Essays on International Stock and Bond Returns

by

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Abstract

This thesis consists of three chapters on the dynamics of asset returns, with a focus on global stocks and bonds. The first chapter investigates the contagion effect between the European stock and bond markets, and between the Greek bond market and other European bond markets. The perspectives of nonlinear contagion effects and the predictability of contagion are also investigated in the first chapter. The main findings are as follows. Firstly, the European sovereign debt crisis generally leads to contagion effects between domestic stock and bond markets, and this is more likely in relatively smaller countries. The financial crisis had generally led to a higher level of flight-to-quality, whilst this has also been found over the tranquil period, especially in the relatively larger countries. Secondly, the contagion effect between the Greek and other European bond markets started appearing at least four months earlier than the beginning of the European debt crisis[1]. Thirdly, strongly significant copula estimation results reinforce the findings of the existence of nonlinear contagion effect in the Eurozone area. In addition, the information asymmetry carried by the counterpart of the GJR model significantly increases the ability of the Student-t copula to detect changes of dependence structure. Finally, conditional volatility as an explanatory variable is found to be statistically significant in explaining and predicting the contagion across at least five countries, and the level of exchange rate shows its predictive power in contagion for at least four countries. The interest rate (the level of risk free rate for the Eurozone area) is found to have the weakest predictive power amongst all the explanatory variables considered.

The second chapter examines the bi-directional relationships between stock returns

[1]The beginning of the European debt crisis is defined as the time the Greek government asks for the bailout from the institutions of IMF/EU, namely 23 April 2010, (Dajcman, 2012).

and trading volume, and between trading volume and volatility. By using the nonlinear Granger causality test, we find the existence of both bi-directional relations between stock returns and trading volume, and between trading volume and volatility. Further to this, from limiting the sample period to the widely known tranquil period (1994 to 2006), an interesting result is found. In comparison to the full sample test, statistically significant nonlinear results are also observed from the tranquil period. However, the nonlinear feedback from stock returns to trading volume, and the nonlinear feedback from volatility to trading volume are shown to be much stronger during the tranquil sample period than the other way round.

The third chapter evaluates the effects of fundamental factors on international stock returns. Dividend, earnings and interest rate are considered as fundamental factors. The results from the international stock markets are mixed: some markets see dividends playing a more significant role in explaining the variation of stock returns, and some markets see earnings playing a more significant role. However, neither dividend nor earnings can predict the returns changes in a few markets. In order to investigate this problem, we take one step further through estimating the effects of changes of interest rates upon dividend and earnings discount models. However, our analysis only finds a slight influence there. This suggests that other unexamined factors are more important, consequently, further research is required for clarification.

Overview

International equity markets, especially the stock and sovereign bond markets, have attracted tremendous interest from both academics and practitioners. Two topics related to the international equity markets are of particular interest for this dissertation. Firstly, the effect of contagion and flight-to-quality effects across assets and markets, and secondly the correlation between equity returns and endogenous variables. This research paper aims to generate an understanding of the characteristics of equity returns, such as the interdependence of different assets' returns, and their driving factors. This is undertaken in order to answer questions, including how to forecast the changes of market returns, and how to lower loss-making due to unstable and risky market conditions.

The first topic deals with the problem of contagion across assets and countries, and in first chapter contagion is defined as co-movements and co-exceedances of returns. This topic has been extensively researched over the past few decades. The early effort of Engle and Sheppard (2001) puts forward the theory of dynamic conditional correlation (DCC). Their associated methodological approach models the dynamic comovements of returns across assets and countries. The DCC-GARCH model currently is a popular model for researching the topic of contagion and flight-to-quality across equity markets. Apart from the DCC-GARCH model, there are also several other approaches that can investigate the contagion and flight-to-quality phenomenon. These include the moving average indicator originated by Dajcman (2012), multinomial logistic regression, and the copula-GARCH model, amongst others. These approaches have gained increasing importance in correlation researches, and therefore are all employed in the first chapter.

The first chapter of this thesis engages in the analysis of the contagion effect, we estimate contagion effect using four approaches for different perspectives. The multi-methodology used in this chapter includes several approaches. These include contagion and flight-to-quality indicators, dynamic conditional correlation (DCC) GARCH, two-period copula-GARCH and multinomial logistic regression. The contributions are introduced after every summary of methodological approach. First of all, our estimation starts by following the basic approach of Dajcman (2012) (dynamic conditional correlation and moving average indicator of flight-to-quality), this develops the core contagion that the sharp fall of one market may transfer the panic to another markets. This will thus cause a joint decline of stock and bond index returns. Contagion in this chapter is also defined as jointly linked decline in several markets, as per Baur and Lucey (2009) and Baig and Goldfajn (1999). Following the same line of reasoning for the flight-to-quality indicator (FTQ), we build a bespoke contagion indicator (CI), this allows comprehensive examination of the co-movements of stock and bond returns. In order to develop our research, the DCC-GARCH model is used to display dynamically the correlations between stocks and bonds. In this approach, we contribute an uprated CI model that is additionally defined and constructed. It allows the joint analysis of CI and FTQ to help more accurately find the dominant phenomenon during the different periods. The second approach that we use to look into the comovement of bond index returns for the cross-country perspective is based on Chiang, Jeon, and Li (2007), where the DCC-GARCH model is also employed. The Greek bond market is assumed by many commentators and academics, as the source country of the European sovereign debt crisis, and contagion is widely delimited as high levels of both correlations and dynamic volatility. To the best of our knowledge, we operate the first use of the DCC-GARCH model to look into contagion across European bond markets. Consequently, this chapter contributes more insights of the bond markets in Europe into the limited academic literature. This analysis brings new evidence, finding that contagion occurs during the European debt crisis, with neighbouring bond markets indeed being affected by this contagion effect. Based mainly on Adel and Salma (2012) and Huang, Lee, Liang, and Lin (2009), the third approach estimates the nonlinear contagion effect using a two-period copula GARCH model. Our contribution to this approach is made unique, by integrating a factor examining the information asymmetry into the copula estimation. This allows the models assumptions to be much closer to reality[2]. Finally, the predictability of contagion is evaluated via multinomial logistic regression, with three possible covariates including conditional volatility, exchange rate and interest rate all considered. We relate the Logit estimations to the European bond markets, this means that the covariations of the covariates and the probability of contagion occurrence can be observed clearly.

The main results from this study are as follows. First, the results show that the dynamic conditional correlations between stock and bond index returns are generally negative (with exceptions of Portugal, Spain and Greece), this possibly implies the flight-to-quality. Second, the global financial crisis tends to increase the flight-to-quality indicator and the European debt crisis tends to increase the contagion indicator. Third, contagion across the European bond markets becomes increasingly significant at least four months before the Greek government requests a bailout from the International Monetary Fund. Fourth, the modified copula-GARCH model helps find the nonlinear contagion caused by the European debt crisis. In addition, it appears that adding asymmetry information into the copula-GARCH structure, that sees increases in the explanatory power of the Student-t copula in capturing the changes of tail dependence. Finally, the estimations of the multinomial logistic regression suggest that conditional volatility significantly explains contagion across

[2]Using asymmetry information carried by GJR is able to make the estimations much closer to reality. See Huang, Lee, Liang, and Lin (2009).

five markets. Whilst the level of exchange rate could significantly explains the contagion across four markets. However, the explanatory power of the level of interest rate is significantly weaker than that of volatility and exchange rate. This is highly similar to the results attained by Bae, Karolyi, and Stulz (2003) when they studied stock markets.

The results of first chapter are related to some academic papers. First, the research on the contagion effect is classified into two branches. One branch of the literature focuses on the causal factors of contagion. These include various monetary and financial sectors' vulnerability and the contagious crisis, see Almeida, Campello, Laranjeira, and Weisbenner (2012), Rose and Spiegel (2010), Frankel and Saravelos (2010) and Tong and Wei (2011). The other branch emphasizes that contagion spreads through financial institutions (For related articles, see Allen and Gale (2000), Lagunoff and Schreft (2001) and Van Rijckeghem and Weder (2000)). This chapter is closely related to the first branch of literature that studies contagion amongst global financial markets during contagious crises. Finally, King and Wadhwani (1990) studied the evidence for the formation of contagion, showing that the decline of prices in one market can impact on the value of assets in other markets, thus giving rise to changes in their prices through the unobservable information channels. All the related articles show that contagion can be observed if one uses the appropriate approaches.

The second topic of this study, which has also been extensively studied in the existing academic literature, relates to the relationship between stock returns and trading volume, and the relationship between trading volume and volatility. Market participants tend to attach a lot of importance to trading volume as it carries information about future changes of asset prices. In order to examine the properties of trading volume, the second chapter linearly and nonlinearly estimates both the relations between return and volume and between volume and volatility. This approach follows the basic structure of Hiemstra and Jones (1994). Our work nevertheless adds to the literature via the following aspects: (1) We additionally generate estimations for correlation between volatility and volume. (2) The correlations between volatility and volume can be similarly evaluated through both linear and nonlinear Granger causality tests. (3) The estimation of the relationships between stock returns and trading volume, and between trading volume and conditional volatility are implemented in a joint system.

In the second chapter, we examine both linear and nonlinear relations between stock return and volume, and between trading volume and volatility. Following Granger (1969) and Hiemstra and Jones (1994), we adopt both linear and nonlinear Granger causality tests. In addition, conditional variance as modeled by Nelson (1990)'s EGARCH is used to create estimations via a nonlinear Granger causality test. Our research contributes to the existing literature in two central ways. First, we use a joint vector autoregression system with three variables in the nonlinear Granger causality test, i.e., stock returns, return volatility, and trading volume. The joint vector autoregression system allows for a comprehensive analysis of these three variables' relationships and avoids potential inefficient or biased statistical inferences (see Pagan (1984) and the references therein). In this modified system, we especially model conditional variance by EGARCH, which allows negative as well as positive shocks. The model is consistent with the real variations of stock returns' distribution, as authoritatively asserted by Nelson (1990). Second, this chapter allows for both linear and nonlinear Granger causality estimations as investigating the correlations between three variables of stock returns, trading volume and volatility. As far as we are aware, this is the first study that simultaneously takes stock returns, trading volume and conditional volatility into account in the nonlinear Granger causality estimations. This makes the model more flexible, and allows its potential to identify structural breaks in the relationship between the variables.

The empirical findings are as follows. First, a statistically significant bi-directional nonlinear causality is found between the factors in all markets studied in this paper, this is contrary to the results gained in linear estimations which only suggest a one-directional causality for some markets. Second, we carry out robustness tests for both linear and nonlinear Granger causality. We limit the sample period from the beginning of the year 1994 to the end of the year 2006. This period has the best known tranquil market conditions without the effects of banking and financial crisis. Some interesting results are found. First, the linear Granger causality test results are much stronger when compared to the full sample results. Second, similar to what we find for the full sample period, we also find a significant bi-directional causality relationship for the tranquil period with the nonlinearity test. However, we noticed that the two uni-directional causalities from returns to trading volume and from volatility to trading volume are much stronger than those the other way round. The overall evidence therefore shows that certain market conditions (i.e., a specific crisis or a calm period) may lead to these relations becoming more significant. This relationship is not only found in our paper, but also in Griffin, Nardari, and Stulz (2007). They find the more significant feedback from stock returns to trading volume with waved, volatile and capricious market conditions.

The second chapter is also highly relevant to some academic articles. Chen, Firth, and Rui (2001) asserted that stock returns cause trading volume, and more information can be derived through the joint dynamics of trading volume and stock returns than that from research with univariate dynamics of stock returns. The results of Chen, Firth, and Rui (2001) show surprisingly the similar results to what we find in the robustness tests we undertake upon the tranquil market conditions. As Gallant, Rossi, and Tauchen (1992) stated, previous empirical findings often emphasize the contemporaneous causal relationship between prices and volume. However, it is worth noting that there are a few articles focusing on cross correlations, for example, Hiemstra and Jones (1994), they applied linear and nonlinear Granger causality tests to explore the dynamic relationship between stock returns and volume for the US market. In addition, Andersen (1996) used a theoretical microstructure to examine the relationship between trading volume and return volatility.

Third, what drives stock prices up? This has become an important topic with many different factors advocated by researchers. Examples are fundamental factors such as dividend and earnings (Lamont (1998), Shiller (1990), and Hodrick (1992)), investor behavior factors (Bizjak, Brickley, and Coles (1992)), interest rate (Kang, Pekkala, Polk, and Ribeiro (2011), Hjalmarsson (2010) and Cremers (2002)), and bubble factors (Diba and Grossman (1988) and Wang (2003)). In the third chapter, we examine three of these specific factors: dividend, earnings and interest rates. We study three of these factors effects on the international stock and sovereign bond returns.

This element is a widely studied area, with a body of academic literature arguing over stock price influences, the research is nebulous and not evidentially clear. Gourieroux and Jasiak (2001), Park (2010) and Uddin and Chowdhury (2005) document a positive impact of dividend on stock returns, however Uddin and Chowdhury (2005) and Fama and French (1988) document a negative effect. Concerning the effect of earnings, Campbell and Shiller (1987), Datta and Dhillon (1993) and Wang (2003) find a positive effect, whilst conversely Jaffe, Keim, and Westerfield (1989) find that the effect changes and can be uncertain over time. Seelig (1974) claims positive impacts of interest rates on stock returns, and Shiller and Beltratti (1992) claim negative impact of interest rates on stock returns, respectively. The main model used in this chapter is a dynamic present value model, based on Campbell and Shiller (1988) and later further developed by Campbell and Shiller (1988a), Kanas (2005) and Jiang and Lee (2005). We contribute to the literature by developing the 3-variable VAR system into a 4-variable system, and make it possible to incorporate interest rates into the joint system estimations.

For the estimation of the joint system, we find some interesting results in this chapter. First, our findings document the explanatory power of dividend on stock prices. Second, the explanatory power of earnings in predicting stock prices is also documented for some markets. Finally, we find that neither the dividend discount model nor the earnings discount model are able to predict the future changes of stock returns. Due to the different standpoints for the effect of interest rate on stock prices, we exclude the influence of interest rate on the dividend discount model and earnings discount model. Instead, we create a new constraint via analysis without interest rate in a nonlinear Wald test. We thus find that the predictive power of these models improves in Norway and Colombia, but remains unchanged for Chile and Argentina. The fundamental prices of Norway and Colombia are therefore much closer to actual market prices.

We finally relate the findings of the third chapter to seminal academic articles. The relatively earlier research examining stock returns, dividend and earnings together is best emphasized in Campbell and Shiller (1988). The results of Campbell and Shiller (1988) with VAR system show that the ratio of earnings to prices has a strong explanatory power for the changes of stock returns. This result is also found in Lewellen (2004) and Easton and Harris (1991). Further to this, Fama and French (1988), Ang and Bekaert (2007) and Lewellen (2004) document a predictability of stock returns from using dividend. Interest rate in predicting the stock price is the least discussed area in the existing literature, such as Shiller and Beltratti (1992), Shiller and Beltratti (1992) and Connolly, Stivers, and Sun (2005). However, Campbell and Ammer (1993) find evidence that the correlation between risk-free interest rate and stock returns is too weak to be significant. All in all, it is difficult to find a unified and definite empirical result for the impact of interest rate on stock returns.

Chapter 1

Contagion in the Markets of the European Sovereign Debt Crisis

1.1 Introduction

The European sovereign debt crisis starting from the Greek debt crisis gives a background to this paper. Since the Greek bailout request in the year 2010, European sovereign bond markets have been highly volatile. As the Greek government asked for the bailout from International Monetary Fund and abnormally excessive deficit of Greek government had been found by European Commission, the systematic risk across European bond markets attracted a lot of attention (Dajcman, 2012). The bailout itself resulted in a package of EUR 20 billion, which was thus supported and financed for the countries whose fiscal policies are difficult to further sustain.

Our study focuses on the contagion risks in these countries, which is a big worry for European investors. For example, Constancio (2011) suggests the restructuring of Greek debt may give rise to new financial crises spreading across the neighbouring sovereign bond markets. The German minister of Finance argues it is hard to sustain both the domestic fiscal policies and financial support for Greece, which can lead to a chain reaction caused by a sovereign default. Our study seeks to generate an understanding of how to find and estimate the European bond contagion, and searching for the driving factors of European area contagion. This can be of help for investors to rationally avoid the risk of contagion by making adjustments to their investment portfolios, and properly predict the contagion by observing the fundamental factors to lower the future possible loss-making in time.

The specific focus is on the European bond contagion caused by the Greek debt crisis, and the study therefore generates two central researching goals. First, we seek to analyse the sovereign bond contagion across assets and countries in both linear and nonlinear ways. Second, we seek to identify the factors that can predict the bond contagion in European area. The research questions are as follows: first, how do the comovements of stock and bond index returns change over time? Second, can contagion effects propagate from the Greek bond market to neighbouring bond markets? Finally, which of following factors can predict the probability of contagion occurrence, conditional volatility, exchange rates or interest rates?

The empirical analysis leads to five important findings. First, for cross-asset prospective, we find volatile and overall negative dynamic correlations between stock index returns and sovereign bond index returns over a recent decade. This is related to the findings of Dajcman (2012) and Baur and Lucey (2009), and is consistent with a phenomenon of flight-to-quality. Second, the findings show that the Global financial crisis increases the flight-to-quality indicator (FTQ) for most countries and the European debt crisis increases the contagion indicator (CI) across European stock and bond markets, more pronounced in small countries. Third, from the Greek debt crisis, non-zero dynamic conditional correlation is found between Greek bond market and each of eight European bond markets. Most interestingly, our results show that cross-country bond contagion appears at least four months earlier than the time the Greek government asks for the bailout from International Monetary Fund, possibly implying that the information of sovereign bond markets is easily accessed, and investors find it easier to predict the future changes of bond markets than to predict the future changes of stock markets[1]. Fourth, we nonlinearly estimate the

[1] Chiang, Jeon, and Li (2007) find the evidence that the stock contagion appears after the time the Asian financial crisis happened in the source country of Thailand.

contagion in the turmoil period (during the European debt crisis). After adding the asymmetry information carried by the counterpart of GJR model with normal distribution, the Student-t copula becomes more powerful to capture the changes of tail dependence. Finally, the predictability of contagion occurrence is found with multinomial logistic regression. In order to derive the evidence for the predictability of contagion, we employ three covariates, such as conditional volatility, exchange rate and interest rate, and data covering the period from 2001 to 2014. The results suggest that conditional variance is strongly significant to explain the contagion across at least five countries, exchange rate is able to explain the contagion across at least four countries. However, interest rate has a weaker significance to predict the contagion occurrence across European bond markets.

We contribute to the literature in several ways: first, by following the approach of Adel and Salma (2012) and Huang, Lee, Liang, and Lin (2009), we integrate the asymmetry information of GJR model with the innovations following the normal and student-t distributions into the estimation of two-period copula-GARCH. The method with asymmetry information will help make the assumption much closer to reality. Second, to the best of our knowledge, we are the first to apply multinomial logistic regression to the European bond markets. It may offer more insights into a limited strand of the literature on contagion across European bond markets. Third, we additionally show the CI in moving window, and combine the analysis of FTQ with the analysis of CI. The comparison of two indicators will help identify the most dominant effect from flight-to-quality and contagion for the specific periods. The variation and the degree of contagion and flight-to-quality can be intuitively observed over time, as well. Finally, we expand the data period to the year 2014. In comparison to the existing literature, the expanded sample period includes the entire crisis information, may offer more insights for a strand of existing literature.

In order to address the research questions properly, we employ a multi-methodology including dynamic conditional correlation GARCH (DCC-GARCH), moving average indicators of flight-to-quality and contagion, copula-GARCH and multinomial logistic regression to discuss the European bond contagion for cross-asset perspective, cross-country perspective, nonlinearity perspective and predictability perspective. First, based on the approaches of Engle and Sheppard (2001) and Dajcman (2012), we adopt DCC-GARCH model and compute the moving average indicators for flight-to-quality and contagion. In this approach, we additionally define the contagion indicator (CI) in the same way as defining FTQ, and combine the analysis of CI with FTQ to find the most dominant phenomenon. Hence, the first methodology we organize is to characterize the dynamic conditional correlations (DCC) between European stock and bond index returns, FTQ and CI for cross-asset perspective. Second, we apply the DCC-GARCH again to look into the contagion for cross-country perspective during the European debt crisis. We follow the approach of Chiang, Jeon, and Li (2007)[2] to set Greek sovereign bond market as a source market of European debt crisis, and then the dynamic correlations are estimated between the Greek bond index return and each of eight index returns of Germany, France, the UK, Belgium, Denmark, Netherland, Portugal and Spain. Multivariate GARCH models with the similar univariate counterparts of DCC-model have been extensively used to observe the market volatility (See, for instance, Bollerslev (1990), Hamao, Ronald, and Victor (1990), Illmanen (2003), Skintzi and Apostolos (2006) and Longin and Bruno (1995).). The DCC-GARCH model based on multivariate GARCH model can produce the covariances over time, and helps characterize the time-varying correlation between two variables. To the best of our knowledge, the earliest effort for using the DCC approach is tried by Engle and Sheppard (2001). Thereafter, the DCC approach is widely developed and well documented by Baur and Lucey (2009), Chiang, Jeon, and Li (2007), Engle (2012), Papavassiliou (2014). Third, we also explore the nonlinear contagion[3] across countries in both pre- and post-crisis

[2]Chiang, Jeon, and Li (2007) decide the Thai stock market to be a source market of the Asian financial crisis.

[3]To differentiate linear and nonlinear dependence, we do a brief explanation. The dependence

periods by using copula GARCH approach. The combination of approaches of Adel and Salma (2012) and Huang, Lee, Liang, and Lin (2009) is implemented in this paper. We follow Adel and Salma (2012) to use both tranquil and volatile periods for the estimations of two-period copula-GARCH, and follow Huang, Lee, Liang, and Lin (2009) as well to add the asymmetry information by using the GJR model with the mean innovations following the normal and student-t distributions. The advantages of our approach are that two-period estimations will help observe the dependence structure changes over two periods intuitively, and the results from the estimations with asymmetry information will be much closer to reality. Finally, the probability of contagion occurrence is evaluated over a recent decade with multinomial logistic regression. We similarly use the multinomial logistic regression of Bae, Karolyi, and Stulz (2003) with three covariates, which are conditional variance, exchange rate and interest rate. The evidence for the relationships between bond returns and the chosen covariates has been well documented in the existing literature. For example, conditional volatility, exchange rate and interest rate are separately taken into the account with bond returns by Heath, Jarrow, and Morton (1992), Fidora, Fratzscher, and Thimann (2007) and Downing and Zhang (2004). The documented evidence improves our model to include three variables into the joint system of multinomial logistic regression. In addition, by following Greene (2012), we compute the marginal effect based on the coefficients of multinomial logistic regression. The marginal effect will be conducive to observe the changes of probability of contagion occurrence following the unit changes of covariates.

As yet, the existing researches provide the definitions and a number of empirical works on flight-to-quality and contagion. For example, in the financial crisis,

is called linear if, the correlation between two returns $r_{1,t}$ and $r_{2,t}$ is one, then $r_{1,t} = \alpha + \beta r_{2,t}$, for $\alpha \in \mathbb{R}$ and $\beta > 0$ for positive correlation and $\beta < 0$ for negative correlation. The nonlinear dependence is classified into two cases. First, two returns can be uncorrelated but dependent in the squares: an increase in volatility involves an increase in the other's volatility. Second, two returns can be uncorrelated but dependent only on the tails: returns comove only as seeing the extreme movements. In this part, we mainly discuss the latter case. See Joe (1997).

investors may move capital from riskier stock markets to the safer sovereign bond markets, this herding behavior may lead to the decrease in stock prices and the increase in bond prices. The uni-directional transmission of the capitals from risky stock markets to bond markets creates a flight-to-quality effect. Flight-to-quality is well documented by a strand of articles (e.g. Afonso, Arghyrou, and Kontonikas (2012), Cox and Rennie (2008), Baele, Bekaert, Inghelbrecht, and Wei (2013), Baur and Lucey (2009) and Dajcman (2012)). In addition, two definitions of contagion are used in this paper. The first defines contagion as the simultaneous decline of the assets' returns, namely a positive correlation of the assets prices (Baur and Lucey, 2009). Second, contagion also can be defined as coexceedances such as Bae, Karolyi, and Stulz (2003). For example, the exceedance is chosen from the smallest and largest five percent returns from one return series, and that the exceedances across the countries are found on the same trading days is called coexceedance also defined as contagion. The contagion effects are documented in a strand of contagion literature (see, Bae, Karolyi, and Stulz (2003), Baig and Goldfajn (1999), Kaminsky and Reinhart (2000), Baur and Lucey (2009) and Aloui, Aissa, and Nguyen (2011)). Specifically, the contagion effects across different assets in the European markets are investigated by Mink and Haan (2013), Afonso, Furceri, and Gome (2011) and Castellacci and Choi (2015). In this paper, we add to this literature on the European bond contagion with more insights and findings. However, some are critical to the contagion literature. For example, Forbes and Rigobon (2002) and Briere, Chapelle, and Szafarz (2012) claim that there is no real contagion effect, only interdependence caused by a common unobservable factor. However, in our paper, the contagion caused by the comprehensive information is observed and captured by the chosen empirical ways.

The chapter is structured as follows: In section 2, we present the econometric framework of DCC-GARCH model for stock index return and bond index return, define the moving average indicators of flight-to-quality and contagion, specify the copula-GARCH approach with asymmetry information and characterize the multinomial logistic regression with the covariates of conditional variance, exchange rate and interest rate. The sample data series and their preliminary statistics are also presented. In section 3, we explicate the empirical findings, and discuss the DCC, FTQ and CI for cross-asset and cross-country perspectives. The changes of the tail dependence and the driving factors of contagion occurrence are also demonstrated and discussed by using two-period copula GARCH and multinomial logistic regression. Section 4 concludes.

1.2 Flights and Contagion

1.2.1 Econometric Framework

Our methodology includes the DCC-GARCH model, moving average indicators, two-period copula-GARCH and multinomial logistic regression. The multi-methodology used has four advantages. First, DCC-GARCH approach models covariance matrix for two variables over time. It is conducive to observe the dynamic correlations along with sample period. Second, using moving average indicators will help show the level of contagion and flight-to-quality more intuitively and clearly. The most dominant phenomenon can also be found by comparing both indicators. Third, two-period copula-GARCH is advantageous to nonlinearly model the contagious effect. The changes of dependence structure can be evaluated with two classified periods including the tranquil and turmoil market conditions. In addition, the asymmetry information carried by GJR-model and residuals following student-t distribution benefits for making the assumption much closer to reality. Finally, multinomial logistic regression exogenously estimates the probability of contagion occurrence. Through inserting the covariates, it helps find the impact of endogenous variables on probability of contagion events.

DCC-GARCH Model, FTQ and CI

Comovement of the different assets is widely researched by using multivariate GARCH models in a strand of articles (Berben and Jensen (2009); Arouri, Bellah, and Nguten (2010); Baur and Lucey (2009); Engle and Sheppard (2001); Dajcman (2012) and Engle (2002)). The DCC-GARCH model as a typical multivariate GARCH model attracts a large of academic attention. In our paper, we use DCC-GARCH model by following Engle and Sheppard (2001) to observe the comovement of stock index returns and sovereign bond index returns for nine European markets of Germany, France, the UK, Belgium, Denmark, Netherland, Portugal, Spain and

Greece. DCC-GARCH model assumes that the demeaned value of returns, r_{kt} [4], from k assets is conditionally normal with zero expectation value and covariance matrix H_t, where r_{kt} denotes the return of one asset from k assets at time t. The returns series of stock index and sovereign bond index of a particularly selected country, including the information set available at time t-1, have the following distribution (the similar theory of Engle and Sheppard (2001)):

$$r_t|\zeta_{t-1} \sim N(0, H_t)$$

and

$$H_t \equiv D_t R_t D_t \tag{1.1}$$

where D_t is the $K \times K$ diagonal matrix of time varying conditional SDs from the univariate GARCH models with $\sqrt{h_{it}}$ on the ith diagonal, and R_t is the time-varying correlation matrix. Next, the log likelihood of this estimator is written as follows:

$$\begin{aligned} L &= -\frac{1}{2}\sum_{t=1}^{T}(klog(2\pi) + log(|H_t|) + r_t^{'}H_t^{-1}r_t) \\ &= -\frac{1}{2}\sum_{t=1}^{T}(klog(2\pi) + log(|D_t R_t D_t|) + r_t^{'}D_t^{-1}R_t^{-1}D_t^{-1}r_t) \\ &= -\frac{1}{2}\sum_{t=1}^{T}(klog(2\pi) + 2log|D_t| + log(|R_t| + \epsilon_t^{'}R_t^{-1}\epsilon_t) \end{aligned} \tag{1.2}$$

where ϵ_t satisfies the distribution of $\epsilon_t \sim N(0, R_t)$, which is the residual standardized by their conditional standard deviation. The factors of D_t are written by univariate GARCH models:

$$h_{it} = w_i + \sum_{p=1}^{P_i}\alpha_{ip}r_{it-p}^2 + \sum_{q=1}^{Q_i}\beta_{iq}h_{it-p} \tag{1.3}$$

[4] Engle and Sheppard (2001) assert that all assets' returns, before putting into the DCC-GARCH model, need to be demeaned. The expected value of demeaned returns series is close to zero. Additionally, as Engle (2002) points out, the standard errors of the DCC-GARCH model do not depend on the model choice of filtration. In our paper, following Engle and Sheppard (2001), we use the simplest mean equation of GARCH (1,1) to filter the return series.

for $i = 1, 2, \ldots, k$, equation 1.3 has the usual GARCH restrictions of non-negativity and stationarity. For example, the variances exhibit non-negativity, and $\sum_{p=1}^{P_i} \alpha_{ip} + \sum_{q=1}^{Q_i} \beta_{iq} < 1$, where lag length p, q are unnecessary to be same. The specification of GARCH model is not limited to the simple GARCH(p,q), however can choose any GARCH-type models with normally distributed errors satisfying with the stationarity condition and non-negativity restriction.

The expression of dynamic conditional correlation is defined as:

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\bar{Q} + \sum_{m=1}^{M} \alpha_m(\epsilon_{t-m}\epsilon_{t-m}^{'}) + \sum_{n=1}^{N} \beta_n Q_{t-n} \tag{1.4}$$

and

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{1.5}$$

where M is the lag length of the innovation term, and N is the lag length of lagged correlation matrices. $\bar{Q}$ is the unconditional covariance of the standardized residuals derived from the first-stage estimation, and Q_t^* is a diagonal matrix consisted of square root of the diagonal elements of Q_t:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & 0 & \ldots & 0 \\ 0 & \sqrt{q_{22,t}} & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \ldots & \sqrt{q_{kk,t}} \end{bmatrix} \tag{1.6}$$

The elements of R_t will be

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{1.7}$$

$\rho_{ij,t}$ is the conditional correlation between asset i and asset j. The DCC estimators are tested for each of sample markets, with the demeaned stock index returns and demeaned bond index returns. After computing the dynamic conditional correlation, and by following the approach of Dajcman (2012) and Dajcman (2013), indicator of flight-to-quality (FTQ) is defined as that a negative stock index return and a negative change of sovereign bond yield[5] coexist on the same trading day. In the similar way, the indicator of contagion (CI) is also defined as that a negative stock market return and a positive change of sovereign bond yield coexist on the same trading day. In order to observe the phenomena of flight-to-quality and contagion during the different periods, we calculate a moving window indicators of flight-to-quality and contagion around a particular day t in Excel[6] by using raw stock index returns and sovereign bond yield. A simple moving window average for any time t is computed based on the previous 20 trading days equal to an available calendar month. For the FTQ, the moving window can take the value of either one (if a negative stock market return and a negative bond yield change can be observed in every trading day of 20 observations) or zero (if a negative stock market return and a negative bond yield return cannot be observed in any one of 20 trading days). For the CI, the moving window can take the value of either one (if a negative stock market return and a positive bond yield return can be observed in every trading day of 20 observations) or zero (if a negative stock market return and a positive bond yield return cannot be observed in any one of 20 trading days). Therefore, the FTQ and the CI are located between the value of 0 and 1. When the FTQ or the CI infinitely get closer to 1 at time t, flight-to-quality or contagion phenomena could be extremely durable around the time t.

[5] In accordance with Gulko (2002), in the period of financial crisis, investors tend to bid up the price of sovereign bond by moving the capital from the risky place to the safer place, such as bond market, so that the reduced bond yield will be observed (negative bond yield changes).

[6] a. For the FTQ (flight-to-quality indicator), we first use IF function in which we create a condition of choosing negative returns of stock index and negative changes of bond yield at a particular time t, and 1 for true and 0 for false. For two new series calculated from the negative stock index return and negative changes of bond yield only with the value of 1 and 0, we use IF function again and create a condition that the sum of two new series is equal to 2, to filtrate the situation that a negative stock market return and a negative bond yield return are observed on the same trading day. Finally, we compute the moving window average to derive the FTQ.
b. For the CI (contagion indicator), we use the similar approach, but just create the new logical conditions.

Two-period Copula-GARCH Approach

To capture the nonlinear contagion, we apply the bi-variate copula-GARCH approach to look into the changes of tail dependence. First of all, following Huang, Lee, Liang, and Lin (2009), we construct marginal distributions based on the basic GARCH and GJR models [7]. The simplest GARCH (1,1) is considered with both of standard normal distribution and standardized student-t distribution, which is:

$$\begin{aligned}
x_t &= \mu + \omega_t \\
\omega_t &= \sigma_t \epsilon_t \\
\sigma_t^2 &= \alpha_0 + \alpha_1 \omega_{t-1}^2 + \beta \sigma_{t-1}^2 \\
\epsilon_t &\sim N(0,1) \ or \ \epsilon_t \sim t_\Phi
\end{aligned} \tag{1.8}$$

where, we have $\mu{=}E(x_t){=}E(E(x_t|I_{t-1})){=}E(\mu_t){=}\mu$ which is the unconditional mean of return, and conditional variance is $\sigma_t^2 = Var(x_t|I_{t-1}) = Var(\omega_t|I_{t-1})$, I_{t-1} is information set at time t-1. The GARCH model has the restrictions, such as $\alpha_0 > 0$, $\alpha_1 \geqslant 0$, $\beta \geqslant 0$, and $\alpha_1 + \beta < 1$. With a standardized student-t distribution, the condition of GARCH is $\alpha_1 Var(\epsilon_t) + \beta < 1$. Φ is degree of freedom. Maximum likelihood is used to estimate the GARCH parameters, with information set $I_{t-1} = \omega_0, \omega_1, \cdots, \omega_{t-1}$. Then, the joint density function could be expressed as $f(\omega_1, \cdots, \omega_t) = f(\omega_t|I_{t-1}) f(\omega_{t-1}|I_{t-2}) \cdots f(\omega_1|I_0) f(\omega_0)$. The maximum likelihood test function for the series $\omega_1, \cdots, \omega_t$ is:

$$LLF = \sum_{k=0}^{t-1} f(\omega_{t-k}|I_{t-k-1}) \tag{1.9}$$

ϵ_t following distributions (normal or student-t) can be evaluated by using volatility equation, and maximum likelihood estimates are gained by equation 1.9. Before

[7] Being different from GARCH model, GJR model includes the counterpart with the asymmetric effort, which may help copula to show the dependence structure better and make assumption closer to reality.

building the copulas, the marginal distribution of X_{t+1} is calculated from series of $(x_1, x_2, \cdots, x_t)$, as follows:

$$\begin{aligned}
&P(X_{t+1} \leqslant x|I_t) = P(\omega_{t+1} \leqslant (x-\mu)|I_t) \\
&= P(\epsilon_{t+1} \leqslant \frac{(x-\mu)}{\sqrt{\alpha_0 + \alpha_1\omega_t^2 + \beta\sigma_t^2}}|I_t) \\
&Then \\
&= N(\frac{(x-\mu)}{\sqrt{\alpha_0 + \alpha_1\omega_t^2 + \beta\sigma_t^2}}|I_t),\ if\ \epsilon_t \sim N(0,1) \\
&= t_\Phi(\frac{(x-\mu)}{\sqrt{\alpha_0 + \alpha_1\omega_t^2 + \beta\sigma_t^2}}|I_t),\ if\ \epsilon_t \sim t_\Phi
\end{aligned} \tag{1.10}$$

The GJR model with innovations following normal and student-t distributions will be introduced next.

$$\begin{aligned}
&x_t = \mu + \omega_t \\
&\omega_t = \sigma_t\epsilon_t \\
&\sigma_t^2 = \alpha_0 + \alpha_1\omega_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma s_{t-1}\omega_{t-1}^2 \\
&\epsilon_t \sim N(0,1)\ or\ \epsilon_t \sim t_\Phi
\end{aligned} \tag{1.11}$$

Where, s_t is dummy variable which takes the value of one as ϵ_t is negative, zero otherwise, satisfying with the condition of $s_t = \binom{1,\ \omega_t<0}{0,\ \omega_t\geqslant 0}$. Similarly, the GJR model also has the constraints that $\alpha_0 > 0$, $\alpha_1 \geqslant 0$, $\beta \geqslant 0$, $\gamma + \beta \geqslant 0$ and $\alpha_1 + \beta + \frac{1}{2}\gamma < 1$.

Being better than the traditional GARCH(1,1), the GJR model involves the counterpart with the asymmetry information which is carried by dummy variable and its coefficient γ in equation 1.11. If γ is positive, the negative waves will produce more significant volatility than the same size of positive waves. The marginal distribution for GJR model is similar to the one for the traditional GARCH in equation 1.10, which is written as:

$$
\begin{aligned}
&P(X_{t+1} \leqslant x|I_t) = P(\epsilon_{t+1} \leqslant \frac{(x-\mu)}{\sqrt{\alpha_0 + \alpha_1\omega_t^2 + \beta\sigma_t^2 + \gamma s_t \epsilon_t^2}}|I_t) \\
&Then \\
&= N(\frac{(x-\mu)}{\sqrt{\alpha_0 + \alpha_1\omega_t^2 + \beta\sigma_t^2 + \gamma s_t \epsilon_t^2}}|I_t),\ if\ \epsilon_t \sim N(0,1) \\
&= t_\Phi(\frac{(x-\mu)}{\sqrt{\alpha_0 + \alpha_1\omega_t^2 + \beta\sigma_t^2 + \gamma s_t \epsilon_t^2}}|I_t),\ if\ \epsilon_t \sim t_\Phi
\end{aligned}
\tag{1.12}
$$

The marginal series obtained from equation 1.10 and 1.12 as variables will be used into copula estimations, which is introduced in next section.

All types of copulas are built based on Sklar's theorem [8] which shows very important basic structure of copulas. Let D be an n-dimensional function with margins $F_1, F_2, \cdots, F_n$, and then there should be a copula C for the real $x_1, \cdots .x_n$,

$$
\begin{aligned}
D(x_1, \cdots, x_n) &= P(X_1 \leqslant x_1, \cdots, X_n \leqslant x_n) \\
&= C(P(X_1 \leqslant x_1), \cdots, P(X_n \leqslant x_n)) \\
&= C(F_1(x_1), \cdots, F_n(x_n))
\end{aligned}
\tag{1.13}
$$

If distribution function D is continuous, then in the light of Sklar's theorem, the probability distribution function could be divided into the parts of a marginal distribution and a dependence structure. A dependence structure is represented by a copula, and the changes of dependence structure are reflected by the relevant parameters of copulas. This could be clearly seen that the density of D is expressed as follows:

$$
\begin{aligned}
d(x_1, \cdots, x_n) &= \frac{\partial^n D(x_1, \cdots, x_n)}{\partial x_1, \cdots, \partial x_n} \\
&= \frac{\partial^n C(F_1(x_1), \cdots, F_n(x_n))}{\partial F_1, \cdots, \partial F_n} \times \prod_1^i \frac{\partial F_i(x_i)}{\partial x_i} \\
&= c(u) \times \prod_i f_i(x_i)
\end{aligned}
\tag{1.14}
$$

[8] See Sklar (1959).

