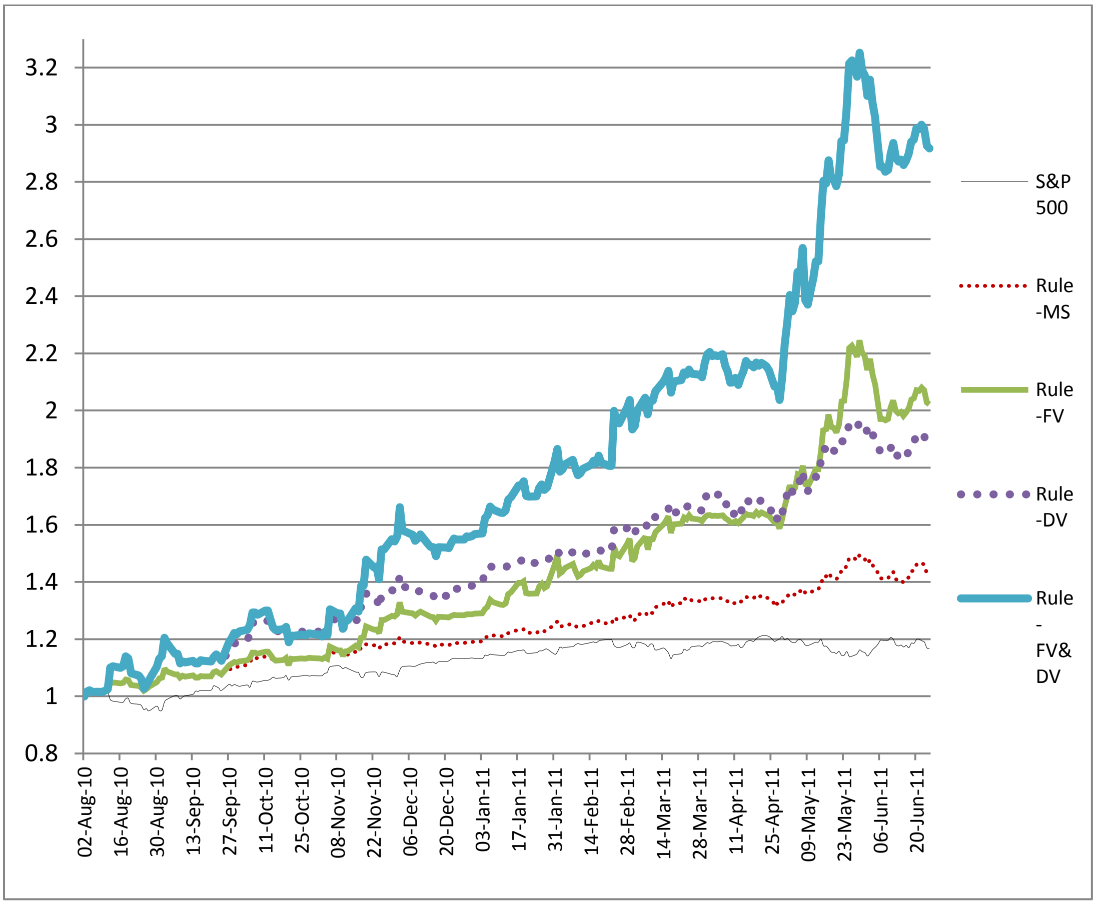


Figure 6.2 B: Daily Return of the Fund (Trading Rule MS)

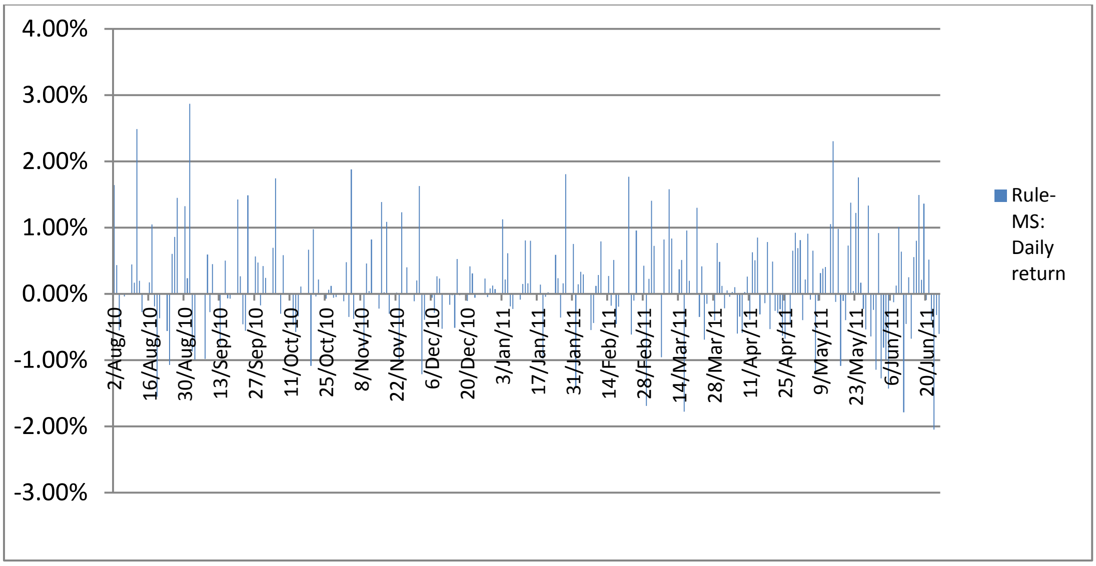


Figure 6.3 C: Daily Returns of the Fund (Trading Rule FV)

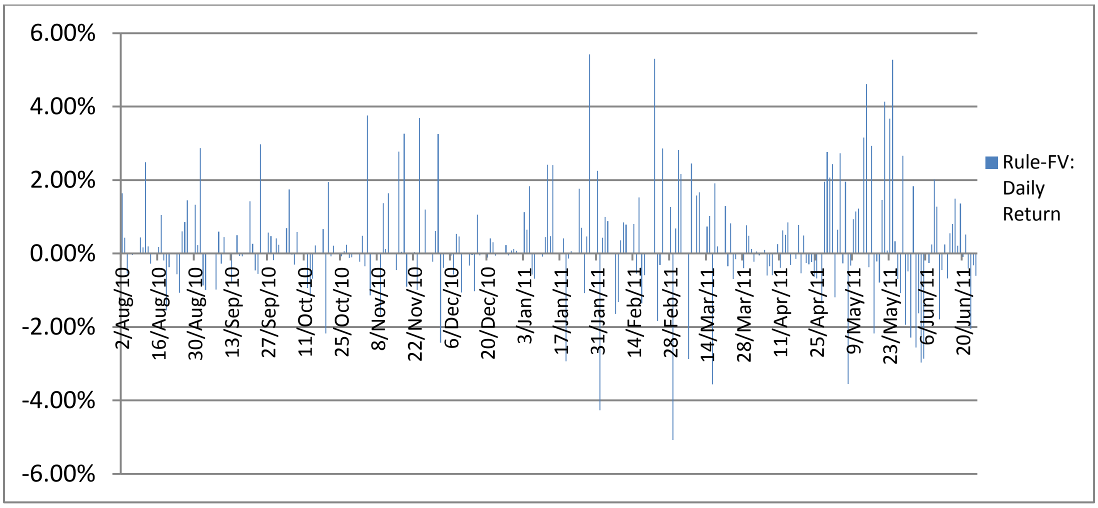


Figure 6.4 D: Daily Returns the Fund (Trading Rule -DV)

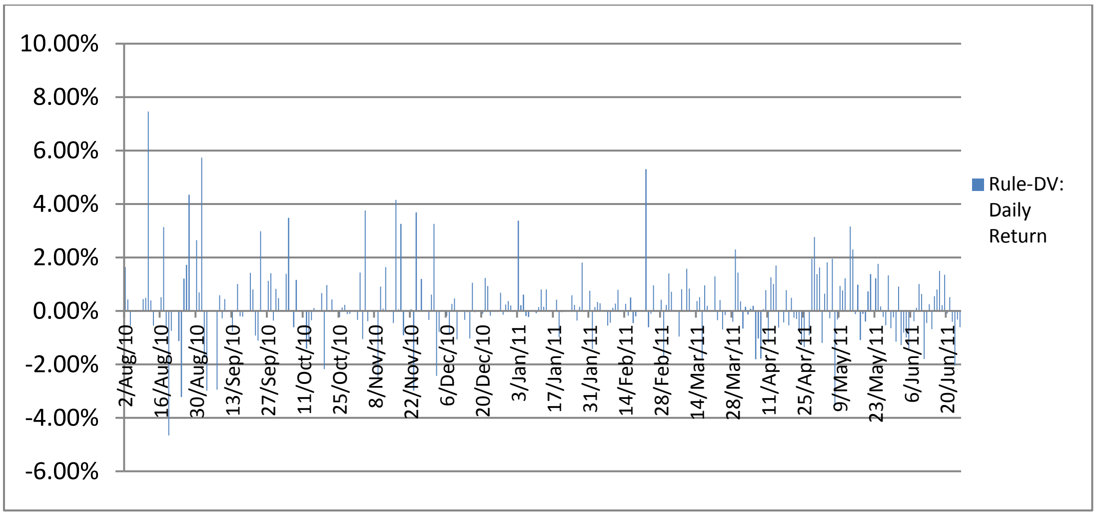


Figure 6.5 E: Daily Returns of the Fund (Trading Rule FV&DV)

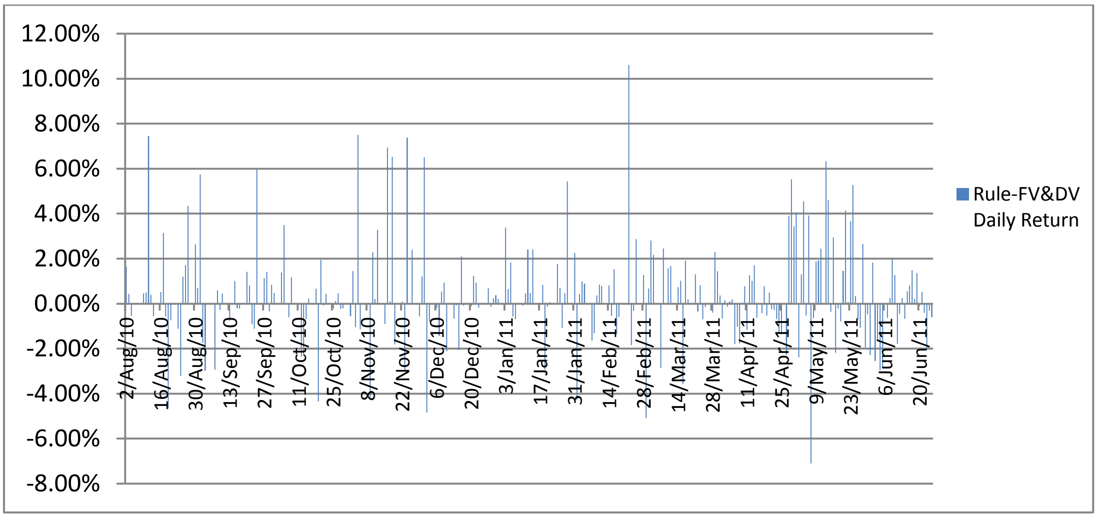


Figure 6.2: Fund Values for Trading the FTSE100 Index (when Japan is regarded as the Signalling Market)