Where, $u_i = F_i(x_i)$, $i = 1, 2, \cdots, n$. $c(u)$ is a copula density function. If all marginal variables are continuous, copula distribution C is unique and in general, otherwise is determined by the range of marginal distributions functions, $Range\ of\ F_1 \times \cdots \times Range\ of\ F_n$ (Sklar, 1959).

In our case, based on the different copulas' specialities, we choose three copulas from the large copula family, such as Gaussian, Student-t and Clayton copulas. For example, the Student-t copula is good at describing the symmetric tail dependence and tail independence, and Clayton copula is good at describing the asymmetry tail dependence[9].

(1)Gaussian Copula

We set u_i to represent probability function $F_i(x_i)$. Gaussian is one type of copulas with the multivariate normal distribution which is defined by follows:

$$C_{Gaussian}(u_1, u_2; \rho) = \varphi_\rho(\varphi^{-1}(u_1), \varphi^{-1}(u_2)) \tag{1.15}$$

φ_ρ is a joint distribution, which is consisted of the multivariate normal distributions, ρ is dependence parameter of Gaussian copula, and φ is a standard normal distribution function.

(2)Student-t Copula

The traditional correlation to show the dependence structure implies Student-t copula which is based on the multivariate t distribution. Student-t copula is most closely related to Gaussian copula, which can be expressed by:

$$C_\rho^T(u_1, u_2; \rho, \Phi) = t_\rho(t_\Phi^{-1}(u_1; \Phi), \cdots, t_\Phi^{-1}(u_2; \Phi); \rho, \Phi) \tag{1.16}$$

where t_ρ is the cumulative density function (CDF) of a multivariate student's t distribution, and the degree of freedom parameter is Φ. Due to the dependence between degrees of freedom and degree of tail dependence, Student-t copula attracts

[9]See Rodriguez (2007).

the increasing attention. The extremely large value for degrees of freedom will make distribution infinitely get close to Gaussian one, and a small value for Φ will increase the degree of tail dependence. Briefly, as the degree of freedom increases to infinite, the Student-t copula converges to the Gaussian copula. Compared with Gaussian copula, Student-t copula draws heavy tail events, and shows tail dependence structure better.

(3)Clayton Copula

The Clayton copula is put forward by Clayton (1978). The CDF is defined as:

$$C_{Clayton}(u_1, u_2; \delta) = (u_1^{-\delta} + u_2^{-\delta} - 1)^{-\frac{1}{\delta}} \tag{1.17}$$

where δ belongs to the range of $[-1, \infty)$.

For marginal functions and copulas, we employ the maximum likelihood method to estimate the parameters in two steps, which will save amount of computer time. First, the log-likelihood function for both of marginal function and copula is written as:

$$L(\theta) = \sum_{i=1}^{T} ln\ c(F_1(x_{1i}; \theta_1), F_2(x_{2i}; \theta_2), \cdots, F_n(x_{ni}; \theta_n)) + \sum_{i=1}^{T} \sum_{j=1}^{n} ln f_j(x_{ji}; \theta_j) \tag{1.18}$$

where, we have a set of parameters for marginal and copula functions, θ. Through maximizing the equation 1.18, the maximum likelihood estimator can be obtained:

$$\hat{\theta}_{MLE} = arg\ max\ l(\theta) \tag{1.19}$$

After the maximum likelihood estimation, we further apply the Inference Functions for Margins Method (IFM) proposed by Shih and Louis (1995). IFM method is used in two steps, two-step procedure is much easier than one step method with only maximum likelihood estimation, saving the computer time a lot. The first stage is to estimate the parameters for marginal functions, θ_1, and the expression is shown as:

$$\hat{\theta}_1 = arg\ max\ \theta_1 \sum_{i=1}^{T}\sum_{j=1}^{n} ln\ f_j(x_{ji};\theta_1) \tag{1.20}$$

Equation 1.20 shows the performance of estimation for the univariate marginal distributions. In second step, with the estimator of $\hat{\theta}_1$, we estimate for the copula parameters (the first part of 1.18) in the following function:

$$\hat{\theta}_2 = arg\ max\ \theta_2 \sum_{i=1}^{T} ln\ c(F_1(x_{1i};\theta_1), F_2(x_{2i};\theta_2), \cdots, F_n(x_{ni};\theta_n);\theta_2,\hat{\theta}_1) \tag{1.21}$$

Then, we have Inference Function for Margins estimator as:

$$\theta_{IFM} = (\hat{\theta}_1, \hat{\theta}_2)' \tag{1.22}$$

For two estimated stages, we use maximum likelihood method on them equally.

Multinomial Logistic Regression

The predictability of contagion is evaluated by following another approach of multinomial logistic regression of Bae, Karolyi, and Stulz (2003). The multinomial Logit model is summarized as follows. In addition, based on the coefficients of multinomial Logit model, marginal effect is also computed by following the method of Greene (2012).

In the majority of researches, exceedances [10] with respect to the extreme positive and negative returns are usually modeled as a dichotomous variable. However, according to the researching requests in our paper, modeling coexceedances [11] to find the contagion needs to classify the categories to construct the polychotomous variable. The categories are classified on the basis of the number of coexceedances across European bond markets. The advantage of multinomial logistic regression

[10] Exceedance in this paper is defined as 5% largest positive value on the top tail of returns distribution and 5% smallest negative value on the bottom tail of returns distribution.

[11] Coexceedance is therefore defined as that exceedances across countries are observed on the same trading days.

is exogenous estimating the probabilities in a polychotomous variable, and showing the value of probabilities intuitively. The probability associated with the category i of k possible categories is symbolled as P_i, thus a multinomial distribution can be expressed by,

$$P_i = exp(\beta_i' x)/[1 + \sum_{j}^{k-1} exp(\beta_j' x)] \tag{1.23}$$

x is the covariates vector and β_i is the coefficient of covariate for the ith category. The model can be estimated by log likelihood function, which is given by

$$logL = \sum_{i=1}^{n} \sum_{j=1}^{k} I_{ij} log P_{ij} \tag{1.24}$$

where I_{ij} is a unit vector, the elements of the unit vector are equal to one if ith observation satisfies with the condition of jth category, and zero otherwise. P_{ij} is the function of coefficients β. Like all kinds of regressions, Goodness-of-fit of multinomial logistic regressions can be measured, by the pseudo-R^2 approach[12].

$$pseudoR^2 = 1 - [logL_\theta / logL_\gamma] \tag{1.25}$$

where log(.) is the natural logarithm. The rationale of this formula is that log L playing a role in nonlinear regression is analogous to the sum of squares of the residual in linear regression. Consequently, the higher value pseudo-R^2 we find, the better model fitness will be. This formula is coincident with a proportional reduction in 'error variance'. L_θ is unrestricted likelihood for the estimators of model, and L_γ is restricted likelihood for the constant only.

In order to estimate the coexceedances across European bond markets in multinomial logistic regression, we clarify the categories for possible events in polychotomous variable. According to the number of coexceedances[13], and so as to capture more

[12] This is McFadden (1974)'s pseudo R-square. Goodness-of-fit of multinomial logistic regression cannot be estimated by the equivalent R-square in OLS regression. However, it can be interpreted through pseudo R-square, the higher value pseudo-R^2 we find, the better model fitness will be.

[13] See Table 1.8: Summary statistics of coexceedances for both of positive and negative tails.

possible results, we restrict our categories into 6 levels for 6 events. For example, event 0 indicates that there is no coexceedance found on the same trading day, and event 6 indicates 5 or more than 5 coexceedances found on the same trading day, likewise for other events. In the Logit model, the category 0 is the benchmark line whose estimations are not reported. In table 1.9, the categories from 1 to 5 are exogenously tested for both top and bottom tails. Following the basic approach of Bae, Karolyi, and Stulz (2003), three covariates are tested in our models, such as conditional volatility, the level of exchange rate and the level of interest rate [14]. Our estimations are separately applied for both of top and bottom tails. Finally, the probability of contagion occurrence at each specific category, P_i, can thus be calculated in the function 1.26. And, with the unconditional mean values, the covariates can be separately and endogenously estimated for each of six categories.

$$P_i^* = exp(\beta_i^{'} x^*)/[1 + \sum_{j=1}^{k-1} exp(\beta_j^{'} x^*)] \tag{1.26}$$

Following the approach of Greene (2012) [15], we choose x^* as unconditional mean value of x, and marginal effect [16] of the event probability is computed to show that as every unit of the independent covariates increases, how the probability of events will change.

[14]Conditional volatility of return is modeled by a simple univariate EGARCH(1,1) model. The level of Exchange rate is calculated by the exchange rates from British pound to US dollar, Danish krone to US dollar and Euro to US dollar. The level of interest rate in the model is calculated by the typical three-month short term rates of interest. For the level of exchange rate, we calculate weighted average of three exchange rates for the European region. And, we also calculate weighted average of interest rate as the level of interest rate of European region. The data covering the period of Jan 2, 2001 to May 22, 2014 is extracted from Datastream International.

[15]See Greene (2012), Chapter 18.

[16]In Greene (2012), marginal effect is computed as the partial derivatives of probability to covariates.

1.2.2 Data Description and Preliminary Statistics

We employ the data covering the period from 2 Jan 2001 to 22 May 2014 which encompasses all recent financial and debt crises. By following Baur and Lucey (2009), the sample data selects daily continuously compounded MSCI stock index of Germany, France, the UK, Belgium, Denmark, Netherland, Portugal and Spain, and JP Morgan bond index of the UK, Belgium, Denmark, Netherland, Portugal and Spain. For Greek stock index return, and German, French and Greek sovereign bond indices returns, we collect them from datastream[17]. Sovereign bond indices are sovereign total return indices with more than ten years maturities. We also calculate the return of stock index and the return of sovereign bond index with logarithm formula of $ln(P_t) - ln(P_{t-1})$ (where P_t is index value at time t). In order to build the moving average indicators of flight-to-quality and contagion, we also employ the JP Morgan government bond yield with more than 10 years maturities as well, the logarithm formula of return is $ln(P_t) - ln(P_{t-1})$. All sample data are obtained from *Datastream* database and all indices are chosen in local currency.

Table 1.1 presents all preliminary statistics of sample data. It reports mean, standard deviation, JB statistics for normality, first order autocorrelation and LM test for ARCH effects with 10 lags. For the statistics of bond markets, Greek sovereign bond market has the lowest mean return among sample markets. The Greek bond index also has the lowest standard deviation that shows the relatively smooth variation. JB statistics reject normality for all countries. Bond index returns show a small autocorrelation for most of markets, the relatively higher first order autocorrelation is found in Portuguese, Spanish and Greek bond markets, respectively. The LM tests produce statistically significant results for ARCH effects with 10 lags, it shows that bond index returns strongly rely on their past values. For the second part of table 1.1, we also report some descriptive statistics for stock markets. The Greek stock market has the negative and lowest stock index return, and has the lowest standard

[17] We can directly find the required data from the equity and bond categories of Datastream.

deviation as well. Normality is rejected for all markets at 1% significance level by the JB statistics. Stock markets show the even smaller autocorrelation than that of bond markets. And the significant ARCH effects are found in all countries. The results of LM test finally suggest the Goodness-fit of the GARCH-type models to our data series. It allows using any GARCH-type models into our latter estimations.

Table 1.2 reports the results of time series' stationarity estimated by unit root tests. The stationarity of data series is examined by choosing Augmented Dickey-Fuller test(Simplest ADF(1)). The strong rejection of null hypothesis shows that stationary process in the raw stock index returns and sovereign bond index returns can be found for all countries. It meanwhile means that the employed data has been ready to enter into our tests.

We report unconditional stock-bond returns correlation matrix in table 1.3. In table 1.3, unconditional correlation coefficients are negative in Germany, France, the UK, Belgium, Netherland and Denmark, with the exception of Spain, Portugal and Greece. Although the unconditional correlation coefficients are positive in Spain, Portugal and Greece, they are relatively unremarkable, only are 0.0705, 0.1182 and 0.2058. As a result, when investors' profits overall increase (decrease) in the bond markets, profits will decrease (increase) in the stock markets in most of European countries. The unconditional correlation shows the disadvantage that the results cannot display the changes of correlation between assets over time.

1.3 Empirical Results

1.3.1 Cross-asset Analysis, FTQ and CI indicators

Before the DCC estimations, Ljung-Box Q-statistics are computed for residuals, the results of Q-statistics show that the null hypothesis of no serial correlation cannot be rejected for the time series of residuals. To estimate the DCC across stock and bond, we use the bond index returns rather than bond yield to evaluate the dynamic conditional correlations, because the produced results intuitively exhibit the correlations, are easy to read. The plots of DCCs are shown in figures 1.1 to 1.9. For each figure (a) of nine figures, all of them show volatile comovement between stock index returns and sovereign bond index returns. The volatile comovement between stock index returns and sovereign bond index returns is similarly obtained in Baur and Lucey (2009), Dajcman (2012), Gulko (2002), Connolly, Stivers, and Sun (2005) and Dajcman (2013). The overall negative correlations of nine countries are observed over the sample period, the results are similar to Baur and Lucey (2009), Dajcman (2012) and Dajcman (2013). From the figures, we can see that the turmoil periods somewhat cause the sharp changes of dynamic conditional correlation, and the effect of the different crises on dynamic conditional correlations is slightly different. For example, the effect of IBB (International Bubble Burst) on the DCCs between stock and bond lasts for a relatively longer time, and the impact of MEC (Middle East Financial Markets Crash) on the DCCs is moderate. Along our sample period, the global financial crisis and the European debt crisis attracting the academic attention cause the positive or negative changes of dynamic correlations in the European region. In other words, we find mixed results of dynamic conditional correlations for the different turmoil periods. We point out the important crises[18] along the sample

[18]Our sample includes: WTC (Sep 11 attacks on World Trade Center); IBB, Internet Bubble Burst (IBB is pointed out on 21 May 2002, at the same time, the Dow Jones Industrial reached the peak point.); MEC, Middle East financial markets crash (From the beginning of May 2006); GFC, Global financial crisis (From 16 September 2008, the Lehman Brothers close to bankrupt is denoted); GDC, Greek Debt Crisis(On 23 April 2010, the Greek government requested a bailout

period, and the countries on which these crises have the negative impact, such as WTC (with the negative impact on Germany, France, Belgium, Denmark, Netherland, Portugal and Spain), IBB (with the negative impact on Germany, France, UK, Denmark, Netherland, Spain and Greece), MEC(with the negative impact on Denmark and Greece), GFC (with the negative impact on Germany, France, Belgium, Denmark, Netherland, Portugal Spain and Greece), GDC (with the negative impact on Germany, France, Belgium, Denmark and Netherland), IDC (with the negative impact on France, Belgium, Netherland and Spain), PDC (with the negative impact on France and Portugal) and ITDC (with the negative impact on Germany, France, Belgium, Denmark, Netherland, Portugal and Spain). For the majority of sample countries, dynamic conditional correlation turns positive and more volatile around 2 Jan 2012. The DCCs of France, Portugal and Spain turn positive significantly after global financial crisis denoted from 16 September 2008.

Our motivation prompts us to focus on the period of the European sovereign debt crisis, starting from the Greek debt crisis. Portugal, Spain and the source country Greece show the DCCs turning positive obviously, after the time the Greek government requested the bailout from International Monetary Fund (namely, the time for the Greek debt crisis denoted, or the start of the European debt crisis.), we can see that the influence of the European debt crisis on Portugal, Spain and Greece lasts to "today". Highly positive correlations may imply cross-asset contagion, and the decline of their stock markets. This is related to a worry of Constancio (2011) and Mink and Haan (2013). They worry about that a restructuring of Greek debt may give rise to a new financial crisis in the European Union, especially in France and Germany, which is highly exposed to Greece. Due to the worry of Constancio (2011) and Mink and Haan (2013), we finally report the DCCs of Germany and

from the EU/IMF); IDC, Ireland Debt Crisis (1 September 2010); PDC, Portugal Debt Crisis (From 16 May 2011, a bailout of financial support from Eurozone was approved for Portugal.) and ITDC, Italy Debt Crisis (From the early July 2011, the financial markets expectation for Italy bailout request reached a level, at which other European markets with sovereign crisis had asked for a support yet).

France.

For Germany, in the turmoil periods, the dynamic conditional correlation becomes significantly negative, and stays at a low level, such as WTC (-0.6), IBB (-0.4), GFC(-0.7), GDC(-0.7), IDC(-0.65) and ITDC(-0.65). For France, WTC, IBB, GFC, GFC, GDC, IDC, PDC and ITDC show negative DCCs at average levels of -0.55, -0.45, -0.3, -0.65, -0.65, -0.65, -0.65 and -0.65, respectively. Indicating high levels of the possible flight-to-quality, the lowest correlations may show that the German and French stock markets are impacted most by the Global Financial crisis and the European debt crisis. Through defining the specific conditions of flight-to-quality and contagion, we may obtain more accurate information by analysing the moving average indicators (FTQ in fig.(b)and CI in fig.(c)).

We compute the moving average indicators to show the dynamic level of flight-to-quality and contagion. It makes sense that the higher the indicator is, the more remarkable the phenomenon will be. In the latter analysis, flight-to-quality indicator is denoted as FTQ, contagion indicator is denoted as CI, and we combine the analysis of CI with FTQ to find the most dominant phenomenon. From the fig.1.1 to fig.1.9, WTC and IBB increase FTQ obviously for most European countries, except for Denmark and Netherland. The global financial crisis exploding from the year 2008 influences European markets heavily. For example, GFC increases FTQ significantly for all countries, and FTQ is much higher than CI. It possibly implies that during the period of GFC, European investors tend to move their capitals from the stock markets to the sovereign bond markets, so that the price of stock drops and the price of sovereign bond increases. The European debt crisis starting from the year 2010 (from the Greek debt crisis onward) also causes big waves of the correlations between European stocks and bonds, and mixed results are found. We will show more details in the following paragraph.

More specifically, before the year 2007, the German FTQ has been remaining an average level of 0.4 which is higher than the contemporaneous CI that is only 0.2

on average. And then, the global financial crisis increases the German FTQ to a level of 0.5, and FTQ increases to a higher level in the period of the European debt crisis including GDC, IDC, PDC and ITDC. Similar results are obtained for France. The French CI drops to a level of zero many times, it lowers the average level of CI and indicates that after the global financial crisis the French CI remains a lower level than FTQ. The flight-to-quality of France is the dominant phenomenon over the observed period. Comparing the British FTQ with the British CI, both of FTQ and CI equally reach a level of 0.4 on average before the middle of 2007. The equal levels of FTQ and CI reflect a long lasting tranquil market condition of the UK. However, the tranquil market condition of the UK starts changing from the period of the global financial crisis (Sep 2008). The British FTQ increases dramatically to the maximum level of 0.65. In contrast, CI has a lower level, only remains an approximate level of 0.2. The changes of FTQ and CI imply that the global financial crisis decreases the stock returns and increases the bond returns. The investors of the UK seem to promptly move their capital from the stock market to sovereign bond market. During the European debt crisis between the year 2010 and 2012, FTQ of the UK still remains a relatively high level, approximately 0.45. The level of the contemporaneous CI is only 0.1. In this case, we infer that the European debt crisis unlikely strikes the British investors' confidence in investing the local sovereign bond, their herding investment behaviour make the bond safer and more profitable. After the analysis of the large countries, we also find some interesting results from the relatively smaller countries.

The Belgian FTQ and CI are only around 0.2 from the beginning of MEC. That there is approximate 0.2 unit increase of FTQ could be found from the period of the global financial crisis. Although this change of the Belgian FTQ is moderate, the strong flight-to-quality and the weak contagion are still captured by contemporaneously comparing FTQ (0.5) and CI (0.2). We surprisingly notice that both of the Belgian FTQ and CI have the low value below 0.4 at the very beginning of the

European debt crisis (the periods of the Greek debt crisis and the Irish debt crisis). However, at the later stage of the European debt crisis, CI starts climbing up to a level of 0.55, which is much higher than its contemporaneous FTQ. From the figures, the Belgian stock and bond markets slowly react to the negative information of the European debt crisis, but once the Belgian investors realize the general market risk they will have a violent reaction, and then adjustment in time. In contrast with other countries, Denmark likely has a durable investment preference, because FTQ has been staying at an average level of 0.5 from the global financial crisis afterward (for at least four years). The higher FTQ and the lower CI indicate the strong preference of the bond investment in Denmark. For Netherland, CI shows the most volatile contagion, but the level of contagion is not significant. The FTQ of Netherland reaches a maximum level of 0.5 at the beginning of the European debt crisis, even reaches a level of 0.7 in the Irish debt crisis, showing that Dutch investors heavily rely on the local sovereign bond even if the neighbouring bond markets have the strong general market risk. The overall results of Netherland are analogous to what we observed in Denmark, their overall FTQ is higher than their CI. All above concludes that the general market risk of the source market of the European debt crisis may not necessarily affect the performance of the neighbouring countries. Figure 1.7 (b) (c) and figure 1.8 (b) (c) present the results for FTQ and CI of Portugal and Spain. Like all results concluded from above, the global financial crisis pushes their FTQ. From the year 2010 to the year 2011, contagion becomes more dominant due to the CI level of 0.6. Most importantly, as a source country of the European debt crisis, Greece inevitably captures more attention. It in fact produces many significant results in our paper. First, fig.1.9 (a) shows that over the period from the beginning to the year 2009, DCC always remains negative, until the year 2010. Second, after the Greek debt crisis, the Greek dynamic correlation turns positive and increases to an incredibly high level. In our opinion, it implies highly positive comovements of the Greek stock and bond returns. Similar variation of DCC is found from Portugal and Spain. In this case, the stock and bond markets of Portugal and Spain may have higher exposure to the shocks of the Greek bond market, the relatively small economic entities, such as Portugal and Spain, may be more likely to be influenced by the waves of the Greek bond market. The high CI (0.65) of Greece may indicate that the explosion of the Greek debt crisis undoubtedly impacts on Greek sovereign bond market, simultaneously, also sorely affect its stock market.

1.3.2 Cross-country Sovereign Bond Analysis on Contagion

From Figure 1.9, we are able to see the sharp increase of the Greek dynamic correlation between stock and bond during the European debt crisis, and similar changes are found from Portugal and Spain as well. This result motivates our empirical works to engage in contagion investigations for cross-country perspective, during the European debt crisis from 23 April 2010 (GDC) to the early July 2011 (ITDC). We follow the cross-country DCC-GARCH approach of Chiang, Jeon, and Li (2007), and choose the Greek sovereign bond market to be a source market of the European debt crisis. We also follow their approach to limit our estimated sample period to the turmoil period. The estimated sample therefore includes the period from the middle of the year 2009 to the middle of the year 2012, it ensures the limited sample period that can include all turmoil information of the European debt crisis, and all possible insights on the cross-country contagion of the European debt crisis will be produced.

We present the logarithm returns of sovereign bond indices in Fig.1.10 to visualize the returns for nine markets. A clustering phenomenon of larger volatility simultaneously appears in nine countries after the mid-year 2010 (the time for the Greek debt crisis denoted), and sustains for a long time. This phenomenon is not only observed in figure 1.10, but it also is successfully modeled by the existing literature of (Bollerslev, Chou, and Kroner, 1992) with the traditional GARCH model. Before we estimate the dynamic correlation coefficients, the statistics of Greek bond index return are stressed. The statistics show negative returns on average, the statistically significant ARCH effect is found by LM (Lagrange Multiplier) test with 10 lag-length. The results of preliminary statistics indicate that the GARCH-type model will fit the data very well, and goodness-fit of the GARCH-type models is found for all European countries.

By following the theory of Chiang, Jeon, and Li (2007), cross-country contagion is defined as a comovement of stocks, the comovement is modeled by the DCC-GARCH. The appearance of stock contagion during the Asian financial crisis is denoted by the significantly high level of dynamic conditional correlation, the range of "high level" is defined from 0.3 to 0.47. In other words, contagion can be found if DCC falls into the range from 0.3 to 0.47. This range as the benchmark value will be considered in the latter analysis. In addition, if a increasingly positive correlation is found, it means that the turmoil information increases the contagion more or less. In our paper, we apply this approach to the European bond markets, and observe the contagion caused by the European debt crisis. The usage of DCC-GARCH helps us to produce covariance matrices and estimate the changes of covariance matrices over time.

In addition, we show the time-varying conditional volatility over the whole sample period in Figure 1.11. The conditional volatility increases sharply from the end of 2009 and starts decline in the middle of 2012. The cross-country contagion is denoted if the high level of DCC and conditional volatility is found simultaneously. The period with the high level of volatility also indicates the duration of tranquil period.

The approach of Chiang, Jeon, and Li (2007) is employed in our paper and equation 1.7 is expressed for the bivariate case:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\overline{q}_{12} + \alpha u_{1,t-1}u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{[(1-\alpha-\beta)\overline{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}]}\sqrt{[(1-\alpha-\beta)\overline{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}]}} \tag{1.27}$$

We follow Engle and Sheppard (2001), the DCC-GARCH model can be used to maximize the log-likelihood function (equation 1.2) by using a two-step approach. Hence, the equation 1.2 is rewritten as:

$$l_t(\vartheta,\varphi) = [-\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + log|D_t|^2 + \varepsilon_t^{'} D_t^{-2}\varepsilon_t)] + [-\frac{1}{2}\sum_{t=1}^{T}(log|R_t| + u_t^{'} R_t^{-1} u_t - u_t^{'} u_t)] \tag{1.28}$$

ϑ denotes the parameters in D_t, and φ denotes the parameters in R_t. The first part of the right-hand side of equation (1.28) is the volatility counterpart, this part includes the sum of individual GARCH likelihoods. The estimated parameters in D_t can be used to maximize the likelihood function in the first stage (first part of equation 1.28). The second stage (the second part of the right-hand side of the equation 1.28) encompasses the correlation component of the likelihood function, this part can be maximized to estimate the correlation coefficients. Chiang, Jeon, and Li (2007) show the advantage of the dynamic correlation coefficient which is more flexible in finding the comovement between two return series than the unconditional correlation coefficient. Dynamic conditional correlation also intuitively reflect the variations of comovement over time.

Figure 1.12 show the estimates of dynamic conditional correlations between the Greek sovereign bond market and each of eight European bond markets, such as Germany, France, UK, Belgium, Denmark, Netherland, Portugal and Spain. During the year 2010 and the year 2011 [19], we find a high level of the dynamic conditional correlations for all countries, with the exception of France. However, before the year 2010, the dynamic conditional correlation of France shows a dramatic increase for approximately four months. The DCC across the Greek and Spanish bond markets even reach a maximum level of 0.8 at very beginning of 2010, and the effect lasts for more than a year. So, the relatively high level of DCC between Greece-Spain possibly implies that the Spanish bond market had the high exposure to the Greek bond market. This result is highly coincident with the cross-asset result of the Spanish markets. Most interestingly, the overall increase of all DCCs is found around the year 2010. The time for the start of the DCCs' increase is at least four month earlier than the time the Greek government asked for a bailout from the institutions (the

[19] We also plot the time-varying dynamic conditional correlations, from the start of the year 2001. The results show that dynamic conditional correlations substantially stay at high level, maybe due to the very similar tranquil market conditions across the European bond markets. That we find the high dynamic conditional coefficients from the end of 2009 to the middle of 2012 (with extremely high level of conditional volatility, in figure 1.11) is more likely attributed to contagion.

time for the Greek debt crisis denoted on 23 April 2010). In other words, the herding behaviour of bond returns appears earlier than the time for the debt crisis denoted. The opportunity of anticipating the bond contagion may be implied by the early herding behaviours.

We compare the results of the European bond markets with the literature of Chiang, Jeon, and Li (2007) on the Asian stock markets. Chiang, Jeon, and Li (2007) claim that the impact of the Asian financial crisis at the beginning phases only stays at the source country of Thailand, and only affects the local investment decisions. However, the investors' panic starts spreading from the source country to the neighbouring markets in the mid-phases of the Asian financial crisis. This phenomenon shows that the herding behaviours of stock returns appear after the time for the Asian financial crisis denoted. Obviously, the results concluded by Chiang, Jeon, and Li (2007) are quite different from what we found from the European bond markets. Hence, the earlier appearance of bond contagion is explained in the possible sense that the public information of sovereign debt situation is easily captured by investors, so that the investors may be easier to predict the covariation of the European bond markets than to predict the covariation of the stock markets. The contagion found in this part can be explained as that the European investors would like to follow the major investment decisions made by the majority of investors in the source country of Greece, in order to avoid the possible systematic risks.

Mink and Haan (2013) fear that in the European debt crisis Germany and France highly exposed to Greece. However, in our paper, the dynamic conditional correlations between the Greece and each of the UK, Germany and France are 0.3 on average, are relatively moderate around the year 2010. The contemporaneous DCCs of Belgium, Denmark and Spain are relatively higher than that of the UK, Germany and France. It means the relatively smaller countries are more susceptible than the relatively larger countries. In addition, that the DCC of the UK has the similar variation of the DCC of Germany may be explained as the very similar exposure of the British and German bond markets to the Greek bond market. It is worth noting that the DCC of France appears a brief and significant increase before the European debt crisis claimed, and then drops down to zero on average. This unawares phenomenon and the subsequently long time tranquil market conditions dazzle us a lot, and may be further researched and explained by the future efforts.

1.3.3 Contagion Analysis: Copula-GARCH Approach

The sample includes daily returns of nine European sovereign bond indices, from 2 Jan 2001 to 22 May 2014. In order to estimate the changes of dependence structure, the whole sample period is decomposed into two sub-periods[20]. One period takes the tranquil market conditions in account, the other one is relatively turmoil period. The decomposition of the sample period is based on with three reasons. First, Dajcman (2012) denotes that the time for the occurrence of the Greek Debt Crisis is 23 April 2010, which is the time the Greek government requested a bailout from the institution of EU/IMF. Second, Adel and Salma (2012) claims a tranquil period that is characterized by calm volatility, and a turmoil period that is characterized by frantic volatility (The relevant evidence can be partially summarized from fig.1.10). Finally, the evidence summarized from fig.1.11 shows that for most of countries, the occurrence of contagion happened at least four months prior to the time the Greek government requested a bailout from EU/IMF. In summary, we determine the bound date between "a tranquil period" and "a crisis period" in the light of all above evidences. The bound date should be earlier than the dates summarized from above evidence, so that the post-crisis period will include all turmoil information of the European debt crisis. Therefore, the bound date is decided to be 1 Sep 2009. Thus, the pre-crisis period of European sovereign debt crisis is from 2 Jan 2001 to 1 Sep 2009, and the post-crisis period is from 2 Sep 2009 to 22 May 2014.

In the approach of copula-GARCH, we consider the marginal method presented in section 1.2.1, and the traditional GARCH model and GJR model following normal and student-t distributions to add the asymmetry information. Specifically, we use the univariate GARCH model to derive the univariate marginal model. Allowing the univariate GARCH model helps produce the probability distributions and the results of maximum likelihood (See table 1.4 and 1.5). In table 1.4 and 1.5, parameters of

[20]Following two-period approach of Adel and Salma (2012) will help observe the changes of the copula parameters.

the GARCH-normal, GARCH-t, GJR-normal and GJR-t are respectively estimated and reported. As a result, all parameters for two-period are statistically significant and non-zero, which therefore are sufficient for the copula estimation. We also present the results for the AIC (Akaike information criterion) and BIC (Bayesian information criterion). The results show all estimated AIC and BIC lying between -11 and -8.

Three copulas are applied in our estimation, they are Gaussian, Student-t and Clayton, respectively. We continue to test the parameters of three chosen copulas, the results are shown in table 1.6 and 1.7. We use Inference function for margins (IFM) method as a default copula estimation method. Following Rodriguez (2007), Kendall's tau is used to estimate the parameters of Student-t Copula, is defined as:

$$\rho_{\tau} = \frac{2}{\pi} arcsin(\rho) \tag{1.29}$$

.

Table 1.6 reports the estimations for the dependence parameters of three copulas and model fitness, during the period of 2 Jan 2001 to 1 Sep 2009. And table 1.7 reports those during the period of 2 Sep 2009 to 22 May 2014. We first focus on the copula fit for the pre-crisis sample. For GARCH models, with the relatively smaller values of AIC and BIC, Gaussian and Student-t seem to be better fitting copulas overall. For GJR models, Gaussian and Student-t copulas are overall better fitting copulas as well. And then, during the the period of 2 Sep 2009 to 22 May 2014 (post-crisis sample), we find the mixed results for the copula fitness. Although there are big differences among AIC and BIC of different countries, they are still acceptable.

From table 1.6 and 1.7, all parameters for dependence between Greece and each of eight European countries are positive and strongly significant. We surprisingly find a significant increase for all dependence parameters of copulas from the table 1.6 and

1.7. The high level of nonlinear dependence somewhat reflects the strongly nonlinear contagion and indicates that all European sovereign bond markets are highly exposed to the Greek bond market. The nonlinear results of copula GARCH model support the conclusions obtained by cross-country DCC-GARCH approach. After adding the asymmetry information by using GJR-normal model, the parameters of Student-t copula sharply increases from 0.004 to 0.1380 on average (the most growth). This growth is significantly larger than the increase of the other dependence parameters. Hence, we consider that the asymmetry information of GJR-normal model will be robust in improving the explanatory power of Student-t copula. The Student-t copula becomes more sensitive to detecting changes in the dependence structure. Relating this result to Rodriguez (2007), they put forward that Student-t copula is often used on the symmetric tail dependence and tail independence. Nonetheless, we find that Student-t copula will be more powerful to detect the changes of tail dependence, with the asymmetry counterpart of GJR-normal model.

All in all, sovereign bond contagion has been found by the two-period analysis of dependence parameters. Furthermore, different types of GARCH-type models, especially in GJR-normal model, may increase or decrease the copula's ability of estimating the changes of the extreme tail dependence.

1.3.4 Contagion analysis within European region: Multinomial Logistic Regression

In addition to most research that defines contagion as co-movement of index returns, in order to properly implement multinomial logistic regression, we adopt another contagion definition that is return coexceedance. The exceedance is defined as the returns falling into the set of the lowest and highest 5% observations on the return distribution, and coexceedance therefore is defined as the number of the returns' exceedances observed on the same trading day. The negative coexceedances represent the level of negative contagion for the region, the more coexceedances are found, more contagious the crisis will be in this region. According to the requirement of multinomial Logit model, we firstly summarized the number of the trading days for coexceedances. The results are reported in table 1.8. More specifically, we report coexceedances for the bottom tail (negative extreme value) on the left hand side of table, and top tail (positive extreme value) on the right hand side. For each of the sample countries, we compute the joint exceedances of one country on the particular trading day with the other eight markets. If on one trading day, a extreme return is observed in benchmark market and i[21] in the other eight, it would be signed as i+1 coexceedances for this market. In the light of the number of coexceedances, we classify seven categories indicating counts of the number of joint exceedances. First, the coexceedances on the bottom tail are summarized. Out of 3493 observations, 2884 trading days fall into the category of that there is no extreme return in any market. The number of trading days with only one negative exceedance is 273 in total. From table 1.8, we derive almost symmetric statistics between top tail and bottom tail. For 2853 trading days out of 3493 observations, there is no positive coexceedance found in the top tail. 283 trading days with only one exceedance are found. There is a slight asymmetry found from the category of two coexceedances

[21] i could be equal to 0, 1, 2, ..., 8.

in the top tail and bottom tail. For instance, 137 observations with 2 coexceedances are found in the top tail, but only 112 trading days with 2 coexceedances can be computed in the bottom tail. Besides, the number of trading days with more than 6 coexceedances in the bottom tail is greater than that in the top tail. We therefore conjecture that the impact of the negative events may be stronger than the impact of the positive events on the European bond markets. In table 1.8, we not only present total counts of the number of coexceedances, but we also show the markets' frequency of extreme returns in sample period.

The markets with the most frequent negative coexceedances are Belgium and Netherland which have 73 trading days with more than six markets' coexceedances, 22 and 27 out of all 31 days with five markets' coexceedances in bottom tail. France also shows highly regular negative coexceedances, there are 72 out of all 73 days with more than six coexceedances, and 26 out of all 31 days with 5 coexceedances. France and Netherland are the countries with the most regular positive coexceedances. In France and Netherland, there are all of 59 trading days with more than 6 coexceedances and, 31 and 39 out of all 41 trading days with 5 coexceedances in top tail. Greece sees the largest number of trading days with only one exceedance, 72 for the bottom tail and 77 for the top tail. It means that Greece has the most volatile market conditions over the whole sample period. Actually, the Greek bond market does not always have a large number of negative coexceedances with the other neighbouring markets, it may make sense that the changes of Greek bond returns are prior to the changes of neighbouring bond returns, therefore the Greek coexceedances across neighbouring countries cannot be always found on the same trading days.

Table 1.9 and 1.10 provide the estimations of the multinomial Logit model for the European markets. The results will help answer the central research questions of what and how the covariates can explain the probability of contagion occurrence. We separately estimate the coefficients of models for negative and positive extreme returns, and also calculate the marginal effect. The negative and positive coexceedances are estimated in six models. Models (1) to (3) exogenously estimate the negative coexceedances, and the others estimate the positive coexceedances. In model (1), we estimate for the bottom tail with constants only, model (2) includes the estimations of constants and one covariate of conditional volatility, and model (3) endogenously estimate the constants, and three covariates of volatility, exchange rate and interest rate. For top tail, models (4) to (6) repeat. For the first model of the bottom tail, only estimations of intercept are reported, and the constants in model (1) imply the corresponding probability of events for each category. Model (1) suggests the probability of 85.7% for the case that there is no exceedance in any European market (not reported in tables). β_1 of -2.357 denoting the coefficient for the contagion across one market (event of Y=1) implies the occurrence probability of 7.98% [22]. In the same way, for the other events of bottom tail, the probabilities of contagion occurrence across two to five countries (Y=2, 3, 4 and 5) are 3.28%, 2.21%, 1.46% and 0.91%, respectively. Based on the constants of model (4), we also calculate the probabilities of contagion occurrence for top tail. They from event 1 to event 5 are 8.1%, 3.9%, 2.0%, 1.4% and 2.9%, respectively. Without the influence of covariates, the probabilities of contagion occurrence across countries are much closer to the frequency summarized in table 1.8. In model (2), we add a covariate of conditional variance to the multinomial logistic regression, and the statistically significant results are found for all categories from event 1 to 5.