Figure 6.6 A Fund Value £m

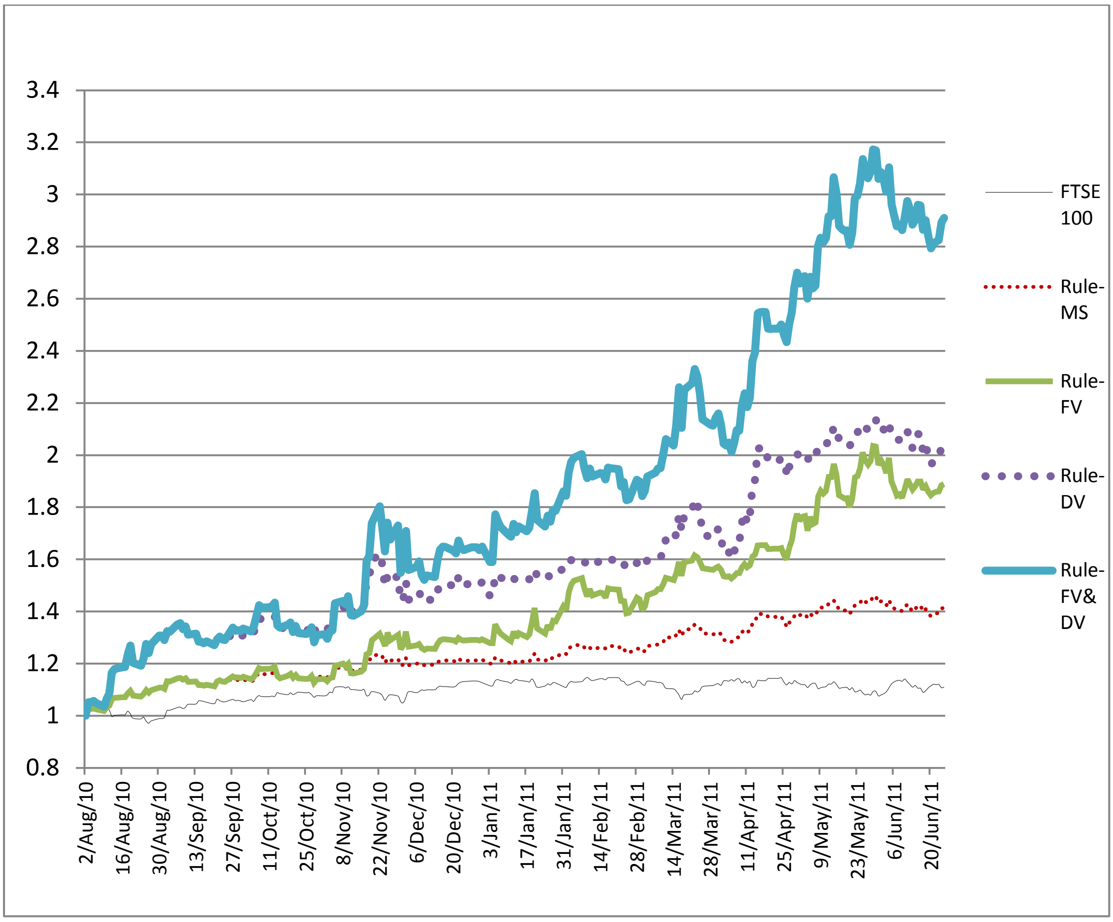


Figure 6.2 B: Daily Returns of the Fund (Trading Rule MS)

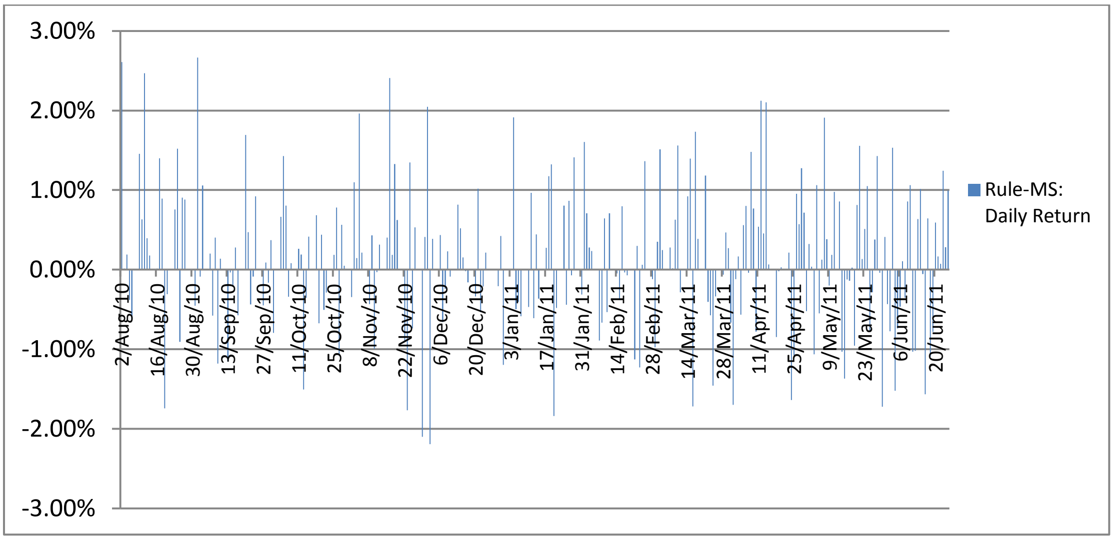


Figure 6.2 C: Daily Returns of the Fund (Trading Rule FV)

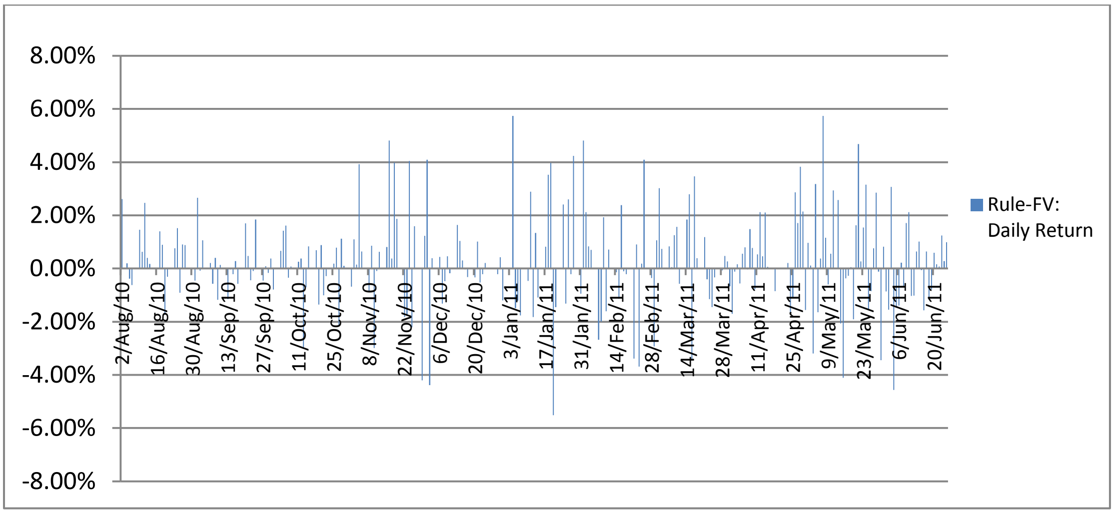


Figure 6.2 D: Daily Returns of the Fund (Trading Rule DV)

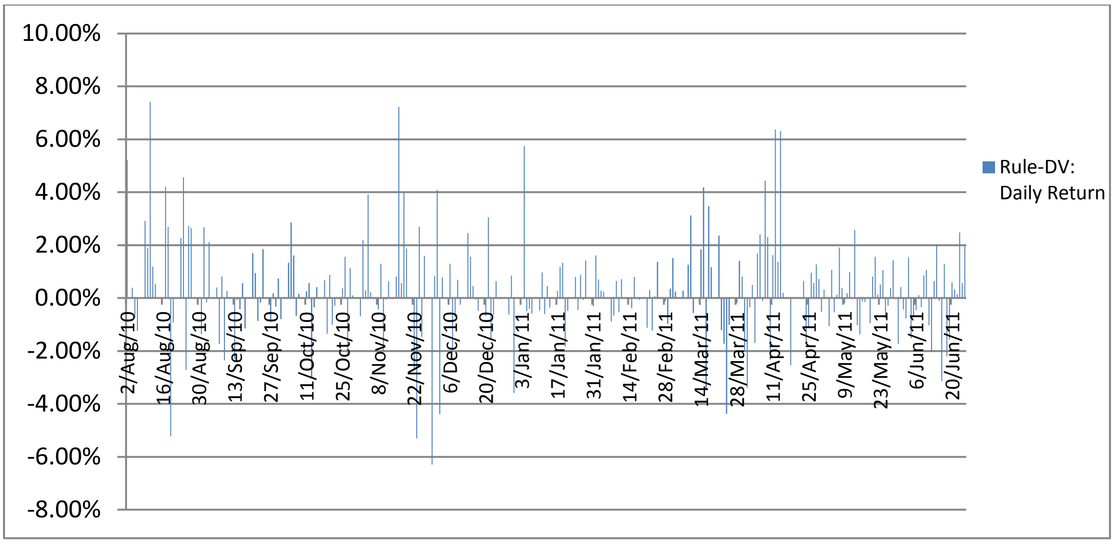


Figure 6.2 E: Daily Returns of the Fund (Trading Rule FV&DV)

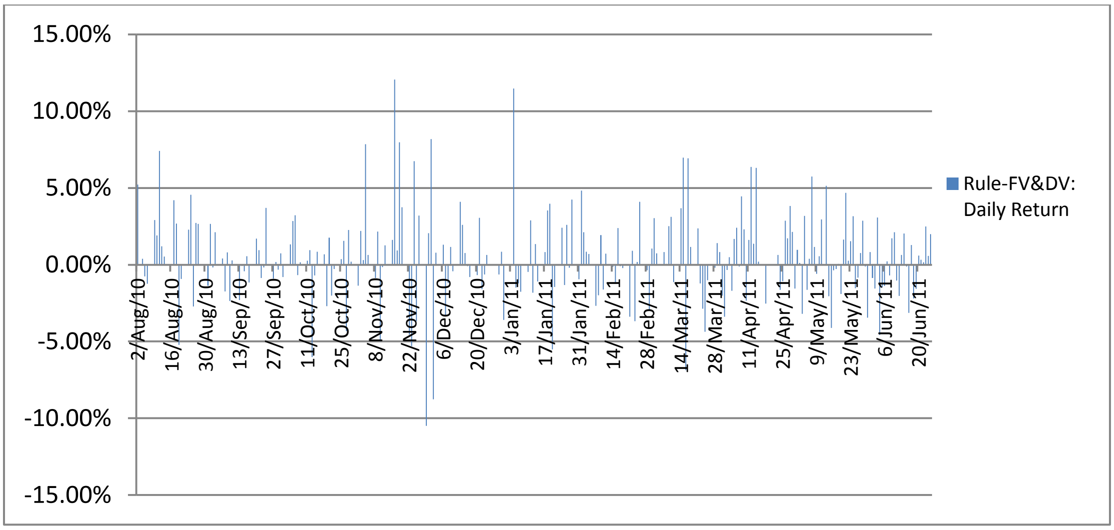


Figure 6.3: Fund Values for Trading the FTSE100 index (when the US is regarded as the Signalling Market)