In model (3), we add three covariates, which are conditional volatility, the level of exchange rate and the level of interest rate. We calculate the weighted average of the exchange rates (Ex.) from euro, Danish Krone and British pound to US dollar, and interest rate (Int.) is calculated by the equally-weighted average of interest rates in local currency. There are three results summarized from model (3). First, the coefficients of conditional volatility are strongly significant for the

[22] The probability of contagion occurrence can be calculated by the function, $exp(\beta_1)/[1 + \sum_k exp(\beta_{0k})]$.

events from "Y=1" to "Y=5". Second, the coefficients of exchange rate for all events are statistically significant, with one exception of the event "Y=5". Finally, the coefficients of interest rate are less significant than volatility and exchange rate. The significant coefficients of interest rate are only found for the events of "Y=1" and "Y=2". Top tail in model (6) presents the analogous results. For example, the coefficients of conditional volatility are significant for the contagion across in at least five countries, and coefficients of exchange rate are significant for the contagion across at least four countries. The interest rate is also weakly significant for the contagion across the European bond markets.

In order to look into the specific influence of the covariates on the probability of contagion occurrence, the marginal effect based on the coefficients displayed in table 1.9 is computed by following the approach of Greene (2012). The marginal results are presented in table 1.10. In model (2), we find a strongly significant marginal effect for conditional volatility for all five categories. The strong significance denotes that the conditional volatility is able to explain and predict the contagion across at least five countries or more than five countries. In addition, the positive marginal effect also indicates that as every unit of conditional volatility increases, it will increase the probability of contagion occurrence (from "Y=1" to "Y=5") more or less, but the power of the marginal effect along the line of categories from "Y=1" to "Y=5" gradually subsides. For example, if conditional volatility increases by one unit, then the probability of event "Y=1" will increase by 0.479 unit, and the event "Y=5" will increase by 0.043 unit. Symmetric effects of conditional volatility for top tail coexceedance is found in model (5). The marginal effect derived from model (3) will help us to answer the question of whether conditional volatility, exchange rate and interest rate significantly impact on the probability of contagion occurrence for bottom tail. As a result, the significant marginal effect of conditional volatility for all five categories shows that as the conditional volatility stays at very high level, it will increase the probability of contagion occurrence across at least five countries.

In other words, conditional volatility is able to strongly explain the contagion across the European bond markets. The level of exchange rate is also able to explain the contagion across at least four countries. The level of interest rate weakly explains the contagion in the European region. Model (6) estimates three covariates for top tail. The significant results for both of conditional volatility and exchange rate are found for all five categories. However, the marginal effect result of exchange rate for the top tail is mixed. For instance, two negative marginal effects at 5% significance level and two positive marginal effects at 10% significance level are observed. This indicates when the level of exchange rate increases, it may decrease the probability of positive coexceedances (at 5% level), and it also may increase the probability (at 10% level). In other words, exchange rate changes have bi-lateral effect on the probability of positive coexceedances. Consistent with Bae, Karolyi, and Stulz (2003), we also obtain the result that interest rate has only very limited explanatory power for either bottom tail or top tail coexceedances. It is worth noting that adding covariates of exchange rate and interest rate raises the $Pseudo-R^2$, and the models of bottom tail have a little higher $Pseudo-R^2$ than the models of top tail. It means that the models with three covariates will explain the negative coexceedances better than the positive coexceedances. However, there is a weird result that the explanatory power of interest rate for top tail is strongly significant for the events of "Y=3" and "Y=5", but is strongly insignificant for other events of "Y=1", "Y=2" and "Y=4". In addition, two significant marginal coefficients of interest rate for bottom tail are of opposite signs.

We surprisingly find that our results derived from the European bond markets are closely related to the results estimated by Bae, Karolyi, and Stulz (2003) in the international stock markets. They claim that conditional volatility and exchange rate are statistically significant in predicting the contagion across the international stock markets, and interest rate shows the relatively weak explanatory power and similarly weird results. In our opinion, stock and sovereign bond markets may share the common underlying information channel linking with three covariates. The covariates possibly transmit the information to the stock and bond markets by a joint unobservable channel.

Overall, three findings are concluded from table 1.9 and 1.10. First, there is no evidence that the events (Y=1, 2, 3, 4, 5) are less or more likely for the top tail than for the bottom tail. Second, with the statistically significant partial derivatives (marginal effect) in the bottom tail, it can be seen that the influence of the exchange rate on the probability of contagion occurrence is almost same as of conditional volatility. In other words, both conditional volatility and exchange rate can strongly explain the contagion in the bottom tail. Finally, interest rate can merely explain the contagion across the European bond markets in bottom tail, and even does not have any explanatory power for contagion across 3, 4, and 5 or more than 5 countries in bottom tail, and across 1, 2 and 4 countries in top tail. Because our initially research focus is on the predictability of contagion in the European area, we additionally estimate the models with lagged covariates in the same way. The general results are same as of tests with contemporary covariates. That is to say, for both the bottom tail and top tail, we find the statistically significant results for conditional volatility and exchange rate, and the weak predictive power of interest rate. They therefore are not reported in tables.

1.4 Conclusion

This part concludes the chapter's methodology, overall findings and the recent articles related to our research.

We used multi-methodology to investigate contagion across the European stock and bond, the contagion across the European bond markets, nonlinear contagion and the predictability of contagion in the European area. The applied approaches are dynamic conditional correlation GARCH model, moving average indicators, two period copula-GARCH model and multinomial logistic regression, respectively. First, for a cross-asset perspective, we used the DCC-GARCH model to estimate the correlations between the European stock and bond indices returns. In addition, by following the approach of Dajcman (2012) and the relevant notions of Gulko (2002), we constructed two moving average indicators of flight-to-quality and contagion, so that the phenomena of flight-to-quality and contagion could be intuitively observed over time. Second, for cross-country perspective, by following the approach of Chiang, Jeon, and Li (2007), we still used the DCC-GARCH model to estimate contagion across the European bond markets. A relatively high level of the comovements between Greek bond return and each of eight European bond markets were found. Third, for nonlinear perspective, we proposed to use the two-period copula GARCH model by following Adel and Salma (2012), and incorporated the counterparts with the asymmetry information into the copula approach. In fact, adding the asymmetry information helps offer more new insights on the changes of dependence structure tested by using diverse copulas. Finally, predictability of contagion was estimated by following the similar multinomial Logit model of Bae, Karolyi, and Stulz (2003). In our paper, we incorporated the covariates of conditional volatility, exchange rate and interest rate in the model, as well. Based on the coefficients of multinomial logistic regression, the marginal effect of Greene (2012) was computed thereafter.

By using the multi-methodology, more specific findings are produced to answer the research questions from different perspectives. First, for cross-asset perspective, overall negative correlations were found for sample European countries. It is closely related to the results of Baur and Lucey (2009). The correlations estimated by DCC-GARCH model are strongly effected by the turmoil period, so are FTQ and CI. Generally, flight-to-quality and contagion over the sample period are volatile in all the European countries. The financial crisis tends to decrease the DCC and increase flight-to-quality for most countries, and the debt crisis tends to increase the DCC and increase the contagion especially in the relatively smaller countries, such as Portugal, Spain and Greece. For example, the DCCs of Portugal, Spain and Greece increase dramatically from the beginning of the European debt crisis, and their contagion stays at the extremely high level as well. However, the impact of the European debt crisis is not always on all European countries, especially in the relatively larger countries, such as Germany, France and the UK. In other words, the sample period of the European debt crisis produced inconsistent results in the European region. Second, for cross-country perspective, we divided a sample period into the particularly turmoil period, namely the European debt crisis. As a result, the relatively high DCCs denote that during the European debt crisis, contagion defined as comovement stays at the relatively high level, and generally starts decreasing around the middle of 2011. Compared with DCCs during the middle of 2011 to 2012, the contagion (denoted by the relatively high level of DCCs) appears at least four month earlier than the beginning of the European debt crisis (denoted by the Greek debt crisis). It means that the herding behaviours of investors in sovereign debt crisis appears earlier than that in financial crisis. In other words, it implies that the investors possibly find it easier to forecast the general market risk in sovereign bond markets than to forecast the risk in stock markets.

Nonlinear estimation was also implemented with the modified two-period copula GARCH approach, and two main findings were established. First, after the explosion of the European debt crisis, the dependence parameters of all copulas increase dramatically. The significant increase in the nonlinear dependence structure shows the likely contagion between the Greek bond market and the others. Second, after adding asymmetry information by using the counterparts of GJR-normal model, the Student-t copula becomes more sensitive to the changes of dependence structures. In our opinion, the different GARCH-type models may be able to improve the explanatory power of some copulas to a certain extent.

Finally, for the perspective of predictability of the bond contagion, three driving factors were evaluated with multinomial logistic regression. The main findings are also presented. First, according to the intercepts of multinomial logistic regression without covariates, we computed the probability of contagion occurrence across i countries, i could be equal to 1 to 5 or more than 5. Second, the statistically significant results denote that conditional volatility is able to explain the contagion across at least five countries, and exchange rate is significant to explain the contagion across at least four countries. The interest rate too weak to explain contagion, and also produces some puzzling results. Third, based on the coefficients of multinomial logistic regression, we compute the marginal effect to look into the specific impact of the significant factors, conditional volatility and exchange rate. For a unit increasing conditional volatility and exchange rate, the probability of contagion occurrence will somewhat increase. It shows that the conditional volatility and exchange rate have a particular effect on the bond contagion, and this effect will gradually subside as our estimation includes more countries. Relating our results to Bae, Karolyi, and Stulz (2003), we surprisingly found that they, from the international stock markets, find extremely similar results as what we found from the European bond markets. They claimed that conditional volatility can explain the stock contagion across at least five countries, exchange rate can explain the contagion across four countries at least, and interest rate has weaker explanatory power and produces the similar puzzling results. This surprising similarity may suggest that there may be a joint unobservable channel delivering the information of significant driving factors to both of stock and bond markets.

The most important findings can be concluded by three viewpoints. First, contagion indeed exists across the different markets and assets, especially in stock and sovereign bond markets. Second, contagion can be effectively captured a few months ahead of time by using one or several ways. Finally, three factors of conditional volatility, the level of exchange rate and the level of interest rate are able to help investors predict the probability of contagion occurrence. Referring to these results, investors can adjust their portfolios in time and lower amount of loss-making in their investment.

At the end of this chapter, we relate our findings to quite recent studies. Although only a limited strand of current studies investigate the contagion in European area, as expected, some articles on the contagion during the European debt crisis are still found, such as Mink and Haan (2013), Afonso, Furceri, and Gome (2011) and Castellacci and Choi (2015). Their findings confirm the existence of contagion, are generally coincident with what we found by using multi-methodology. However, there are some researches having the different opinions. For example, Forbes and Rigobon (2002) claim that there should be not a contagion in the markets, only the high interdependence caused by a common unobservable factor. The coherent findings of Forbes and Rigobon (2002) are theoretically developed by Briere, Chapelle, and Szafarz (2012). Our empirical evidence shows that the contagion is caused by complex reasons, so that it is difficult to say that the comovement is only driven by a common factor. That the resultant effect of multi-factors on the comovement of returns is significantly apparent may be interpreted as contagion more reasonably. In other word, contagion is caused by the effect of the multiple elements, or the comprehensive effect of the crisis. Consequently, our empirical works provide evidence that contagion already existed, and as the existing standpoints expressed, could be defined as comovement and coexceedances across assets and countries.

Table 1.1: Summary statistics for bond and stock index returns

Markets	Germany	France	UK	Belgium	Denmark	Netherland	Portugal	Spain	Greece
Bond markets									
Mean	1.02E-4	1.07E-4	1.99E-4	2.11E-4	2.00E-4	1.99E-4	2.11E-4	2.06E-4	5.47E-05
Stdev	0.0013	0.0011	0.0037	0.0026	0.0027	0.0024	0.0057	0.0035	9.33E-4
JB-stat	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A_1	0.083	0.0069	0.031	0.171	0.031	0.047	0.213	0.155	0.202
ARCH(10)	214.78***	358.32***	422.47***	722.72***	422.48***	279.11***	177.32***	240.47***	153.27***
Stock markets									
Mean	5.49E-5	2.77E-4	1.64E-4	1.08E-4	3.45E-4	6.22E-5	-1.93E-5	1.87E-4	-1.17E-4
Stdev	0.0221	0.0893	0.0122	0.0139	0.0127	0.0144	0.0117	0.0157	0.0475
JB-stat	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A_1	-0.016	-0.034	-0.047	0.057	0.026	-0.017	0.061	0.006	0.066
ARCH(10)	661.52***	638.58***	827.30***	561.58***	870.19***	924.22***	372.87***	465.37***	406.10***

Note: Mean is average value of daily logarithm returns of bond and stock index. Stdev is standard deviation. JB-stat denotes the Probability of Jarque-Bera test for normality. A_1 refers to the first-order autocorrelation. ARCH (10) indicates the chi-square of the lagrange Multiplier (LM) test for autoregressive conditional heteroskedasticity effects with 10 lag-length. $***$ indicates that the null hypothesis is rejected at 1% significance level

Table 1.2: The standard unit root test (ADF(1) test) for bond and stock returns

	Germany	France	UK	Belgium	Denmark	Netherland	Portugal	Spain	Greece
R_b	-54.382	-55.185	-36.736	-49.723	-57.295	-56.362	-18.783	-32.587	-19.200
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R_s	-60.022	-29.386	-28.604	-55.788	-57.553	-28.355	-55.555	-37.204	-55.270
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: R_b is daily bond index returns of Germany, France, the UK, Belgium, Denmark, Netherland, Portugal, Spain and Greece and $R_s$is daily stock index returns.

Table 1.3: The unconditional stock-bond correlation matrix

	Germany	France	UK	Belgium	Netherland	Spain	Portugal	Denmark	Greece
Germany	**-0.4350**	0.8374	0.7769	0.6592	0.5609	0.2903	0.1438	0.8565	0.0220
France	0.8990	**-0.3491**	0.6829	0.8350	0.8551	0.5005	0.2193	0.7359	0.1356
UK	0.8252	0.9021	**-0.3741**	0.5722	0.7851	0.2768	0.1573	0.7537	0.7769
Belgium	0.7329	0.8082	0.7698	**-0.2116**	0.7597	0.6367	0.3100	0.6024	0.1953
Netherland	0.8537	0.9272	0.8678	0.8128	**-0.4076**	0.3588	0.1905	0.9058	0.9056
Spain	0.7894	0.8697	0.7891	0.7191	0.8136	**0.0705**	0.4050	0.2068	0.2902
Portugal	0.6180	0.6841	0.6420	0.5897	0.6421	0.7063	**0.1182**	0.1284	0.3692
Denmark	0.6205	0.6826	0.6748	0.6218	0.6609	0.6017	0.5474	**-0.2997**	0.8565
Greece	0.4228	0.4523	0.4218	0.4091	0.4382	0.4474	0.4392	0.4252	**0.2058**

Note: Main diagonal reports unconditional correlation between stock and bond. The upper triangular matrix reports the information of unconditional value of bond-bond correlation and lower triangular matrix embraces unconditional stock-stock correlation between each market. The correlation coefficients on diagonal line contain the unconditional value of stock-bond correlation.

Table 1.4: Parameter estimates of GARCH with normal and Student-t distributions for pre-crisis period (2 Jan 2001-1 Sep 2009).

	GARCH-normal																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.017	0.001	8.27E-5	2.71E-5	9.16E-4	2.68E-4	7.52E-4	2.69E-4	0.002	4.49E-5	0.002	0.004	0.002	4.34E-5	0.001	4.17E-3	0.002	4.65E-5
	(0.006)^a		(0.002)^a		(0.000)^a		(0.005)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
α_0	0.001	4.39E-5	0.002	6.13E-4	1.60E-4	6.39E-5	1.92E-4	6.46E-4	0.005	1.98E-4	0.004	1.56E-4	0.004	1.67E-4	0.002	9.69E-4	6.78E-3	2.48E-5
	(0.007)^a		(0.037)^b		(0.024)^b		(0.002)^a		(0.010)^b		(0.018)^b		(0.024)^b		(0.074)^c		(0.006)^a	
α_1	0.039	0.006	0.037	0.006	0.033	0.006	0.041	0.006	0.039	0.006	0.041	0.006	0.038	0.006	0.031	0.005	0.042	0.006
	(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
β	0.950	0.009	0.956	0.007	0.959	0.007	0.951	0.008	0.952	0.008	0.951	0.009	0.955	0.008	0.957	0.006	0.946	0.009
	(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
LLF	9114.8		11708.0		11759.6		11641.0		9853.5		10158.7		9919.0		9983.1		9795.2	
AIC	-8.726		-10.352		-10.398		-10.293		-9.434		-9.726		-9.497		-9.558		-9.378	
BIC	-8.716		-10.342		-10.388		-10.283		-9.423		-9.716		-9.486		-9.547		-9.367	
	GARCH-t																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.002	6.3E-4	9.94E-4	2.70E-5	0.001	2.67E-4	8.51E-3	2.70E-4	0.002	4.45E-4	0.002	3.81E-4	0.002	4.32E-4	0.002	4.10E-4	0.003	4.61E-4
	(0.002)^a		(0.000)^a		(0.000)^a		(0.001)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
α_0	1.14E-3	5.77E-4	1.85E-3	8.37E-4	1.88E-3	8.65E-4	1.69E-3	7.97E-4	7.06E-4	3.15E-4	4.53E-4	2.35E-4	5.28E-4	2.57E-4	2.40E-4	1.51E-4	9.56E-5	4.07E-4
	(0.048)^b		(0.017)^b		(0.029)^b		(0.033)^b		(0.025)^b		(0.054)^c		(0.040)^b		(0.025)^b		(0.019)^b	
α_1	0.042	0.009	0.038	0.008	0.033	0.007	0.040	0.008	0.041	0.009	0.040	0.009	0.039	0.009	0.034	0.008	0.044	0.010
	(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
β	0.948	0.012	0.954	0.010	0.957	0.010	0.953	0.010	0.943	0.013	0.949	0.013	0.950	0.012	0.962	0.010	0.939	0.014
	(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
Φ	9.7132	2.2895	10.5916	2.7325	11.2032	3.0046	9.4100	2.0268	8.6037	1.9265	7.0921	1.2692	9.1394	2.1586	8.2302	1.7076	8.6936	1.9840
	(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a		(0.000)^a	
LLF	9129.5		11720.8		11771.3		11658.5		9871.0		10187.1		9934.7		10003.4		9812.2	
AIC	-8.740		-10.363		-10.408		-10.308		-9.450		-9.753		-9.511		-9.577		-9.394	
BIC	-8.726		-10.351		-10.395		-10.296		-9.437		-9.739		-9.498		-9.564		-9.380	

$^{a.b.c.}$ denotes the marginal significance level at 1%, 5% and 10%

Table 1.4 (continued): Parameter estimates of GARCH with normal and Student-t distributions for post-crisis period (2 Sep 2009-22 May 2014).

	GARCH-normal																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.002	0.001	0.001	0.000	0.001	0.004	0.006	0.004	0.003	6.00E-4	0.002	8.14E-4	0.002	6.53E-4	0.003	9.70E-4	0.004	8.68E-4
	$(0.060)^c$		$(0.095)^c$		$(0.002)^a$		$(0.050)^b$		$(0.000)^a$		$(0.026)^b$		$(0.000)^a$		$(0.072)^c$		$(0.000)^a$	
α_0	1.80E-3	8.06E-4	7.91E-3	2.53E-3	8.39E-3	2.30E-3	4.55E-3	2.61E-3	3.42E-3	5.59E-4	1.35E-3	4.92E-4	9.59E-4	3.53E-4	4.04E-3	7.77E-4	2.69E-3	5.08E-4
	$(0.026)^b$		$(0.002)^a$		$(0.003)^a$		$(0.081)^c$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
α_1	0.030	0.007	0.057	0.011	0.090	0.015	0.031	0.008	0.135	0.015	0.048	0.009	0.048	0.009	0.322	0.014	0.125	0.009
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
β	0.958	0.010	0.910	0.019	0.870	0.023	0.953	0.015	0.825	0.016	0.939	0.0108	0.937	0.012	0.783	0.007	0.871	0.009
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
LLF	5750.7		6262.9		6366.5		6136.1		6378.7		6061.8		6382.8		5163.6		5791.7	
AIC	-8.180		-10.160		-10.329		-9.955		-9.074		-8.623		-9.080		-7.345		-8.239	
BIC	-8.166		-10.144		-10.312		-9.938		-9.059		-8.618		-9.065		-7.330		-8.224	
	GARCH-t																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.002	0.001	0.001	0.004	0.001	0.003	7.42E-3	4.55E-3	0.003	5.82E-5	0.002	7.90E-5	0.003	6.37E-5	0.003	9.43E-5	0.003	7.87E-5
	$(0.088)^c$		$(0.003)^a$		$(0.001)^a$		$(0.013)^b$		$(0.000)^a$		$(0.010)^a$		$(0.001)^a$		$(0.006)^a$		$(0.000)^a$	
α_0	1.73E-3	9.60E-4	6.47E-3	2.95E-3	6.84E-3	2.65E-3	4.43E-3	3.08E-3	4.27E-3	1.10E-3	1.31E-3	6.47E-4	8.05E-4	4.04E-4	2.38E-3	8.40E-4	3.51E-3	1.18E-3
	$(0.071)^c$		$(0.029)^b$		$(0.010)^a$		$(0.015)^b$		$(0.000)^a$		$(0.043)^b$		$(0.046)^b$		$(0.004)^a$		$(0.003)^a$	
α_1	0.030	0.009	0.058	0.015	0.086	0.019	0.035	0.011	0.157	0.028	0.056	0.013	0.054	0.122	0.412	0.115	0.148	0.025
	$(0.001)^a$		$(0.002)^a$		$(0.000)^a$		$(0.002)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
β	0.959	0.012	0.916	0.023	0.882	0.027	0.950	0.019	0.796	0.029	0.933	0.015	0.935	0.014	0.731	0.028	0.850	0.020
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
Φ	11.209	3.104	9.617	2.469	8.949	2.151	12.294	4.061	6.018	1.018	9.040	2.311	10.144	2.822	2.681	0.249	4.844	0.654
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.003)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
LLF	5760.5		6274.3		6380.5		6142.6		6412.5		6074.6		6393.0		5389.1		5850.9	
AIC	-8.193		-10.178		-10.350		-9.963		-9.121		-8.640		-9.093		-7.664		-8.322	
BIC	-8.174		-10.157		-10.329		-9.923		-9.102		-8.621		-9.075		-7.646		-8.303	

$^{a.b.c.}$ denotes the marginal significance level at 1%, 5% and 10%

Table 1.5: Parameter estimates of GJR with normal and Student-t distributions for pre-crisis period (2 Jan 2001-1 Sep 2009).

	GJR-normal																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.002	6.47E-5	9.40E-3	2.77E-3	9.71E-4	2.74E-5	8.23E-3	2.77E-3	0.001	4.60E-5	0.001	4.00E-5	0.002	4.44E-5	0.002	4.28E-5	0.002	4.75E-4
	$(0.003)^a$		$(0.000)^a$		$(0.000)^a$		$(0.002)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
α_0	1.21E-3	4.55E-4	1.39E-3	5.75E-3	1.39E-4	5.95E-5	1.88E-3	6.28E-3	4.68E-4	1.94E-4	3.46E-4	1.55E-4	3.53E-4	1.61E-4	1.78E-4	9.89E-5	5.66E-4	2.35E-4
	$(0.008)^a$		$(0.015)^b$		$(0.019)^b$		$(0.002)^a$		$(0.016)^b$		$(0.025)^b$		$(0.028)^b$		$(0.072)^c$		$(0.016)^a$	
α_1	0.050	0.010	0.046	0.008	0.040	0.008	0.049	0.009	0.050	0.098	0.054	0.009	0.053	0.010	0.041	0.008	0.054	0.010
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
β	0.949	0.010	0.959	0.007	0.961	0.007	0.951	0.008	0.953	0.009	0.953	0.009	0.956	0.008	0.967	0.006	0.950	0.009
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
γ	-0.021	0.012	-0.022	0.009	-0.016	0.009	-0.017	0.011	-0.023	0.011	-0.028	0.010	-0.031	0.011	-0.020	0.009	-0.026	0.011
	$(0.078)^c$		$(0.019)^b$		$(0.072)^c$		$(0.015)^b$		$(0.035)^b$		$(0.003)^a$		$(0.003)^a$		$(0.019)^b$		$(0.022)^b$	
LLF	9116.2		11710.3		11760.9		11642.1		9855.6		10162.6		9923.1		9985.6		9797.5	
AIC	-8.727		-10.354		-10.399		-10.293		-9.435		-9.729		-9.500		-9.560		-9.380	
BIC	-8.714		-10.341		-10.386		-10.281		-9.422		-9.716		-9.487		-9.547		-9.375	
	GJR-t																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.003	6.35E-4	0.001	2.72E-4	0.001	2.69E-5	8.94E-4	2.72E-4	0.002	4.48E-4	0.002	3.82E-4	0.002	4.34E-4	0.002	4.13E-4	0.003	4.64E-4
	$(0.001)^a$		$(0.000)^a$		$(0.000)^a$		$(0.001)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
α_0	1.09E-3	5.69E-4	1.66E-3	7.68E-3	1.69E-3	8.09E-4	1.65E-3	7.80E-4	6.50E-4	3.01E-4	3.97E-4	6.22E-5	4.71E-4	2.38E-5	2.31E-4	1.48E-4	8.24E-4	3.76E-4
	$(0.055)^c$		$(0.031)^b$		$(0.036)^b$		$(0.034)^b$		$(0.031)^b$		$(0.073)^c$		$(0.047)^b$		$(0.019)^b$		$(0.028)^b$	
α_1	0.050	0.012	0.046	0.011	0.040	0.010	0.046	0.011	0.050	0.013	0.051	0.013	0.052	0.013	0.043	0.011	0.054	0.014
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
β	0.949	0.012	0.957	0.009	0.959	0.009	0.953	0.010	0.947	0.013	0.952	0.013	0.953	0.011	0.963	0.009	0.943	0.014
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
γ	-0.016	0.014	-0.021	0.012	-0.015	0.012	-0.013	0.013	-0.018	0.015	-0.022	0.013	-0.028	0.018	-0.018	0.012	-0.021	0.015
	$(0.026)^b$		$(0.083)^c$		$(0.021)^b$		$(0.040)^b$		$(0.021)^b$		$(0.073)^c$		$(0.043)^b$		$(0.027)^b$		$(0.016)^b$	
Φ	9.916	2.407	10.890	2.893	11.454	3.146	9.521	2.087	8.881	2.055	7.324	1.361	9.612	2.405	8.445	1.809	9.031	2.138
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
LLF	9130.1		11722.3		11772.1		11658.9		9871.8		10188.6		9937.0		10004.7		9813.2	
AIC	-8.740		-10.364		-10.408		-10.308		-9.450		-9.754		-9.513		-9.577		-9.394	
BIC	-8.723		-10.349		-10.393		-10.293		-9.434		-9.737		-9.496		-9.561		-9.378	

$^{a.b.c.}$ denotes the marginal significance level at 1%, 5% and 10%

Table 1.5 (continued): Parameter estimates of GJR with normal and Student-t distributions for post-crisis period (2 Sep 2009-22 May 2014).

	GJR-normal																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.002	0.001	0.001	4.15E-3	0.001	3.85E-3	8.55E-3	4.64E-4	0.002	6.16E-3	0.003	8.21E-4	0.002	6.61E-4	0.002	0.001	0.002	8.89E-4
	$(0.056)^c$		$(0.007)^a$		$(0.001)^a$		$(0.065)^c$		$(0.000)^a$		$(0.008)^a$		$(0.001)^a$		$(0.009)^a$		$(0.045)^b$	
α_0	1.26E-3	4.81E-4	7.11E-3	2.35E-3	8.43E-3	2.38E-3	2.36E-3	1.12E-3	3.27E-3	5.27E-4	9.14E-4	3.82E-4	7.89E-4	3.17E-4	4.30E-3	8.24E-4	1.62E-3	3.22E-4
	$(0.008)^a$		$(0.003)^a$		$(0.000)^a$		$(0.035)^b$		$(0.000)^a$		$(0.016)^b$		$(0.013)^b$		$(0.000)^a$		$(0.000)^a$	
α_1	0.031	0.006	0.062	0.013	0.101	0.018	0.032	0.008	0.113	0.018	0.053	0.010	0.057	0.011	0.386	0.018	0.016	0.006
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.007)^a$	
β	0.972	0.007	0.918	0.018	0.869	0.024	0.974	0.007	0.832	0.015	0.952	0.009	0.944	0.011	0.779	0.007	0.920	0.006
	$(0.003)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
γ	-0.024	0.008	-0.018	0.015	-0.020	0.020	-0.029	0.009	0.030	0.020	-0.027	0.011	-0.024	0.012	-0.117	0.025	0.126	0.011
	$(0.003)^a$		$(0.027)^b$		$(0.032)^b$		$(0.002)^a$		$(0.014)^b$		$(0.015)^b$		$(0.038)^b$		$(0.000)^a$		$(0.000)^a$	
LLF	5753.0		6263.2		6366.9		6139.2		6379.4		6063.9		6384.4		5167.0		5811.1	
AIC	-8.182		-10.160		-10.327		-9.958		-9.074		-8.625		-9.081		-7.348		-8.265	
BIC	-8.164		-10.139		-10.307		-9.937		-9.055		-8.606		-9.062		-7.329		-8.246	

	GJR-t																	
	Greece		Germany		France		UK		Belgium		Denmark		Netherland		Portugal		Spain	
Para.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.	Value	Std.
μ	0.002	0.001	0.001	4.03E-4	0.001	3.61E-4	9.12E-4	4.54E-4	0.002	5.87E-4	0.002	7.93E-4	0.002	6.40E-4	0.002	6.40E-4	0.002	7.93E-4
	$(0.043)^b$		$(0.002)^a$		$(0.000)^a$		$(0.044)^b$		$(0.000)^a$		$(0.005)^a$		$(0.000)^a$		$(0.000)^a$		$(0.020)^b$	
α_0	1.27E-3	5.82E-4	6.03E-4	2.80E-3	6.75E-3	2.64E-3	2.56E-3	1.68E-3	4.12E-3	1.05E-4	9.96E-4	5.51E-4	6.78E-4	3.68E-4	6.78E-4	3.68E-4	1.86E-3	6.07E-4
	$(0.029)^b$		$(0.031)^b$		$(0.011)^b$				$(0.000)^a$		$(0.071)^c$		$(0.065)^c$		$(0.065)^c$		$(0.068)^c$	
α_1	0.030	0.008	0.060	0.018	0.095	0.024	0.037	0.011	0.128	0.032	0.061	0.015	0.061	0.015	0.061	0.015	0.003	0.008
	$(0.000)^a$		$(0.001)^a$		$(0.000)^a$		$(0.001)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.068)^c$	
β	0.974	0.008	0.920	0.022	0.882	0.027	0.969	0.011	0.804	0.029	0.942	0.013	0.940	0.013	0.940	0.013	0.922	0.012
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
γ	-0.026	0.010	-0.009	0.020	-0.017	0.026	-0.029	0.013	0.042	0.037	-0.024	0.016	-0.021	0.016	-0.021	0.016	0.147	0.026
	$(0.013)^b$		$(0.065)^c$		$(0.052)^c$		$(0.022)^b$		$(0.049)^b$		$(0.014)^b$		$(0.020)^b$		$(0.007)^a$		$(0.000)^a$	
Φ	11.510	3.231	9.676	2.555	8.964	2.168	13.445	4.851	5.980	1.012	9.337	2.486	10.50	3.031	10.500	3.030	5.042	0.679
	$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.006)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$		$(0.000)^a$	
LLF	5762.4		6274.4		6380.7		6144.7		6413.1		6075.5		6393.7		6393.7		5868.42	
AIC	-8.194		-10.145		-10.349		-9.965		-9.121		-8.640		-9.093		-9.093		-8.345	
BIC	-8.172		-10.151		-10.323		-9.940		-9.098		-8.632		-9.070		-9.070		-8.323	

$^{a.b.c.}$ denotes the marginal significance level at 1%, 5% and 10%

Table 1.6: Parameter estimates of copula families-GARCH and model selection statistics for pre-crisis period (2 Jan 2001-1 Sep 2009).

Copula	Para.	Germany	France	UK	Belgium	Denmark	Netherland	Portugal	Spain
					GARCH-normal				
Gaussian	ρ	0.0450	0.0431	0.0455	0.0604	0.0479	0.0491	0.0412	0.0530
	LLF	217.864	282.181	390.093	590.124	342.278	477.110	378.193	450.789
	AIC	-435.339	-563.961	-776.186	-1178.247	-680.552	-950.219	-752.386	-897.577
	BIC	-434.181	-562.819	-764.739	-1172.601	-669.263	-938.931	-741.098	-886.289
Student-t	ρ	0.0411	0.0468	0.0400	0.0450	0.0480	0.0455	0.0451	0.0513
	Φ	1.5	1.7	2.1	2.0	1.7	1.8	2.7	1.4
	LLF	171.467	279.958	304.661	464.339	472.464	514.300	393.818	478.426
	AIC	-342.734	-559.715	-607.321	-926.678	-942.828	-1026.599	-785.636	-954.853
	BIC	-342.161	-559.143	-601.597	-921.034	-937.284	-1020.955	-779.992	-949.208
Clayton	δ	0.7801	0.7747	0.5229	0.5842	0.5141	0.5963	0.5679	0.5902
	LLF	144.342	187.166	198.262	276.240	264.446	324.118	249.492	302.743
	AIC	-288.485	-374.133	-394.524	-550.480	-526.891	-646.236	-496.983	-603.487
	BIC	-287.912	-373.561	-388.800	-544.836	-521.247	-640.592	-491.339	-597.843
					GARCH-t				
Gaussian	ρ	0.0411	0.0423	0.0534	0.0460	0.0492	0.0444	0.0481	0.0531
	LLF	199.195	281.621	418.937	282.019	335.490	344.316	413.989	318.245
	AIC	-397.990	-562.843	-833.873	-560.038	-666.979	-684.632	-823.978	-632.489
	BIC	-396.845	-561.699	-822.426	-548.750	-655.691	-673.344	-812.690	-621.201
Student-t	ρ	0.0461	0.0439	0.0342	0.0461	0.0531	0.0454	0.0511	0.0490
	Φ	1.5	1.7	2.1	2.0	1.7	1.8	2.7	1.4
	LLF	211.359	275.807	164.125	335.501	465.566	384.511	268.637	355.776
	AIC	-422.519	-551.414	-326.249	-669.001	-929.132	-767.023	-535.274	-709.552
	BIC	-421.946	-550.841	-320.526	-663.357	-923.488	-761.379	-529.630	-703.908
Clayton	δ	0.7803	0.8500	0.5301	0.5668	0.8500	0.5592	0.5235	0.5725
	LLF	136.248	247.609	66.641	343.632	2282.755	187.500	91.475	195.201
	AIC	-272.297	-495.018	-131.282	-685.263	-563.510	-372.999	-180.949	-388.401
	BIC	-271.725	-494.446	-125.559	-679.619	-557.866	-367.355	-175.305	-382.757

Note: ρ is the dependence parameter of Gaussian copula and Student-t copula. Φ is degree of freedom parameter. δ is the dependence parameter of Clayton copula.

Table 1.6 (continued): Parameter estimates of copula families-GJR and model selection statistics for pre-crisis period (2 Jan 2001-1 Sep 2009).

Copula	Para.	Germany	France	UK	Belgium	Denmark	Netherland	Portugal	Spain
GJR-normal									
Gaussian	ρ	0.0460	0.0460	0.0431	0.0422	0.0001	0.0529	0.0523	0.0530
	LLF	206.018	282.194	426.334	413.983	292.475	381.608	277.053	339.369
	AIC	-411.635	-563.989	-848.668	-823.966	-580.950	-759.215	-550.105	-674.737
	BIC	-410.491	-562.844	-837.221	-812.678	-569.663	-747.927	-538.817	-663.450
Student-t	ρ	0.0020	0.0075	0.0013	0.0012	0.0049	0.0050	0.0050	0.0051
	Φ	1.5	1.7	2.1	2.0	1.7	1.8	2.7	1.4
	LLF	233.340	265.966	198.012	606.316	472.878	412.580	287.005	316.660
	AIC	-466.480	-531.733	-394.025	-1210.632	-943.756	-823.160	-572.009	-1263.201
	BIC	-465.907	-531.160	-388.301	-1204.988	-938.112	-817.516	-566.365	-1240.900
Clayton	δ	0.7406	0.7811	0.4469	0.3665	0.5151	0.3920	0.3461	0.3827
	LLF	154.945	187.351	37.470	41.146	264.668	122.932	-12.092	84.637
	AIC	-309.691	-373.929	-72.939	-80.291	-527.336	-243.863	26.184	-167.274
	BIC	-309.119	-370.501	-67.216	-74.648	-521.692	-238.219	31.828	-161.630
GJR-t									
Gaussian	ρ	0.0400	0.0441	0.0479	0.0502	0.0481	0.0396	0.0597	0.0495
	LLF	232.686	281.628	418.969	154.745	335.403	222.647	127.903	186.961
	AIC	-464.972	-561.711	-833.938	-305.489	-666.805	-441.293	-251.806	-369.921
	BIC	-463.827	-559.856	-822.491	-294.201	-655.517	-430.005	-240.518	-358.633
Student-t	ρ	0.0466	0.0364	0.0391	0.0506	0.0510	0.0225	0.0500	0.0571
	Φ	1.5	1.7	2.1	2.0	1.7	1.8	2.7	1.4
	LLF	234.818	258.080	28.073	160.966	117.048	218.818	96.912	175.681
	AIC	-469.437	-515.387	-63.869	-319.931	-232.095	-435.635	-191.824	-349.361
	BIC	-468.865	-510.960	-58.146	-314.287	-226.451	-429.991	-186.180	-343.717
Clayton	δ	0.7435	0.8500	0.5068	0.5424	0.8500	0.5536	0.5325	0.5493
	LLF	154.368	247.659	249.404	369.426	283.331	422.403	330.808	394.901
	AIC	-308.536	-495.119	-496.808	-736.851	-564.662	-842.805	-659.615	-787.801
	BIC	-307.964	-494.547	-491.084	-731.207	-559.018	-837.161	-653.971	-782.157

Note:ρ is the dependence parameter of Gaussian copula and Student-t copula. Φ is degree of freedom parameter. δ is the dependence parameter of Clayton copula.

Table 1.7: Parameter estimates of copula families-GARCH and model selection statistics for post-crisis period (2 Sep 2009-22 May 2014).

Copula	Para.	Germany	France	UK	Belgium	Denmark	Netherland	Portugal	Spain
GARCH-normal									
Gaussian	ρ	0.1242	0.1270	0.1011	0.0945	0.0903	0.1225	0.1000	0.1117
	LLF	296.940	-294.093	388.667	-204.350	148.618	103.873	-369.649	-367.148
	AIC	-608.113	592.186	-791.567	412.699	-293.235	-203.746	743.297	738.296
	BIC	-597.880	602.419	-781.334	423.195	-282.739	-193.251	753.793	748.792
Student-t	ρ	0.2029	0.1000	0.1161	0.1042	0.0955	0.1638	0.1337	0.1688
	Φ	1.9	1.7	2.3	2.2	2.0	1.9	1.6	1.8
	LLF	244.330	-293.269	298.458	-171.493	242.698	148.351	-352.978	-424.303
	AIC	-314.802	441.520	-437.684	344.986	-483.396	-294.702	707.955	850.605
	BIC	-312.230	443.795	-431.238	350.234	-478.148	-289.454	713.203	855.853
Clayton	δ	0.9349	1.0342	1.0000	1.3084	1.4881	1.5149	0.6104	1.0372
	LLF	308.309	-301.794	321.858	-259.459	112.598	66.734	-389.584	-437.204
	AIC	-623.733	605.587	-650.831	520.917	-223.195	-131.468	781.168	876.408
	BIC	-618.617	610.703	-645.715	526.165	-217.947	-126.220	786.416	881.656
GARCH-t									
Gaussian	ρ	0.1282	0.0955	0.1264	0.0763	0.0884	0.0995	0.1002	0.1362
	LLF	300.340	-297.449	461.935	-201.150	143.963	14.938	-373.791	-460.150
	AIC	-614.913	598.897	-938.103	407.594	-283.926	-25.876	751.581	924.300
	BIC	-604.680	609.129	-927.870	408.588	-273.431	-15.380	762.077	934.795
Student-t	ρ	0.1350	0.1239	0.1482	0.0975	0.1440	0.1006	0.1499	0.0943
	Φ	1.9	1.7	2.3	2.2	2.0	1.9	1.6	1.8
	LLF	46.734	-175.093	98.791	-176.232	227.909	62.168	-356.90	-511.396
	AIC	-240.575	390.541	-895.401	354.464	-453.818	-122.337	715.810	1024.791
	BIC	-237.508	395.080	-890.805	359.712	-448.570	-117.089	721.058	1030.039
Clayton	δ	1.9351	1.0349	1.0462	1.3500	1.8500	0.8573	2.0218	1.0371
	LLF	311.696	-305.218	325.269	1516.832	1509.776	12.276	-356.905	-521.866
	AIC	-630.507	612.435	-657.655	-3031.664	-3017.552	-22.552	715.810	1045.731
	BIC	-625.391	617.551	-652.538	-3026.416	-3012.304	-17.304	721.058	1050.979

Note: ρ is the dependence parameter of Gaussian copula and Student-t copula. Φ is degree of freedom parameter. δ is the dependence parameter of Clayton copula.

Table 1.7 (continued): Parameter estimates of copula families-GJR and model selection statistics for post-crisis period (2 Sep 2009-22 May 2014).

Copula	Para.	Germany	France	UK	Belgium	Denmark	Netherland	Portugal	Spain
					GJR-normal				
Gaussian	ρ	0.0970	0.0925	0.1000	0.1279	0.1890	0.1175	0.1447	0.1231
	LLF	296.287	-294.093	412.414	-201.985	150.394	52.240	-449.601	-340.418
	AIC	-606.807	592.186	-839.061	407.970	-296.787	-100.479	903.202	684.835
	BIC	-596.574	602.419	-828.828	418.467	-286.290	-89.982	913.699	695.332
Student-t	ρ	0.1647	0.1110	0.1384	0.1087	0.1212	0.1502	0.1678	0.1422
	Φ	1.9	1.7	2.3	2.2	2.0	1.9	1.6	1.8
	LLF	105.420	-318.273	94.563	-169.061	243.672	83.443	-468.742	-355.971
	AIC	-360.717	522.128	-570.591	340.122	-485.343	-164.886	939.483	713.941
	BIC	-353.846	528.100	-563.910	345.370	-480.094	-159.638	944.731	719.189
Clayton	δ	1.0000	1.0149	1.0001	1.3100	1.4890	0.4415	1.0560	1.0683
	LLF	307.546	-413.002	321.109	-258.534	113.770	-35.846	-480.539	-410.532
	AIC	-622.208	828.003	-649.335	519.068	-225.540	73.692	963.077	823.063
	BIC	-617.092	833.120	-644.218	524.316	-220.292	78.941	968.325	828.311
					GJR-t				
Gaussian	ρ	0.1149	0.1186	0.1096	0.0991	0.0970	0.1289	0.0997	0.1378
	LLF	299.689	-296.650	320.528	-206.445	145.743	-50.949	-371.855	-344.783
	AIC	-613.610	597.300	-655.288	416.890	-287.485	105.898	747.710	693.565
	BIC	-603.377	607.532	-645.055	427.387	-276.988	116.395	758.207	704.062
Student-t	ρ	0.1296	0.1268	0.1220	0.1129	0.1177	0.1027	0.1024	0.1110
	Φ	1.9	1.7	2.3	2.2	2.0	1.9	1.6	1.8
	LLF	156.779	-556.778	94.780	-425.137	237.981	-22.329	-354.641	-572.641
	AIC	-298.357	541.524	-562.071	852.274	-473.962	46.658	711.281	1147.281
	BIC	-295.040	548.298	-556.133	857.522	-468.713	51.906	716.529	1152.529
Clayton	δ	1.9814	1.0342	1.9546	1.8500	1.8500	1.4905	1.1625	1.0699
	LLF	459.265	-304.543	449.204	1527.919	1521.424	102.560	-392.656	-414.774
	AIC	-2916.529	611.085	-298.640	-3053.838	-3040.848	-203.120	787.312	831.548
	BIC	-2911.412	616.201	-289.129	-3048.5901	-3035.600	-197.871	792.561	836.797

Note:ρ is the dependence parameter of Gaussian copula and Student-t copula. Φ is degree of freedom parameter. δ is the dependence parameter of Clayton copula.

Table 1.8: Summary statistics of co-exceedances for daily emerging market index returns, Jan 1, 2001 to May 22, 2014.

	Number of negative co-exceedances							Number of positive co-exceedances						
	$\geqslant 6$	5	4	3	2	1	0	0	1	2	3	4	5	$\geqslant 6$
Greece	9	7	24	30	53	72	2884	2853	77	51	26	9	6	5
Germany	69	25	31	18	22	9	2884	2853	20	16	19	33	33	53
France	72	26	28	15	19	14	2884	2853	14	22	17	31	31	59
UK	55	20	21	27	8	43	2884	2853	47	15	23	19	25	45
Belgium	73	22	27	22	15	15	2884	2853	10	35	21	30	24	54
Denmark	64	18	29	25	23	15	2884	2853	21	24	28	23	27	51
Netherland	73	27	40	21	9	4	2884	2853	2	16	21	37	39	59
Portugal	30	3	8	30	37	66	2884	2853	60	52	26	7	9	20
Spain	59	11	9	22	38	35	2884	2853	32	43	29	11	11	48
Total	73	31	50	70	112	273	2884	2853	283	137	70	50	41	59

Note: The positive (negative) exceedances for daily index returns are described as the highest (lowest) five percent of all returns lying on the top tail (bottom tail) of distribution. Coexceedance is defined as the joint appearance of exceedances across daily international indices. We set up seven categories from 0 to 6, which represent the number of markets having an exceedance on the same trading day. If on one trading day, the extreme return is observed in benchmark market and i (i could be equal to 0, 1, 2, ..., 8.) in the other eight markets, it would be signed as i+1 coexceedances for this market. For example, the category 6 indicates more than six coexceedances observed on the same trading day. The table is summarized from 3493 observations.

Table 1.9: Summary statistics of co-exceedances for daily European market index returns (Coefficients), Jan 1, 2001 to May 22, 2014.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
Europe	Coeff.	Prob.	Coeff	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff	Prob.	Coeff	Prob.
β_{01}(Con.)	-2.357	0.000^a	-3.407	0.000^a	-3.411	0.000^a	-2.310	0.000^a	-3.145	0.000^a	-3.142	0.000^a
β_{02}	-3.248	0.000^a	-4.388	0.000^a	-4.459	0.000^a	-3.036	0.000^a	-4.074	0.000^a	-4.083	0.000^a
β_{03}	-3.718	0.000^a	-5.074	0.000^a	-5.073	0.000^a	-3.707	0.000^a	-4.696	0.000^a	-4.743	0.000^a
β_{04}	-4.054	0.000^a	-5.132	0.000^a	-5.138	0.000^a	-4.044	0.000^a	-5.197	0.000^a	-5.213	0.000^a
β_{05}	-4.532	0.000^a	-5.199	0.000^a	-3.852	0.000^a	-3.350	0.000^a	-4.284	0.000^a	-4.319	0.000^a
β_{11}(Vol.)			8.262	0.000^a	8.181	0.000^a			7.002	0.000^a	6.958	0.000^a
β_{12}			8.175	0.000^a	8.754	0.000^a			8.029	0.000^a	7.881	0.000^a
β_{13}			9.551	0.000^a	9.566	0.000^a			7.800	0.000^a	7.491	0.000^a
β_{14}			8.388	0.000^a	8.379	0.000^a			8.534	0.000^a	8.389	0.000^a
β_{15}			6.091	0.000^a	5.134	0.000^a			7.523	0.000^a	7.229	0.000^a
β_{21}(Ex.)					7.278	0.002^a					-2.787	0.021^b
β_{22}					4.365	0.000^a					-5.891	0.051^c
β_{23}					4.385	0.034^b					2.381	0.073^c
β_{24}					7.700	0.009^a					1.853	0.094^c
β_{25}					3.068	0.394					1.488	0.123
β_{31}(Int.)					5.898	0.059^c					2.761	0.136
β_{32}					1.924	0.070^c					-1.776	0.111
β_{33}					1.552	0.262					-4.571	0.000^a
β_{34}					1.361	0.711					-1.016	0.172
β_{35}					1.762	0.535					-3.921	0.000^a
Log-likelihood	-2548.55		-2302.12		-2284.17		-2573.65		-2358.64		-2340.40	
$Pseudo-R^2$			0.0967		0.1037				0.0835		0.0906	

Note: The level of coexceedance of bond index return is modeled as polychotomous variable. For example, if probability is defined as P_i, thus i is associated with the number of coexceedances observed on the same trading day, which, in this paper, could be classified into six hierarchies of 0, 1, 2, 3, 4, 5 meaning 0, 1, 2, 3, 4, 5 and more coexceedances separately. In our multinomial Logit model, covariates of conditional volatility (Vol.), daily exchange rate (Ex.) and short-term interest rate (Int.) are added, and calculated on their equally-weighted value for European region. The conditional volatility is derived by the simplest EGARCH (1, 1).

$^{a.b.c.}$ denotes the marginal significance level at 1%, 5% and 10%

Table 1.10: Summary statistics of co-exceedances for daily European market index returns (Marginal effect), Jan 1, 2001 to May 22, 2014.

	Bottom tails						Top tails					
	(1)		(2)		(3)		(4)		(5)		(6)	
Europe	Mar.	Prob.	Mar.	Prob.	Mar.	Prob.	Mar.	Prob.	Mar.	Prob.	Mar.	Prob.
β_{11}(Vol.)			0.479	0.000^a	0.470	0.000^a			0.438	0.000^a	0.439	0.000^a
β_{12}			0.198	0.000^a	0.187	0.000^a			0.227	0.000^a	0.221	0.000^a
β_{13}			0.122	0.000^a	0.122	0.000^a			0.115	0.000^a	0.104	0.000^a
β_{14}			0.088	0.000^a	0.087	0.000^a			0.084	0.000^a	0.080	0.000^a
β_{15}			0.043	0.000^a	0.023	0.000^a			0.161	0.000^a	0.147	0.000^a
β_{21}(Ex.)					0.414	0.004^a					-2.010	0.015^b
β_{22}					0.327	0.000^a					-1.899	0.045^b
β_{23}					0.048	0.029^b					0.415	0.040^b
β_{24}					0.079	0.070^c					0.926	0.078^c
β_{25}					0.061	0.169					1.374	0.099^c
β_{31}(Int.)					-0.437	0.074^c					0.377	0.106
β_{32}					0.459	0.070^c					-0.514	0.143
β_{33}					0.218	0.270					-0.717	0.000^a
β_{34}					0.069	0.347					-0.088	0.152
β_{35}					0.021	0.554					-0.903	0.000^a

Note: Based on the models in table 5, we calculate the partial derivatives of probability associated with independent variables at their mean value
$^{a.b.c.}$ denotes the marginal significance level at 1%, 5% and 10%

Figure 1.1: Germany: DCC, FTQ and CI

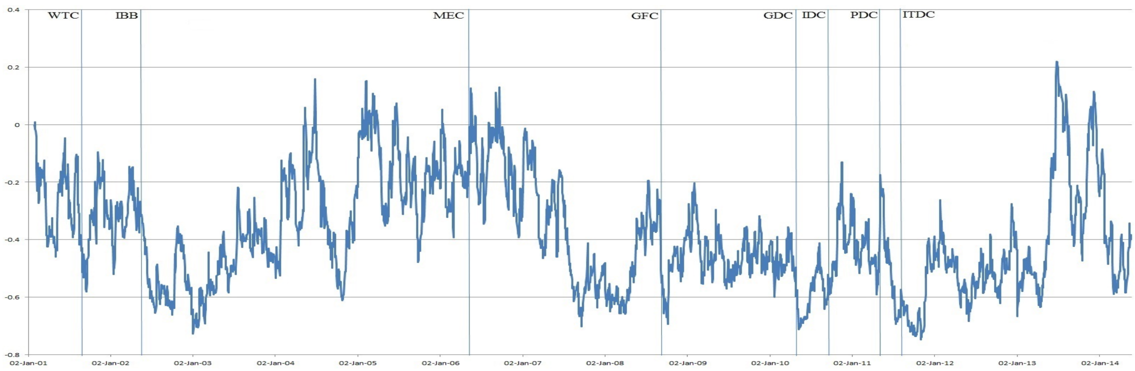


Figure.1.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Germany.

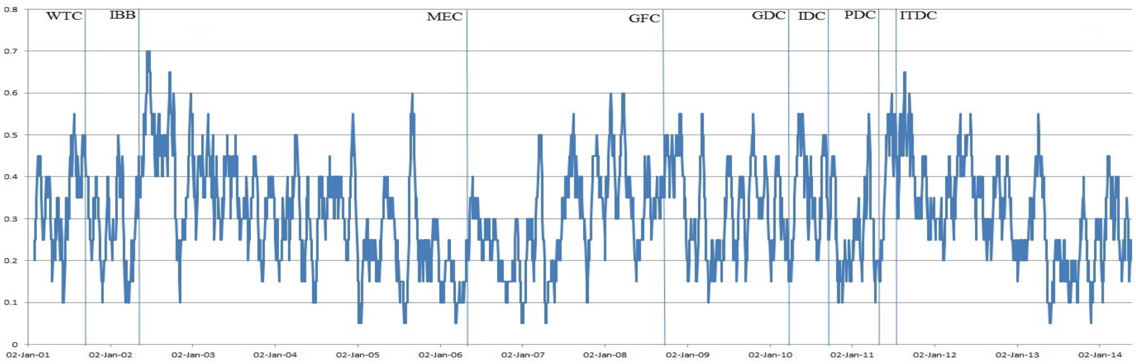


Figure.1.(b) FTQ indicator for Germany.

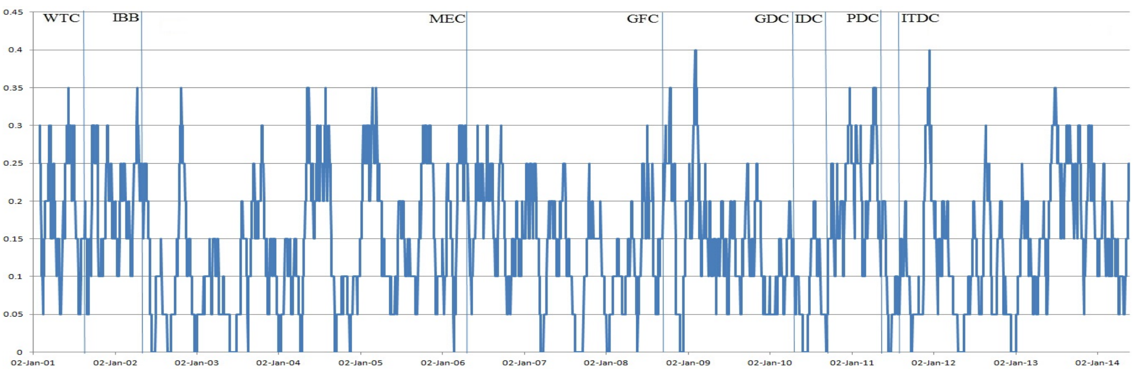


Figure.1.(c) CI indicator for Germany.

Figure 1.2: France: DCC, FTQ and CI

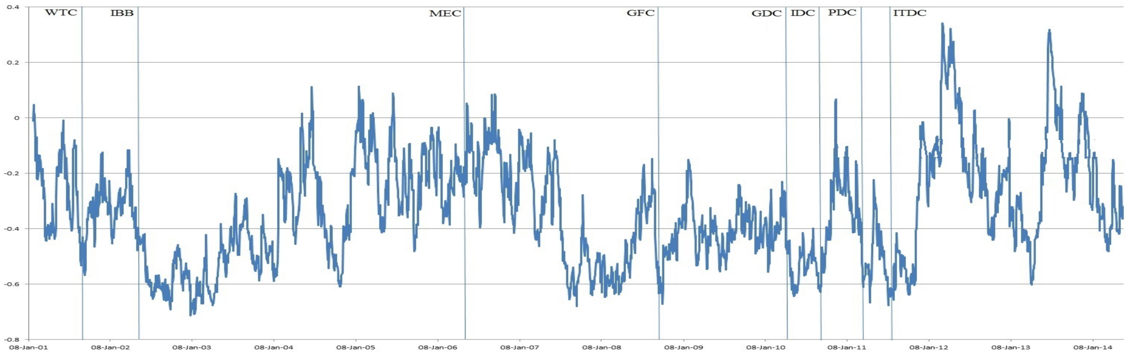


Figure.2.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for France.

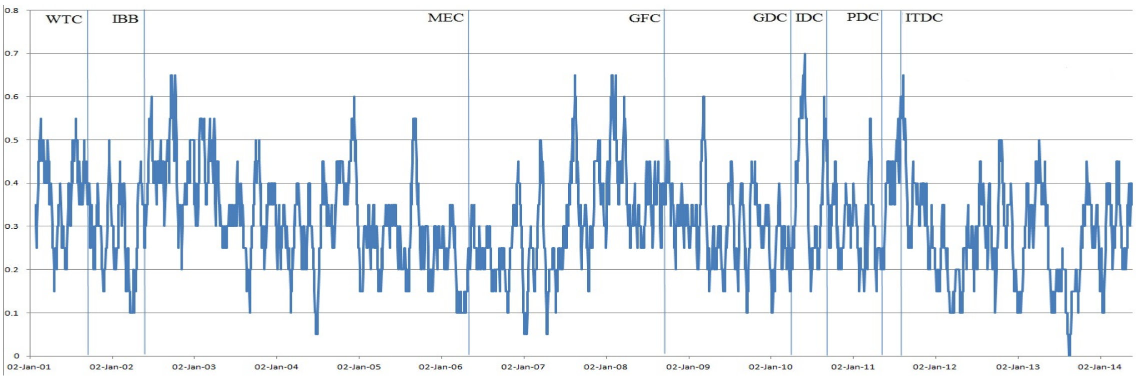


Figure.2.(b) FTQ indicator for France.

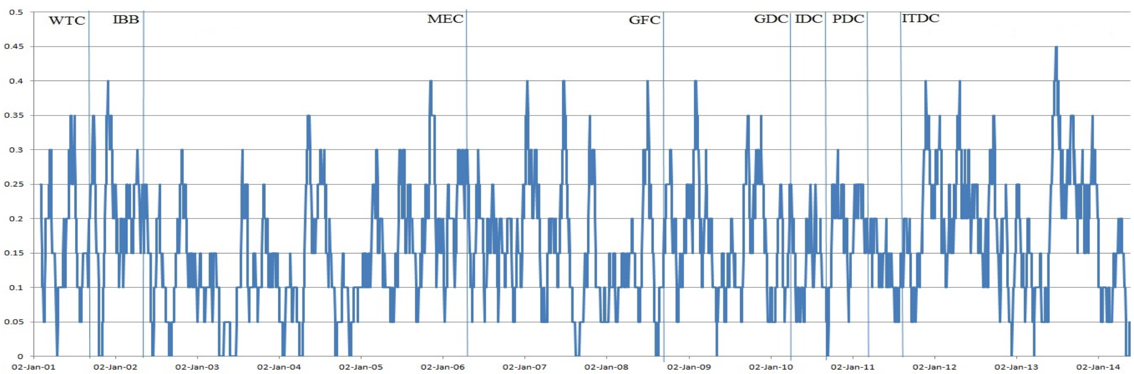


Figure.2.(c) CI indicator for France.

Figure 1.3: The UK: DCC, FTQ and CI

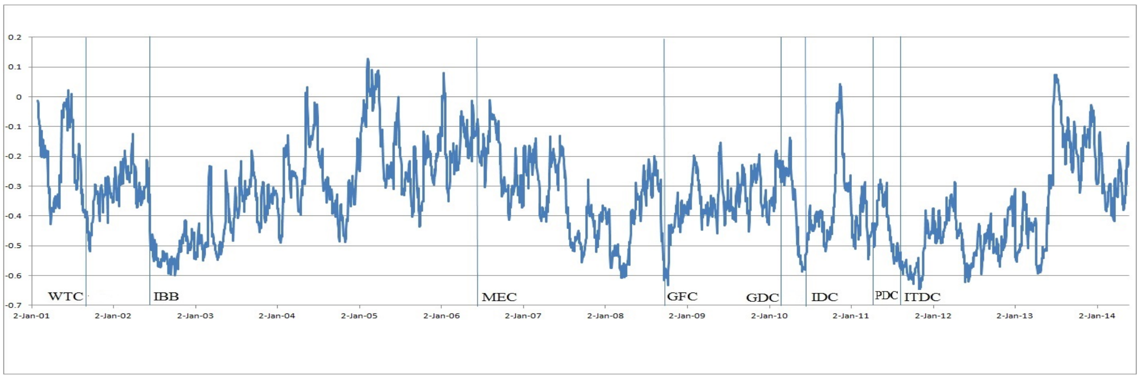


Figure.3.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for the UK.

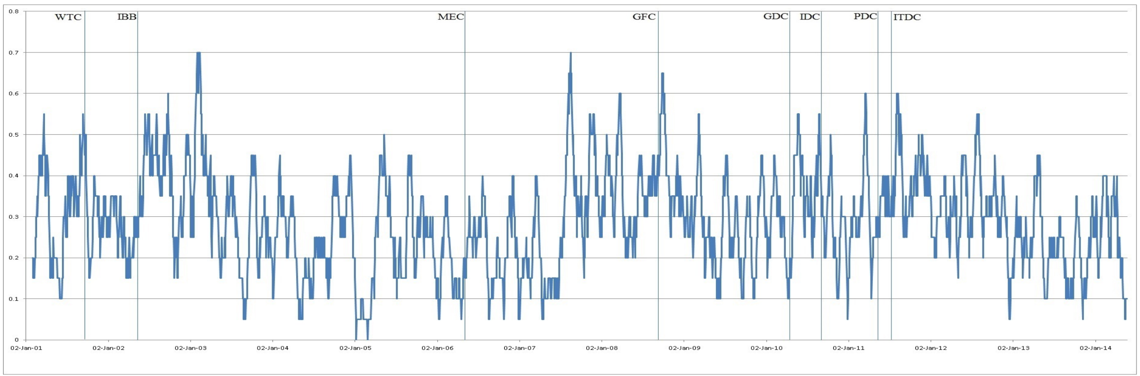


Figure.3.(b) FTQ indicator for the UK.

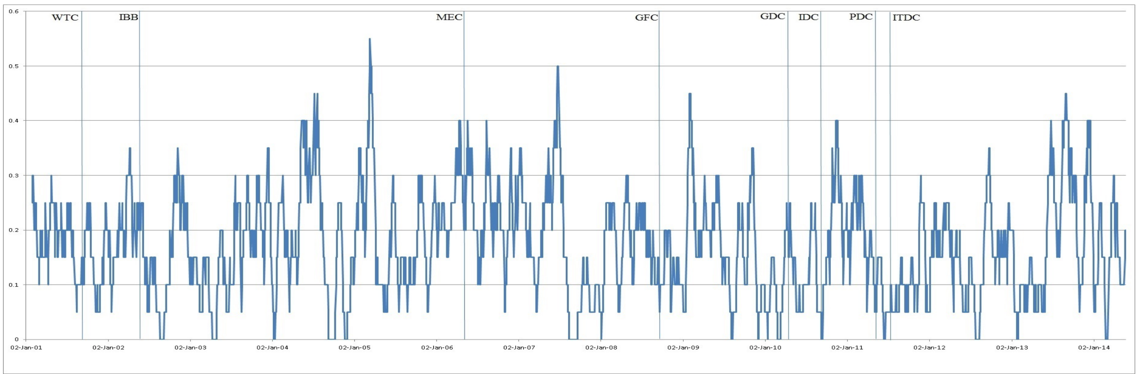


Figure.3.(c) CI indicator for the UK.

Figure 1.4: Belgium: DCC, FTQ and CI

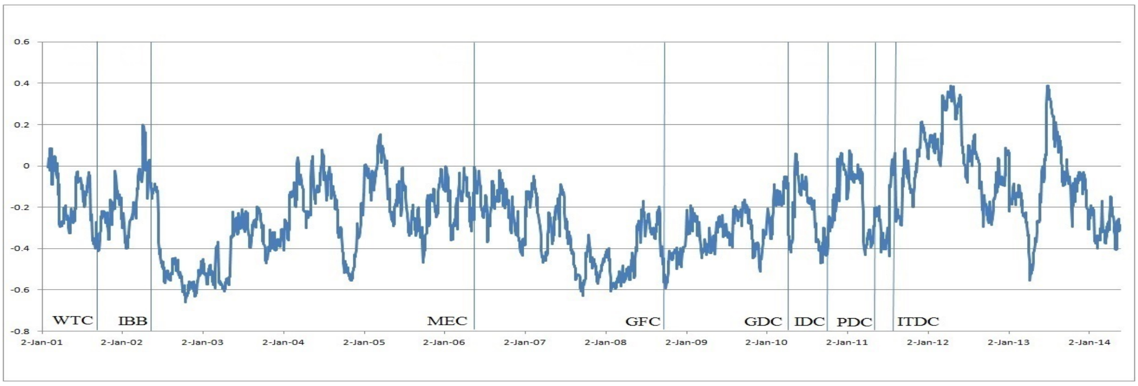


Figure.4.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Belgium.

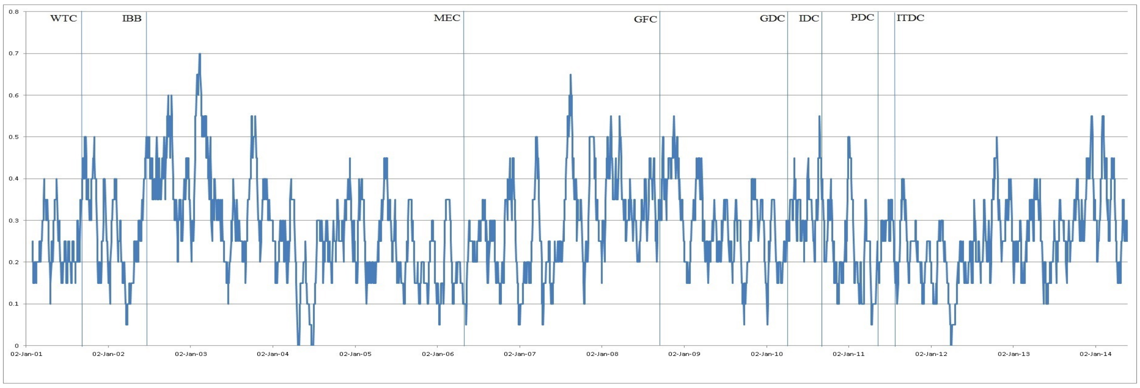


Figure.4.(b) FTQ indicator for Belgium.

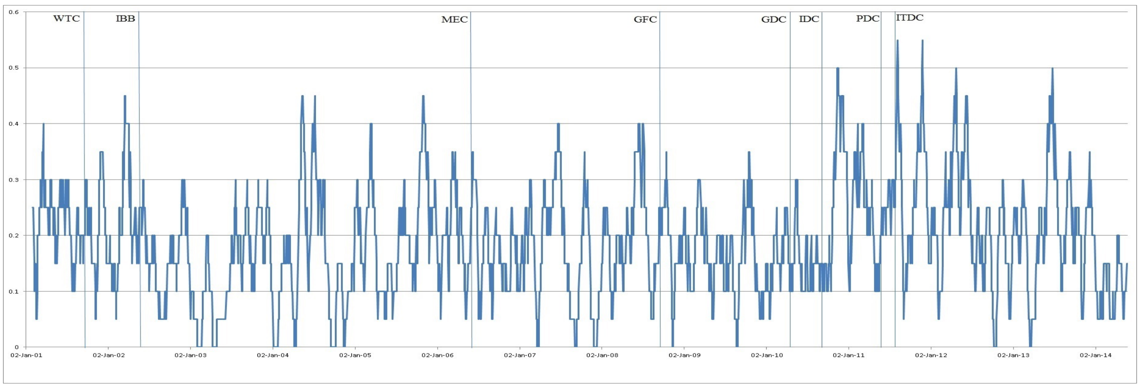


Figure.4.(c) CI indicator for Belgium.

Figure 1.5: Denmark: DCC, FTQ and CI

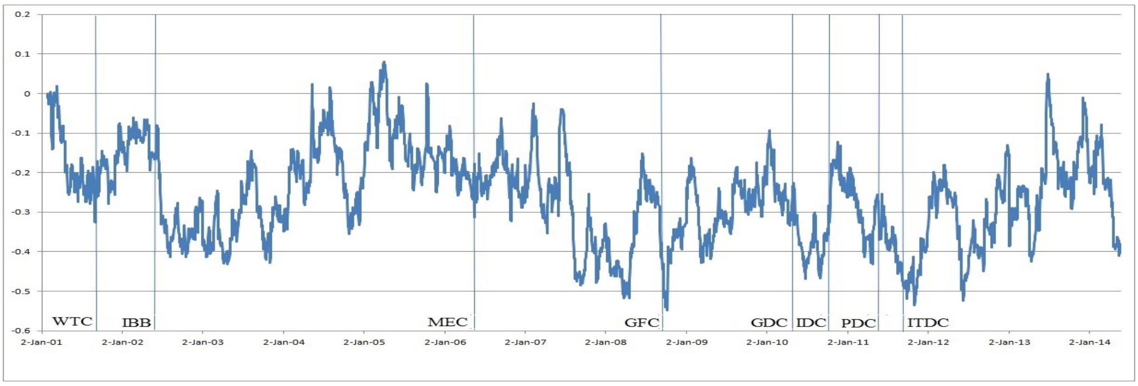


Figure.5.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Denmark.

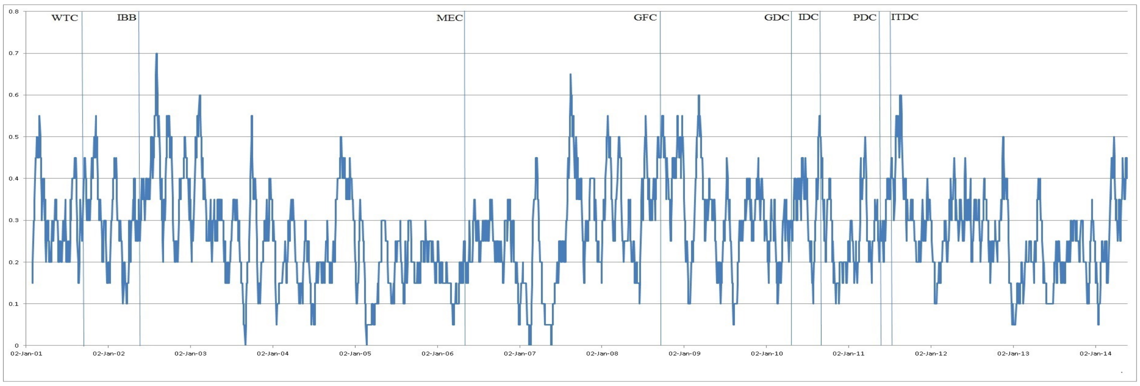


Figure.5.(b) FTQ indicator for Denmark.

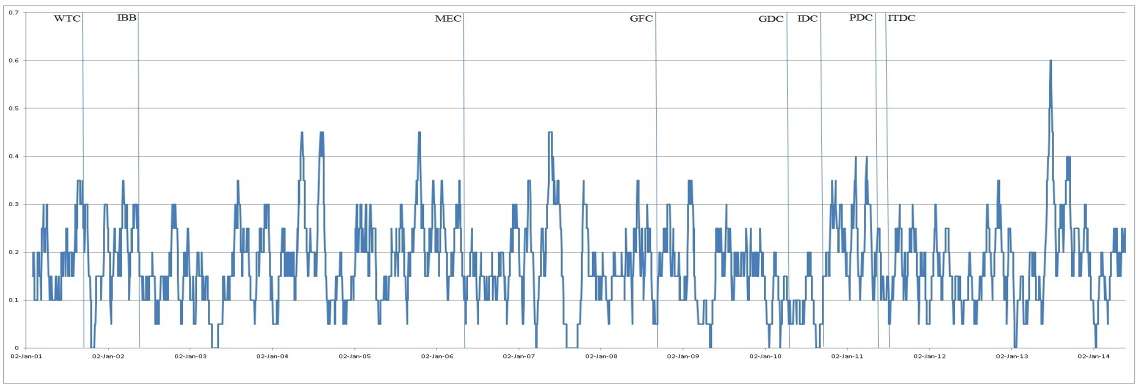


Figure.5.(c) CI indicator for Denmark.

Figure 1.6: Netherland: DCC, FTQ and CI

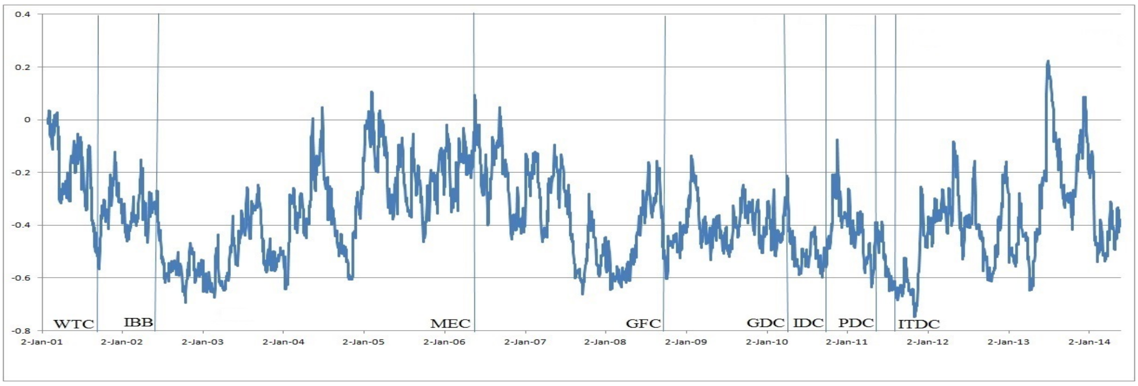


Figure.6.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Netherland.

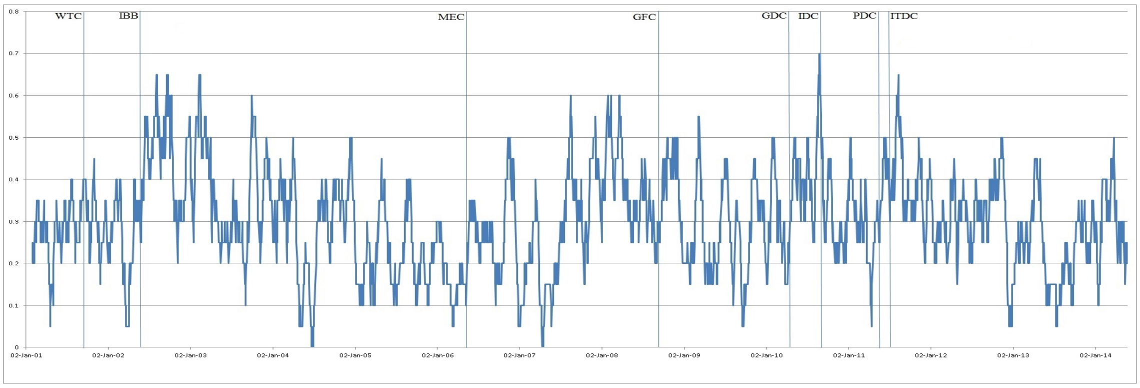


Figure.6.(b) FTQ indicator for Netherland.

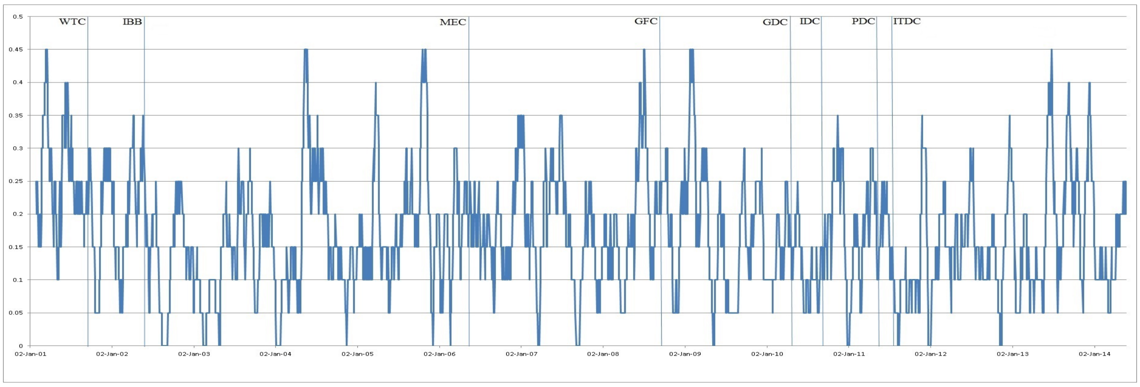


Figure.6.(c) CI indicator for Netherland.

Figure 1.7: Portugal: DCC, FTQ and CI

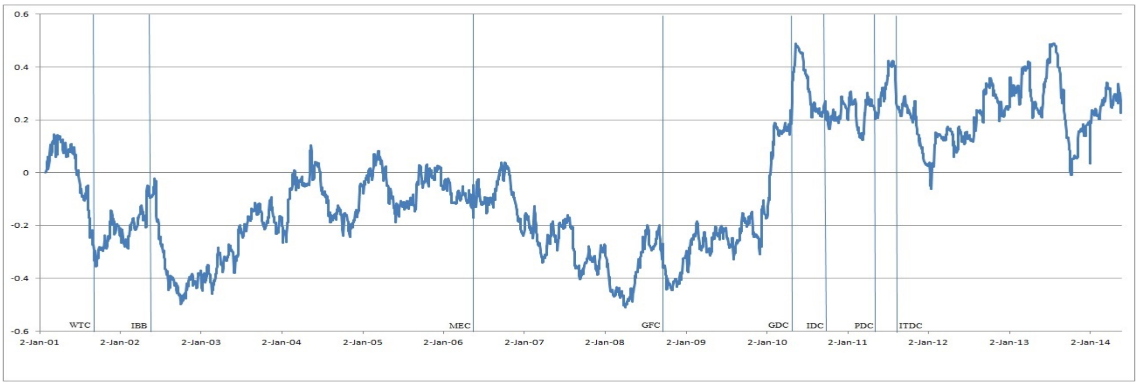


Figure.7.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Portugal.