Figure 6.3 A Fund Value £m

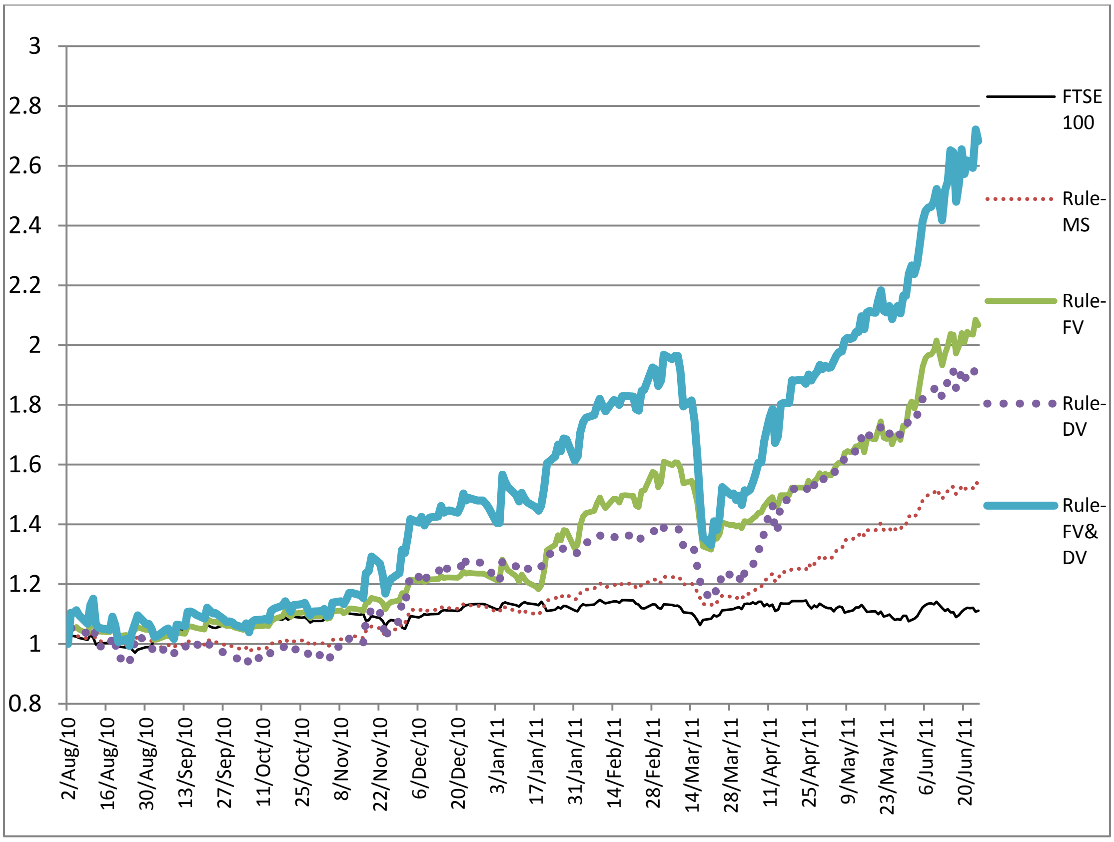


Figure 6.3 B: Daily Returns of the Fund (Trading Rule MS)

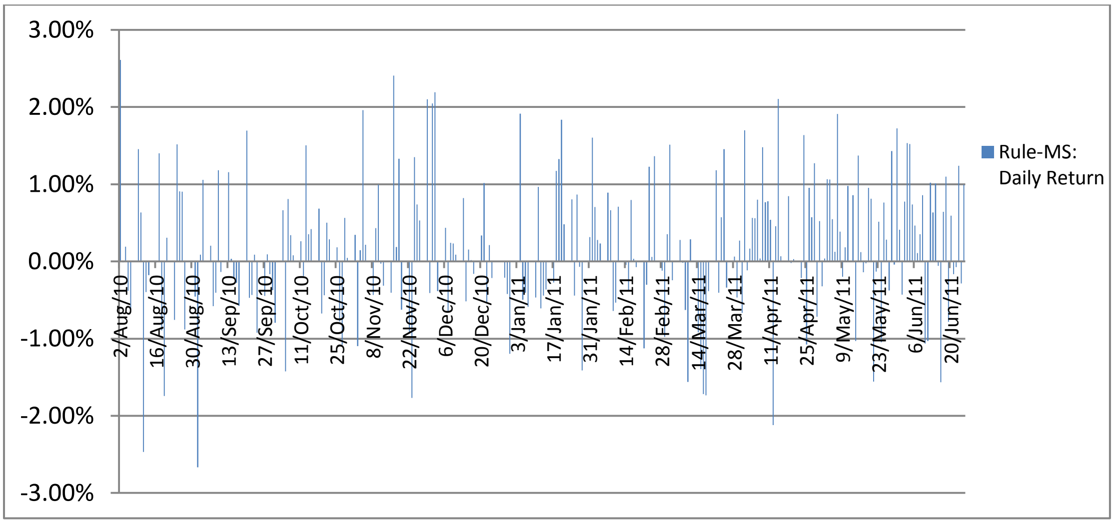


Figure 6.3 C: Daily Returns of the Fund (Trading Rule FV)

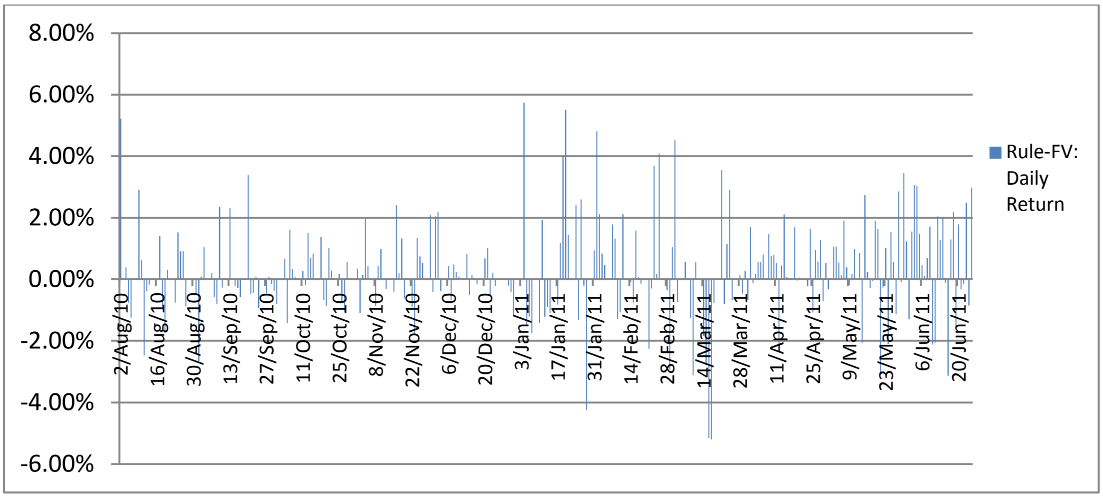


Figure 6.3 D: Daily Returns of the Fund (Trading Rule DV)

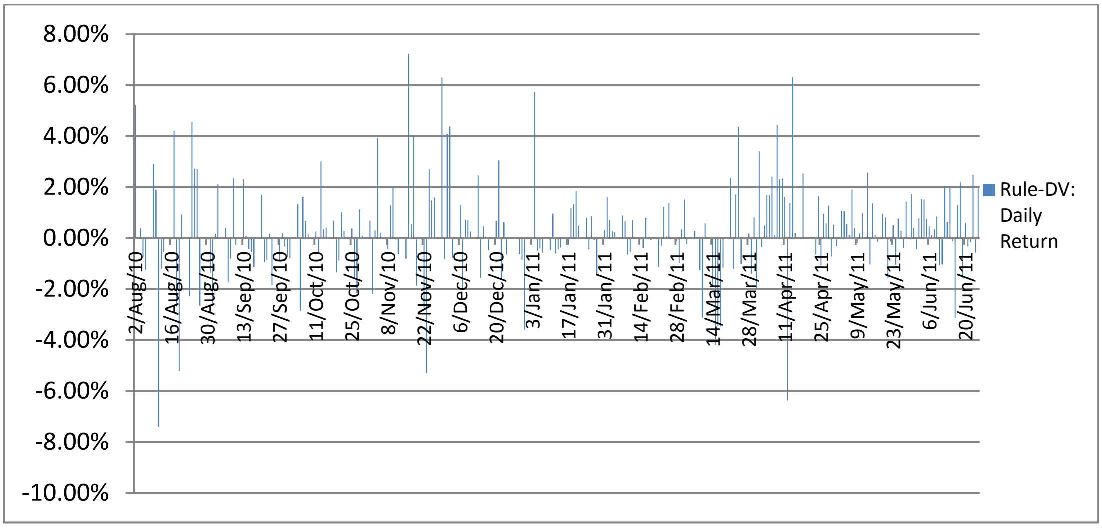


Figure 6.3 E: Daily Returns of the Fund (Trading Rule FV&DV)

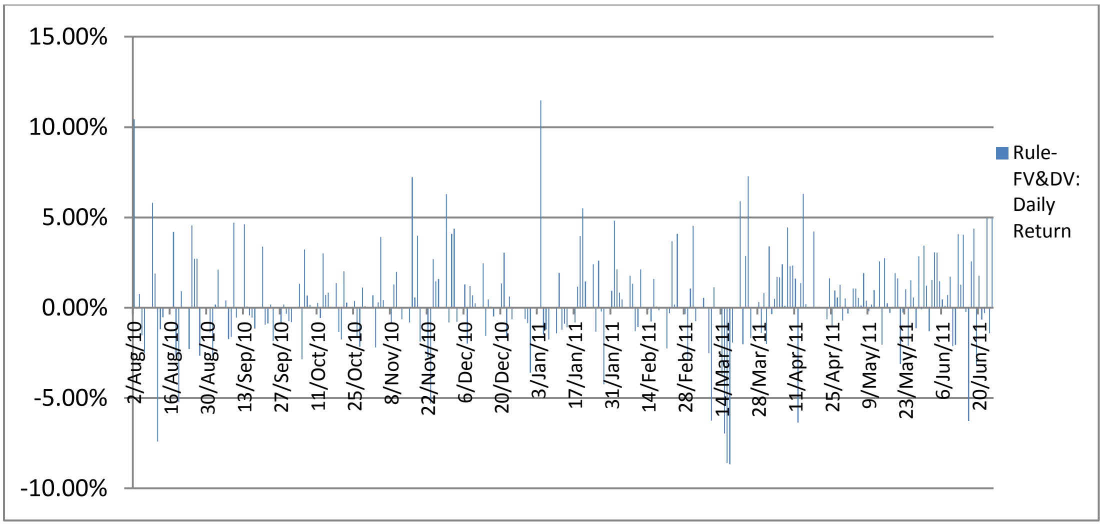


Figure 6.4: Fund Values for Trading the TOPIX index (when the US is regarded as the Signalling Market)

Figure 6.4 A Fund Value ¥m

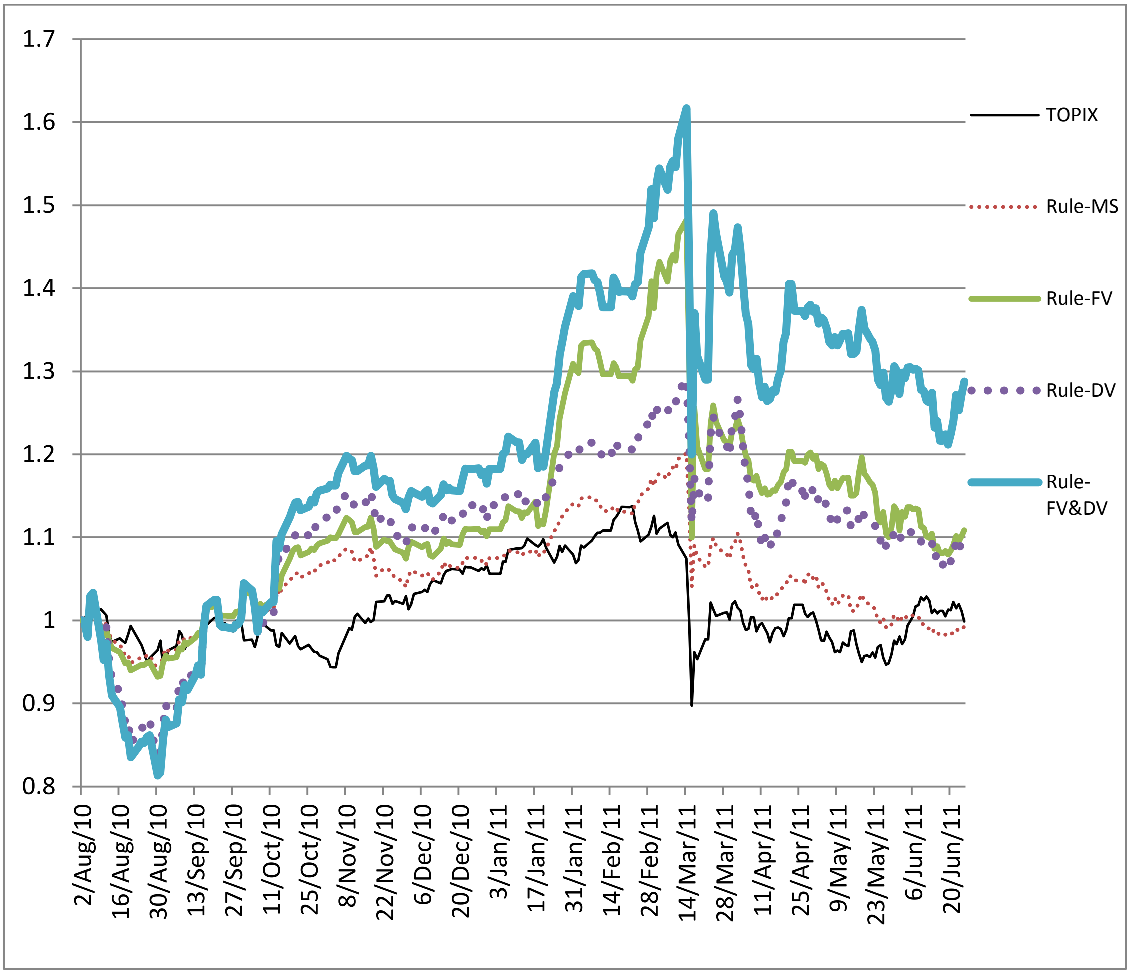


Figure 6.4 B: Daily Returns of the Fund (Trading Rule MS)