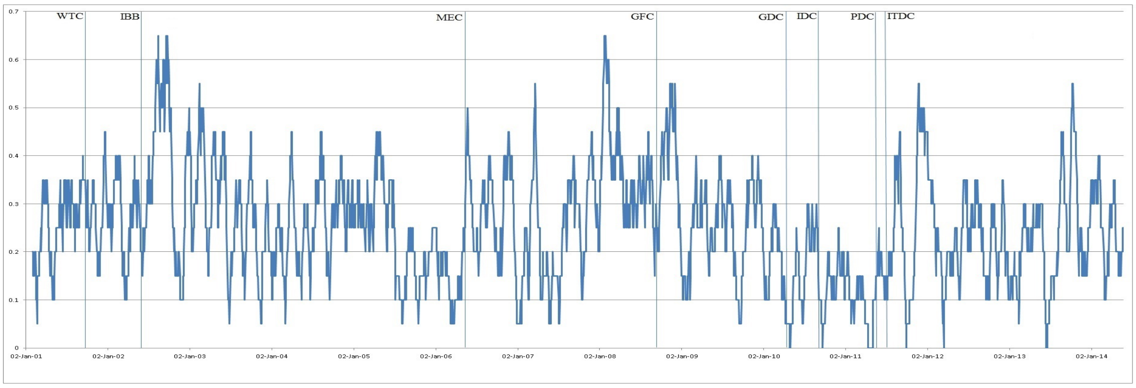


Figure.7.(b) FTQ indicator for Portugal.

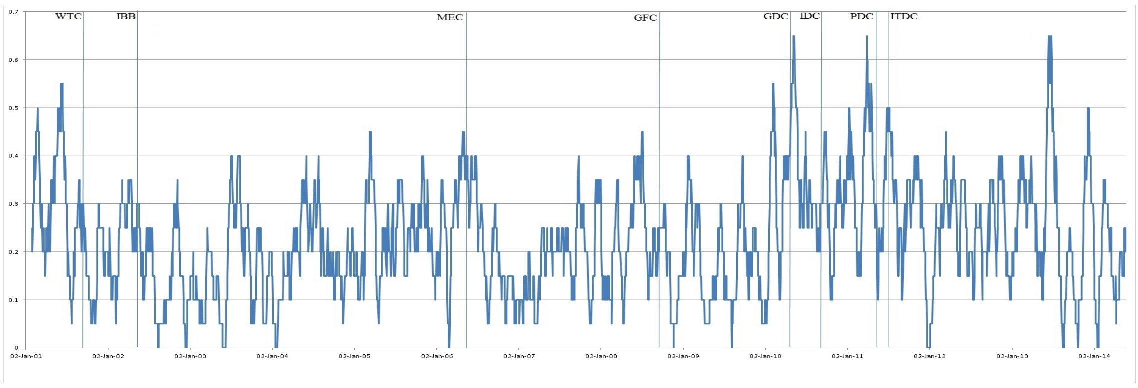


Figure.7.(c) CI indicator for Portugal.

Figure 1.8: Spain: DCC, FTQ and CI

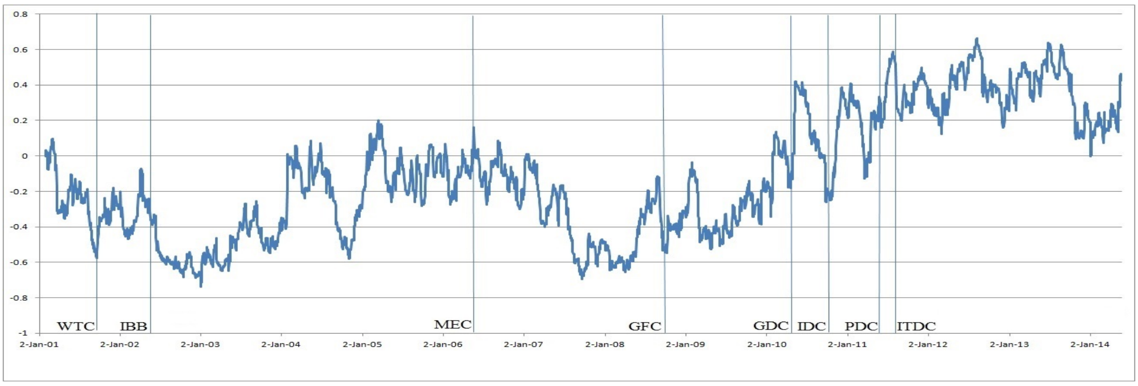


Figure.8.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Spain.

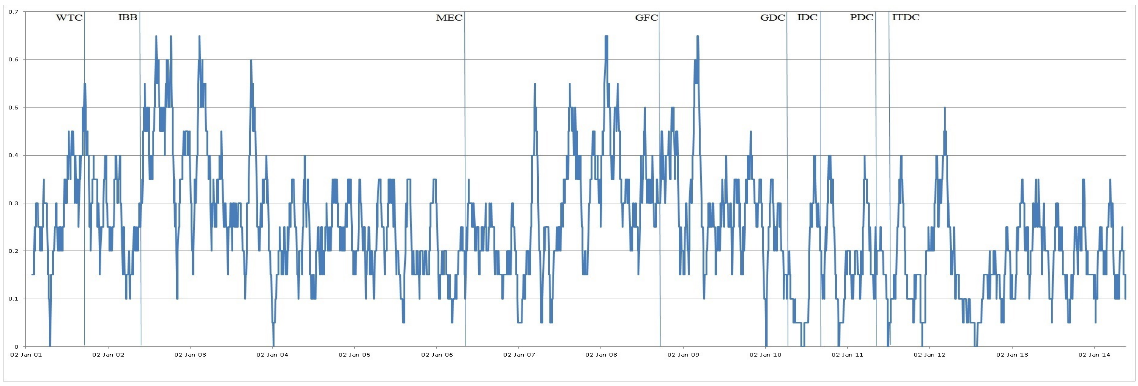


Figure.8.(b) FTQ indicator for Spain.

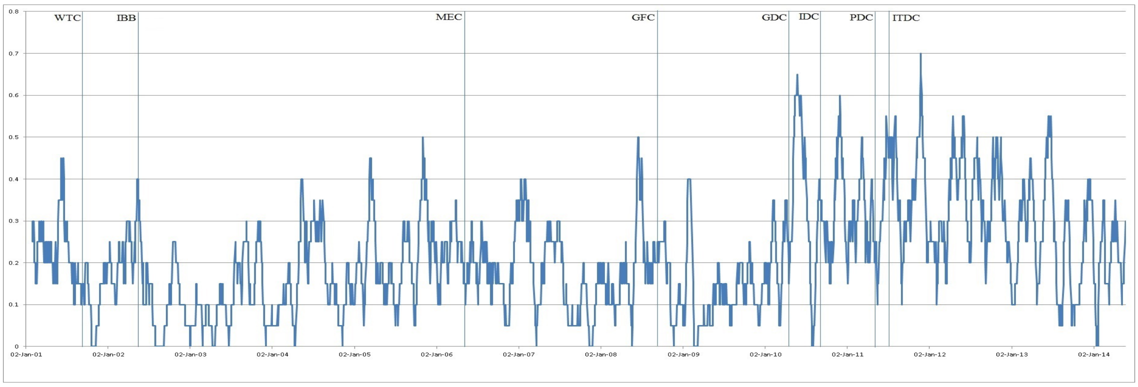


Figure.8.(c) CI indicator for Spain.

Figure 1.9: Greece: DCC, FTQ and CI

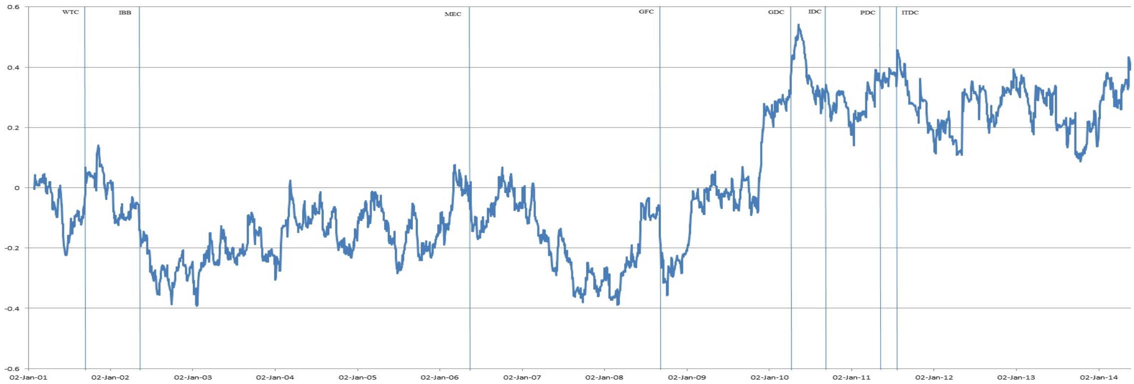


Figure.9.(a) The dynamic correlation between stock market returns and the sovereign bond market returns for Greece.

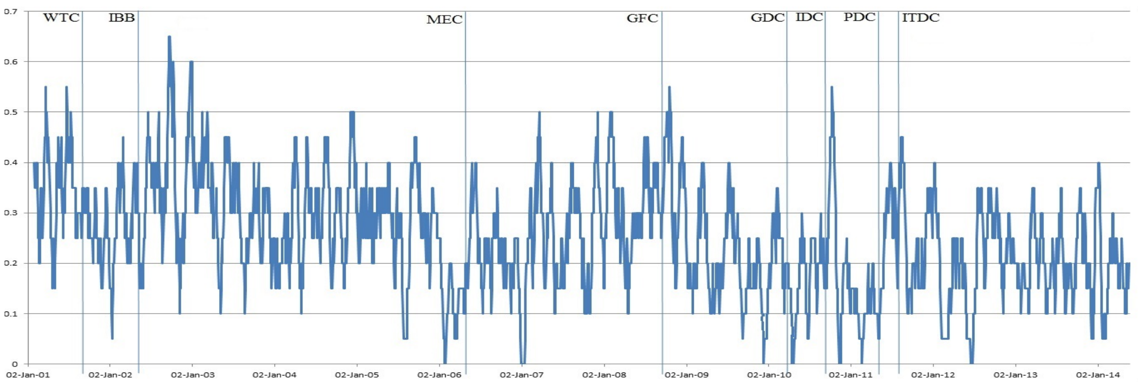


Figure.9.(b) FTQ indicator for Greece.

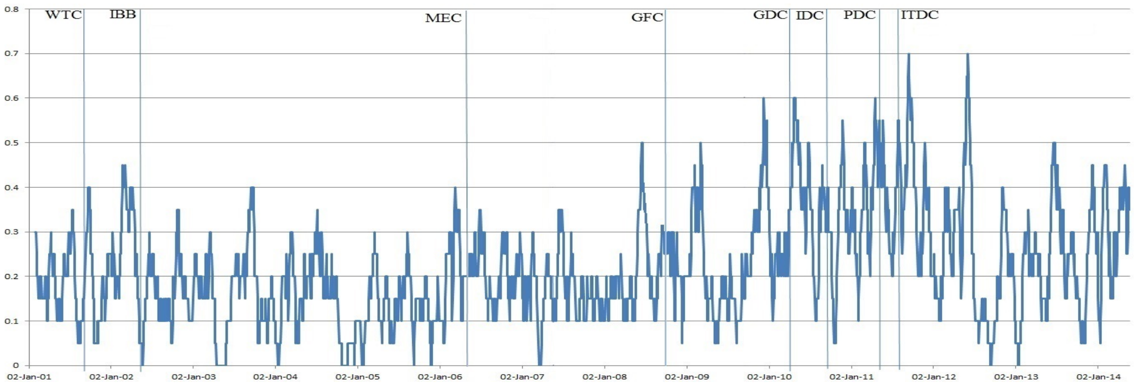


Figure.9.(c) CI indicator for Greece.

Figure 1.10: Daily sovereign bond returns (1/2/2001-5/22/2014). All sovereign bond returns are first differences of natural logarithms of the bond indices.

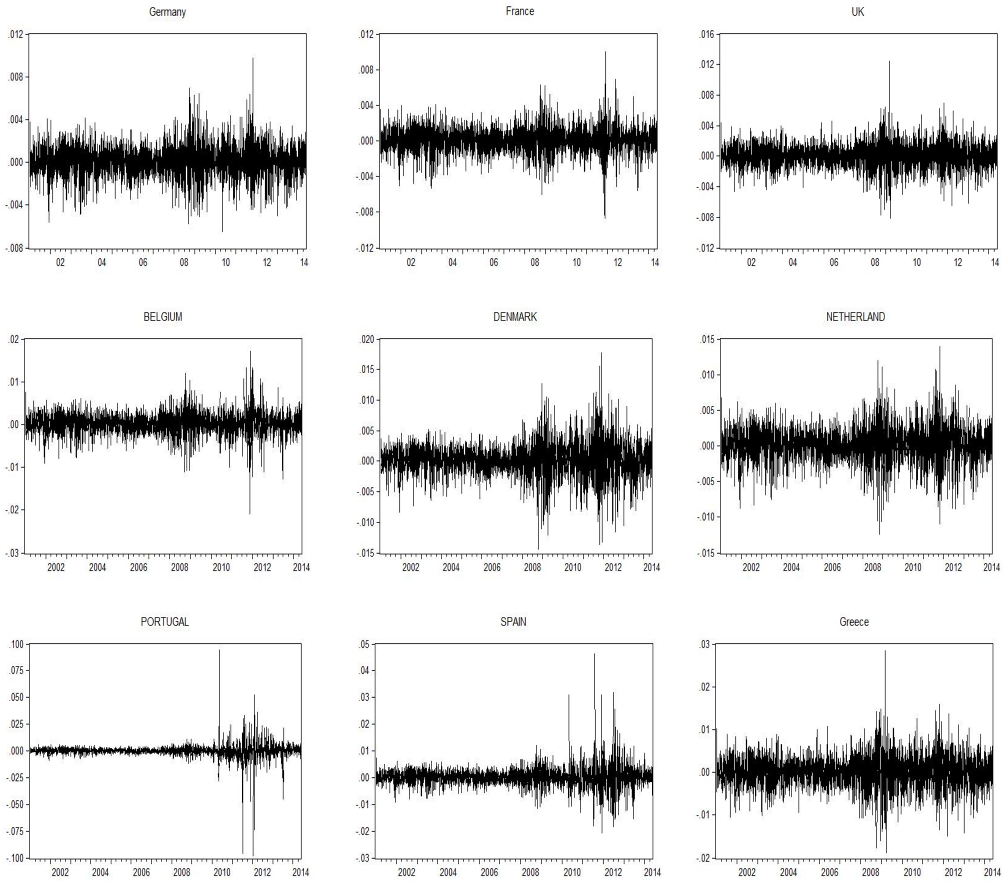


Figure 1.11: Conditional variance (1/2/2001-5/22/2014). The consistent volatility is modeled by the simplest GARCH model.

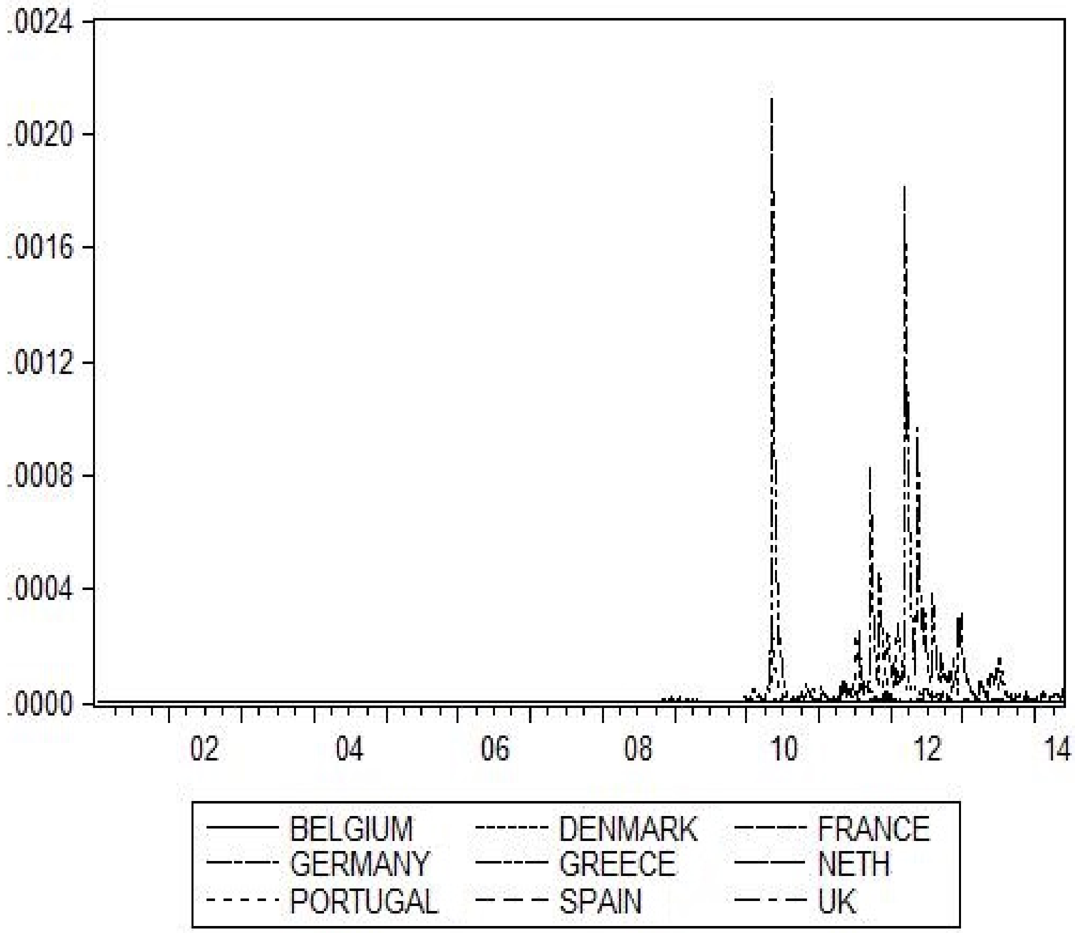
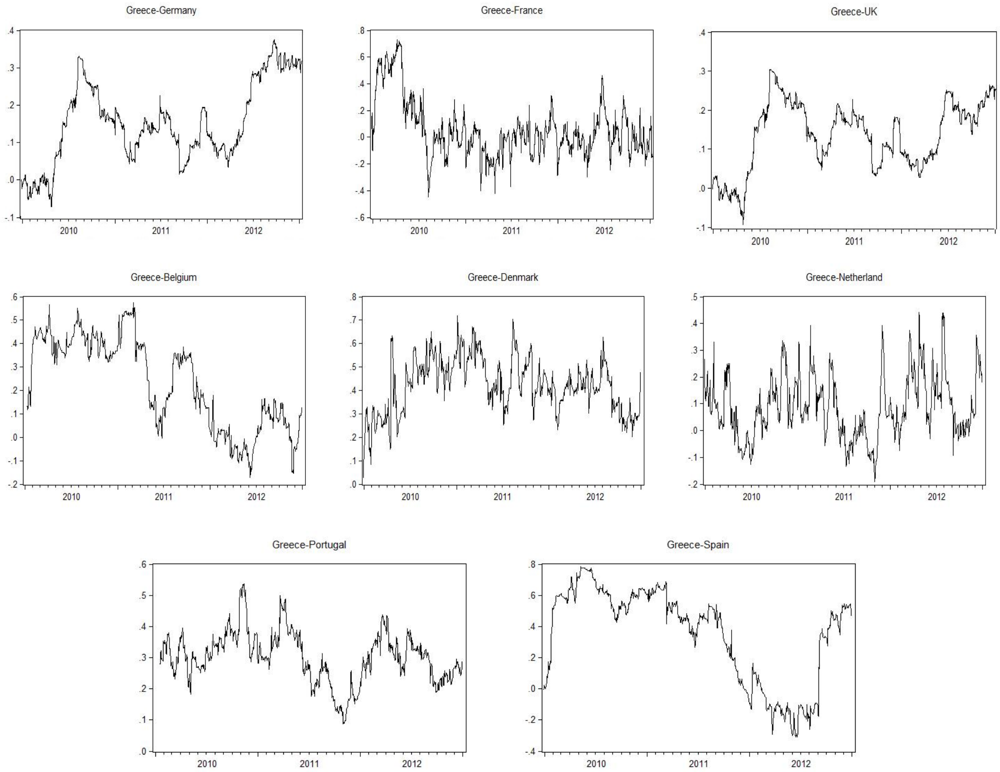


Figure 1.12: Dynamic correlation estimates for sovereign bond index returns of Greece and those of the other eight European countries.



Chapter 2

The nonlinear relationship between stock returns, trading volume, and volatility: International evidence

2.1 Introduction

The relationship between stock returns and trading volume and that between trading volume and volatility have been extensively studied in the literature. For the former, a large and voluminous literature has documented evidence of positive relation between stock returns and trading volume (see, for example, Copeland (1976), Jennings, Starks, and Fellingham (1981) and more recently Griffin, Nardari, and Stulz (2007)); while others show that the relation is negative (see Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998), and Chordia, Subrahmanyam, and Anshuman (2001) among others). Meanwhile, the relationship between trading volume and volatility has attracted no less attention in the literature as accurate modeling and forecasting of volatility is essential for asset pricing, portfolio management, and risk management (see, for example, Lamoureux and Lastrapes (1990), Jones, Kaul, and Lipson (1994), Darrat, Rahman, and Zhong (2003), and Fleming and Kirby (2011)). In existing literature, both relationships are widely researched in linear way, and are estimated solely. Hiemstra and Kramer (1993) assert that nonlinear model has a better accuracy in estimations than linear way. This motivates us to find nonlinear relationships between stock returns, trading volume and volatility. In order to further improve the research, both relationships are estimated in a joint system, sharing the same information.

Building upon this basic model, Baek and Brock (1992) put forward a nonparametric statistical method for unveiling the nonlinear relations that are not detected by conventional linear causality tests. This method is widely adopted in many fields, such as money and income (Baek and Brock, 1992), aggregate stock returns and macroeconomic elements (Hiemstra and Kramer, 1993), and producer and consumer price indices (Jaditz and Jones, 1993).

In this paper, we re-investigate the relations between stock returns, return volatility, and trading volume in a unified framework by simultaneously studying the relationship between the three variables. The existing literature seldom analyzes the joint system of these three variables simultaneously.[1] However, the partial evaluation of pair-wise relationship of the variables can potentially hide the true underlying dynamics and result in inefficient or biased statistical inference (see Pagan (1984) and the references therein).

When conducting econometric tests, we follow the seminal paper by Hiemstra and Jones (1994) and allow both linear and nonlinear Granger causality relations between stock returns, return volatility, and trading volume. Hiemstra and Jones (1994) modify the nonlinear Granger causality model of Baek and Brock (1992) to study the dynamic relation between stock returns and trading volume of the

[1] For example, Darrat, Rahman, and Zhong (2003) follow a two-step procedure in which volatility is first modeled via GARCH before tests on trading volume and volatility are performed.

DJIA stock index. They show that allowing a nonlinear causality relation provides additional insight and reveals a significant bi-directional Granger causality between returns and volume. The linear Granger causality test in their results only reports a uni-directional causality from returns to trading volume.

In this paper, we link the above strands of literature and make two contributions. First and foremost, we implement a simultaneous estimation of stock returns, return volatility, and trading volume in a joint vector autoregression (VAR) system. In this way, the dynamics of the three variables can be modeled together to provide a comprehensive analysis of their relationship. In particular, we specify stock returns and trading volume in the VAR to study the causal relation between the two variables. At the same time, the variance of stock returns, endogenously generated from the EGARCH model, also enters the VAR together with trading volume to measure the causal relation between volatility and trading volume.

The second contribution is that we allow both linear and nonlinear Granger causality in exploring the relationship between the three variables. To the best of our knowledge, this is the first study to conduct nonlinear Granger causality test on the relationship between stock returns, return volatility, and trading volume.[2] The nonlinear causality test has become increasingly prominent in the literature as it is more flexible and able to capture potential structural breaks in the relation between variables (see, for example, Qiao and Lam (2011), Beine, Capelle-Blancard, and Raymond (2008), Anoruo (2011), and Cakan (2013)). The importance of testing nonlinear relationship is also documented in different asset classes, including the stock index futures market (Abhyankar (1998)) and the energy market (Benhmad

[2] Chuang, Liu, and Susmel (2012) study the simultaneous relationship between the three variables using data from 10 Asian markets but they only allow linear causality relation.

(2012)), among others.

With data from 12 emerging and 12 developed markets over a long sample period, our empirical results show that there is a strong bi-directional nonlinear causality between stock returns and trading volume, and between trading volume and volatility for all markets. This is contrary to the linear Granger causality test results, which suggests only uni-directional causality for some of the markets.

In addition, we perform robustness test for both linear and nonlinear Granger causality using a shorter sample of relatively tranquil market conditions from the beginning of 1994 to the end of 2006, just before the onset of the recent banking and financial crisis. The robustness tests generate interesting results in comparison to the full sample test results. First, we observe much stronger linear Granger causality relation between the variables, especially from stock returns to trading volume, and from volatility to trading volume. For example, for the whole sample period, that volatility feedback to trading volume is significant only for 2 markets but this increases to 18 countries for the shorter sample, out of which 14 are significant at 1% level. Similarly, the number of markets seeing significant Granger causality from stock returns to trading volume goes up from 11 for the whole sample to 18 for the shorter sample, out of which 14 are significant at 1% level.

Second, although the significant bi-directional results remain unchanged qualitatively for the nonlinear tests, we observe that feedback from stock returns to trading volume, and that from volatility to trading volume are much stronger than the opposite direction for the shorter sample. This is especially true for the feedback from volume changes to volatility. For the long sample, this is significant at 1% level for all 24 markets. For the short sample, however, only 7 countries see a 1% significance for this causality.

Taken together, the above results suggest that the linear causality test is not able to detect relationship between the variables when potential structural breaks exist in the data due to the financial crisis, and the nonlinear causality test is more flexible and reliable in this regard. In addition, although stock returns and trading volume, and trading volume and volatility exert significant influence on each other, the relation can be more dominant in one direction under certain market conditions.

Our paper is also related to Griffin, Nardari, and Stulz (2007), which explores the return-volume relation in 46 countries. Interestingly, they show that the relation is stronger in economies that are more opaque, volatile, and less integrated to the global stock markets. We test a long sample period of 24 developed and developing countries and find that the nonlinear Granger causality relation is strong in all markets.

The rest of the paper is organized as follow. In Section 2, we outline the methodology for linear and nonlinear Granger causality tests. Section 3 describes data. We analysis empirical results and robustness tests in Section 4. Finally, Section 5 concludes.

2.2 Methodology

In this section, we follow closely Hiemstra and Jones (1994) and outline the linear Granger causality test and the bivariate nonlinear causality model first proposed in Baek and Brock (1992). We adopt the EGARCH model to describe stock return volatility.

2.2.1 Linear Granger Causality Test

Following Granger (1969) and, more recently, Hiemstra and Jones (1994), we let $\{X_t\}$ and $\{Y_t\}$ denote two strictly stationary time series. The conditional probability distribution $F(X_t|\mathbf{I}_{t-1})$ for $\{X_t\}$ given the bivariate information set $\mathbf{I}_{t-1}$ comprising an Lx-length lagged vector of X_t,

$$\mathbf{X}_{t-Lx}^{Lx} \equiv (X_{t-Lx}, X_{t-Lx+1}, \ldots, X_{t-1}),$$

and an Ly-length lagged vector Y_t,

$$\mathbf{Y}_{t-Ly}^{Ly} \equiv (Y_{t-Ly}, Y_{t-Ly+1}, \ldots, Y_{t-1}),$$

is expressed as follows:

$$F(X_t|\mathbf{I}_{t-1}) = F(X_t|(\mathbf{I}_{t-1} - \mathbf{Y}_{t-Ly}^{Ly})). \tag{2.1}$$

The bivariate information set I_{t-1} is defined as a set comprising Lx-length and Ly-length lagged vectors. If equation 2.1 does not hold, it implies that the past value of $\{Y_t\}$ contains information for predicting the current and future values of $\{X_t\}$, and $\{Y_t\}$ is said to strictly Granger cause $\{X_t\}$. Similarly, we can modified the information set by including the current value of Y as follows:

$$F(X_t|\mathbf{I}_{t-1}) = F(X_t|(\mathbf{I}_{t-1} + Y_t)). \tag{2.2}$$

If equation 2.2 does not hold, it indicates that Y_t instantaneously Granger causes X_t. Following Hiemstra and Jones (1994), we adopt a linear reduced form Vector Autoregression (VAR) and estimate the following system of equations to test Granger causal relations:

$$\begin{aligned} X_t &= A(L)X_{t-1} + B(L)Y_{t-1} + U_{X,t} \\ Y_t &= C(L)X_{t-1} + D(L)Y_{t-1} + U_{Y,t} \qquad\qquad t = 1, 2, 3, \dots, \end{aligned}$$

where $A(L)$, $B(L)$, $C(L)$, and $D(L)$ are lag polynomials of orders a, b, c, and d in the lag operator L. The error terms $U_{X,t}$ and $U_{Y,t}$ are assumed to be mutually independent and individually $i.i.d$ distributed with zero mean and constant variance. If coefficients in $B(L)$, i.e. B_i $(i = 1, \dots, b)$, are jointly significantly different from zero, the null hypothesis that Y does not Granger cause X can be rejected. On the other hand, if coefficients in $C(L)$ are jointly significantly different from zero, the null hypothesis that X does not Granger cause Y can be rejected. In addition, the bi-directional causality (or feedback) exists if the coefficients in $B(L)$ and $C(L)$ are jointly different from zero.

2.2.2 Nonlinear Granger Causality Test

The nonlinear Granger causality test is based on the bivariate nonlinear model proposed by Brock (1991), which establishes a simple bivariate nonlinear model and shows how it can compensate the inadequacy of the linear Granger causality test to uncover nonlinear predictive power. The model is specified as follows:

$$X_t = \beta Y_{t-L} \cdot X_{t-M} + \varepsilon_t, \tag{2.3}$$

where $\{Y_t\}$ and $\{\varepsilon_t\}$ are mutually independent and individually *i.i.d.* $N(0,1)$ time series with mean zero and unit variance, β is a parameter, L and M are lag lengths, and X_t depends on past values of Y_t. Building upon this basic model, Baek and Brock (1992) propose a nonparametric statistical method for unveiling the nonlinear relations that are not detected by conventional linear causality test. In specific, Baek and Brock (1992) consider two stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, $t = 1, 2, \ldots$. Denote the m-length lead vector of X_t by $\mathbf{X}_t^m$, and denote the Lx-length and Ly-length lag vectors of X_t and Y_t by $\mathbf{X}_{t-Lx}^{Lx}$ and $\mathbf{Y}_{t-Ly}^{Ly}$, respectively:

$$\begin{aligned}
\mathbf{X}_t^m &\equiv (X_t, X_{t+1}, \ldots, X_{t+m-1}), \qquad m = 1, 2, \cdots, \ t = 1, 2, \cdots, \\
\mathbf{X}_{t-Lx}^{Lx} &\equiv (X_{t-Lx}, X_{t-Lx+1}, \cdots, X_{t-1}), \ Lx = 1, 2, \cdots, \ t = Lx+1, Lx+2, \cdots, \\
\mathbf{Y}_{t-Ly}^{Ly} &\equiv (Y_{t-Ly}, Y_{t-Ly+1}, \cdots, Y_{t-1}), \quad Ly = 1, 2, \cdots, \ t = Ly+1, Ly+2, \cdots.
\end{aligned} \tag{2.4}$$

For given values of m, Lx, and $Ly \geqslant 1$ and for $e > 0$, Y does not strictly Granger cause X if:

$$\begin{aligned}
\Pr(||\mathbf{X}_t^m - \mathbf{X}_s^m|| &< e| \ ||\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}|| < e, ||\mathbf{Y}_{t-Ly}^{Ly} - \mathbf{Y}_{s-Ly}^{Ly}|| < e) \\
&= \Pr(||\mathbf{X}_t^m - \mathbf{X}_s^m|| < e| \ ||\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}|| < e),
\end{aligned} \tag{2.5}$$

where $\Pr(\cdot)$ indicates probability and $||\cdot||$ is the maximum norm.[3] On the left-hand side of equation 2.5, the probability is the conditional probability that two arbitrary m-length lead vectors of X_t are within a distance e of each other, given that the corresponding Lx-length lag vector of $\{X_t\}$ and the Ly-length lag vector of $\{Y_t\}$ are

[3] The maximum norm for $Z \equiv (Z_1, Z_2, \cdots, Z_K)$ is defined as $\max(Z_i)$, $i = 1, 2, \ldots, K$.

within e of each other. The expression on the right-hand side of equation 2.5 is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ are within e of each other, given that their corresponding Lx-length lag vectors are less than e of each other.

In order to implement a nonlinear Granger causality test based on equation 2.5, the corresponding ratio of joint probability to the above conditional probability is proposed.[4] Define:

$$\begin{aligned}
C1(m+Lx, Ly, e) &\equiv \Pr(||\mathbf{X}_{t-Lx}^{m+Lx} - \mathbf{X}_{s-Lx}^{m+Lx}|| < e, ||\mathbf{Y}_{t-Ly}^{Ly} - \mathbf{Y}_{s-Ly}^{Ly}|| < e), \\
C2(Lx, Ly, e) &\equiv \Pr(||\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}|| < e, ||\mathbf{Y}_{t-Ly}^{Ly} - \mathbf{Y}_{s-Ly}^{Ly}|| < e), \\
C3(m+Lx, e) &\equiv \Pr(||\mathbf{X}_{t-Lx}^{m+Lx} - \mathbf{X}_{s-Lx}^{m+Lx}|| < e), \\
C4(Lx, e) &\equiv \Pr(||\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}|| < e). \qquad (2.6)
\end{aligned}$$

The nonlinear Granger causality condition in equation 2.5 can be expressed as:

$$\frac{C1(m+Lx, Ly, e)}{C2(Lx, Ly, e)} = \frac{C3(m+Lx, e)}{C4(Lx, e)}, \qquad (2.7)$$

for given values of $m, Lx, Ly \geqslant 1$ and $e > 0$. To estimate and test the condition in equation 2.7, we re-write equation 2.6 as the correlation-integral estimators of joint

[4] The maximum norm allows $\Pr(||\mathbf{X}_t^m - \mathbf{X}_s^m|| < e,\ ||\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}|| < e)$ to be written as $\Pr(||\mathbf{X}_{t-Lx}^{m+Lx} - \mathbf{X}_{s-Lx}^{m+Lx}|| < e)$.

probabilities as follows:

$$
\begin{aligned}
C1(m+Lx, Ly, e, n) &\equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(\mathbf{x}_{t-Lx}^{m+Lx}, \mathbf{x}_{s-Lx}^{m+Lx}, e)\cdot I(\mathbf{y}_{t-Ly}^{Ly}, \mathbf{y}_{s-Ly}^{Ly}, e),\\
C2(Lx, Ly, e, n) &\equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(\mathbf{x}_{t-Lx}^{Lx}, \mathbf{x}_{s-Lx}^{Lx}, e)\cdot I(\mathbf{y}_{t-Ly}^{Ly}, \mathbf{y}_{s-Ly}^{Ly}, e),\\
C3(m+Lx, e, n) &\equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(\mathbf{x}_{t-Lx}^{m+Lx}, \mathbf{x}_{s-Lx}^{m+Lx}, e),\\
C4(Lx, e, n) &\equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(\mathbf{x}_{t-Lx}^{Lx}, \mathbf{x}_{s-Lx}^{Lx}, e). \qquad (2.8)
\end{aligned}
$$

with $t, s = \max(Lx, Ly)+1, \ldots, T-m+1$, $n = T+1-m-\max(Lx, Ly)$, and $I(\mathbf{Z}_1, \mathbf{Z}_2, e)$ denote a kernel that equals 1 when two conformable vectors $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are within the maximum-norm distance e of each other, and 0 otherwise. With the joint probability estimators of equation 2.8, the nonlinear Granger noncausality condition in equation 2.5 can be evaluated. Under the condition that all variables must be strictly stationary and weakly dependent, and if Y_t cannot Granger cause X_t, then we have:

$$
\sqrt{n}\left(\frac{C1(m+Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} - \frac{C3(m+Lx, e, n)}{C4(Lx, e, n)}\right) \sim N(0, \sigma^2(m, Lx, Ly, e)). \qquad (2.9)
$$

Equation 2.9 is then applied to residuals $(u_{X,t}, u_{Y,t})$ from the VAR model:

$$
z_t = Az_{t-1} + \varepsilon_t, \qquad (2.10)
$$

where A is (2×2) matrix of coefficients, $z_t = (X_t, Y_t)$, and ε_t is a vector of error term.

The empirical VAR model in compact form is expressed as follows:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} a(L) & b(L) \\ c(L) & d(L) \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} u_{X,t} \\ u_{Y,t} \end{bmatrix} \qquad t = 1, 2, \ldots, \tag{2.11}$$

The null hypothesis is that Y_t does not strictly Granger cause X_t, and X_t does not strictly Granger cause Y_t.

In this paper, we are interested in exploring the relationship between stock returns, trading volume, and volatility. We adopt the EGARCH model, a popular method in the literature due to its ability to capture volatility persistence and asymmetric response to news to measure volatility (Nelson (1990, 1991)). The EGARCH (p, q) model is specified as follows:

$$\begin{aligned} \tilde{r}_t &= \varepsilon_t, \qquad \varepsilon | I_{t-1} \sim N(0, \sigma_t^2) \\ \tilde{\sigma}_t^2 &= \alpha_0 + \alpha_1 \ln(\tilde{\sigma}_{t-1}^2) + \cdots + \alpha_p \ln(\tilde{\sigma}_{t-p}^2) &(2.12) \\ &+ \beta_1 \left[\varphi \left(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) + \gamma \left(|(\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}})| - \sqrt{2/\pi} \right) \right], &(2.13) \end{aligned}$$

where $\tilde{r}_t$ and $\tilde{\sigma}_t^2$ denote detrended stock returns and volatility of detrended returns, respectively.[5]

We let $\{X_t\}$ and $\{Y_t\}$ be the time series of detrended trading volume $\tilde{V}_t$ and $\tilde{\sigma}_t^2$. Equation 2.11 can be re-written as follows:

$$\begin{aligned} \tilde{V}_t &= a(L)\tilde{V}_{t-1} + b(L)\tilde{\sigma}_{t-1}^2 + u_{\tilde{V},t} \\ \tilde{\sigma}_t^2 &= c(L)\tilde{\sigma}_{t-1}^2 + d(L)\tilde{V}_{t-1} + u_{\tilde{\sigma}^2,t}, \qquad t = 1, 2, \cdots, T. &(2.14) \end{aligned}$$

[5] Stock returns and trading volume are detrended to induce stationarity. Volatility is modelled on detrended returns. See Section 3 for more detail.

In a similar vein, $\{X_t\}$ and $\{Y_t\}$ can also denote the time series of detrended stock returns and trading volume. Hence equation 2.11 can be expressed as follows:

$$\begin{aligned} \tilde{r}_t &= a(L)\tilde{r}_{t-1} + b(L)\tilde{V}_{t-1} + u_{\tilde{r},t} \\ \tilde{V}_t &= c(L)\tilde{V}_{t-1} + d(L)\tilde{r}_{t-1} + u_{\tilde{V},t}, \qquad t = 1, 2, \cdots, T. \end{aligned} \tag{2.15}$$

Finally, equation 2.9 is applied to the residuals of equations 2.14 and 2.15 to perform the nonlinear Granger causality test.