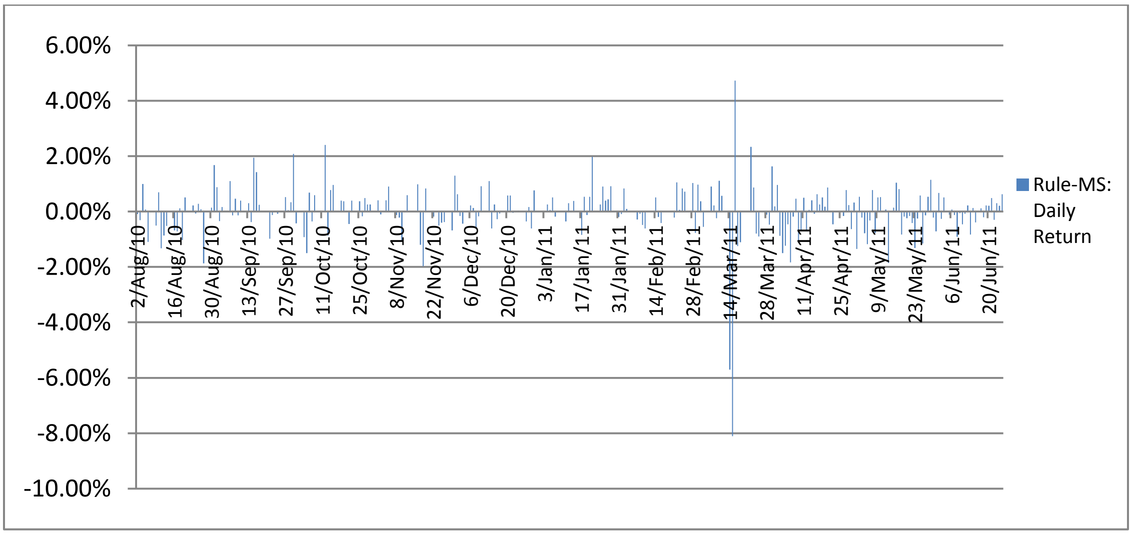


Figure 6.4 C: Daily Returns of the Fund (Trading Rule FV)

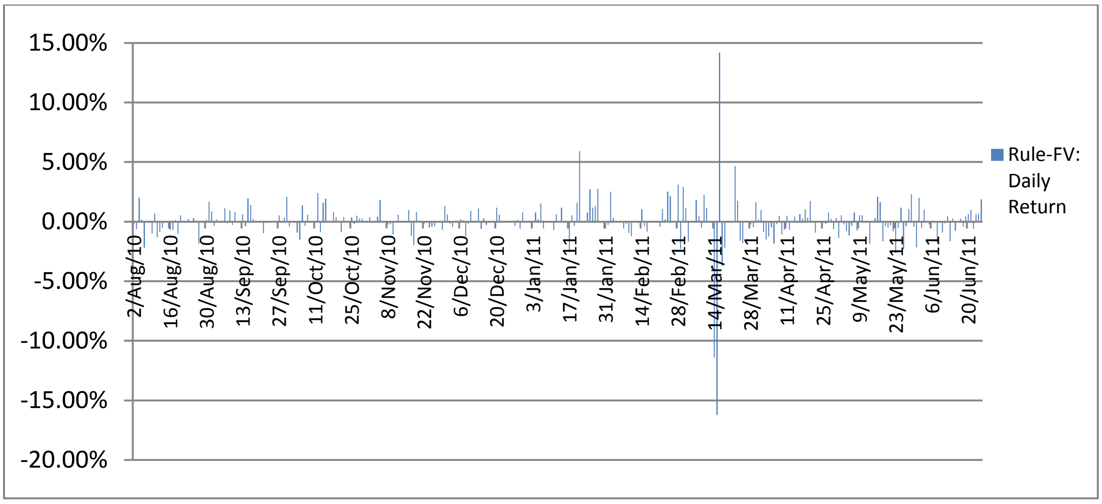


Figure 6.4 D: Daily Returns of the Fund (Trading Rule DV)

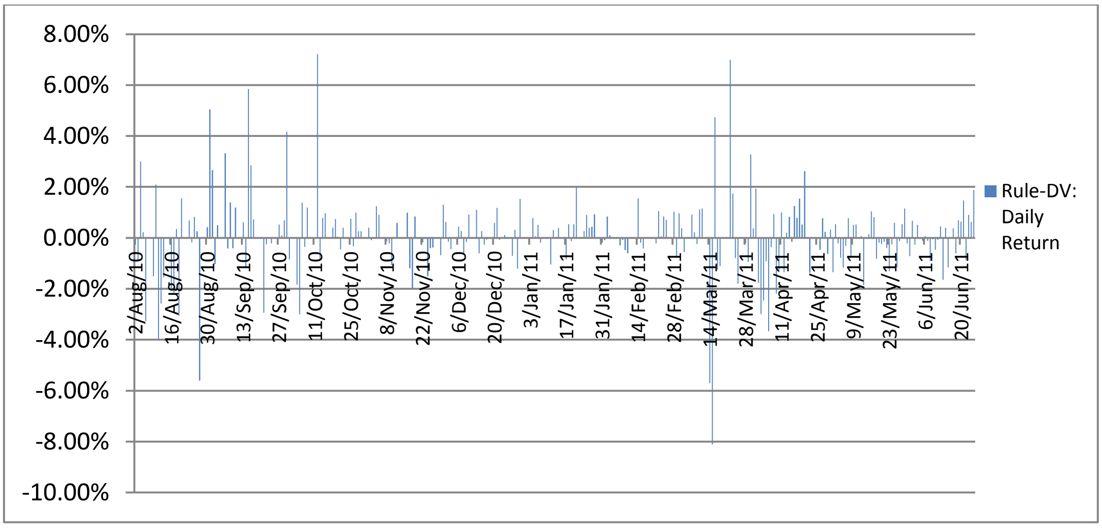


Figure 6.4 E: Daily Returns of the Fund (Trading Rule FV&DV)

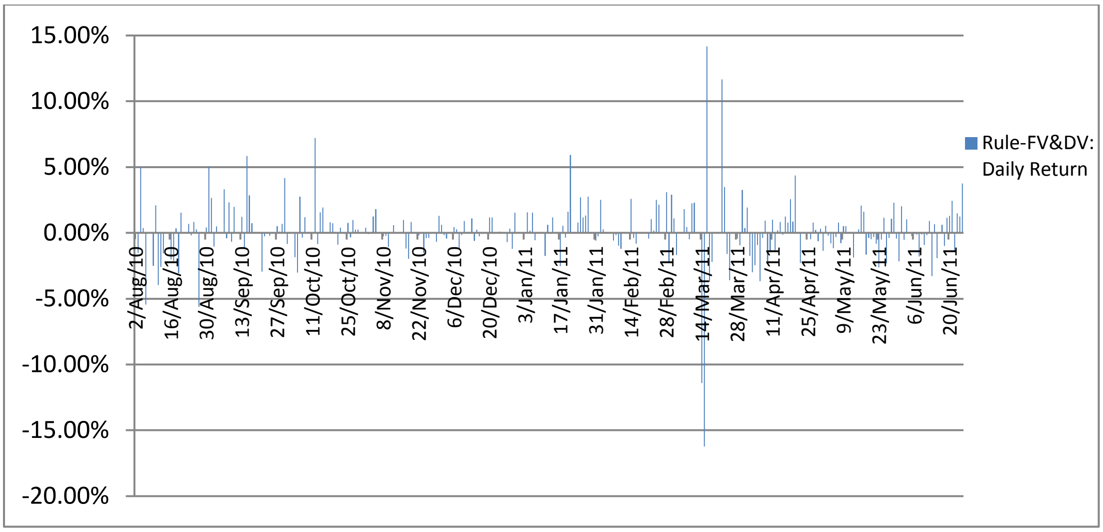


Figure 6.5: Fund Values for Trading the TOPIX index (when the UK is regarded as the Signalling Market)

Figure 6.5 A: Fund Value ¥m

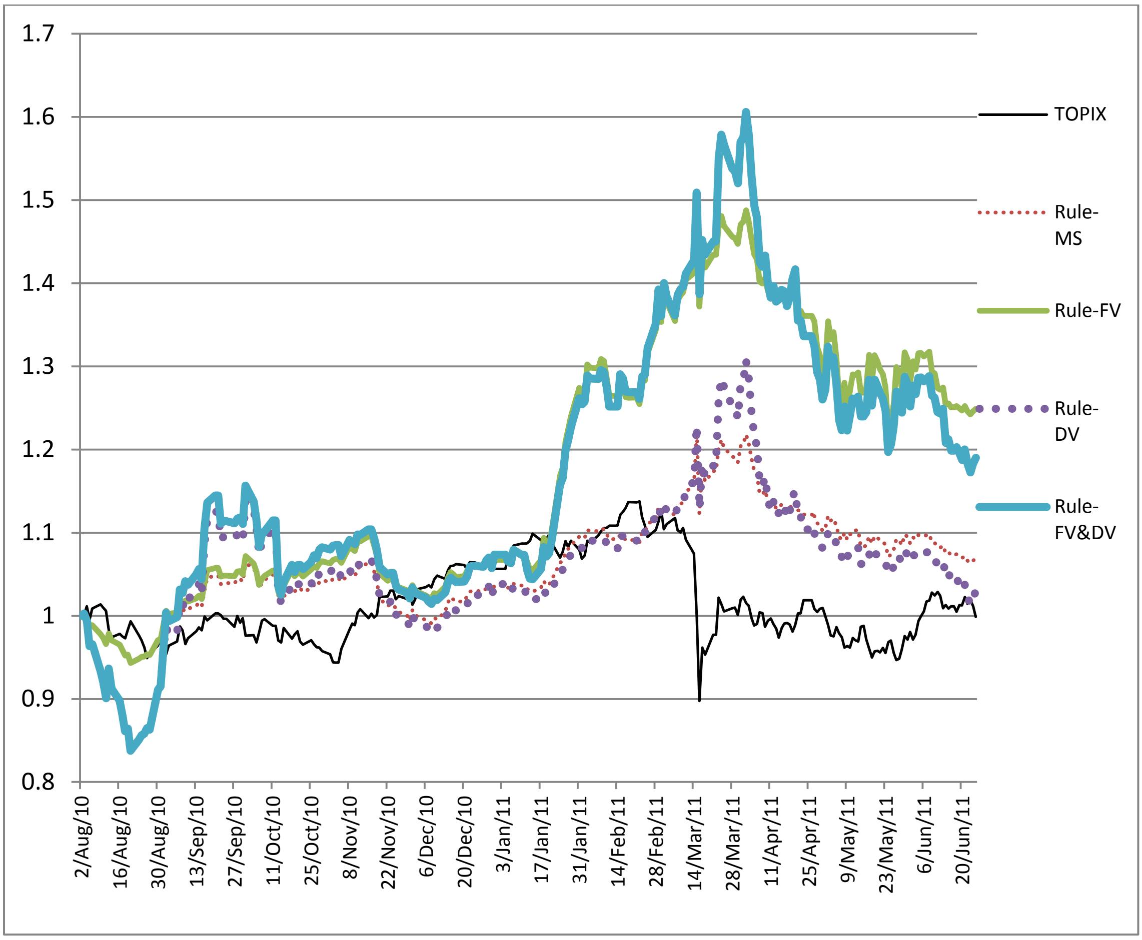


Figure 6.5 B: Daily Returns of the Fund (Trading Rule MS)

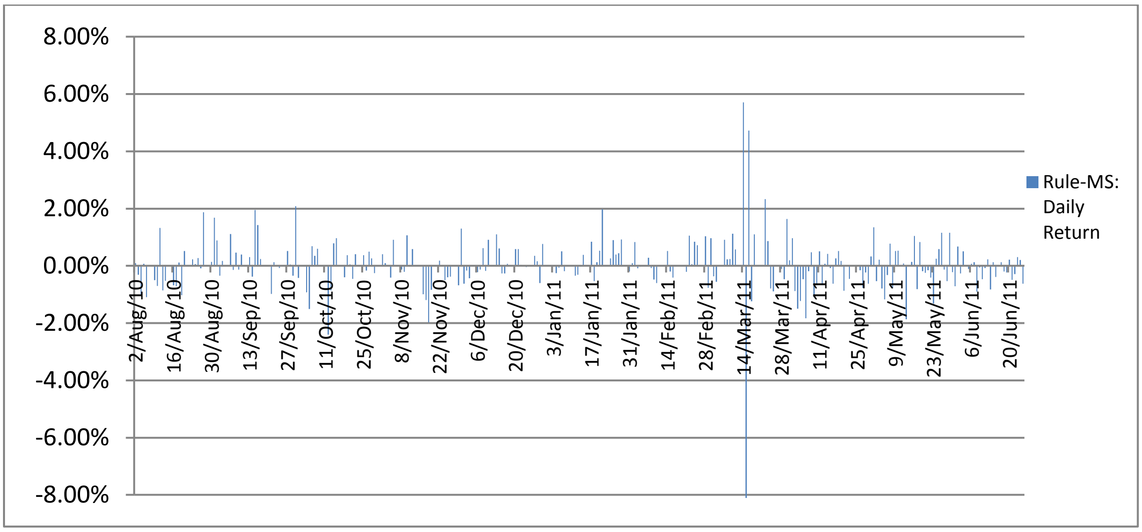


Figure 6.5 C: Daily Returns of the Fund (Trading Rule FV)

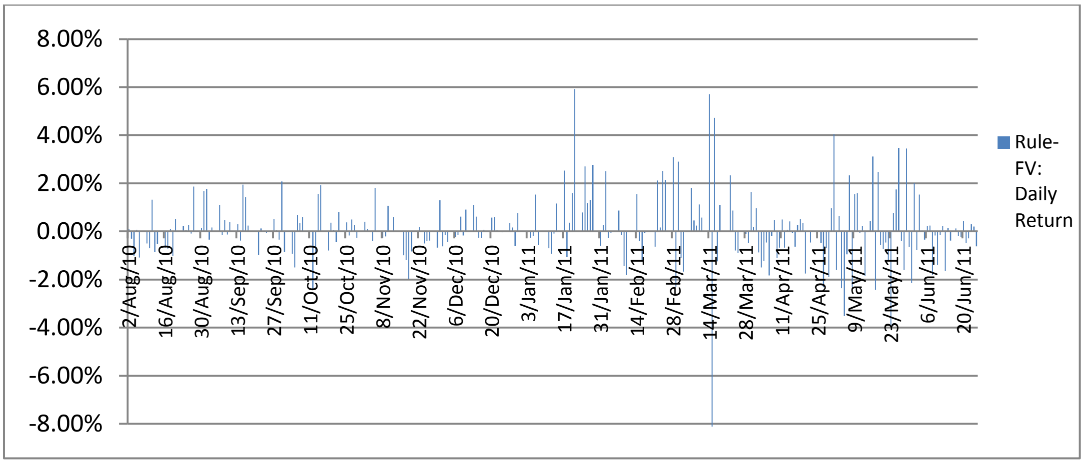


Figure 6.5 D: Daily Returns of the Fund (Trading Rule DV)

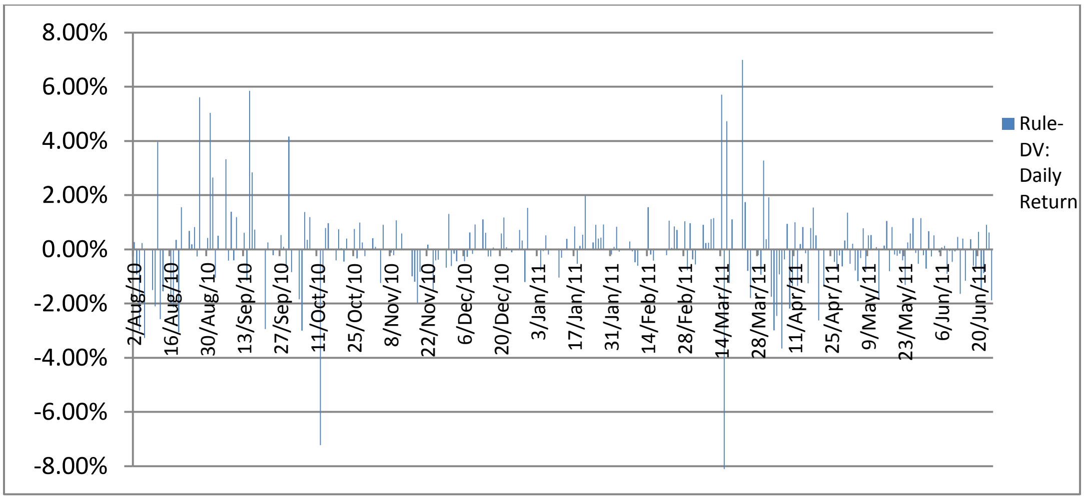


Figure 6.5 E: Daily Returns of the Fund (Trading Rule FV&DV)

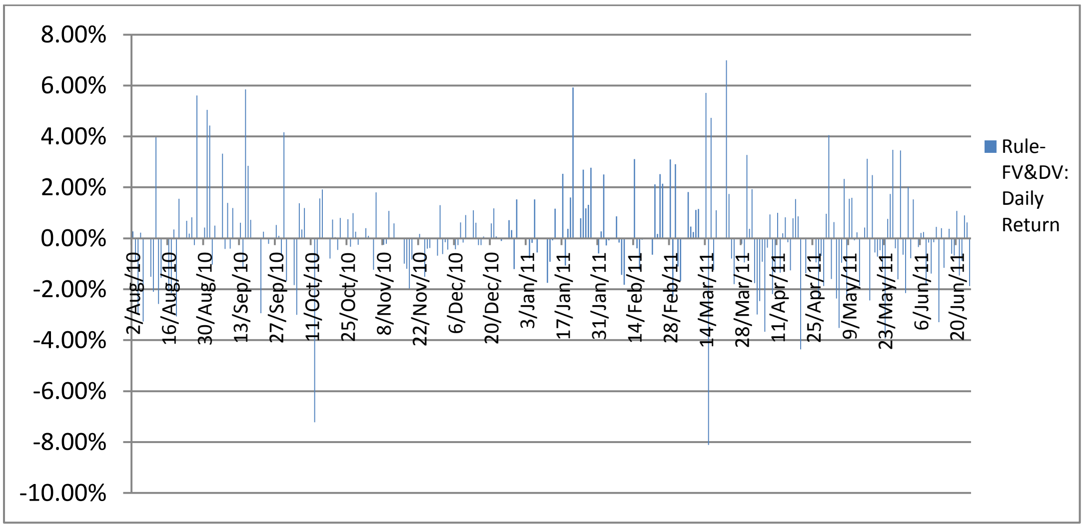


Figure 6.6: Fund Values for Trading the S&P 500 Index at Transaction Costs of 0.1% (when Japan is regarded as the Signalling Market)

Fund Value ($m)

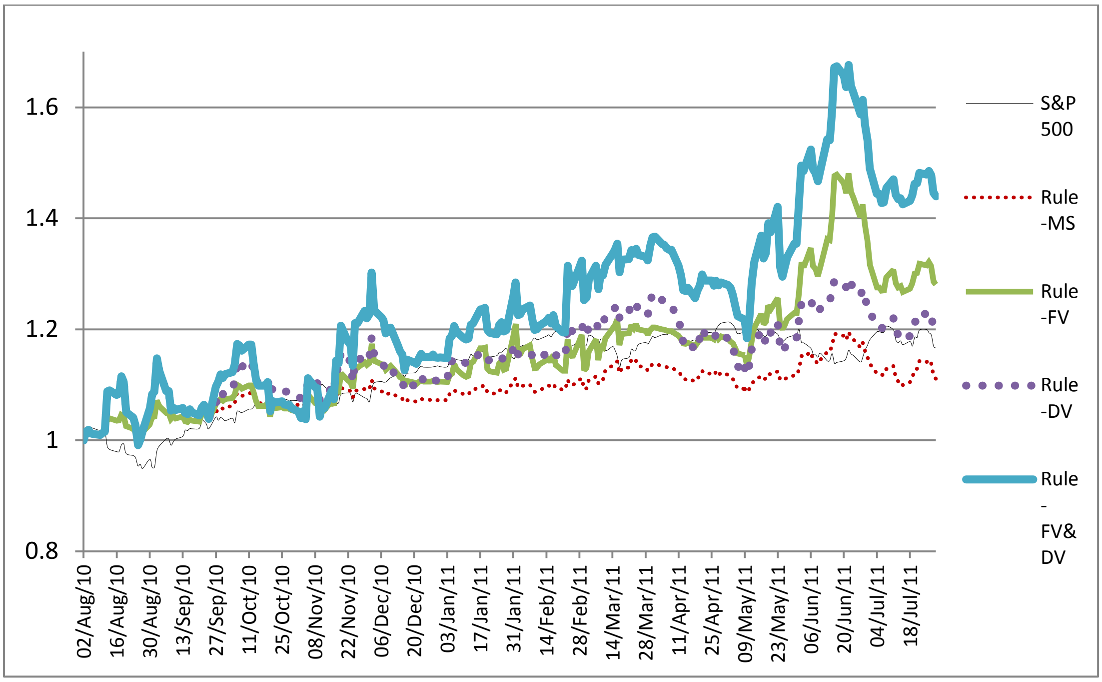


Figure 6.7: Fund Values for Trading the FTSE100 Index at Transaction Costs of 0.1% (when Japan is regarded as the Signalling Market)

Fund Value (£m)

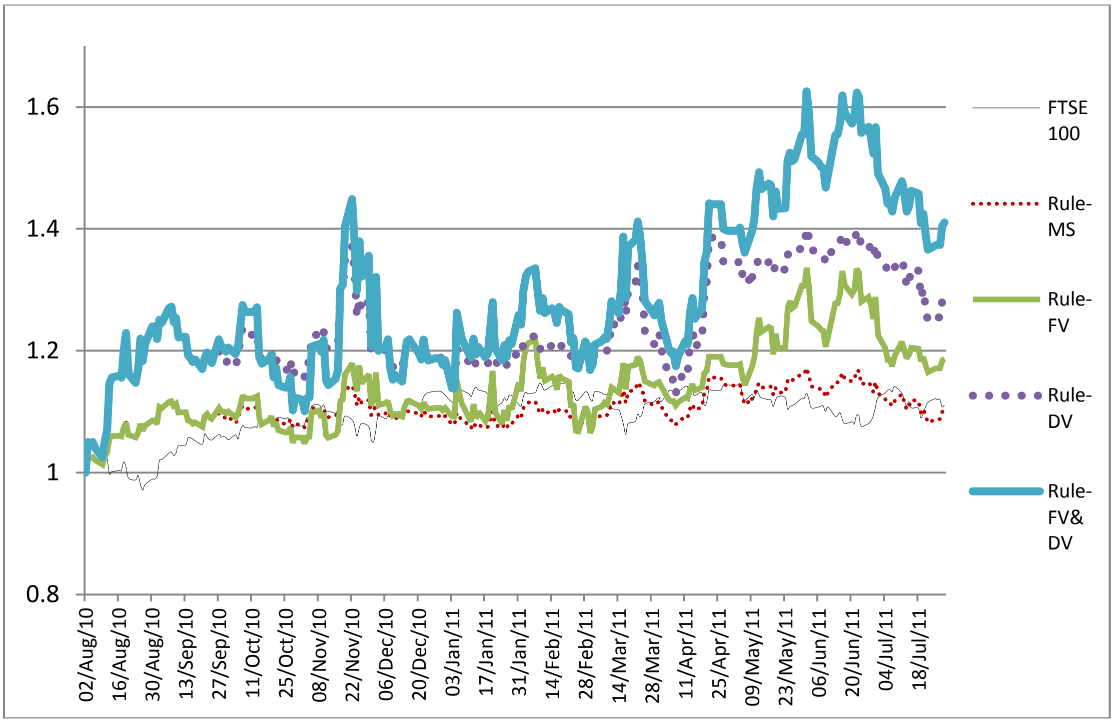


Figure 6.8: Fund Values for Trading the FTSE100 Index at Transaction Costs of 0.1% (when the US is regarded as the Signalling Market)