2.3 Data

We use daily stock market indices and trading volume for 24 markets obtained from the Datastream. They include developed markets such as the US, UK, Canada, Denmark, Germany, France, Switzerland, and Japan, and still developing markets such as Argentina, Brazil, Chile, Colombia, and Indonesia, and generally cover the period from 1973-2013. The sample period for each market is summarized in Table 2.1.

We compute stock returns as the logarithmic changes of stock market indices over consecutive trading days, $r_t = \ln(\frac{P_t}{P_{t-1}})$, where P_t and P_{t-1} are the stock index on days t and $t-1$, respectively. Similarly, we obtain volume changes as the logarithmic changes of volume over consecutive trading days, $V_t = \ln(\frac{V_t}{V_{t-1}})$, where V_t and V_{t-1} are trading volume on days t and $t-1$, respectively. Following Hiemstra and Jones (1994) and Lo and Wang (2000), in order to induce stationarity in the time series we detrend both stock returns and volume changes by regressing the time series on a deterministic function of a linear time trend term (see equation (14) in Lo and Wang

(2000)). This procedure yields the detrended time series for stock returns $\tilde{r}_t$ and $\tilde{V}_t$ to be utilized in the VAR model. We adopt the EGARCH model on the detrended returns to estimate return volatility.

Table 2.2 reports the descriptive statistics of the detrended stock returns, volume changes, and variance series. We also report the first-order autocorrelation, the sum of the autocorrelations from the first order to fifth order, and the ARCH effect with 10 lag-length for detrended stock returns. Overall the emerging markets show higher standard deviation than developed markets with Argentina having the highest value at 0.034, and Canada with the lowest at 0.010. The first-order autocorrelation tends to be very close to zero for most markets with the exception of India whose first-order autocorrelation is 0.082. The average sum of the first five autocorrelations is -0.007 for developed markets, and 0.009 for developing markets. The LM statistics are statistically significant at the 1% level for all markets, indicating the existence of the time-varying volatility and that a GARCH-type model is appropriate for measuring volatility. The Jarque-Bera test, which is not reported to save space, strongly rejects the normality assumption for stock returns for all markets.

For detrended volume changes, the standard deviation of volume changes is higher than that of stock returns for all markets but the developed markets tend to have lower standard deviation than the developing markets (0.346 vs. 0.447). The Jarque-Bera test has also strongly rejected normality assumption for detrended volume changes. Trading volume shows similar autocorrelation persistence as stock returns. The return variance has very small sample mean. Interestingly, return variance shows substantially higher autocorrelations, which means that it is much more persistent than stock returns and volume changes.

Table 2.3 summarizes the results of the augmented Dickey-Fuller (ADF) unit root test for the three variables considered in our paper (Dickey and Fuller (1979, 1981) and Said and Dickey (1984)). We relate the results of ADF test to the estimation of variables' stationarity. The probabilities of unit root test for detrended stock returns, trading volume and variance are all statistically significant. The test statistics suggest that all detrended variables are stationary and therefore they are suitable for the VAR model.

2.4 Empirical Results and Analysis

The linear and nonlinear Granger causality test results for the two relationships, i.e., that between stock returns and trading volume, and between volatility and trading volume, are summarized in Tables 2.4 to 2.7. Table 2.4 reports the linear Granger causality test result between stock returns and trading volume, including lag lengths of both dependent and independent variables, and the F-statistics with p-values. We notice that Mexico has the longest lags (23) for stock returns, while the UK, Brazil and Greece have the longest lags (2) for trading volume. Under the null hypothesis that volume changes do not Granger cause stock returns, the null remains valid for all markets. This indicates that there is no evidence of unidirectional causality from trading volume to stock returns during the sample period. Put differently, knowing volume changes does not help improve forecasts of current and future stock returns. On the other hand, under the null hypothesis of Granger noncausality from stock returns to trading volume, the null can be rejected at the 1% level for Denmark, France, Brazil, Philippine and Thailand, at the 5% level for Germany and Japan, and at the 10% level for the UK, Taiwan, Singapore, and

Malaysia. These suggest that stock returns tend to have strong feedback effect on trading volume in these markets. In other words, information contained in stock returns helps forecast volume changes for these markets.

In Table 2.5, we summarize the linear causal relation between trading volume and return volatility. First, the Granger causality from trading volume to volatility is observed in the US at the 1% level and in Germany and Brazil at the 5% level. Six other countries including the UK, France, Singapore, Argentina, Greece and Thailand see evidence of this causality at the 10% significance level. On the other hand, there is weaker evidence for volatility to Granger cause trading volume. For Denmark and Singapore, the null that volatility does not Granger cause volume changes is rejected at the 1% and 5% level, respectively. For the rest of the markets, we found no information in volatility that can help forecast trading volume as the null hypothesis of no Granger causality cannot be rejected. Taken together, Singapore is the only market that experiences a bi-directional relation between volume and volatility. For nine other markets, there is uni-directional feedback effect, and it tends to be from trading volume to volatility.

Overall, Tables 2.4 and 2.5 suggest that the three variables are rather disconnected over the entire sample period with linear causality relationship in only a few markets. However, our long sample period includes the Asian financial crisis in 1997 and the recent financial and banking crisis since 2007. As a result, the linear causality test may not be adequate to capture a potentially time-changing relationship between the variables. For example, structural breaks may exist in the relation between stock returns, trading volume, and volatility during the whole sample. We therefore employ the modified Baek and Brock test proposed in Hiemstra and Jones

(1994) which is nonlinear causality test. The values of the lead length m, the lag lengths Lx and Ly, and Ly and Lz, and the scale parameter e are chosen according to the Monte Carlo simulations in Hiemstra and Jones (1994).[6] The modified model, shown in equation 2.9, is applied to the estimated VAR residuals.

Table 2.6 re-examines the causality between stock returns and trading volume via a nonlinear causality test. We estimate the nonlinear causal relation for each market from lag 1 to lag 8 and report only the test statistics with the smallest lag and the corresponding lag length for each market in this table. CS and TVAL denote the difference between the two conditional probabilities in equation 2.7 and the standardized test statistics in equation 2.9, respectively.

As we can see, the smallest TVAL value is 4.049 and 3.380 for Taiwan and Denmark, respectively, when testing whether volume Granger causes stock returns and whether stock returns Granger cause volume. Both statistics are significant at the 1% significance level. Hence there is a very strong bi-directional nonlinear Granger causality relation between stock returns and trading volume for all markets. In addition, this strong bi-directional relation between stock returns and trading volume holds for all lag lengths from 1 to 8. Put differently, with the more flexible nonlinear test, we reveal a strong bi-directional feedback between volume and stock returns so that stock returns contain information that helps improve forecast of trading volume; at the same time, knowing trading volume also helps forecast current and future stock returns. Since the TVAL values are larger for rejecting the null that stock returns do not Granger cause volume changes, there is evidence suggesting that

[6] Hiemstra and Jones (1994) give three values of 0.5, 1 and 1.5 to the scale parameter e, the analogous results could be equally derived with three values of e. However, in specific, to implement the test we set the scale parameter $e = 0.5\sigma$, which is only one helping derive the results in our paper, possibly because of the basic attributes of data series. We also select the lead length at 1, and $Lx = Ly = Lz$ for the common lag length from 1 to 8.

stock returns are able to provide more feedback to trading volume than the other way round.

The nonlinear Granger causality test results between trading volume and volatility are summarized in Table 2.7. Similar to Table 2.6, we observe a strong bi-directional causality between trading volume and volatility. The smallest test statistic for the null hypothesis that volume changes do not Granger cause volatility is 4.010 for Thailand, and for the null that volatility does not Granger cause volume changes it is 4.043 for the US. Given that the test statistics are significant at the 1% level for all markets, there is strong evidence that volume changes and volatility are able to exert feedback to each other.

Robustness Checks

Due to the severity of the recent banking and financial crisis and its potential impact on the empirical results discussed above, as a robustness check we re-examine the linear and nonlinear relation between stock returns, trading volume, and volatility with a shorter sample from January 1994 to December 2006. Our shorter sample period excludes the impact of the recent banking crisis although it still covers the Asian financial crisis in 1997 and the dotcom bubble at the turn of the century. The linear test results for the short sample are summarized in Tables 2.8 and 2.9, and the nonlinear test results are reported in Tables 2.10 and 2.11.

In Table 2.8, we observe much stronger causality relation between stock returns and trading volume for the shorter sample from the linear tests. The null that volume has no feedback to stock returns is rejected for eight countries, compared with none in Table 2.4 for the full sample. These include rejection at the 1% level for Denmark, Taiwan, and Thailand. There is also a stronger causality from stock returns to volume. The null that stock returns do not Granger cause trading volume is rejected for 18 markets, including 14 markets whereby the rejection is significant at the 1% level. When we take the two hypothesis tests together, we observe a bi-directional Granger causality between stock returns and volume for seven countries, including highly significant relation for Taiwan and Thailand at the 1% level. In addition, we see that feedback from stock returns to volume is stronger than the other way round, similar to the observation in Table 2.6 for the nonlinear Granger causality test for the whole sample period.

Table 2.9 shows a similar story to Table 2.8 for the relationship between volatility and trading volume. For the shorter sample, we uncover more markets that see significant causality relation between trading volume and volatility at higher significance level when compared to the full sample. There is the bi-directional causality for 10 countries, including highly significant relation (at the 1% level for both directions) for Hong Kong and Thailand. Also similar to the pattern in Table 2.8, the relation is stronger in one direction than the other. Out of 24 markets we examine, 18 of them see significant feedback effect from volatility to trading volume, out of which 14 are significant at the 1% level.

Empirical findings from Tables 2.8 and 2.9 reveal an interesting pattern that the linear Granger causality relationship is much stronger over the shorter sample period than that over the entire sample reported in Tables 2.4 and 2.5. As the shorter sample period covers relatively tranquil market conditions before the onset of the US banking crisis, the results again substantiate the failing of the linear Granger causality test to capture the dynamic relationship between economic variables, something that

Hiemstra and Jones (1994) has emphasized in their article.

Table 2.10 summarizes the nonlinear causality results between stock returns and trading volume for the shorter sample. Similar to Table 2.6 for the full sample, there is a clear bi-directional relation between the two variables. Unlike Table 2.6, however, there is an apparent difference in the significance of rejecting the two null hypotheses. For the null that stock returns do not Granger cause volume, the smallest TVAL is highly significant at 4.781. However, for the null that volume changes do not Granger cause stock returns, for four countries, it can only be rejected at the 5% level. This suggests a stronger feedback from stock returns to volume than the other way round, and this is consistent with the results from linear test reported in Table 2.8.

Table 2.11 reports the nonlinear causality results between volume and volatility for the shorter sample. From this table we can see that all of the markets considered in our paper still exhibit bi-directional causality. However, the causality from volatility to volume seems to be stronger than the causality from volume to volatility. For example, the causality from volatility to volume is significant at the 1% level for all the countries except for Greece, which is significant at the 5% level. However, with regard to causality from volume to volatility, only 7 countries see highly significant statistics with all other countries seeing statistics significant at lower levels: either at the 5% or the 10% level. Hence, consistent with the findings in Table 2.9, these results indicate that information tends to flow from volatility to volume, and that volatility contains more information that helps improve forecasts of trading volume.

To summarize, comparing the results reported in Tables 2.4 and 2.5, these additional robustness tests suggest that the linear causality test is not flexible enough to recover dynamic relationships when they experience potential structural breaks. Hence it is always advisable to perform the nonlinear Ganger causality test, which is more flexible and powerful, alongside linear tests. Our results also show that although stock returns and trading volume, and volume and volatility provide feedback to each other and contain information that helps predict current and future values for each other, the relationship can be stronger in one particular direction under certain market conditions.

2.5 Conclusion

The causal relationships between stock returns and trading volume, and between trading volume and volatility attract huge interest in the literature but very few papers focus on both of the causal relationships between them in the same system. In this article, we adopt a system of VAR models and follow Hiemstra and Jones (1994) in exploring both linear and nonlinear Granger causal relations between the three variables. By using the joint system of linear and nonlinear models, the approach is able to avoid the problem of model misspecification, but also capture more complex nonlinear causal relation between the variables.

We perform simultaneous estimations of the relation between stock returns and trading volume, and of the relation between trading volume and volatility. Our findings are summarized as follows. First, after removing the effect of time predictive power, the linear Granger causality test shows no evidence that volume Granger causes stock returns, and only a handful markets reject the null that stock returns cannot Granger affect volume. For the relationship between trading volume and volatility, under the hypothesis of volume does not Granger cause volatility, statistical significance is obtained for even fewer markets. And only two markets, namely Denmark and Singapore, can reject the null that volatility does not Granger cause volume changes. In contrast, the results for the nonlinear Granger test suggest that the null hypothesis of pair-wise no Granger causality between stock returns and volume changes and between volume changes and volatility can be rejected for all markets at high level of statistical significance.

We also undertake robustness tests for both linear and nonlinear Granger causality for a shorter sample period from 1994 to 2006 when the markets were relatively calm. We find that the linear Granger causality test produced more significant results at higher significance level for the shorter sample period, and we observe a stronger feedback effect from stock returns to volume, and from volatility to volume. The nonlinear causality rest results remain the same qualitatively in that bi-directional causality exists between stock returns and volume, and between volume and volatility. Moreover, consistent with the linear results for the shorter sample, the non-linear test also reveals a stronger feedback from stock returns to volume, and from volatility to volume.

Table

Table 2.1: The markets and the corresponding sample periods

Market	Sample period
US	1 Feb 1973 to 11 Nov 2013
UK	1 Jan 1965 to 11 Nov 2013
Canada	1 Feb 1973 to 11 Nov 2013
Denmark	1 Jan 1973 to 11 Nov 2013
Germany	1 Jan 1973 to 11 Nov 2013
France	1 Jan 1973 to 11 Nov 2013
Hong Kong	1 Jan 1973 to 11 Nov 2013
Japan	1 Jan 1973 to 11 Nov 2013
New Zealand	1 Apr 1988 to 11 Nov 2013
Norway	1 Feb 1980 to 11 Nov 2013
Taiwan	9 Sept 1987 to 11 Nov 2013
Singapore	1 Jan 1973 to 11 Nov 2013
Argentina	1 Apr 1988 to 11 Nov 2013
Brazil	7 Apr 1994 to 11 Nov 2013
Chile	7 Mar 1989 to 11 Nov 2013
Colombia	1 Feb 1992 to 11 Nov 2013
Greece	1 Apr 1988 to 11 Nov 2013
India	1 Jan 1990 to 11 Nov 2013
Korea	9 Sept 1987 to 11 Nov 2013
Malaysia	1 Feb 1986 to 11 Nov 2013
Mexico	1 Apr 1988 to 11 Nov 2013
Philippine	9 Sept 1987 to 11 Nov 2013
Poland	3 Jan 1994 to 11 Nov 2013
Thailand	1 Feb 1987 to 11 Nov 2013

Table 2.2: Descriptive statistics for detrended stock returns, trading volume, and volatility

In this table, $\tilde{r}_t$, $\tilde{V}_t$, and $\tilde{\sigma}_t$ denote detrended stock returns, detrended trading volume changes, and variance estimated from the EGARCH model. Stdev is the standard deviation. AC(1) refers to the first-order autocorrelation and AC(5) refers to the sum of the first five autocorrelations. ARCH (10) indicates the chi-square of the Lagrange Multiplier (LM) test for autoregressive conditional heteroskedasticity effect with 10 lag length.

	US	UK	Canada	Denmark	Germany	France	HK	Japan	NZ	Norway	Taiwan	Singapore
Detrended stock returns $\tilde{r}_t$												
Observations	10654	12738	10649	10655	10655	10652	10653	10654	6740	8828	6822	10655
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.011	0.012	0.010	0.013	0.012	0.013	0.018	0.013	0.012	0.017	0.019	0.014
AC(1)	0.000	0.001	0.001	0.001	0.000	0.001	-0.002	0.000	0.000	0.001	-0.002	0.001
AC(5)	-0.067	-0.012	0.001	-0.012	-0.020	-0.023	0.009	-0.007	0.009	-0.064	0.018	0.082
ARCH(10)	129.190	225.172	304.824	39.481	109.085	164.911	23.095	64.301	73.937	140.25	137.38	174.43
Detrended volume changes $\tilde{V}_t$												
Observations	8682	3892	7377	3879	4940	4740	4682	3886	4063	5635	3687	5959
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.220	0.260	0.495	0.337	0.309	0.304	0.281	0.546	0.406	0.404	0.278	0.308
AC(1)	-0.016	0.005	-0.004	-0.004	-0.001	0.001	-0.008	-0.007	0.002	0.003	-0.006	-0.009
AC(5)	-0.205	-0.019	-0.093	0.004	-0.014	-0.012	-0.077	-0.072	-0.022	0.001	-0.009	-0.079
Variance $\tilde{\sigma}_t^2$												
Observations	10654	12738	10649	10655	10655	10652	10653	10654	6740	8828	6822	10655
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AC(1)	0.974	0.973	0.982	0.998	0.981	0.973	0.833	0.946	0.967	0.969	0.988	0.960
AC(5)	4.646	3.738	4.734	4.964	4.720	4.615	3.138	4.383	3.680	4.589	4.827	4.271

(Continued)

	Argentina	Brazil	Chile	Colombia	Greece	India	Korea	Malaysia	Mexico	Philippine	Poland	Thailand
Detrended stock returns $\tilde{r}_t$												
Observations	6739	5045	6350	5696	5740	6220	6820	7261	6739	6823	5134	7001
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.034	0.020	0.012	0.020	0.019	0.017	0.030	0.016	0.018	0.016	0.020	0.019
AC(1)	0.002	0.004	-0.001	0.000	0.003	0.082	0.001	0.000	-0.001	-0.001	0.001	-0.002
AC(5)	0.033	-0.065	0.045	-0.008	-0.004	0.082	-0.002	0.000	0.050	-0.024	-0.020	0.018
ARCH(10)	16.053	114.861	133.866	10.523	52.722	42.119	139.365	31.175	123.206	43.699	79.433	117.043
Detrended volume changes $\tilde{V}_t$												
Observations	3635	2904	3565	3482	4494	2732	4071	4986	3812	4087	3563	5043
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Stdev	0.409	0.271	0.550	0.901	0.395	0.404	0.319	0.296	0.465	0.605	0.361	0.389
AC(1)	-0.012	-0.021	0.001	-0.008	-0.005	0.046	-0.002	-0.008	0.005	-0.010	0.005	-0.006
AC(5)	-0.134	-0.216	-0.039	-0.154	-0.027	0.045	-0.029	-0.100	-0.006	-0.095	-0.015	-0.149
Variance $\tilde{\sigma}_t^2$												
Observations	6739	5045	6350	5696	6740	6220	6820	7261	6739	6823	5134	7001
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
AC(1)	0.943	0.966	0.974	0.950	0.983	0.982	0.998	0.986	0.973	0.964	0.973	0.949
AC(5)	4.220	4.566	4.610	4.290	4.724	4.686	4.960	4.655	4.655	4.419	4.624	4.239

Table 2.3: The unit root test results

In this table, we report the ADF(1) unit root test results for detrended stock returns, trading volume changes, and variance. The p-values are in parentheses.

	US	UK	Canada	Denmark	Germany	France	HK	Japan	NZ	Norway	Taiwan	Singapore
$\tilde{r}_t$	-17.181	-18.394	-17.146	-43.488	-23.617	-103.092	-24.419	-103.199	-26.551	-15.120	-19.434	-22.027
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\tilde{V}_t$	-8.032	-33.762	-9.776	-13.886	-69.832	-10.189	-11.153	-10.238	-11.385	-72.584	-6.796	-26.055
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\tilde{\sigma}_t^2$	-9.149	-9.462	-8.766	-5.472	-9.010	-9.665	-22.184	-12.370	-9.219	-7.782	-6.558	-12.849
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	Argentina	Brazil	Chile	Colombia	Greece	India	Korea	Malaysia	Mexico	Philippine	Poland	Thailand
$\tilde{r}_t$	-14.979	-10.774	-15.999	-16.983	-20.974	-17.451	-26.529	-11.915	-15.049	-17.451	-18.378	-20.738
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\tilde{V}_t$	-11.159	-13.586	-39.569	-20.858	-11.524	-30.654	-9.825	-70.002	-60.578	-8.405	-58.479	-12.373
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\tilde{\sigma}_t^2$	-7.219	-6.610	-8.617	-10.291	-6.839	-6.297	-4.832	-4.655	-7.611	-8.598	-6.547	-10.677
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2.4: Linear Granger causality test for stock returns and trading volume

In this table, Lx and Ly denote the number of lags of the detrended series of stock returns and trading volume changes. Both lag lengths are chosen via the Bayesian Information Criterion (BIC). The p-value indicates the marginal significance level of the F test statistic. For Panel A, the null hypothesis is that volume changes do not Granger cause stock return; for Panel B, the null is that stock returns do not Granger cause volume changes. And ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	H_0: Volume changes do not Granger cause stock returns				H_0: Stock returns do not Granger cause volume changes			
	Lx	Ly	F stat	p-value	Lx	Ly	F stat	p-value
US	1	1	0.083	0.821	1	8	0.621	0.433
UK	6	2	8.082	0.114	1	6	5.598*	0.056
Canada	1	1	3.905	0.298	1	11	1.937	0.191
Denmark	6	1	2.857	0.424	37	38	12.229***	0.000
Germany	1	1	0.548	0.594	1	5	8.245**	0.035
France	1	1	2.688	0.349	2	17	12.012***	0.000
HK	1	1	0.729	0.550	1	1	18.181	0.147
Japan	1	1	0.463	0.620	1	37	6.236**	0.017
NZ	1	1	0.655	0.567	1	1	1.455	0.441
Norway	7	1	5.508	0.317	1	1	9.833	0.197
Taiwan	2	1	10.722	0.211	1	1	73.999*	0.074
Singapore	1	1	1.814	0.407	1	2	14.767*	0.062
Argentina	2	1	2.279	0.327	1	1	15.052	0.161
Brazil	9	2	5.196	0.172	2	8	8.804***	0.009
Chile	3	1	1.305	0.554	1	1	0.013	0.927
Colombia	1	1	0.424	0.633	1	6	1.134	0.328
Greece	1	2	6.781	0.121	1	1	11.734	0.181
India	1	1	1.724	0.414	1	1	5.313	0.261
Korea	1	1	8.379	0.212	1	1	27.871	0.119
Malaysia	1	1	0.067	0.839	1	2	9.568*	0.091
Mexico	23	1	2.606	0.458	1	1	1.138	0.479
Philippine	1	1	2.927	0.337	1	11	21.370***	0.000
Poland	1	1	2.490	0.360	1	1	0.953	0.508
Thailand	1	1	8.294	0.213	1	7	68.413***	0.000

Table 2.5: Linear Granger causality test for trading volume and volatility

In this table, Lx and Ly denote the number of lags of the detrended series of trading volume and volatility. Both lag lengths are chosen via the Bayesian Information Criterion (BIC). The p-value indicates the marginal significance level of the F test statistic. For Panel A, the null hypothesis is that volume changes do not Granger cause volatility; for Panel B, the null is that volatility does not Granger cause volume changes. And ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	H_0: Volume changes do not Granger cause volatility				H_0: Volatility does not Granger cause volume changes			
	Lx	Ly	F stat	p-value	Lx	Ly	F stat	p-value
US	6	5	39.558***	0.000	8	1	7.267	0.279
UK	5	1	61.485*	0.097	6	1	5.597	0.312
Canada	20	1	12.562	0.219	11	1	4.138	0.367
Denmark	5	1	5.593	0.310	37	38	11.571***	0.000
Germany	1	1	160.987**	0.049	1	1	8.365	0.212
France	2	1	66.491*	0.086	17	1	7.484	0.281
HK	11	1	36.486	0.128	1	1	11.436	0.183
Japan	6	1	12.084	0.217	37	1	1.074	0.659
NZ	11	1	11.870	0.223	1	1	2.014	0.391
Norway	25	1	27.540	0.169	1	1	7.886	0.217
Taiwan	5	1	28.914	0.140	1	1	5.599	0.254
Singapore	7	1	62.567*	0.097	1	2	19.981**	0.046
Argentina	7	1	74.601*	0.089	1	1	5.574	0.255
Brazil	28	2	21.471**	0.045	8	2	7.087	0.129
Chile	7	1	5.812	0.309	1	1	0.897	0.517
Colombia	3	1	0.735	0.749	6	1	2.833	0.426
Greece	2	2	116.877*	0.065	1	1	13.273	0.170
India	5	1	0.153	0.949	1	1	1.441	0.442
Korea	25	1	2.958	0.434	1	1	0.319	0.672
Malaysia	20	1	40.674	0.123	1	1	9.945	0.195
Mexico	25	1	6.850	0.294	1	1	1.343	0.453
Philippine	8	1	28.742	0.143	11	1	8.660	0.208
Poland	1	1	15.202	0.159	1	1	5.316	0.261
Thailand	5	1	123.835*	0.068	7	1	20.334	0.169

Table 2.6: Nonlinear Granger causality test for stock returns and trading volume

In this table, Lx and Ly denote the number of lags on the residuals series, CS and TVAL denote the difference between the two conditional probabilities in equation 2.7 and the standardized test statistic in equation 2.9, respectively. For Panel A, the null hypothesis is that volume changes do not Granger cause stock returns; for Panel B, the null is that stock returns do not do not Granger cause volume changes. And *** denotes statistical significance at the 1% level.

	H_0: Volume changes do not Granger cause stock returns			H_0: Stock returns do not Granger cause volume changes		
	$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
US	1	0.0090	6.942***	8	0.0224	7.989***
UK	1	0.0069	5.980***	1	0.0091	8.156***
Canada	8	0.0190	8.825***	8	0.0165	7.146***
Denmark	1	0.0064	5.084***	1	0.0017	3.380***
France	1	0.0038	4.187***	8	0.0192	9.019***
Germany	1	0.0110	6.009***	8	0.0229	8.632***
HK	1	0.0061	6.334***	8	0.0282	8.147***
Japan	1	0.0111	5.147***	1	0.0055	6.025***
NZ	8	0.0222	5.463***	8	0.0262	8.705***
Norway	1	0.0063	4.263***	8	0.0231	9.078***
Taiwan	1	0.0041	4.049***	8	0.0234	8.267***
Singapore	1	0.0102	5.294***	8	0.0265	8.118***
Argentina	1	0.0082	5.135***	1	0.0052	5.629***
Brazil	1	0.0052	4.935***	8	0.0254	8.964***
Chile	1	0.0114	5.549***	1	0.0082	7.115***
Colombia	8	0.0245	6.028***	1	0.0152	8.777***
Greece	1	0.0053	4.767***	1	0.0117	7.096***
India	1	0.0115	5.027***	1	0.0039	3.901***
Korea	8	0.0256	8.140***	8	0.0292	7.897***
Malaysia	1	0.0085	4.610***	8	0.0241	8.463***
Mexico	1	0.0184	6.616***	8	0.0284	9.104***
Philippine	1	0.0055	4.217***	8	0.0213	8.453***
Poland	1	0.0053	4.355***	1	0.0106	6.097***
Thailand	1	0.0081	6.994***	1	0.0078	5.964***

Table 2.7: Nonlinear Granger causality test for trading volume and volatility

In this table, Lx and Ly denote the number of lags on the residuals series, CS and TVAL denote the difference between the two conditional probabilities in equation 2.7 and the standardized test statistic in equation 2.9, respectively. For Panel A, the null hypothesis is that volume changes do not Granger cause volatility; for Panel B, the null is that volatility does not Granger cause volume changes. And *** denotes statistical significance at the 1% level.

	H_0: Volume changes do not Granger cause volatility			H_0: Volatility does not Granger cause volume changes		
	$Lx = Ly$	CS	$TVAL$	$Lx = Ly$	CS	$TVAL$
US	1	0.0116	6.802***	8	0.0040	4.043***
UK	1	0.0076	6.369***	8	0.0085	7.424***
Canada	1	0.0570	5.455***	1	0.0079	6.860***
Denmark	1	0.0054	5.145***	1	0.0055	5.033***
France	1	0.0156	6.098***	8	0.0068	5.460***
Germany	1	0.0160	6.761***	8	0.0156	7.405***
HK	8	0.0153	6.424***	8	0.0168	6.527***
Japan	1	0.0139	6.671***	1	0.0146	6.502***
NZ	8	0.0165	7.005***	1	0.0109	6.492***
Norway	8	0.0153	5.850***	1	0.0057	5.347***
Taiwan	8	0.0107	7.354***	8	0.0046	4.543***
Singapore	1	0.0100	5.902***	1	0.0064	5.334***
Argentina	1	0.0198	8.902***	1	0.0099	5.552***
Brazil	1	0.0141	6.663***	1	0.0110	6.705***
Chile	8	0.0210	8.742***	1	0.0087	6.536***
Colombia	1	0.0082	6.383***	1	0.0108	6.472***
Greece	8	0.0180	7.003***	1	0.0059	5.435***
India	1	0.0096	6.533***	1	0.0098	5.723***
Korea	1	0.0077	6.444***	8	0.0112	6.486***
Malaysia	1	0.0087	7.396***	1	0.0090	5.401***
Mexico	1	0.0044	4.646***	8	0.0123	5.506***
Philippine	8	0.0132	8.223***	1	0.0042	4.459***
Poland	1	0.0092	5.701***	1	0.0125	5.555***
Thailand	8	0.0034	4.010***	8	0.0036	4.392***

Table 2.8: Linear Granger causality test for stock returns and trading volume: Robustness test

In this robustness test, we use data for the relatively tranquil period from 3 January 1994 to 31 December 2006 to perform the linear Granger causality test between stock returns and trading volume. In the table, Lx and Ly denote the number of lags of the detrended series of stock returns and trading volume changes. Both lag lengths are chosen via the Bayesian Information Criterion (BIC). The p-value indicates the marginal significance level of the F test statistic. For Panel A, the null hypothesis is that volume changes do not Granger cause stock return; for Panel B, the null is that stock returns do not Granger cause volume changes. And ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	H_0: Volume changes do not Granger cause stock returns				H_0: Stock returns do not Granger cause volume changes			
	Lx	Ly	F stat	p-value	Lx	Ly	F stat	p-value
US	1	1	0.716	0.398	1	1	14.472***	0.000
UK	1	1	1.410	0.235	1	1	6.150**	0.013
Canada	1	1	0.267	0.606	1	1	0.435	0.509
Denmark	1	1	12.199***	0.000	1	1	3.479*	0.062
Germany	1	1	3.832**	0.050	1	1	7.082***	0.008
France	1	1	0.396	0.529	1	1	6.922***	0.009
HK	1	1	4.432**	0.035	1	1	25.000***	0.000
Japan	1	1	0.782	0.377	1	1	12.912***	0.000
NZ	1	1	1.202	0.273	1	1	2.841*	0.092
Norway	1	1	0.662	0.416	1	1	0.611	0.435
Taiwan	1	1	7.952***	0.005	1	1	51.826***	0.000
Singapore	1	1	1.712	0.191	1	1	10.111***	0.002
Argentina	1	1	0.393	0.531	1	1	20.194***	0.000
Brazil	1	1	5.393**	0.020	1	1	1.753	0.186
Chile	1	1	0.336	0.562	1	1	0.126	0.722
Colombia	1	1	1.029	0.310	1	1	1.039	0.308
Greece	1	1	2.285	0.131	1	1	6.823***	0.009
India	1	1	0.632	0.427	1	1	2.208	0.138
Korea	1	1	1.733	0.188	1	1	15.887***	0.000
Malaysia	1	1	3.094*	0.079	1	1	8.263***	0.004
Mexico	1	1	0.640	0.424	1	1	5.605**	0.018
Philippine	1	1	0.021	0.885	1	1	15.063***	0.000
Poland	1	1	3.558*	0.059	1	1	19.225***	0.000
Thailand	1	1	18.485***	0.000	1	1	40.968***	0.000

Table 2.9: Linear Granger causality test for trading volume and volatility: Robustness test

In this robustness test, we use data for the relatively tranquil period from 3 January 1994 to 31 December 2006 to perform the linear Granger causality test between volatility and trading volume. In the table, Lx and Ly denote the number of lags of the detrended series of trading volume and volatility. Both lag lengths are chosen via the Bayesian Information Criterion (BIC). The p-value indicates the marginal significance level of the F test statistic. For Panel A, the null hypothesis is that volume changes do not Granger cause volatility; for Panel B, the null is that volatility does not Granger cause volume changes. And ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	H_0: Volume changes do not Granger cause volatility				H_0: Volatility does not Granger cause volume changes			
	Lx	Ly	F stat	p-value	Lx	Ly	F stat	p-value
US	1	1	2.482	0.115	1	1	34.002***	0.000
UK	1	1	0.821	0.365	1	1	1.664	0.197
Canada	1	1	0.297	0.586	1	1	6.319**	0.012
Denmark	1	1	2.068	0.151	1	1	0.713	0.399
Germany	1	1	4.424**	0.036	1	1	46.035***	0.000
France	1	1	1.065	0.302	1	1	27.202***	0.000
HK	1	1	11.7267***	0.000	1	1	47.437***	0.000
Japan	1	1	7.019***	0.008	1	1	1.561	0.212
NZ	1	1	0.323	0.569	1	1	6.520**	0.011
Norway	1	1	0.780	0.377	1	1	12.592***	0.000
Taiwan	1	1	3.109*	0.078	1	1	4.587**	0.032
Singapore	1	1	6.365**	0.012	1	1	17.932***	0.000
Argentina	1	1	2.258	0.133	1	1	53.355***	0.000
Brazil	1	1	1.599	0.206	1	1	27.421***	0.000
Chile	1	1	7.450***	0.006	1	1	4.124**	0.042
Colombia	1	1	0.628	0.428	1	1	0.711	0.399
Greece	1	1	4.465**	0.035	1	1	79.401***	0.000
India	1	1	0.455	0.500	1	1	7.095***	0.008
Korea	1	1	0.683	0.409	1	1	0.799	0.372
Malaysia	1	1	6.118**	0.013	1	1	17.889***	0.000
Mexico	1	1	0.476	0.490	1	1	1.404	0.236
Philippine	1	1	4.595**	0.032	1	1	17.274***	0.000
Poland	1	1	3.132*	0.077	1	1	12.723***	0.000
Thailand	1	1	18.830***	0.000	1	1	112.409***	0.000

Table 2.10: Nonlinear Granger causality test for stock returns and trading volume: Robustness test

In this robustness test, we use data for the relatively tranquil period from 3 January 1994 to 31 December 2006 to perform the nonlinear Granger causality test between stock returns and trading volume. In the table, Lx and Ly denote the number of lags on the residuals series, CS and TVAL denote the difference between the two conditional probabilities in equation 2.7 and the standardized test statistic in equation 2.9, respectively. For Panel A, the null hypothesis is that volume changes do not Granger cause stock returns; for Panel B, the null is that stock returns do not Granger cause volume changes. And *** and ** denote statistical significance at the 1% and 5% level, respectively.

	H_0: Volume changes do not Granger cause stock returns			H_0: Stock returns do not Granger cause volume changes		
	$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
US	1	0.047	6.686***	1	0.073	17.758***
UK	1	0.267	9.887***	1	0.117	18.346***
Canada	1	0.037	10.013***	1	0.140	16.333***
Denmark	1	0.054	8.567***	8	0.147	13.360***
France	1	0.025	5.632***	1	0.067	14.533***
Germany	1	0.043	9.775***	1	0.139	11.612***
HK	1	0.032	2.559***	1	0.138	6.885***
Japan	1	0.011	4.992***	1	0.773	17.524***
NZ	1	0.037	8.685***	8	0.116	21.511***
Norway	1	0.059	9.600***	8	0.144	27.957***
Taiwan	1	0.050	10.038***	1	0.076	18.820***
Singapore	1	0.019	2.747***	1	0.127	16.684***
Argentina	2	0.019	2.471***	8	0.067	4.781***
Brazil	1	0.010	2.120**	8	0.033	9.621***
Chile	1	0.005	1.788**	8	0.069	7.537***
Colombia	1	0.020	2.630***	1	0.053	8.841***
Greece	8	0.006	3.309***	8	0.067	9.995***
India	8	0.017	4.160***	8	0.086	7.773***
Korea	8	0.027	2.698***	8	0.088	11.324***
Malaysia	8	0.037	2.853***	8	0.048	13.654***
Mexico	1	0.004	1.749**	8	0.049	13.563***
Philippine	1	0.056	2.986***	8	0.021	11.027***
Poland	2	0.018	2.530***	8	0.087	7.773***
Thailand	1	0.003	1.722**	8	0.074	13.336***

Table 2.11: Nonlinear Granger causality test for trading volume and volatility: Robustness test

In this robustness test, we use data for the relatively tranquil period from 3 January 1994 to 31 December 2006 to perform the nonlinear Granger causality test between volatility and trading volume. In the table, Lx and Ly denote the number of lags on the residuals series, CS and TVAL denote the difference between the two conditional probabilities in equation 2.7 and the standardized test statistic in equation 2.9, respectively. For Panel A, the null hypothesis is that volume changes do not Granger cause volatility; for Panel B, the null is that volatility does not Granger cause volume changes. And ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

	H_0: Volume changes do not Granger cause volatility			H_0: Volatility does not Granger cause volume changes		
	$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
US	3	0.003	2.327**	1	0.043	3.557***
UK	2	0.035	1.985**	1	0.034	4.011***
Canada	8	0.014	1.918**	1	0.024	3.424***
Denmark	1	0.082	3.302***	1	0.109	3.518***
France	1	0.043	2.005**	1	0.133	3.766***
Germany	1	0.015	3.239***	1	0.015	3.238***
HK	1	0.043	1.734**	8	0.245	7.633***
Japan	1	0.014	2.620***	1	0.154	4.218***
NZ	1	0.008	1.998**	1	0.112	5.443***
Norway	1	0.024	2.565***	1	0.132	6.759***
Taiwan	7	0.015	2.290**	1	0.123	8.460***
Singapore	1	0.019	2.657***	8	0.243	4.005***
Argentina	5	0.023	2.269**	1	0.094	3.238***
Brazil	3	0.116	3.335***	1	0.175	8.013***
Chile	1	0.026	2.283**	1	0.004	4.082***
Colombia	1	0.011	1.882**	1	0.008	6.109***
Greece	6	0.182	4.518	8	0.072	2.518**
India	8	0.087	1.752**	1	0.004	3.014***
Korea	1	0.061	2.014**	1	0.040	3.392***
Malaysia	1	0.039	1.556*	1	0.094	4.175***
Mexico	1	0.040	1.700**	2	0.136	7.044***
Philippine	8	0.025	2.064**	1	0.070	5.904***
Poland	1	0.008	1.386*	6	0.014	3.495***
Thailand	2	0.001	1.812**	1	0.216	9.339***

Table 2.12: Summary for significant relationship between return and volume and between volatility and volume

This table summarizes the number of markets which show significant Granger causality relationship between stock returns and trading volume, and trading volume and volatility for the full and shorter sample.

Causality	Significance	Linear (Full sample)	Linear (Shorter sample)	Nonlinear (Full sample)	Nonlinear (Shorter sample)
Return to volume	1 %	5	14	24	24
	5 %	2	2	0	0
	10%	4	2	0	0
	Total	**11**	**18**	**24**	**24**
Volume to return	1%	0	5	24	20
	5%	0	1	0	4
	10%	0	2	0	0
	Total	**0**	**8**	**24**	**24**
Volume to volatility	1%	1	4	24	7
	5%	2	6	0	15
	10%	6	1	0	2
	Total	**9**	**11**	**24**	**24**
Volatility to volume	1%	1	14	24	23
	5%	1	4	0	1
	10%	0	0	0	0
	Total	**2**	**18**	**24**	**24**

Chapter 3

What is the driving force of stock prices? Fundamental factors and interest rate

3.1 Introduction

The extant literature has seen extensive research on the behavior of stock price and its driving factors. The topic on driving factors of stock prices was first raised in the early 1930s by Williams (1938), and then followed by Keynes (1936). Since then, huge amount of work has been done in this regard, yet there is still no consensus on which factor has the main contribution towards the growth of stock prices. From the vast literature, we summarize contributing factors as follows: 1) dividend and earnings (Lamont (1998), Shiller (1990) , and Hodrick (1992)), 2) investor behaviors (Bizjak, Brickley, and Coles (1992)) and 3) interest rate (Kang, Pekkala, Polk, and Ribeiro (2011), Hjalmarsson (2010) and Cremers (2002)). These factors are known as the direct factors, and taken together to estimate in the joint system.

First of all, a strand of literature has focused on the relationship between stock price and dividend. Some of the studies found positive correlation between stock returns and dividend (e.g. Gourieroux and Jasiak (2001); Park (2010); Campbell and Ammer (1993); Kothari and Shanken (1992); Uddin and Chowdhury (2005)).

While other researching papers have documented negative relationship, with a note that negative relationship exists for short term only, see for example Uddin and Chowdhury (2005) and Fama and French (1988). At the same time, the relationship between stock return and earnings attracts no less attention. The positive relationship between stock prices and future earnings is commonly documented in many researching papers. For example, Wang (2003), Campbell and Shiller (1987), Datta and Dhillon (1993), Nichols and Wahlen (2004), Felthman and Ohlson (1995), Ohlson (1995), just to name a few. However, it is also noted in Jaffe, Keim, and Westerfield (1989) that the relationship between earnings and stock prices varies over the different time periods. With regard to the relationship between stock prices and interest rates, we cannot find many research articles except only a few. Researchers often use different types of interest rates to examine the relationship. The commonly used interest rates include term spread, risk free rate, short term and long term interest rate. Therefore it is not surprising to see a mixture of findings about the relationship between interest rate and stock prices. For instance, positive relationship is found in Seelig (1974), and negative relationship is found in Shiller and Beltratti (1992).

In this paper, we try to address the following questions. First, how do the fundamental factors including interest rate, dividend and earnings affect stock prices? Second, do these factors affect stock prices in a systematic way across different stock markets? Third, in each individual market, which factor plays the major role in determining stock prices? And finally, how much information does interest rate carry to fundamental prices, and whether or not does information help to increase the predictive power of fundamental prices. In order to answer these questions, we employ the dynamic present value model and a 4-variable VAR system in our paper. Dynamic present value model allows the expected return to be time-varying, which is a more realistic assumption. Based on the approach initiated by Campbell and Shiller (1988), we use a 4-variable system in which we separate the risk free rate from the rate of return. This allows us to explicitly examine the effect of risk free rate on stock prices. We include 22 international markets which are divided into developed and developing groups in our study, the sample markets are able to support global evidence for our researching questions. And for each market, we sample from the most beginning when data starts to become available in the Datastream. The longest data sample is 48 years for the UK and the shortest data sample is 13 years and 6 months for Brazil. We divide the markets into two groups: developed and developing markets, so that the difference between these two categories of markets can be compared and clearly observed.

This paper contributes to the existing literature in the following aspects. First, we jointly consider the effects of earnings, dividend, risk free rate and risk premium in a 4-variable VAR model, which allows us to observe the endogenous effect of each variable and avoids potential inaccuracy problems commonly encountered in partial system, such as Chuang, Liu, and Susmel (2012). In addition, combination of dynamic present value model and the VAR model makes the whole framework forward-looking and dynamic in nature. Second, the decomposition of rate of return into risk free rate and risk premium allows the explicit investigation of the effect of risk free rate on stock prices. And finally, our data set covers a wide range of international markets over a long period, which allows an extensive investigation of the effect of earnings, dividend and risk free rate.

The rest of the paper is organized as follows: section 2 describes the data and preliminary statistical results. Sections 3 explains the methodology. Section 4 provides and discusses the empirical results. And Section 5 concludes.

3.2 Data and preliminary results

We examine 22 international stock markets, including developed and developing markets, over a longest possible sample periods available in Datastream. The sample markets and sample periods are summarized in Table 3.1. We use the Datastream global equity index level 1 as the market index for each individual market. The Datastream global equity market index is calculated by Datastream and it covers all different sectors in a country. The main advantage of using Datastream global equity index is that it forms a comprehensive and comparable standard for equity research. It also provides good depth of data for each index, including total returns, price-earnings ratios, dividend yield, market value and etc. We use monthly data in this paper. The monthly earnings are calculated by the formula $\frac{Market\ value}{PE\ ratio}$, and dividend is calculated by the formula $dividend\ yield \times market\ vlaue$.

The 3-month Treasury Bill (TB) rate, if available, is used as the risk free rate. When the 3-month Treasury bill rate is not available, 3-month money market rate, or overnight financial rate, or 3-month certificate rate is used as the risk free rate[1]. These interest rates are obtained from the Datastream, International Monetary Foundation (database) and the OECD statistic extracts, respectively.

We provide the preliminary statistics for the returns, risk free rates, dividends and earnings of the developed and developing markets in Tables 3.2 and 3.3, respectively. Looking at the return statistics, we cannot see any obvious difference between the developing and developed markets in terms of the level of returns. In the developed

[1]We use 3-month TB rate as the proxy for risk free rate for the US, Canada, the UK, Germany, Hong Kong, New Zealand, Singapore, Malaysia and Greece; 3-month money market rate for Taiwan, Thailand, India and Korea; 3-month interbank rate for Denmark, Norway. In addition, in the light of Datastream report, I use the same period overnight financing rate for Brazil and certificates rate for Colombia, Indonesia and Mexico.

markets, the highest mean of return is in Hong Kong (0.011) and the lowest is in Taiwan (0.004). In the developing markets, the highest mean return (0.013) is found both in Chile and Mexico and the lowest mean return (0.002) is found both in Indonesia and Argentina. However, the return in developing markets seems to be more volatile than those in developed markets, evidenced by much higher coefficients of variation. The autocorrelation statistics for the return in developed markets are between -0.043 (New Zealand) and 0.118 (the UK). And in the developing markets, the autocorrelation statistics are between 0.038 (Korea) and 0.168 (Chile). The normality test statistics suggest that none of the markets has normal return, and normality is strongly rejected.

Regarding the risk free interest rate, the developed markets seem to have slightly higher risk free rates than those of developing markets. We also note that New Zealand has the most remarkable risk free rate of return, which may lead to a big difference in investors' activities compared with other countries. The coefficient of variation of the risk free interest rate in New Zealand is 44.07, which is comparable with other developed countries. In fact, we note that in developed markets, the coefficient of variation (CV) for risk free interest rates does not vary much across countries: it ranges from 35.21 to 75.12, which indicates a moderate and consistent level of variation across developed countries. However, in developing countries, we see extremely high coefficient of variation. For example, in Indonesia and Brazil, the coefficients exceed 400 and in Greece and Mexico, the coefficients even exceed 700. In other developing countries, the coefficients are in the range of 30.92 and 98.32. So we can say that the variation of risk free interest rate is not consistent across developing countries. Finally, high degree of autocorrelation in risk free rates is commonly observed in all of the markets considered in our paper.

The preliminary statistics for the dividend and earnings tell us the follows. First, dividend and earnings are relatively higher in developed markets and the US ranks the first. Second, the coefficients of variation are generally higher for dividend than for earnings, suggesting that dividend tends to be more volatile than earnings. This is true in both developing and developed markets, with two exceptions in Korea and Argentina. We also see high level of autocorrelation in both dividend and earnings in all the considered markets.

3.3 Methodology

The main methodology employed is from Geltner and Mei (1995) and Chen and Fraser (2010). Let's start with the dynamic present value model:

$$P_t = E_t \sum_{i=1}^{\infty} \frac{1}{\prod_{j=1}^{i}(1+\rho_{t+j})} C_{t+i} \tag{3.1}$$

where P_t is stock price at the end of period t, C_{t+i} is cash flow[2] received by shareholders at the end of time period $t+i$, and ρ_{t+j} is a discount rate for time period $t+j$. The discount rate is allowed to be time-varying, which relaxes the assumption of the traditional present value model and considers the fact that investors' required rate of return may be time-varying. The above equation could also be written as follows:

$$P_t = \frac{1}{1+\rho} E_t(P_{t+1} + C_{t+1}) \tag{3.2}$$

Defining one-period log gross return $R = ln(1+\rho)$, the equation (3.2) can be transformed into the following:

$$R_{t+1} = ln(P_{t+1} + C_{t+1}) - ln(P_t) \tag{3.3}$$

The above nonlinear relationship can be linearized using the first-order Taylor's expansion (Campbell and Shiller, 1988; Chen and Fraser, 2010) [3]:

$$R_{t+1} = k + \mu(p_{t+1} - c_{t+1}) - (p_t - c_t) + \Delta c_{t+1} \tag{3.4}$$

where $p = ln(P)$, $c = ln(C)$, $\mu = \frac{1}{1+exp\overline{(c-p)}}$ and $k = -ln\mu - (1-\mu) \times \overline{c-p}$.

[2]Following Chen and Fraser (2010), cash flow is defined as cash dividend and earnings.

[3]Although the linearized relationship is an approximation, the approximation error is in practice minor (Campbell and Shiller, 1988).

Abbreviating $(p_t - c_t)$ as pc_t, we have:

$$pc_t = k + \mu pc_{t+1} + \Delta c_{t+1} - R_{t+1} \tag{3.5}$$

Equation 3.5 implies that logged P/C ratio is stationary, namely $pc_t \sim I(0)$. Repeatedly substituting for $pc_{t+1}, pc_{t+2}, \cdots$ on the right hand side of equation 3.5 and imposing the terminal condition, $\lim_{j\to\infty} \mu^j p_{t+j} = 0$, so that rational bubbles are not allowed, we get the following:

$$pc_t = \frac{k}{1-\mu} + \sum_{j=0}^{\infty} \mu^j \Delta c_{t+j+1} - \sum_{j=0}^{\infty} \mu^j R_{t+j+1} \tag{3.6}$$

If $c_t \sim I(1)$ then it indicates that Δc_t is stationary, namely $\Delta c_t \sim I(0)$.Taking conditional expectations of both sides of equation 3.6, we have:

$$pc_t = \frac{k}{1-\mu} + \sum_{j=0}^{\infty} \mu^j E_t^c \Delta c_{t+j+1} - \sum_{j=0}^{\infty} \mu^j E_t^c R_{t+j+1} \tag{3.7}$$

Equation 3.7 indicates that the log P/C ratio is equal to the expected discounted value of future cash flow growth in excess of one-period expected return, plus a constant. We further decompose the rate of return R_{t+j+1} into two components: risk free rate r_{t+j+1} and risk premium s_{t+j+1}, and we get the following equation:

$$pc_t = \frac{k}{1-\mu} + \sum_{j=0}^{\infty} \mu^j E_t^c \Delta c_{t+j+1} - \sum_{j=0}^{\infty} \mu^j E_t^c r_{t+j+1} - \sum_{j=0}^{\infty} \mu^j E_t^c s_{t+j+1} \tag{3.8}$$

where all lower case letters in equation 3.8 indicate the logarithm of variables. When dividend/earnings is plugged in the model as cash flow, we call the above models as the dividend/earnings discount models. However, there are some difficulties in direct implementing this model due to the fact that the expectation of interest rate and risk premium in equation 3.8 are not directly observable. Therefore, the VAR approach used in Campbell and Shiller (1988) is employed in this paper to allow the cash flow growth and interest rate to be forecasted within a framework of a 4-variable VAR:

$$\begin{bmatrix} pc_t \\ \Delta c_t \\ r_t \\ s_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} pc_{t-1} \\ \Delta c_{t-1} \\ r_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix} \tag{3.9}$$

The variables in the vectors are demeaned. The above VAR system can be compactly written as:

$$z_t = Az_{t-1} + \varepsilon_t \tag{3.10}$$

where $z_t = (pc_t, \Delta c_t, r_t, s_t)'$, ε_t is a vector of error term, and A is (4×4) matrix of coefficients:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \tag{3.11}$$

The value of z_t in j periods ahead can therefore be forecasted as follows (Campbell and Shiller, 1987; Sargent, 1979):

$$E_t(z_{t+1}) = A^j z_t \tag{3.12}$$

Equation 3.8 can therefore be translated into constraints on the VAR. Specifically, we first need to define some unit vectors to pick up relevant variables by following Campbell and Shiller (1988): $e_1 = [1, 0, 0, 0]', e_2 = [0, 1, 0, 0]', e_3 = [0, 0, 1, 0]', e_4 = [0, 0, 0, 1]'$, such that $e_1' z_t = pc_t, e_2' z_t = \Delta c_t, e_3' z_t = r_t$ and $e_4' z_t = s_t$. We can then replace the expectations in equation 3.8 with forecasted values based on the VAR estimation to get estimated fundamental p/c ratios: pc^*.

$$\begin{aligned} pc_t^* &= \frac{k}{1-\mu} + \sum_{j=0}^{\infty} \mu^j (e_2^{'} - e_3^{'} - e_4^{'}) A^{j+1} z_t && (3.13) \\ &= \frac{k}{1-\mu} + (e_2^{'} - e_3^{'} - e_4^{'})(A + \mu A^2 + \mu^2 A^3 + \cdots) z_t \\ &= \frac{k}{1-\mu} + (e_2^{'} - e_3^{'} - e_4^{'}) A (I - \mu A)^{-1} z_t && (3.14) \end{aligned}$$

Note that the variables in the VAR are transformed into deviation from their means, the constants in equation 3.14 is therefore eliminated. We also use equation 3.14 to implement the tests of differences between actual stock prices and their fundamental prices warranted by cash flow.

$$p_t^* = pc_t^* + c_t \qquad (3.15)$$

In equation 3.15, Chen and Fraser (2010) generate a series for the logged stock prices from the logged fundamental price/cash flow ratio. Hence the logged fundamental stock price index, p_t^* is warranted by cash flow in equation 3.15 and is the optimal forecast of the log-linearized present value of cash flows.

Hence the restriction $pc = pc^*$, i.e., the null hypothesis that the observed p/c ratio (hence actual stock price) equals the fundamental p/c ratio (or the forecasted p/c ratio based on the VAR framework), can be rewritten as:

$$e_1^{'} z_t = (e_2^{'} - e_3^{'} - e_4^{'}) A (I - \mu A)^{-1} z_t \qquad (3.16)$$

where the LHS picks out the observed p/c ratio and the RHS constructs the fundamental p/c ratios. The above is equivalently written as:

$$e_1^{'} - (e_2^{'} - e_3^{'} - e_4^{'}) A (I - \mu A)^{-1} = 0 \qquad (3.17)$$

This includes a set of 4p (number of variables $\times$ lag length) nonlinear restrictions in terms of the individual coefficient. We test these restrictions by the nonlinear Wald test.

In order to shed some light on the reason why in some countries either dividend or earnings does not have explanatory power on stock prices, we examine the effect of risk free interest rate by excluding the interest rate from the fundamental price formation process. We want to examine if risk free interest rate carries some noise which might obscure or disturb the predicting power of either dividend or earnings. This also helps to distinguish that if risk free interest rate increase or decrease the predictive power of dividend/earnings fundamental prices. An indirect method is adopted to investigate the effect of interest rate. Specifically, we first set the null vector e_3 to be $e_3 = [0, 0, 0, 0]'$, so that a fundamental p/c ratio without the effect of interest rate can be constructed. Then, we re-estimate the VAR system regarding three variables and the nonlinear Wald test is used to examine the deviation of the observed p/c ratio from the fundamental p/c ratio without the effect of interest rate. We then compare the Wald test results with their counterparts when interest rate is included to see the effect of interest rate.

3.4 Empirical results

As Bansal, Dittmar, and Kiku (2009) and Vuolteenaho (2002) assert that for the VAR model to be stable, the variables in the model need to be stationary. We first test the stationarity for all the variables and the unit root test results are presented in Table 3.4. Stationarity of log price/earnings ratio, log price/dividend ratio, interest rate and risk premium are rejected for most of the markets, and dividend and earnings growth rates appear to be stationary in all markets. As the variables are nonstationary, they are not allowed to directly put into the VAR model. The method widely used to cope with this problem is adopting the VECM (Vector Error Correction Model). The VECM firstly requires the variables with their first difference, and can correct errors due to using the nonstationary variables. The results in Table 3.5 indicate that first difference of these variables are stationary. The VECM secondly requires that all used variables are cointegrated, therefore Johansen test[4] needs to be conducted between exogenous variable of logged price/dividend ratio (logged price/earnings ratio) and endogenous variables of logged cash flow growth, logged risk free rate and logged excess return to test of cointegration. As a result, cointegration is found among these variables, shows that the variables have a long-run stable relationship. Meanwhile, the result allows us to put the variables into the VECM [5].

3.4.1 Results of the VAR procedure

Table 3.6 and Table 3.7 report the VAR estimation results for developed and developing markets, respectively. All estimations reported in Table 3.6 and Table

[4]The critical values used in tests are taken from Osterwald-Lenum (1992), and the results are shown in Eviews intuitively, therefore are not reported.

[5]The VECM does not accept nonstationary variables unless they are cointegrated.

3.7 are corrected by using the VECM due to nonstationary variables of interest rate and excess return. The optimal lag length l imposed on the VAR model is chosen by the BIC criterion. It is 1 for both dividend and earnings models in all of the markets except for Norway where it is 2 for the earnings model and 1 for the divided model. This means that the earnings model requires more lags than the dividend model in Norway. We also report in the tables the Q statistics, which are the Ljung-Box test statistics for significance of up to the second autocorrelation coefficient. From the table we can see that none of the Q statistics is significant, even at the 10% conventional level. This indicates that the model residuals are serially uncorrelated and therefore the VAR specifications for all the markets are adequate.

Among the four variables, the log price/cash flow ratio has the highest R-squared. As expected, the highest R-squared of the VAR shows that a lagged log p/c ratio naturally contains more explanatory power for its current value than any other variables do.

3.4.2 Results for Non-linear Wald Tests

Non-linear Wald tests are employed to test whether the fundamental p/c ratios are equal to the observed market p/c ratios. This hypothesis is implied by the constraints in equation 3.17. If the fundamental p/c ratios are equal to the observed p/c ratio, then the constraints should hold. Otherwise, the constraints will be broken. We apply the nonlinear Wald test for both the dividend model and earnings model. The dividend model is equation 3.8 when dividend is used as cash flow, while the earnings model is the same equation 3.8, but with earnings plugged in as cash flows. The effect of risk free interest rate is examined separately. The test results are presented in table 3.8, for the developed and developing countries, respectively.

Mixed results are obtained for the nonlinear Wald test. We will first look at the picture for the more developed countries and then the developing markets. Among 11 developed markets, we observe 3 countries (Canada, The UK and Hong Kong) in which earnings tends to have more explanatory power than dividend does at the 5% conventional significance level. For example, the earnings model in Canada cannot be rejected as the Wald test statistic is only 4.824 with the p-value being 0.185, while the dividend model is safely rejected as the Wald test statistic is 35.506 and the p-value is zero. This suggests that earnings contains more information than dividend does for p/c ratios, and hence for stock prices in these countries. However, we see a completely different story in 4 other countries including France, Denmark, Taiwan and Singapore, where dividend seems to have more explanatory power than earnings does. Only in 3 countries including the US, Germany, and New Zealand, we observe that neither dividend model nor earnings model can be rejected. In other words, both dividend and earnings carry important information for p/c ratios and hence stock prices in these countries. And in an interesting country, i.e. Norway, both the dividend model and the earnings model are rejected, meaning that neither dividend nor earnings carry useful information for stock prices. The same results can also be concluded in Figure 3.1 and 3.2. The departure between the actual stock prices and fundamental stock prices constructed by dividends and earnings is able to show the predictive power of fundamental factors. As smaller gap is observed, the stronger predictability of fundamental factors can be found, and vice versa.

3.4.3 Adjusted Results for VAR System and Non-linear Wald Tests

In Tables 3.9-3.11, we examine the effect of interest rate by excluding interest rate in the process of constructing the fundamental prices, and carry out the Wald test for the constraint where interest rate is excluded. For the new constraint, we re-estimate the whole VAR system, and adjusted results are then shown in Table 3.9-3.11. First of all, table 3.9 and 3.10 report the adjusted VAR statistics for all developing and developed markets. The p/c ratio with the highest R-square and the strongly significant Q-statistics are included. The results reported in Tables 3.6 and 3.7, Tables 3.9 and 3.10 also lay the prerequisite for the non-linear Wald test for the new restriction that excludes the effect of interest rate.

Table 3.11 reports nonlinear Wald test results after adjustment of VAR system (with 3-variable). In Norway, Chile, Colombia and Argentina, cutting out the effect of interest rate does bring the interesting stories about the deviation from fundamental p/c ratios to observed p/c ratios. For Norway, the fundamental stock price built by both dividends and earnings seems to have explanatory power for actual stock prices, which cannot be rejected by neither models at the conventional 1% significance level. It means that fundamental stock prices regarding dividends and earnings do seem to contain useful information for predicting the actual stock prices. For another, after excluding the information of interest rate, the fundamental prices constructed by earnings seem to increase the predictability for the actual stock price in Colombia. P-value for fundamental prices regarding earnings increases to 0.305 which shows the strongly predictive power for actual prices in the market of Colombia. Colombian fundamental stock price regarding dividends cannot predict actual stock prices, due to zero p-value for dividend model. We also examine the predictability of adjusted fundamental stock prices for Chile and Argentina, the obscuring effect of interest rate is observed. As we exclude the information of interest rate from fundamental stock prices, the predictive power of both dividends and earnings models dose not turn better obviously. For other markets, all results change by more or less amount, showing the interest rate plays the different roles in sample countries.

When examining the possibly debatable factor of risk free interest rate, some various results are obtained, especially in Norway, Chile, Colombia and Argentina. As interest rate is prevented from entering into formation process of the fundamental stock prices, the explanatory power of both dividends and earnings on stock price appears in Norway, meaning that the fundamental stock price without the information of interest rate could be much closer to the actual one. In Colombia, the earnings model starts having more explanatory power with the restriction that excludes the effect of interest rate. However, in countries of Chile and Argentina, excluding interest rate cannot help provide a better estimate of fundamental prices. Therefore, our future research will endeavor to take a further step in this direction to look for other potential factors that may affect the explanatory power of dividend and earnings on stock prices.

To summarize, we observed dividend's explanatory power in 7 out of the 11 examined developed countries and in 3 out of the 11 examined developing markets. This result suggests that dividend does have explanatory power on stock prices, although not in all countries. This is consistent with the findings in existing literature such as Park (2010), Campbell and Ammer (1993), Kothari and Shanken (1992), Uddin and Chowdhury (2005) Campbell and Shiller (1988), and so on. It also suggests that dividend seems to have stronger explanatory power in developed countries than in developing countries.

Second, in 6 out of the 11 developed countries and in 6 out of the 11 developing countries, we observed the explanatory power of earnings. But again, the result is not consistent across countries in that some countries do not see the explanatory power of earnings.

Admittedly, the risk free interest rate in fundamental stock prices has an important influence on predicting stock prices in most of countries rather than Norway, Chile, Colombia and Argentina. As the debatable factor of interest rate is prevented from entering into the fundamental prices, the predictive ability of fundamentals' is increasingly accurate, such as Norway (both dividends and earnings model) and Colombia (earnings model). However, excluding interest rate cannot increase the explanatory power of fundamentals' for Chile and Argentina. Through comparing the new constraint with the original constraint, the effect of interest rate therefore is observed in all sample markets.

3.5 Conclusion

This paper explored the impact of fundamental factors on stock prices in twenty-two international markets with the VAR model and nonlinear Wald tests. By employing the dynamic present model developed by Geltner and Mei (1995) and Chen and Fraser (2010), we avoid the drawbacks of the basic present value model and allow the discount rate to be time-varying. We consider three fundamental factors, namely, dividend, earnings, and interest rate. And we use the dynamic present value model to calculate how far the actual prices deviate from fundamental prices in the sample markets when different fundamental factors are taken into consideration. When dividend is used in the dynamic present value model, we call the model as divided model; and when earnings are used, we call it earnings model.

With the dividend model, we observed dividend's explanatory power in 7 out of the 11 examined developed countries and in 3 out of the 11 examined developing markets. This result suggests that dividend does have explanatory power on stock prices, although not in all countries. For the earnings model, 6 out of the 11 developed countries and 6 out of the 11 developing countries see the explanatory power of earnings in predicting stock prices. But again, the result is not consistent across countries in that some countries do not see the explanatory power of earnings. The obtained results also suggest that the dividend discount model has a stronger power than earnings in some markets such as the US, France, New Zealand, Taiwan and Singapore, while in some other markets, such as Canada, the UK and Germany, earnings seems to be more likely dominating than dividend with regard to the predicting power on stock prices.

There is an interesting phenomenon that we observed in Norway, Chile, Colombia and Argentina, where neither the dividend discount model nor the earnings discount model can be used to explain the time path of stock price. We therefore further examine the new constraint that uses the null vector to exclude the effect of interest rate, which can remove the noise and obscure placed by interest rate in fundamental stock prices so that, the predicting role of time-varying risk free interest rate could be summarized by the differences between nonlinear Wald test's results of fundamental models and adjusted fundamental models. The results shows that in Norway and Colombia, after eliminating interest rate from the initial constraint, the adjusted models produce prices that are closer to observed market prices. However, this result does not help explaining the phenomenon in Chile and Argentina where neither dividend nor earnings carries useful information towards future stock prices. Therefore our future research will endeavor to take a further step in this direction to look for other potential factors that may affect the explanatory power of dividend and earnings on stock prices.

Table 3.1: The markets and their sample periods.

Developed markets	
US	February 1973 - January 2013
Canada	February 1973 - January 2013
UK	January 1965 - January 2013
Germany	January 1973 - January 2013
France	January 1973 - January 2013
Hong Kong	January 1973 - January 2013
Denmark	February 1973 - January 2013
New Zealand	February 1988 - January 2013
Norway	February 1980 - January 2013
Taiwan	May 1988 - January 2013
Singapore	January 1973 - January 2013
Developing markets	
Thailand	February 1987 - January 2013
Malaysia	February 1986 - January 2013
India	January 1990 - January 2013
Korea	October 1987 - January 2013
Chile	July 1989 - January 2013
Brazil	June 1999 - January 2013
Colombia	March 1993 - January 2013
Greece	January 1990 - January 2013
Indonesia	February 1991- January 2013
Mexico	July 1990 - January 2013
Argentina	July 1997 - January 2013

Table 3.2: Summary statistics for monthly return, risk-free rates, dividend and earnings for developed markets

	US	Canada	UK	Germany	France	Hong Kong	Denmark	New Zealand	Norway	Taiwan	Singapore
Return											
Mean	0.009	0.009	0.010	0.009	0.010	0.011	0.010	0.009	0.010	0.004	0.008
SD	0.053	0.059	0.053	0.058	0.065	0.101	0.056	0.063	0.079	0.109	0.084
Autocorrelation	0.051	0.037	0.118	0.034	0.063	0.090	0.087	-0.043	0.050	0.099	0.102
CV	588.8	655.6	530.0	644.4	650.0	918.0	560.0	700.0	790.0	2725	1050
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Risk-Free Rate %											
Mean	2.875	3.044	4.102	2.851	2.731	2.840	5.028	8.040	6.693	5.028	1.698
SD	2.162	1.589	2.198	1.304	1.589	2.573	3.335	3.543	3.993	3.239	1.214
Autocorrelation	0.985	0.985	0.985	0.988	0.990	0.955	0.970	0.972	0.964	0.948	0.916
CV	75.21	52.25	53.61	45.77	58.18	35.21	66.33	44.07	59.66	64.42	71.49
ND	0.000	0.000	0.002	0.000	0.000	0.017	0.000	0.000	0.000	0.000	0.000
*Dividend(U.S.$*$10^6$))*											
Mean	6.919	0.679	2.135	0.773	1.188	0.655	0.057	0.067	0.133	0.418	0.174
SD	5.386	0.845	2.172	0.836	1.140	0.801	0.064	0.084	0.183	0.427	0.254
Autocorrelation	0.990	0.989	0.995	0.991	0.994	0.990	0.983	0.979	0.984	0.989	0.988
CV	77.833	124.499	101.743	108.087	118.644	122.357	113.48	124.49	138.40	102.15	145.97
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
*Earnings(U.S.$*$10^6$)*											
Mean	3.018	0.268	0.851	0.364	0.443	0.284	0.237	0.093	0.478	0.861	0.700
SD	1.598	0.204	0.464	0.206	0.286	0.246	0.204	0.043	0.386	0.691	0.597
Autocorrelation	0.991	0.990	0.994	0.991	0.994	0.988	0.987	0.966	0.984	0.988	0.984
CV	52.94	76.16	54.57	56.80	64.71	86.66	86.07	46.24	80.75	80.26	85.28
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.042	0.000	0.000	0.000

Note: CV (coefficient of variation) is mean standard deviation multiplied by 100. ND is p-value of Jarque-Bera test for normality distribution.

Table 3.3: Summary statistics for monthly return, risk-free rates, dividend and earnings for developing markets

	Thailand	Malaysia	India	Korea	Chile	Brazil	Colombia	Greece	Indonesia	Mexico	Argentina
Return											
Mean	0.009	0.008	0.008	0.006	0.013	0.009	0.011	0.004	0.002	0.013	0.002
SD	0.109	0.091	0.105	0.109	0.071	0.103	0.084	0.098	0.087	0.092	0.092
Autocorrelation	0.053	0.042	0.109	0.038	0.168	0.089	0.121	0.070	0.097	0.105	0.092
CV	1211	1137	1312	1816	546	1144	763.6	2450	4350	707.7	4600
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.079
Risk-Free Rate %											
Mean	4.175	3.605	7.234	6.418	2.922	1.486	2.200	1.087	1.435	1.134	2.922
SD	4.105	1.559	2.237	4.278	2.137	6.983	1.251	7.880	6.508	8.292	2.137
Autocorrelation	0.984	0.983	0.965	0.973	0.967	0.887	0.993	0.991	0.964	0.957	0.986
CV	98.32	43.25	30.92	59.13	73.14	469.91	56.86	724.93	453.52	731.21	73.13
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
*Dividend(U.S.$*$10^6$))*											
Mean	0.150	0.236	0.255	0.297	0.169	0.098	0.090	0.099	0.114	0.173	0.079
SD	0.148	0.192	0.270	0.242	0.151	0.092	0.128	0.080	0.136	0.136	0.055
Autocorrelation	0.984	0.985	0.984	0.987	0.984	0.986	0.985	0.990	0.985	0.977	0.974
CV	98.714	81.214	106.099	81.599	89.643	93.88	140.22	85.08	119.30	78.613	69.62
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.062
*Earnings(U.S.$*$10^6$)*											
Mean	0.039	0.054	0.111	0.144	0.031	0.074	0.015	0.288	0.021	0.022	0.031
SD	0.032	0.037	0.117	0.130	0.025	0.046	0.007	0.192	0.025	0.017	0.033
Autocorrelation	0.981	0.981	0.988	0.988	0.985	0.983	0.947	0.989	0.976	0.988	0.983
CV	83.38	70.15	105.62	89.79	80.52	62.16	46.67	66.67	119.04	77.27	106.45
ND	0.000	0.000	0.000	0.000	0.000	0.000	0.057	0.000	0.000	0.000	0.000

Note: CV (coefficient of variation) is mean standard deviation multiplied by 100. ND is p-value of Jarque-Bera test for normality distribution.

Table 3.4: Standard unit root test for variables in the VAR model for sample markets

	US	Canada	UK	Germany	France	Hong Kong	Denmark	New Zealand	Norway	Taiwan	Singapore
pd_t	-1.034	-1.782	-2.903	-1.957	-2.930	-4.044	-3.443	-2.043	-3.446	-3.623	-3.443
	(0.742)	(0.389)	(0.045)	(0.305)	(0.050)	(0.001)	(0.007)	(0.268)	(0.007)	(0.006)	(0.007)
pe_t	-1.653	-2.961	-3.010	-3.439	-4.244	-4.636	-3.744	-3.221	-3.165	-2.838	-4.189
	(0.454)	(0.039)	(0.034)	(0.010)	(0.000)	(0.000)	(0.003)	(0.002)	(0.002)	(0.054)	(0.000)
Δd	-20.176	-22.211	-26.881	-19.534	-19.491	-20.991	-19.548	-17.276	-18.416	-15.577	-19.984
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δe	-20.211	-22.556	-22.508	-19.817	-19.219	-19.224	-20.976	-18.867	-20.659	-15.365	-20.684
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r_t	-1.432	-1.577	-1.264	-2.263	-1.942	-2.286	-1.452	-1.732	-1.881	-3.128	-3.281
	(0.152)	(0.125)	(0.206)	(0.023)	(0.052)	(0.023)	(0.556)	(0.413)	(0.340)	(0.025)	(0.016)
s_t	-1.400	-1.544	-1.304	-2.015	-0.856	-2.309	-1.155	-1.137	-1.182	-1.882	-0.781
	(0.162)	(0.123)	(0.192)	(0.280)	(0.392)	(0.022)	(0.249)	(0.256)	(0.237)	(0.061)	(0.435)

	Thailand	Malaysia	India	Korea	Chile	Brazil	Colombia	Greece	Indonesia	Mexico	Argentina
pd_t	-2.563	-2.917	-2.650	-4.335	-2.813	-1.775	-3.637	-2.964	-3.231	-3.582	-1.781
	(0.101)	(0.044)	(0.084)	(0.000)	(0.057)	(0.392)	(0.005)	(0.042)	(0.019)	(0.006)	(0.428)
pe_t	-4.071	-3.267	-2.917	-3.804	-4.604	-3.409	-2.714	-2.6868	-2.052	-3.859	-4.438
	(0.001)	(0.017)	(0.044)	(0.003)	(0.001)	(0.012)	(0.098)	(0.048)	(0.264)	(0.003)	(0.000)
Δd	-16.227	-16.356	-16.793	-13.544	-18.857	-14.027	-14.585	-14.883	-17.718	-16.408	-14.707
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δe	-14.634	-18.425	-15.442	-15.606	-19.367	-12.663	-17.459	-15.924	-14.610	-15.263	-15.472
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r_t	-1.728	-1.578	-2.233	-1.910	-2.412	-3.407	-0.868	-0.443	-2.760	-2.830	-10.722
	(0.085)	(0.115)	(0.195)	(0.057)	(0.139)	(0.011)	(0.642)	(0.898)	(0.065)	(0.055)	(0.000)
s_t	-1.335	-1.803	-2.312	-2.065	-1.775	-1.152	-0.922	-1.591	-2.464	-0.808	-2.159
	(0.183)	(0.072)	(0.168)	(0.259)	(0.077)	(0.251)	(0.357)	(0.113)	(0.126)	(0.419)	(0.178)

Note: pd_t and pe_t indicate logged price/cash flow ratios. Δd and Δe indicate cash flow growth rate. r_t is interest rate and s_t is excess return. The unit root test is carried out to test the stationarity of variables. The Phillips-Perron statistic with chosen bandwidth of Newey-West is reported. The numbers below Phillips-Perron statistics in parentheses are Prob*(p-value).

Table 3.5: Standard unit root test for variables with 1st difference for all sample markets

	US	Canada	UK	Germany	France	Hong Kong	Denmark	New Zealand	Norway	Taiwan	Singapore
Δpd_t	-20.303	-20.865	-22.133	-19.849	-19.990	-20.097	-19.635	-17.813	-18.146	-15.467	-19.931
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δpe_t	-19.725	-20.496	-20.168	-20.456	-19.849	-19.735	-20.214	-19.848	-18.368	-14.911	-18.797
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δr_t	-18.904	-15.774	-19.027	-16.325	-19.932	-21.172	-23.283	-15.254	-28.038	-23.129	-22.570
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δs_t	-19.218	-15.910	-19.048	-14.587	-19.780	-20.720	-15.109	-16.987	-17.651	-24.062	-16.203
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Thailand	Malaysia	India	Korea	Chile	Brazil	Colombia	Greece	Indonesia	Mexico	Argentina
Δpd_t	-16.280	-16.228	-16.460	-15.241	-15.617	-14.453	-13.785	-13.999	-17.731	-16.627	-13.182
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δpe_t	-17.933	-16.761	-14 .917	-15.892	-14.957	-12.979	-17.233	-14.633	-15.640	-16.911	-17.226
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δr_t	-17.050	-12.423	-16.627	-15.434	-11.448	-15.838	-13.923	-15.570	-19.218	-13.011	-23.182
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δs_t	-16.815	-15.254	-17.170	-16.335	-11.842	-13.395	-10.113	-15.785	-17.049	-14.124	-13.071
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Δpd_t and Δpe_t indicate logged price/cash flow ratios with first difference. Δd and Δe indicate cash flow growth rate with first difference. Δr_t is interest rate with first difference and Δs_t is excess return with first difference. The unit root test is carried out to test the stationarity of variables. The Phillips-Perron statistic with chosen bandwidth of Newey-West is reported. The numbers below Phillips-Perron statistics in parentheses are Prob*(p-value).