Fund Value (£m)

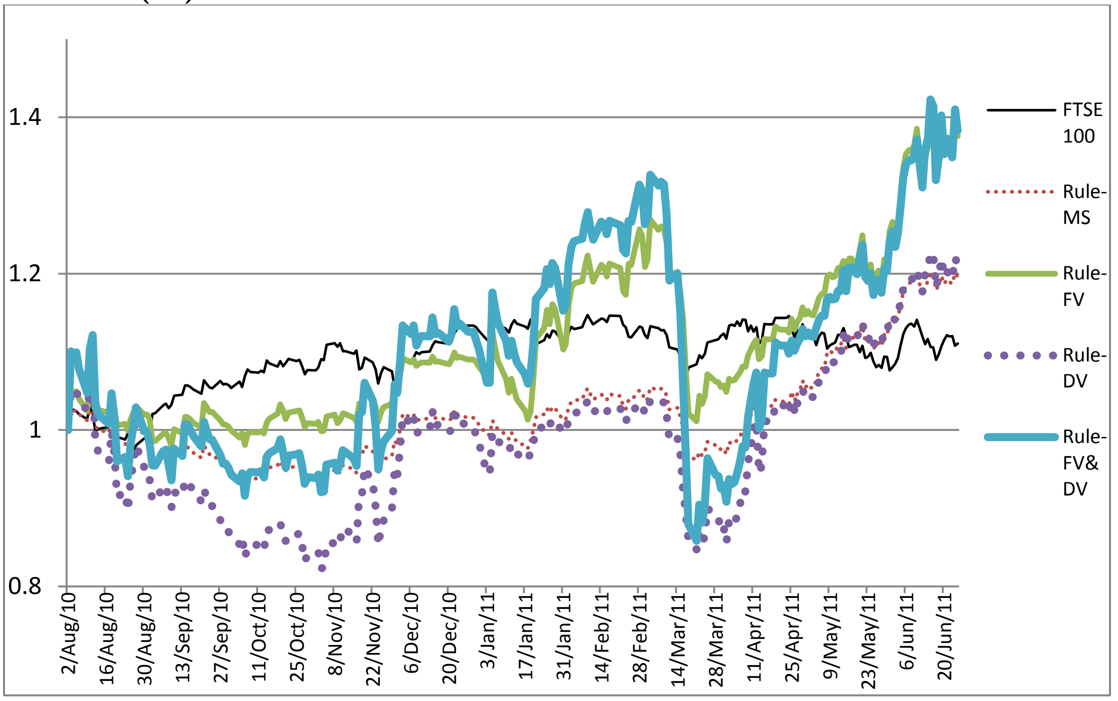


Figure 6.9: Fund Values for Trading the TOPIX Index at Transaction Costs of 0.1% (when the US is regarded as the Signalling Market)

Fund Value (¥m)

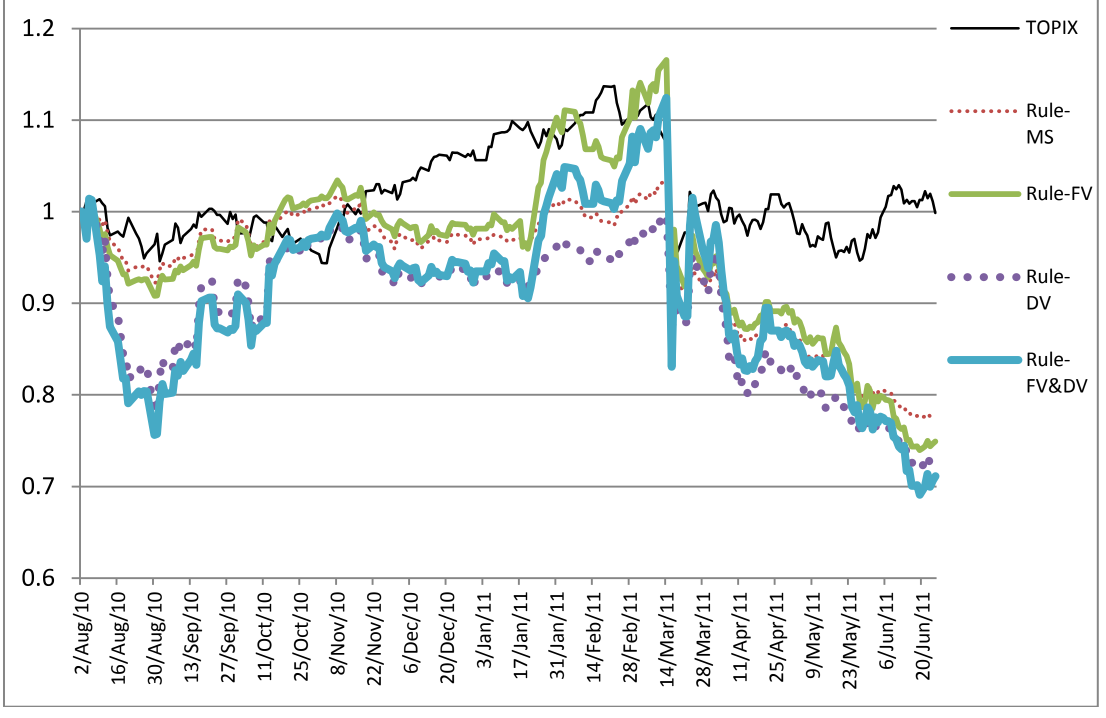
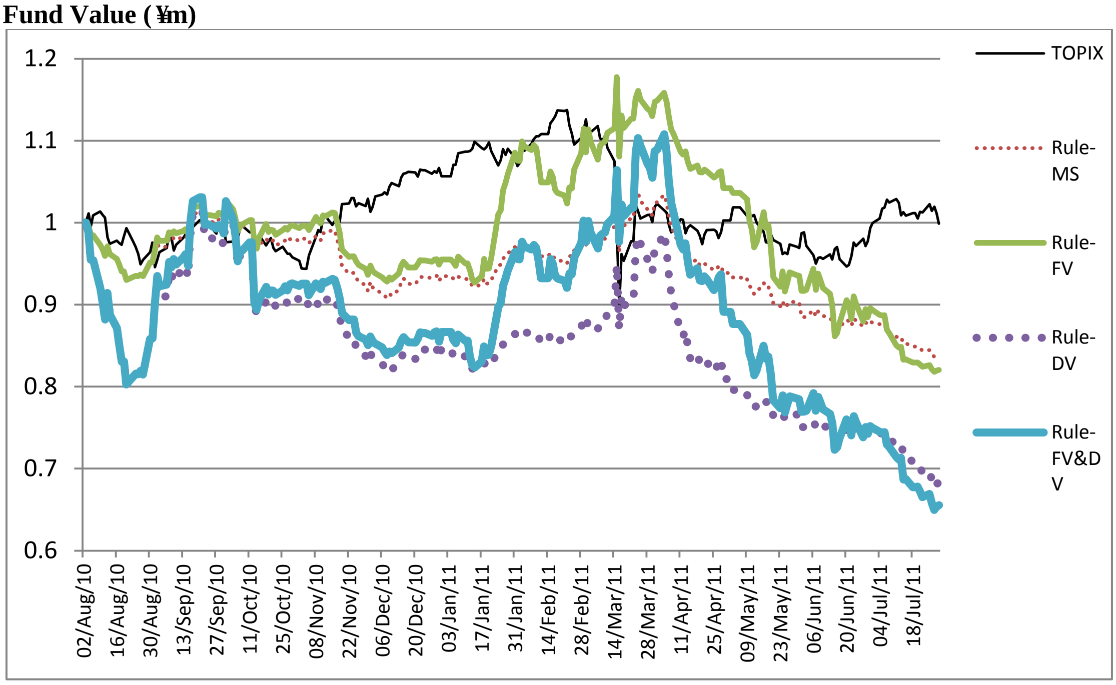


Figure 6.10: Fund Values for Trading the TOPIX Index at Transaction Costs of 0.1% (when the UK is regarded as the Signalling Market)



CHAPTER 7 – CONCLUSIONS, MAIN FINDINGS, LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

7.1 Introduction

This chapter summarises the findings presented in each empirical chapter and draws overall conclusions. In addition, the limitations of this study are discussed and suggestions for future research are made.

The chapter is organised as follows. Section 7.2 presents the main findings of each empirical chapter (i.e. subsections 7.2.1, 7.2.2 and 7.2.3 summarise the results of Chapters 4, 5 and 6, respectively). Section 7.3 offers an overall conclusion. Section 7.4 discusses the limitations of this study and makes suggestions for future research.

7.2 Main Findings

7.2.1 Results from Chapter 4

Chapter 4 investigates the direct information transmission mechanisms in returns, volatility and trading volume across the world's eight biggest international stock markets. By employing the ARCH-type models and intraday data, this study provides strong evidence showing that the meteor shower effect exists not only in stock returns and volatility but also in trading volume.

First, it presents evidence that the ARCH framework is an appropriate methodology to investigate the return spillover effect across international stock markets.

The specific findings are as follows:

- The initial model estimations in Section 4.2.1 indicate that the GARCH(1,1) process is appropriate to model the ARCH effect that is inherent in the financial time series. The AR(1)-GARCH(1,1) model fits the data well and is a proper model to describe the stock return generating process. The model specification appears to be adequate in the sense that the standardised residuals based diagnostic tests show no serious evidence against the model specification, and the parameters designed to capture the ARCH effect are all significant at the 1% level.

- Section 4.2.2 shows that the magnitude and significance of the dynamic return spillover coefficients estimated under the ARCH framework are substantially different from the ones obtained by OLS. The study provides new evidence in favour of the findings of Hamilton (2010), suggesting that the ARCH methodology is more appropriate to obtain accurate estimates of the parameters in light of the dramatic ARCH effect observed in the data.

Second, this study provides strong evidence to support the findings of previous return and volatility spillover research by using a newly complied sample of intraday market index returns data for the world's eight largest international stock markets.

The specific findings are as follows:

- It reports on the absence of a volatility feedback effect in the GARCH-M model for all the markets under investigation. The time-varying conditional variance seems to exert little influence on the expected returns of equity, which is consistent with the results reported by Hamao et al. (1990), Theodossiou and Lee (1993) and Hsin (2004).

- The estimates of the GARCH-GJR and EGARCH models provide evidence about the presence of the asymmetric effect in developed stock markets. A negative shock appears to exert more influence on the conditional variance of index returns in the US, UK, France, Germany, Canada and Japan. In contrast, the asymmetric effect is not statistically significant for the Hong Kong and

Shanghai markets, which are the only two emerging markets under investigation in this study.

- The estimates of the return and volatility spillover model indicate the complexity of the information transmission mechanisms *via* different channels. The return spillover effect can exist with or without the presence of the volatility spillover effect and *vice versa*.

- The comparison of return spillover coefficients estimated across the different ARCH-type models shows that parameter estimators in the mean equation are robust to different specifications of the volatility equations that have modelled some well documented phenomena, such as the asymmetric effect and the international volatility spillover effect.

- The estimation results show that the New York stock market plays an important role in affecting the subsequent daytime returns in the London, Frankfurt, Tokyo and Hong Kong markets. Conversely, the Shanghai stock exchange is the least integrated market among the investigated international stock markets.

- A general pattern is documented whereby meteor shower effects in daytime returns (i.e. positive dynamic return spillovers) are less frequent and weaker between intra-regional markets than inter-regional markets. It is because stock daytime returns are more likely to transmit fully and quickly across intra-regional markets at the same time (e.g. positive and statistically contemporaneous return spillovers) and without too much delay to the next day (e.g. statistically insignificant dynamic return spillovers), due to factors such as synchronous trading hours, tight economic and financial linkages, and so on.

Third, the estimation results of the trading volume spillover model in Section 4.3.2 indicate that trading volume in one market is useful in providing additional information to investors in other international stock markets and may change their incentive to trade. It provides empirical evidence showing that the meteor shower effect also exists in the time series of trading volume. In addition, the first-order autocorrelation behaviour of trading volume is not significantly affected by the impact of the meteor shower effect in trading volume from foreign markets.

The specific findings are as follows:

- The dynamic trading volume spillover coefficient is more likely to be positive and statistically significant between markets located in different regions than between markets from the same region. In other words, the inter-regional meteor shower effect in trading volume tends to be more frequent and pronounced than the intra-regional effect. The statistically insignificant dynamic trading volume spillover effect between markets located in the same region indicates that the information about lagged trading volume from intra-regional markets is of little help in the prediction of trading volume in the domestic market.

- The presence of inter-market dependence in trading volume implies that the information contained in foreign market trading volume can change the domestic investor's incentive to trade. These cross-country Granger-causal relations in trading volume can be interpreted in light of economic theoretical models (e.g. the CGW (1993) model) where trading volume is regarded as a proxy of the risk aversion of traders. The positive and statistically significant trading volume spillovers can be interpreted as evidence suggesting that the changes of liquidity investors' sentiments (e.g. the shifts of their attitudes to risk) have a contagious effect and can be transmitted across countries.

- Section 4.3.2 also shows that the trading volume between two adjacent days in a market is positively correlated (i.e. a day with high trading volume tends to be followed by another day with heavy trading volume). The estimated first-order autocorrelation coefficient of trading volume is not significantly affected by the meteor shower effect in trading volume from foreign markets.

7.2.2 Results from Chapter 5

Chapter 5 investigates the joint dynamics between returns and trading volume in both domestic and international stock market contexts. This study finds strong evidence that trading volume provides information to explain the time-varying nature of stock market price movements and cross-market comovements. The analysis of the joint dynamics of stock returns and trading volume is carried out in the context of the heterogeneous-agent trading model developed by Campbell et al. (1993). The aggregate trading volume of the market is regarded as an indicator that helps market agents to distinguish between two types of price movements in the stock markets: liquidity-based price movements that are usually associated with heavy trading volume and information-based price movements that are normally accompanied by normal or low trading volume.

First, this study presents new evidence indicating that the international return spillover effect is sensitive to the volume of trades in foreign markets. Trading volume provides valuable information to explain the time-varying nature of stock market comovements.

The specific findings are as follows:

- This study shows that the joint-dynamic coefficients (as denoted by β_1), which capture the interactions between foreign market trading volume and returns, are likely to be negative and statistically significant, indicating that the positive return spillovers tend to decrease with the preceding day's trading volume in the foreign markets.

- The estimation results about the dynamics of international return spillovers with respect to different levels of foreign market trading volume (as captured by $\bar{\theta}$) indicate that stock returns accompanied by lower trading volume are likely to spill over to other markets on the next trading day. On the other hand, investors in the domestic market are more likely to react negatively to the foreign price movements associated with higher trading volume.

- This returns-volume dynamic pattern supports the hypothesis of Gagnon and Karolyi (2003) indicating that information-based price movements in one market, which are typically associated with normal or low trading volume, are less likely to be reversed and are more likely to be positively related with the price movements in other markets on the next trading day. Similarly, liquidity-based price movements, which are typically associated with heavy trading volume, are less likely to be positively related with the price movements in other markets on the next trading day because they do not necessarily reflect a fundamental revaluation of stock prices by the market.

- However, this study finds that the joint-dynamic coefficient β_1 could be positive and statistically significant, suggesting that the positive international return spillovers are also likely to increase with trading volume from foreign markets. The estimation results of $\bar{\theta}$ show that the return spillover effects from Japan to the US and UK are stronger following days associated with higher trading volume in the Japanese stock market. This pattern is also evident in the joint dynamics of trading volume and returns spillovers from Hong Kong to the US and UK, from China to the US and from the US and Germany to Japan. The observed new pattern suggests that liquidity-based price movements in the foreign market could have a positive and statistically significant impact on the following day's stock returns in the domestic market. In other words, liquidity-induced price changes can also be transmitted across the borders.

Second, this study confirms the findings in the previous literature showing that trading volume is useful in understanding the behaviour of serial correlations in stock returns. The estimation results indicate a consistent pattern of the joint dynamics between stock returns and trading volume in the domestic market, which can be explained by the CGW (1993) model.

The specific findings are as follows:

- It finds that the estimated joint-dynamic coefficient (as denoted by $\alpha_{1,H}$), which captures the interactive effect between trading volume and stock returns, is negative for each stock market under investigation. This pattern is consistent with the specific prediction of the negative sign of $\alpha_{1,H}$ in the CGW (1993) model, suggesting that price changes accompanied by heavy trading volume tend to be reversed on the next trading day.

- In contrast with the existing literature, this study investigates explicitly the size and significance of return autocorrelations at different levels of trading volume (as captured by $\bar{\gamma}_H$) when analysing the joint-dynamic relations between stock returns and trading volume in the domestic market. The estimation results show that the first-order return autocorrelations are more likely to be negative and significant following days associated with high trading volume. This is empirical evidence in favour of the findings of Campbell et al (1993), indicating that the negative return autocorrelation between two consecutive days tends to be caused by liquidity trading, which is normally associated with heavy trading volume.

- Furthermore, this study shows that the first-order return autocorrelations are more likely to be statistically insignificant when the preceding day's domestic market trading volume is low, implying that the information-based price changes in the domestic market tend to be uncorrelated between two consecutive days. This pattern is reasonable as the arrival of the information that can reflect fundamental revaluation of stock prices by the market is usually stochastic, and this information has been fully and rapidly absorbed in the market in the contemporaneous trading period thus exerting little influence over the next period. However, this study reports a positive first-order return coefficient when trading volume in Canada is very light, indicating that information-based price movements can also cause a return continuation. But the result is only significant at the 10% level.

- The negative and significant first-order autocorrelations of stock market returns following days associated with high trading volume are observed in all the investigated markets except for Germany. However, it is found that the negative first-order return autocorrelation becomes statistically significant at the 1% level following heavy trading volume days in the German stock market when the return spillover effect from the US has been introduced in the model.

7.2.3 Results from Chapter 6

Chapter 6 examines the economic significance of the meteor shower effect in returns by investigating the profitability of regression-based trading rules implemented for market indices in the world's three biggest international stock markets (the US, UK and Japan). The Meteor Shower (MS) model, in which the current daytime return in the domestic market follows the MA(1)-GARCH (1,1) process and is the linear function of the preceding day's daytime return in the foreign market, is specified for the one-step-ahead time series forecasting. The study in this chapter presents evidence showing that trading rules based on the signals from the forecasts of the MS model, are profitable even after considering transaction costs. In addition, it shows that the information about the interactive relation between trading volume and returns is an exploitable phenomenon which investors can exploit profitably.

The specific findings are as follows:

- The results of the holding period return (HPR) reported in subsection 6.4.3 indicate that the active trading rules (i.e. Trading Rule MS, Trading Rule FV, Trading Rule DV, and Trading Rule FV&DV) outperform the passive B&H strategy in every case when transaction costs are not considered. Performance of the funds is also assessed by the time series behaviour of the fund values throughout the out-of-sample period. Time series plots of the fund values confirm that the active trading rules overall outperform the passive B&H strategy. However, it is also apparent that the fund values are more volatile following the leveraged trading strategies.

- Figures for the fund's daily return show that there are more large positive returns than large negative returns over the out-of-sample period, indicating that the meteor shower (MS) model produces more correct signals (than incorrect ones) for large price movements. Furthermore, the relatively high increments of the size of positive daily return for the leveraged trading rules indicate that high leverage factors are being applied on those days when the MS model generates the correct trading signals.

- Figures for the Sharpe ratio indicate that the incrementally higher return of the leveraged trading rules does not come about with disproportionately increased risks. Trading leverages that make use of additional information about the interactive effect between trading volume and returns significantly improve the risk-adjusted performance of the investigated trading strategies.

- This study provides strong evidence that the meteor shower effect from the Tokyo stock exchange can be used to obtain profitable strategy in trading the S&P 500 index and the FTSE100 index even after considering transaction costs. In addition, traders of the FTSE 100 index can receive positive returns by following the active trading strategies incorporating the US market information. The analysis in this chapter shows that the predictability of return captured by the meteor shower model is economically significant.

7.3 Overall Conclusions

This thesis is intended to contribute to the existing international information spillover literature in financial markets. It consists of three empirical chapters (Chapters 4, 5 and 6).

In Chapter 4, the direct information transmission mechanisms across the world's eight largest stock exchanges are examined. The dynamic spillovers in returns, volatility and trading volume are investigated using ARCH-family models. This study employs intraday data and distinguishes between spillovers from markets located in one region (intra-regional) and in different regions (inter-regional). In general, the results highlight the complexity of the information transmission mechanisms *via* different channels. The estimation results provide new evidence in favour of the findings in the existing return and volatility spillover literature. Furthermore, Chapter 4 contributes to the literature by studying the meteor shower effect in trading volume and interpreting it in line with economic implications.

In Chapter 5, the study investigates the transmission of information in returns among international stock markets after considering the interactive effect between trading volume and returns. A new approach to analyse this joint-dynamic relation has been proposed and the results are interpreted in the light of economic theory. The obtained results provide evidence that liquidity-based price movements, which are normally related to high trading volume, can also be transmitted across borders and have a global impact on market performance in other countries. In addition, a general pattern is documented in the domestic market context, where price movements induced by liquidity trades tend to induce a return reversal on the following trading day. On the other hand, information-based price changes, which are usually associated with normal or low trading volume, are less likely to be correlated between two consecutive days in the domestic market. It is important to point out that the approach employed in this study provides richer insights about the joint dynamics between returns and trading volume, which is a new contribution to the existing literature.

In Chapter 6, the economic significance of the international information spillover effect is explored. The signals for trades are generated by the forecasts of the return spillover model, which includes the information about price changes in previously traded foreign markets. In addition, the information about trading volume in both domestic and foreign markets is also built into the trading rules because research in Chapter 5 has shown that trading volume provides valuable information to explain the time-varying nature of stock market movements and cross-market comovements. This study presents evidence showing that the active trading rules based on the signals from the forecasts of the meteor shower model are profitable even after considering transaction costs and that the predictability of return captured by the meteor shower model is economically significant. In addition, the performance of the funds (as measured by the Sharpe ratio) can be significantly improved by increasing trading leverages based on the levels of trading volume in domestic and foreign markets, indicating that the information about the interactive relation between trading volume and returns is an exploitable phenomenon which investors can use to trade profitably. The incremental information it provides improves the fund’s performance results even after adjustment for risk.

7.4 Limitations and Recommendations for Future Research

Although this thesis contributes to the pool of knowledge in return and volatility spillovers across international stock markets, there are limitations that need to be considered in the analysis, interpretation and reporting of results. In addition, there are areas where more research is required for future research. These are summarised in the subsequent paragraphs.

This study employs daily opening and closing price to examine if there are return and volatility spillovers between markets. The use of higher frequency data is another avenue to pursue, and would allow a closer examination of cross-markets linkages over even shorter horizons.

The aggregate market level data is used in this study to analyse the international information spillover effects and to exploit the economic value of the foreign return spillovers. An investigation using individual firm-specific level data is not the focus of this study. However, it is a promising research topic for future studies. For example, Gagnon and Karolyi (2009) examine the international volume-return spillovers relationship for a large sample of cross-listed international stocks using the firm level data, which distinguishes with firm-specific price changes from aggregate price changes, a feature that allows one to measure volume-return spillovers at the firm level in greater precision.

This study finds evidence of nonnormality in stock market index returns and trading volume. Discovery of nonnormality leads to questions concerning the role of higher moments of returns and volume. Following Eastman and Lucey (2008), an investigation into the role of skewness and kurtosis in the analysis of the return and volume time series is an interesting exercise as research into the higher moments of return and volumes may prove fruitful in understating the dynamic of information flow between markets.

The trading strategies designed in this thesis are relatively basic, though they generated economically significant returns. Future research could focus on the construction and simulation of more complex trading strategies relying on the information about interplay between international stock return comovements and trading volume, which has not yet been investigated too deeply by financial academics and practitioners. It is interesting to explore further how beneficial international stock market information is in the domestic market trading.

It is well known that the aggregate stock market indices suffer from survivorship bias e.g. the losers tend to disappear from stock market indices. In particular, when a company delists from the market index, the index uses its last traded price. There are many delisted companies that are put into administration, whose actual returns are only a fraction of those implied by the last traded price. As a result, the market index return is biased up. It is important to investigate the size of the bias induced by using the last traded price for companies that get delisted where actual returns from investors on the stocks are much lower than those implied by their last traded price. However, it is also noteworthy that this is less of a problem for financial practitioners nowadays when it is possible to invest in the exchange-traded fund (ETFs) that track the performance of market index. Investors can simply buy index ETFs that match the returns of the market index.

Other limitations of this study include the lack of an explicit account of the 2008 global financial crisis and the 2010 European sovereign debt crisis. The impact of financial and debt crises on the information transmission mechanisms across international stock markets could also be examined in the future. It is likely that both events may have affected the transmission of information flows as measured by stock returns, volatility and trading volume across international stock markets, however longer time series extending beyond the European sovereign debt crisis of 2010 would be needed to conduct such analysis.

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Appendix A

Table A1: The Dynamics of Return Spillovers (in relation to Turnover by Value) from the UK to other Countries

The tables below reports parameter estimates of $\bar{\theta}$ and β_1 for the following model:

$R_{H,t} = \mu + \alpha R_{H,t-1} + \bar{\theta} R_{F,t-1} + \beta_1 R_{F,t-1}(V_{F,t-1} - \bar{V}_F) + \epsilon_t.$

$h_t = a + b\epsilon_{t-1}^2 + ch_{t-1},$

where μ is a constant; $R_{H,t}$ and $R_{H,t-1}$ denote the daytime return in the domestic market at time *t* and *t-1*, respectively; $R_{F,t-1}$ is the previous daytime return in the foreign market; $V_{F,t-1}$ is the foreign market turnover by value at time *t-1*.

UK($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
France	-0.0227 (0.5420)	0.0499 (0.1638)	0.0642* (0.0808)	0.0880** (0.0245)	0.1419*** (0.0027)	-2.26E-08*** (0.0002)
Germany	-0.1135** (0.0120)	-0.0672 (0.1168)	-0.0581 (0.1809)	-0.0429 (0.3405)	-0.0086 (0.8676)	-1.44E-08** (0.0164)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1750*** (0.0001)	0.1551*** (0.0000)	0.1512*** (0.0000)	0.1447*** (0.0000)	0.1299*** (0.0005)	6.20E-09 (0.4823)
Hong Kong	-0.0134 (0.7008)	-0.0585** (0.0210)	-0.0674** (0.0101)	-0.0822*** (0.0054)	-0.1157*** (0.0066)	1.40E-08* (0.0786)
China	0.0660 (0.2263)	0.0281 (0.4793)	0.0206 (0.6050)	0.0082 (0.8480)	-0.0200 (0.7272)	1.18E-08 (0.2759)

Notes:

1. For all tables, asterisks *, **, and *** represent that regression coefficient is statistically significant at the 10% level (critical value: 1.64), the 5% level (critical value: 1.96), and the 1% level (critical value: 2.58), respectively. The p-values are reported in parentheses.

2. The open-to-close return spillovers cannot be explicitly investigated due to two hours of overlapping trading time between the late afternoon in the European stock markets and early morning in the North American markets. The study excludes this sequence and report "N/A" in tables.

Table A2: The Dynamics of Return Spillovers (in relation to Turnover by Value) from France to other Countries

France ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	-0.2133 *** (0.0004)	-0.1589 *** (0.0046)	-0.1527 *** (0.0067)	-0.1339 ** (0.0213)	-0.1046 * (0.0998)	-2.39E-08 ** (0.0383)
UK	-0.0490 (0.2872)	0.0108 (0.7660)	0.0176 (0.6274)	0.0382 (0.3069)	0.0704 (0.1019)	-2.63E-08** (0.0208)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1506 *** (0.0000)	0.1671 *** (0.0000)	0.1690 *** (0.0000)	0.1747 *** (0.0000)	0.1836 *** (0.0000)	-7.27E-09 (0.5296)
Hong Kong	-0.0258 (0.3824)	-0.0616 *** (0.0072)	-0.0656 *** (0.0057)	-0.0780 *** (0.0053)	-0.0973 *** (0.0097)	1.57E-08 (0.1502)
China	0.0399 (0.4721)	-0.0014 (0.9717)	-0.0061 (0.8774)	-0.0203 (0.6392)	-0.0426 (0.4491)	1.82E-08 (0.3027)

Table A3: The Dynamics of Return Spillovers (in relation to Turnover by Value) from Germany to other Countries

Germany ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
France	0.0794 * (0.0986)	0.0972 ** (0.0407)	0.0987 ** (0.0390)	0.1053 ** (0.0347)	0.1129 ** (0.0343)	-0.0005 (0.3635)
UK	0.0358 (0.3128)	0.0250 (0.4574)	0.0241 (0.4778)	0.0201 (0.5776)	0.0154 (0.6988)	0.0003 (0.5610)
US	N/A	N/A	N/A	N/A	N/A	N/A
Canada	N/A	N/A	N/A	N/A	N/A	N/A
Japan	0.1649 *** (0.0000)	0.1492 *** (0.0000)	0.1479 *** (0.0000)	0.1421 *** (0.0000)	0.1354 *** (0.0000)	0.0005 (0.3798)
Hong Kong	-0.0223 (0.4255)	-0.0527 ** (0.0165)	-0.0553 ** (0.0127)	-0.0665 *** (0.0059)	-0.0796 *** (0.0053)	0.0009 (0.1081)
China	0.0048 (0.9077)	0.0063 (0.8620)	0.0065 (0.8592)	0.0070 (0.8505)	0.0077 (0.8469)	-4.50E-05 (0.9336)

Table A4: The Dynamics of Return Spillovers (in relation to Turnover by Value) from Canada to other Countries

Canada ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.0352 (0.4976)	0.0326 (0.3608)	0.0316 (0.3918)	0.0299 (0.5347)	0.0286 (0.6363)	1.18E-09 (0.9398)
France	-0.0227 (0.5420)	-0.0150 (0.6340)	-0.0080 (0.7995)	0.0036 (0.9287)	0.0120 (0.8097)	-8.01E-09 (0.5515)
UK	0.2721 *** (0.0000)	0.2775 *** (0.0000)	0.2797 *** (0.0000)	0.2832 *** (0.0000)	0.2859 *** (0.0000)	-2.47E-09 (0.8346)
Japan	0.1049 ** (0.0310)	0.1012 *** (0.0009)	0.0997 *** (0.0003)	0.0973 *** (0.0019)	0.0955 ** (0.0151)	1.70E-09 (0.8901)
Hong Kong	0.0010 (0.9808)	-0.0204 (0.4648)	-0.0289 (0.3208)	-0.0429 (0.2599)	-0.0532 (0.2653)	9.74E-09 (0.4213)
China	0.0832 (0.3185)	0.0445 (0.3876)	0.0290 (0.5020)	0.0035 (0.9341)	-0.0153 (0.7626)	1.77E-08 (0.3439)

Table A5: The Dynamics of Return Spillovers (in relation to Turnover by Value) from Japan to other Countries

Japan ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1204 *** (0.0014)	0.1547 *** (0.0000)	0.1649 *** (0.0000)	0.1805 *** (0.0000)	0.2043 *** (0.0003)	-4.01E-11 (0.2396)
France	0.0618 ** (0.0406)	0.0743 *** (0.0013)	0.0780 *** (0.0020)	0.0837 *** (0.0082)	0.0923 ** (0.0394)	-1.46E-11 (0.6016)
UK	0.2699 *** (0.0000)	0.2420 *** (0.0000)	0.2337 *** (0.0000)	0.2211 *** (0.0000)	0.2018 *** (0.0000)	3.26E-11 (0.2186)
Canada	0.0295 (0.3007)	0.0355 * (0.0809)	0.0373 * (0.0725)	0.0400 * (0.0957)	0.0441 (0.1789)	-6.98E-12 (0.7502)
Hong Kong	-0.0848 ** (0.0130)	-0.0492 * (0.0702)	-0.0386 (0.1794)	-0.0225 (0.5081)	0.0021 (0.9632)	-4.16E-11 (0.1334)
China	-0.0498 (0.4405)	-0.0500 (0.1798)	-0.0501 (0.1749)	-0.0502 (0.2643)	-0.0504 (0.4606)	3.15E-13 (0.9953)

Table A6: The Dynamics of Return Spillovers (in relation to Turnover by Value) from Hong Kong to other Countries

HongKong ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.1597 *** (0.0000)	0.1486 *** (0.0000)	0.1474 *** (0.0000)	0.1422 *** (0.0000)	0.1390 *** (0.0001)	6.25E-07 (0.7525)
France	0.0800 ** (0.0252)	0.0982 *** (0.0000)	0.1001 *** (0.0000)	0.1086 *** (0.0000)	0.1138 *** (0.0001)	-1.02E-06 (0.5083)
UK	0.2675 *** (0.0000)	0.2009 *** (0.0000)	0.1937 *** (0.0000)	0.1626 *** (0.0000)	0.1436 *** (0.0000)	3.74E-06 ** (0.0330)
Canada	0.0383 (0.2431)	0.0825 *** (0.0001)	0.0872 *** (0.0000)	0.1078 *** (0.0000)	0.1204 *** (0.0000)	-2.48E-06 (0.1134)
Japan	0.0621 * (0.0595)	0.0350 (0.1996)	0.0320 (0.2611)	0.0194 (0.5978)	0.0117 (0.7873)	1.52E-06 (0.3636)
China	-0.1160 ** (0.0347)	-0.0441 (0.2855)	-0.0364 (0.3913)	-0.0029 (0.9563)	0.0176 (0.7725)	-4.04E-06 (0.1043)

Table A7: The Dynamics of Return Spillovers (in relation to Turnover by Value) from China to other Countries

China ($R_{F,t}$)	$\bar{\theta}_{75\%-100\%}$	$\bar{\theta}_{50\%-75\%}$	$\bar{\theta}_{50\%}$	$\bar{\theta}_{25\%-50\%}$	$\bar{\theta}_{0-25\%}$	β_1
Germany	0.0533 * (0.0996)	0.0292 * (0.0771)	0.0267 * (0.0944)	0.0140 (0.4497)	0.0103 (0.6173)	2.93E-10 (0.2995)
France	0.0285 (0.3449)	0.0126 (0.3984)	0.0109 (0.4428)	0.0025 (0.8749)	5.51E-05 (0.9975)	1.94E-10 (0.4525)
UK	0.0781 ** (0.0043)	0.0464 *** (0.0023)	0.0430 *** (0.0033)	0.0262 * (0.0959)	0.0213 (0.2119)	3.86E-10 * (0.0815)
Canada	0.0109 (0.6350)	0.0265 ** (0.0326)	0.0282 ** (0.0196)	0.0364 *** (0.0092)	0.0388 ** (0.0119)	-1.90E-10 (0.3420)
Hong Kong	-0.0444 ** (0.0242)	-0.0173 (0.1733)	-0.0144 (0.2636)	-8.79E-05 (0.9958)	0.0041 (0.8231)	-3.30E-10* (0.0842)
Japan	-0.0192 0.3898	-0.0185 0.1916	-0.0184 0.1927	-0.0180 0.2863	-0.0179 0.3302	-8.75E-12 0.9647