Table 3.6: VAR statistics for developed markets

Fundamental and markets	l	z_t	$\bar{R}^2$	Q	Fundamental and markets	l	z_t	$\bar{R}^2$	Q
Dividend: US	1	pc_t	0.991	0.009(0.924)	Earnings: HK	1	pc_t	0.881	0.198(0.656)
		Δc_t	0.041	0.002(0.963)			Δc_t	0.123	0.017(0.897)
		r_t	0.097	0.013(0.910)			r_t	0.006	0.009(0.926)
		s_t	0.096	0.011(0.919)			s_t	0.091	0.002(0.958)
Earnings: US	1	pc_t	0.982	0.107(0.743)	Dividend: Denmark	1	pc_t	0.982	0.007(0.934)
		Δc_t	0.052	0.031(0.860)			Δc_t	0.059	0.015(0.903)
		r_t	0.097	0.039(0.843)			r_t	0.094	0.027(0.871)
		s_t	0.096	0.031(0.856)			s_t	0.043	0.000(0.998)
Dividend: Canada	1	pc_t	0.979	0.020(0.888)	Earnings: Denmark	1	pc_t	0.834	0.022(0.881)
		Δc_t	0.007	0.022(0.883)			Δc_t	0.074	0.007(0.932)
		r_t	0.094	0.718(0.397)			r_t	0.134	0.080(0.778)
		s_t	0.093	0.742(0.389)			s_t	0.080	0.005(0.942)
Earnings: Canada	1	pc_t	0.958	0.320(0.858)	Dividend: New Zealand	1	pc_t	0.971	0.058(0.810)
		Δc_t	0.055	0.242(0.876)			Δc_t	0.048	0.142(0.706)
		r_t	0.043	0.644(0.422)			r_t	0.046	0.000(0.986)
		s_t	0.044	0.673(0.412)			s_t	0.050	0.001(0.978)
Dividend: UK	1	pc_t	0.956	0.136(0.713)	Earnings: New Zealand	1	pc_t	0.877	0.255(0.614)
		Δc_t	0.087	0.002(0.965)			Δc_t	0.066	0.040(0.842)
		r_t	0.079	0.040(0.841)			r_t	0.038	0.000(0.994)
		s_t	0.078	0.036(0.850)			s_t	0.096	0.039(0.843)
Earnings: UK	1	pc_t	0.966	0.044(0.835)	Dividend: Norway	1	pc_t	0.977	0.021(0.885)
		Δc_t	0.077	0.147(0.701)			Δc_t	0.085	0.008(0.929)
		r_t	0.031	0.003(0.960)			r_t	0.076	0.021(0.886)
		s_t	0.040	0.002(0.967)			s_t	0.098	0.000(0.999)
Dividend: Germany	1	pc_t	0.970	0.001(0.972)	Earnings: Norway	2	pc_t	0.896	0.974(0.651)
		Δc_t	0.049	0.084(0.772)			Δc_t	0.098	0.090(0.956)
		r_t	0.235	1.480(0.224)			r_t	0.070	0.055(0.973)
		s_t	0.100	1.311(0.252)			s_t	0.092	0.671(0.715)
Earnings: Germany	1	pc_t	0.914	0.003(0.959)	Dividend: Taiwan	1	pc_t	0.877	0.319(0.572)
		Δc_t	0.035	0.053(0.818)			Δc_t	0.109	0.179(0.672)
		r_t	0.216	1.533(0.216)			r_t	0.340	0.001(0.974)
		s_t	0.671	1.335(0.248)			s_t	0.155	0.037(0.848)
Dividend: France	1	pc_t	0.958	0.034(0.854)	Earnings: Taiwan	1	pc_t	0.934	0.640(0.424)
		Δc_t	0.057	0.001(0.971)			Δc_t	0.087	0.016(0.900)
		r_t	0.094	0.018(0.893)			r_t	0.092	0.001(0.971)
		s_t	0.407	0.031(0.861)			s_t	0.093	0.037(0.848)
Earnings: France	1	pc_t	0.944	0.066(0.797)	Dividend: Singapore	1	pc_t	0.972	0.035(0.852)
		Δc_t	0.071	0.001(0.972)			Δc_t	0.079	0.041(0.841)
		r_t	0.150	0.028 (0.866)			r_t	0.104	0.004(0.951)
		s_t	0.073	0.036(0.849)			s_t	0.082	0.018(0.983)
Dividend: HK	1	pc_t	0.866	0.378(0.539)	Earnings: Singapore	1	pc_t	0.945	0.377(0.539)
		Δc_t	0.049	0.041(0.840)			Δc_t	0.137	0.552(0.458)
		r_t	0.026	0.002(0.966)			r_t	0.084	0.014(0.905)
		s_t	0.017	0.000(0.996)			s_t	0.065	0.000(0.988)

Note: Due to nonstationary variables of interest rate and excess return, all estimation results are corrected by the VECM, and then reported. l is the lag length for the VAR model, z_t is the vector including four variables: pc_t the log price/cash flow ratio, Δc_t the cash flow growth rate, r_t the interest rate and s_t the risk premium. $\bar{R}^2$ is the coefficient of determination modulated for lag length. The Q-statistics is the Ljung-Box test statistics for significance of up to the second autocorrelation coefficient. The number in the parentheses behind Q-statistics is probability value (marginal significance level).

Table 3.7: VAR statistics for developing markets

Fundamental and markets	l	z_t	$\bar{R}^2$	Q	Fundamental and markets	l	z_t	$\bar{R}^2$	Q
Dividend: Thailand	1	pc_t	0.938	0.000(0.985)	Earnings: Brazil	1	pc_t	0.819	0.073(0.787)
		Δc_t	0.064	0.007(0.963)			Δc_t	0.083	0.003(0.955)
		r_t	0.063	0.210(0.647)			r_t	0.030	4.821(0.028)
		s_t	0.061	0.184(0.668)			s_t	0.479	0.004(0.952)
Earnings: Thailand	1	pc_t	0.854	0.083(0.774)	Dividend: Colombia	1	pc_t	0.870	0.130(0.718)
		Δc_t	0.247	0.019(0.892)			Δc_t	0.093	0.004(0.948)
		r_t	0.184	0.062(0.804)			r_t	0.034	0.205(0.650)
		s_t	0.044	0.045(0.832)			s_t	0.258	0.184(0.668)
Dividend: Malaysia	1	pc_t	0.943	0.001(0.978)	Earnings: Colombia	1	pc_t	0.935	0.013(0.910)
		Δc_t	0.045	0.024(0.877)			Δc_t	0.074	0.007(0.933)
		r_t	0.102	0.703(0.402)			r_t	0.079	0.000(0.985)
		s_t	0.128	0.206(0.650)			s_t	0.094	0.001(0.975)
Earnings: Malaysia	1	pc_t	0.907	0.019(0.890)	Dividend: Greece	1	pc_t	0.933	0.024(0.878)
		Δc_t	0.108	0.057(0.811)			Δc_t	0.104	0.014(0.907)
		r_t	0.010	0.773(0.379)			r_t	0.032	0.139(0.709)
		s_t	0.033	0.264(0.607)			s_t	0.069	0.005(0.944)
Dividend: India	1	pc_t	0.922	0.000(0.982)	Earnings: Greece	1	pc_t	0.912	0.076(0.783)
		Δc_t	0.135	0.135(0.713)			Δc_t	0.103	0.000(0.977)
		r_t	0.036	0.180(0.671)			r_t	0.012	0.051(0.821)
		s_t	0.064	0.187(0.666)			s_t	0.077	0.006(0.941)
Earnings: India	1	pc_t	0.900	0.011(0.918)	Dividend: Indonesia	1	pc_t	0.943	0.037(0.847)
		Δc_t	0.067	0.006(0.937)			Δc_t	0.157	0.027(0.868)
		r_t	0.009	0.160(0.690)			r_t	0.115	0.007(0.935)
		s_t	0.088	0.152(0.696)			s_t	0.198	0.007(0.935)
Dividend: Korea	1	pc_t	0.850	0.018(0.893)	Earnings: Indonesia	1	pc_t	0.869	0.042(0.839)
		Δc_t	0.181	0.003(0.960)			Δc_t	0.079	0.005(0.943)
		r_t	0.055	0.038(0.847)			r_t	0.317	0.127(0.722)
		s_t	0.075	0.033(0.855)			s_t	0.396	0.126(0.722)
Earnings: Korea	1	pc_t	0.841	0.031(0.860)	Dividend: Mexico	1	pc_t	0.854	0.006(0.937)
		Δc_t	0.116	0.091(0.763)			Δc_t	0.065	0.007(0.935)
		r_t	0.063	0.052(0.819)			r_t	0.054	0.000(0.988)
		s_t	0.068	0.043(0.837)			s_t	0.051	0.004(0.948)
Dividend: Chile	1	pc_t	0.844	0.002(0.965)	Earnings: Mexico	1	pc_t	0.726	0.244(0.621)
		Δc_t	0.040	0.007(0.935)			Δc_t	0.204	0.070(0.791)
		r_t	0.158	0.319(0.572)			r_t	0.043	0.000(0.981)
		s_t	0.137	0.511(0.475)			s_t	0.013	0.011(0.916)
Earnings: Chile	1	pc_t	0.771	0.034(0.854)	Dividend: Argentina	1	pc_t	0.963	0.000(0.998)
		Δc_t	0.111	0.101(0.750)			Δc_t	0.042	0.000(0.980)
		r_t	0.064	0.199(0.655)			r_t	0.282	0.407(0.523)
		s_t	0.095	0.231(0.631)			s_t	0.254	0.510(0.475)
Dividend: Brazil	1	pc_t	0.965	0.025(0.873)	Earnings: Argentina	1	pc_t	0.774	0.000(0.997)
		Δc_t	0.193	0.064(0.801)			Δc_t	0.072	0.008(0.930)
		r_t	0.082	0.076(0.782)			r_t	0.210	0.367(0.545)
		s_t	0.063	0.010(0.920)			s_t	0.228	0.440(0.507)

Note: Due to nonstationary variables of interest rate and excess return, all estimation results are corrected by the VECM, and then reported. l is the lag length for the VAR model, z_t is the vector including four variables: pc_t the log price/cash flow ratio, Δc_t the cash flow growth rate, r_t the interest rate and s_t the risk premium. $\bar{R}^2$ is the coefficient of determination modulated for lag length. The Q-statistics is the Ljung-Box test statistics for significance of up to the second autocorrelation coefficient. The number in the parenthesis behind Q-statistics is probability (marginal significance level).

Table 3.8: Nonlinear Wald Tests for VAR system.

Fundamental and Markets	Restrictions	Nonlinear Wald Test	Fundamental and Markets	Restrictions	Nonlinear Wald Test
The developed markets					
Dividend: US.	4	4.697(0.195)	Dividend: Denmark	4	5.416(0.144)
Earnings: US.	4	6.615 (0.085)	Earnings: Denmark	4	45.235(0.000)
Dividend: Canada	4	35.506(0.000)	Dividend: New Zealand	4	5.245(0.156)
Earnings: Canada	4	4.824(0.185)	Earnings: New Zealand	4	6.487(0.090)
Dividend: UK	4	75.789(0.000)	Dividend: Norway	4	22.929 (0.000)
Earnings: UK	4	6.519(0.089)	Earnings: Norway	8	37.012(0.000)
Dividend: Germany	4	5.648(0.130)	Dividend: Taiwan	4	5.541 (0.136)
Earnings: Germany	4	3.902(0.272)	Earnings: Taiwan	4	20.089 (0.000)
Dividend: France	4	6.104(0.107)	Dividend: Singapore	4	6.765(0.080)
Earnings: France	4	41.855(0.000)	Earnings: Singapore	4	11.327(0.010)
Dividend: Hong Kong	4	42.946(0.000)			
Earnings: Hong Kong	4	3.522(0.318)			
The developing markets					
Dividend: Thailand	4	6.705(0.082)	Dividend: Colombia	4	47.182(0.000)
Earnings: Thailand	4	14.806(0.001)	Earnings: Colombia	4	60.801(0.000)
Dividend: Malaysia	4	29.654(0.000)	Dividend: Greece	4	7.649(0.054)
Earnings: Malaysia	4	6.983(0.072)	Earnings: Greece	4	26.340(0.000)
Dividend: India	4	25.617(0.000)	Dividend: Indonesia	4	4.408(0.221)
Earnings: India	4	6.681(0.076)	Earnings: Indonesia	4	5.796(0.122)
Dividend: Korea	4	13.869(0.003)	Dividend: Mexico	4	33.614(0.000)
Earnings: Korea	4	4.651 (0.199)	Earnings: Mexico	4	3.063(0.382)
Dividend: Chile	4	118.532 (0.000)	Dividend: Argentina	4	81.087(0.000)
Earnings: Chile	4	150.244 (0.000)	Earnings: Argentina	4	75.624(0.000)
Dividend: Brazil	4	50.573(0.000)			
Earnings: Brazil	4	5.347(0.148)			

Note: The number of restrictions of Wald test imposed on the VAR are given by the number of variables times the lag length. The null hypothesis for this test is that the real and fundamental log cash flow ratio are equal to each other. The number in the parenthesis on the right-hand side of Wald statistics are the probability (marginal significance level).

Table 3.9: Adjusted VAR statistics for developed markets

Fundamental and markets	l	z_t	R^2	Q	Fundamental and markets	l	z_t	R^2	Q
Dividend: US	1	pc_t	0.991	0.005(0.924)	Earnings: HK	1	pc_t	0.878	0.317(0.574)
		Δc_t	0.038	0.000(0.978)			Δc_t	0.112	0.019(0.891)
		s_t	0.096	0.019(0.891)			s_t	0.093	0.015(0.903)
Earnings: US	1	pc_t	0.982	0.107(0.743)	Dividend: Denmark	1	pc_t	0.982	0.001(0.971)
		Δc_t	0.050	0.047(0.828)			Δc_t	0.034	0.003(0.955)
		s_t	0.097	0.082(0.775)			s_t	0.099	0.000(0.985)
Dividend: Canada	1	pc_t	0.979	0.122(0.726)	Earnings: Denmark	1	pc_t	0.834	0.012(0.915)
		Δc_t	0.006	0.004(0.952)			Δc_t	0.072	0.002(0.965)
		s_t	0.098	0.577(0.447)			s_t	0.099	0.003(0.960)
Earnings: Canada	1	pc_t	0.957	0.145(0.703)	Dividend: New Zealand	1	pc_t	0.970	0.000(0.984)
		Δc_t	0.048	0.076(0.783)			Δc_t	0.023	0.032(0.858)
		s_t	0.098	0.392(0.531)			s_t	0.099	0.108(0.917)
Dividend: UK	1	pc_t	0.956	0.142(0.707)	Earnings: New Zealand	1	pc_t	0.874	0.174(0.676)
		Δc_t	0.083	0.007(0.932)			Δc_t	0.058	0.037(0.848)
		s_t	0.098	0.021(0.884)			s_t	0.099	0.015(0.903)
Earnings: UK	2	pc_t	0.966	0.060(0.807)	Dividend: Norway	1	pc_t	0.977	0.022(0.883)
		Δc_t	0.075	0.169(0.681)			Δc_t	0.051	0.008(0.929)
		s_t	0.098	0.001(0.972)			s_t	0.099	0.000(0.999)
Dividend: Germany	2	pc_t	0.970	0.000(0.991)	Earnings: Norway	1	pc_t	0.894	0.035(0.851)
		Δc_t	0.041	0.002(0.963)			Δc_t	0.085	0.053(0.819)
		s_t	0.099	0.925(0.336)			s_t	0.099	0.000(0.990)
Earnings: Germany	2	pc_t	0.914	0.002(0.967)	Dividend: Taiwan	1	pc_t	0.877	0.222(0.638)
		Δc_t	0.050	0.001(0.982)			Δc_t	0.107	0.134(0.715)
		s_t	0.099	1.000(0.317)			s_t	0.095	0.059(0.808)
Dividend: France	1	pc_t	0.959	0.057(0.812)	Earnings: Taiwan	1	pc_t	0.932	0.476(0.490)
		Δc_t	0.053	0.010(0.920)			Δc_t	0.075	0.016(0.968)
		s_t	0.099	0.002(0.967)			s_t	0.095	0.042(0.838)
Earnings: France	1	pc_t	0.944	0.021(0.884)	Dividend: Singapore	1	pc_t	0.972	0.052(0.820)
		Δc_t	0.066	0.001(0.979)			Δc_t	0.063	0.041(0.840)
		s_t	0.098	0.000(0.993)			s_t	0.099	0.045(0.832)
Dividend: HK	1	pc_t	0.862	0.442(0.506)	Earnings: Singapore	1	pc_t	0.943	0.403(0.525)
		Δc_t	0.021	0.021(0.884)			Δc_t	0.126	0.564(0.453)
		s_t	0.093	0.009(0.924)			s_t	0.098	0.002(0.961)

Note: l is the lag length for the VAR model, z_t is vector including three variables that pc_t is the log price/cash flow ratio (PD ratio), c_t is the cash flow growth rate and s_t is the variable of risk premium on stock market. $\bar{R}^2$ is the coefficient of determination modulated for lag length. The Q-statistics called Ljung-Box test statistics is the test for residuals on VAR model with up to second lag length. The number in the parenthesis behind Q-statistics is probability (marginal significance level).

Table 3.10: Adjusted VAR statistics for developing markets

Fundamental and markets	l	z_t	$\bar{R}^2$	Q	Fundamental and markets	l	z_t	$\bar{R}^2$	Q
Dividend: Thailand	1	pc_t	0.936	0.053(0.818)	Earnings: Brazil	1	pc_t	0.817	0.087(0.769)
		Δc_t	0.053	0.019(0.889)			Δc_t	0.083	0.003(0.959)
		s_t	0.097	0.105(0.746)			s_t	0.098	0.002(0.965)
Earnings: Thailand	1	pc_t	0.839	0.301(0.583)	Dividend: Colombia	2	pc_t	0.979	0.118(0.731)
		Δc_t	0.179	0.025(0.874)			Δc_t	0.055	0.014(0.907)
		s_t	0.097	0.218(0.641)			s_t	0.098	0.217(0.641)
Dividend: Malaysia	2	pc_t	0.942	0.177(0.674)	Earnings: Colombia	2	pc_t	0.937	0.022(0.883)
		Δc_t	0.034	0.004(0.951)			Δc_t	0.070	0.005(0.944)
		s_t	0.097	0.923(0.337)			s_t	0.099	0.000(0.985)
Earnings: Malaysia	2	pc_t	0.904	0.060(0.807)	Dividend: Greece	1	pc_t	0.932	0.005(0.983)
		Δc_t	0.068	0.048(0.826)			Δc_t	0.091	0.127(0.910)
		s_t	0.097	1.020(0.313)			s_t	0.097	0.001(0.980)
Dividend: India	1	pc_t	0.919	0.000(0.997)	Earnings: Greece	1	pc_t	0.909	0.050(0.823)
		Δc_t	0.025	0.018(0.892)			Δc_t	0.086	0.000(0.994)
		s_t	0.094	0.001(0.976)			s_t	0.097	0.003(0.958)
Earnings: India	1	pc_t	0.899	0.011(0.918)	Dividend: Indonesia	1	pc_t	0.943	0.026(0.873)
		Δc_t	0.043	0.002(0.961)			Δc_t	0.154	0.008(0.927)
		s_t	0.094	0.006(0.936)			s_t	0.094	0.007(0.933)
Dividend: Korea	1	pc_t	0.849	0.004(0.950)	Earnings: Indonesia	1	pc_t	0.867	0.000(0.997)
		Δc_t	0.173	0.000(0.994)			Δc_t	0.070	0.022(0.883)
		s_t	0.096	0.005(0.942)			s_t	0.094	0.129(0.719)
Earnings: Korea	1	pc_t	0.841	0.032(0.858)	Dividend: Mexico	1	pc_t	0.853	0.005(0.944)
		Δc_t	0.094	0.157(0.900)			Δc_t	0.064	0.007(0.934)
		s_t	0.096	0.001(0.980)			s_t	0.099	0.004(0.951)
Dividend: Chile	1	pc_t	0.843	0.000(0.979)	Earnings: Mexico	1	pc_t	0.726	0.222(0.637)
		Δc_t	0.036	0.000(0.993)			Δc_t	0.185	0.032(0.857)
		s_t	0.094	0.366(0.545)			s_t	0.099	0.011(0.918)
Earnings: Chile	1	pc_t	0.766	0.000(0.998)	Dividend: Argentina	1	pc_t	0.963	0.002(0.968)
		Δc_t	0.074	0.001(0.977)			Δc_t	0.033	0.008(0.977)
		s_t	0.095	0.133(0.715)			s_t	0.094	0.761(0.448)
Dividend: Brazil	1	pc_t	0.960	0.004(0.949)	Earnings: Argentina	1	pc_t	0.776	0.001(0.997)
		Δc_t	0.045	0.053(0.817)			Δc_t	0.102	0.010(0.901)
		s_t	0.098	0.012(0.914)			s_t	0.091	0.185(0.791)

Note: l is the lag length for the VAR model, z_t is vector including three variables that pc_t is the log price/cash flow ratio (PD ratio), c_t is the cash flow growth rate and s_t is the variable of risk premium on stock market. $\bar{R}^2$ is the coefficient of determination modulated for lag length. The Q-statistics called Ljung-Box test statistics is the test for residuals on VAR model with up to second lag length. The number in the parenthesis behind Q-statistics is probability (marginal significance level).

Table 3.11: Nonlinear Wald Tests for adjusted VAR system without interest rate

Fundamental and Markets	Restrictions	Nonlinear Wald Test	Fundamental and Markets	Restrictions	Nonlinear Wald Test
The developed markets					
Dividend: US.	3	37.047(0.000)	Dividend: Denmark	3	2.935(0.399)
Earnings: US.	3	54.434(0.000)	Earnings: Denmark	3	2.919(0.404)
Dividend: Canada	3	29.957(0.000)	Dividend: New Zealand	3	3.120 (0.373)
Earnings: Canada	3	25.864(0.000)	Earnings: New Zealand	3	4.800(0.187)
Dividend: UK	3	22.841(0.000)	Dividend: Norway	3	6.163 (0.104)
Earnings: UK	6	12.468(0.052)	Earnings: Norway	3	9.118(0.028)
Dividend: Germany	6	6.232(0.397)	Dividend: Taiwan	3	3.847 (0.278)
Earnings: Germany	6	17.435(0.008)	Earnings: Taiwan	3	10.333(0.016)
Dividend: France	3	9.361(0.025)	Dividend: Singapore	3	2.987(0.394)
Earnings: France	3	5.283(0.152)	Earnings: Singapore	3	4.280(0.233)
Dividend: Hong Kong	3	2.927(0.403)			
Earnings: Hong Kong	3	9.665(0.022)			
The developing markets					
Dividend: Thailand	3	51.719(0.000)	Dividend: Colombia	6	24.739(0.000)
Earnings: Thailand	3	8.390(0.039)	Earnings: Colombia	6	7.175(0.305)
Dividend: Malaysia	6	32.390(0.000)	Dividend: Greece	3	8.761(0.033)
Earnings: Malaysia	6	6.588 (0.361)	Earnings: Greece	3	6.147(0.105)
Dividend: India	3	63.491(0.000)	Dividend: Indonesia	3	3.307(0.347)
Earnings: India	3	8.117(0.044)	Earnings: Indonesia	3	3.020(0.389)
Dividend: Korea	3	9.689 (0.021)	Dividend: Mexico	3	5.231(0.156)
Earnings: Korea	3	6.608(0.085)	Earnings: Mexico	3	9.190(0.027)
Dividend: Chile	3	18.311(0.000)	Dividend: Argentina	3	70.879 (0.000)
Earnings: Chile	3	19.201(0.000)	Earnings: Argentina	3	65.907(0.000)
Dividend: Brazil	3	22.669(0.000)			
Earnings: Brazil	3	3.101(0.376)			

Note: The restrictions of Wald test are imposed on the VAR, which are given by the number of variables times the lag length. The null hypothesis for this test is that the real and fundamental log cash flow ratio are same. The number in the parenthesis on the right-hand side of Wald statistics are the probability (marginal significance level).

Figure 3.1: Actual and fundamental stock prices for developed markets.

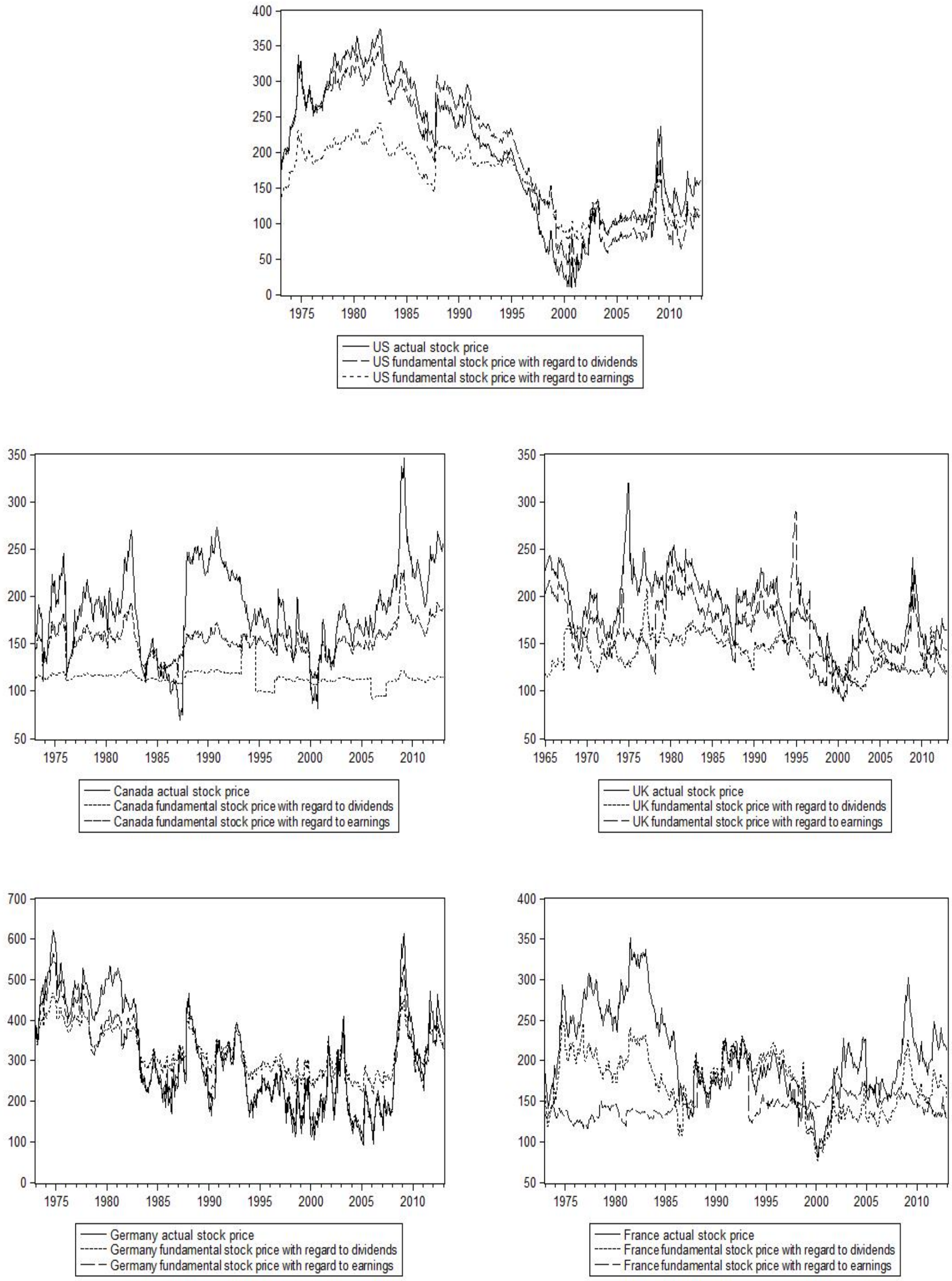


Figure 3.1: Continued

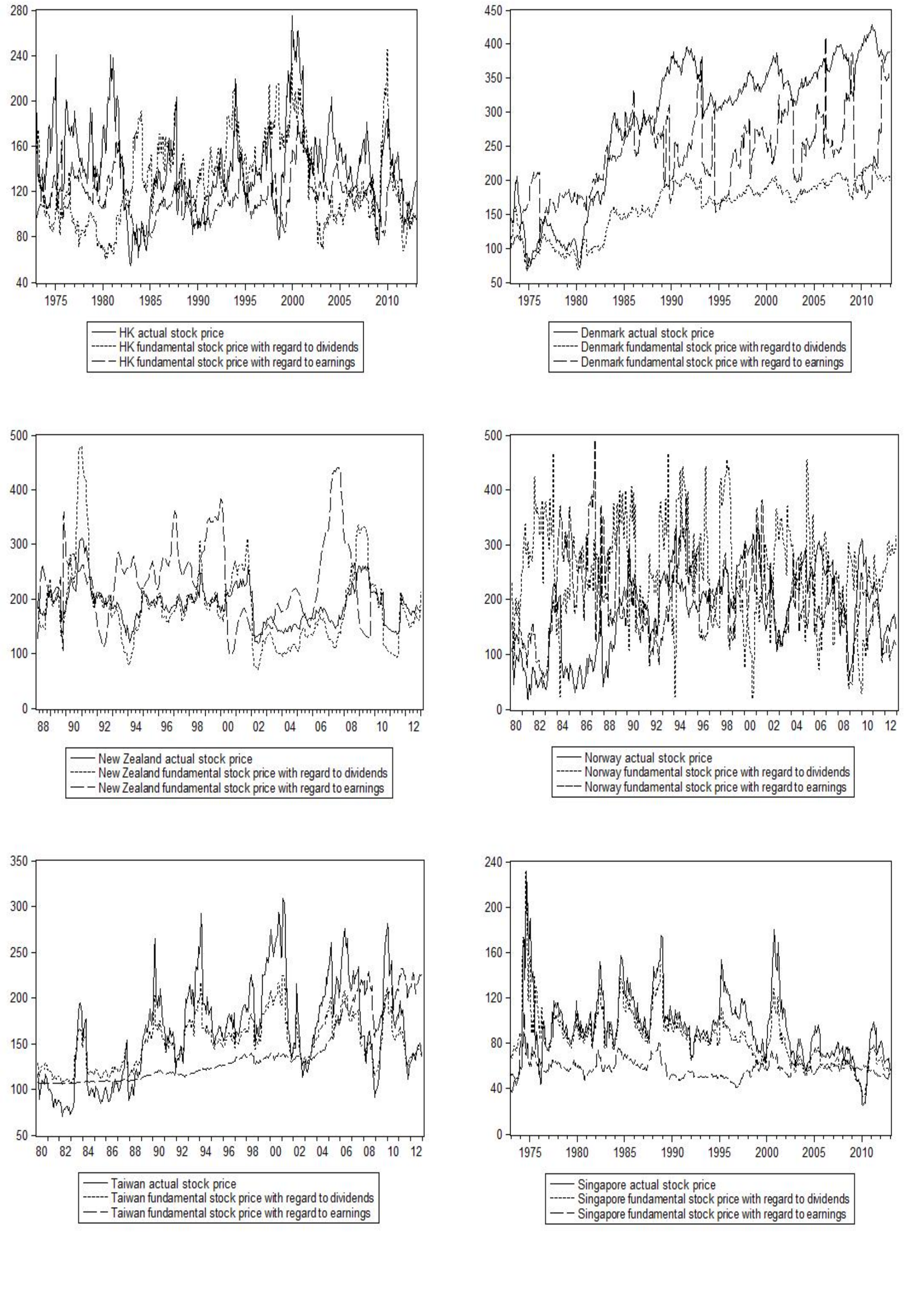


Figure 3.2: Actual and fundamental stock prices for developing markets.

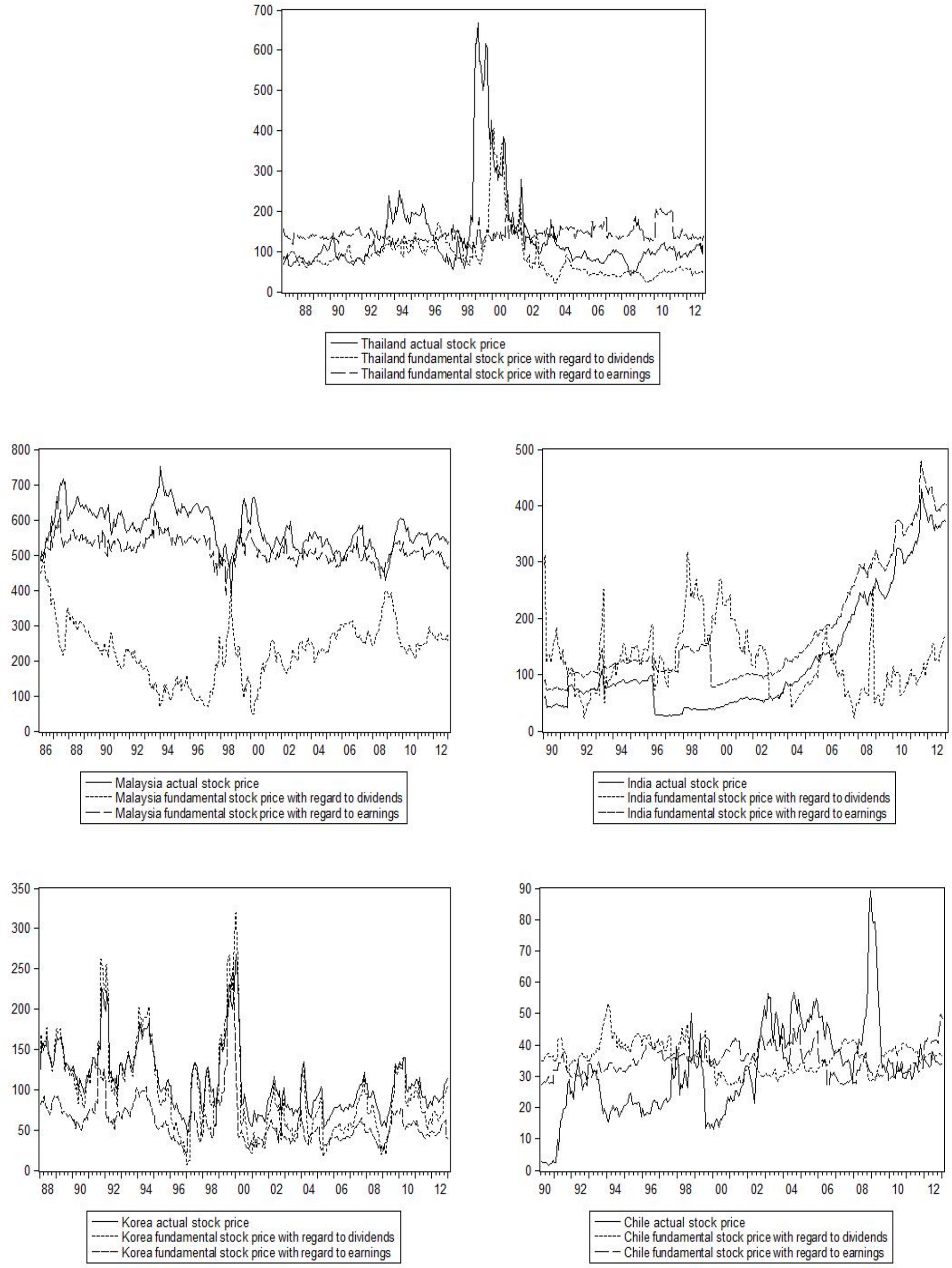
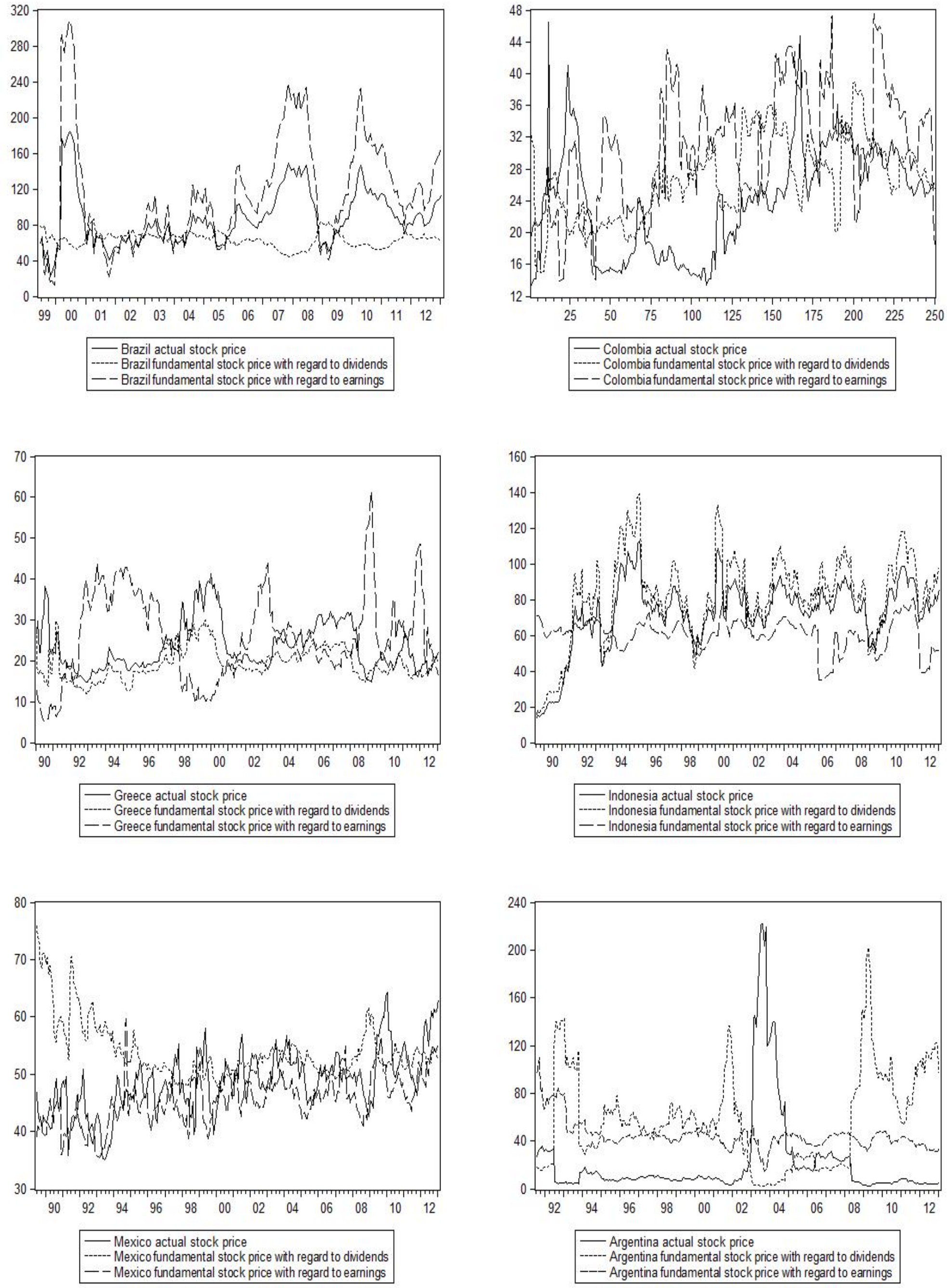


Figure 3.2: Continued



Concluding Remarks

The theories of contagion normally describe the phenomenon that as financial markets decline, the panic caused by asset price drops spreads across assets and across markets. Therefore, contagion is defined as asset's price comovements and coexceedances. In the first chapter, we employ three different methodologies to examine contagion with the data set of European markets. Our prior research target is to answer whether we can identify the contagion during the European sovereign debt crisis initiated from the Greece. First, we follow Engle and Sheppard (2001) and Dajcman (2012) to model dynamic conditional correlation and compute the moving window average for flight-to-quality and contagion indicators. We use both indicators to avoid a potential one-sided account of the problem caused by the sole use of the flight-to-quality indicator or contagion indicator. Second, copula-GARCH approach is used to examine nonlinear contagion effects. Three copulas are chosen from the large copula family, in the light of their different focuses on dependence distributions. There are two points that we want to note regarding the estimation process. First, following Huang, Lee, Liang, and Lin (2009), we adopt the GJR model, which helps to add asymmetric information into copula-GARCH framework, and to take the theoretical assumptions much closer to the real situation. Second based on Adel and Salma (2012), we divide the sample period into two sub-sample: pre-crisis and post-crisis, and compare the different dependence between the two periods in terms of the estimated copula coefficients. Finally, we find evidence for the driving factors of contagion defined as coexceedances. With the multinomial logistic regression model by Bae, Karolyi, and Stulz (2003), we examine the explanatory power of three variables: conditional volatility, exchange rate and interest rate. The results suggest that three variables have some explanatory power for contagion, but not the interest rate. We further compute the marginal effect of the three predictive variables following the approach of Greene (2012), and the results suggest that the volatility ranks the first, exchange the second and interest rate the last in terms of their predictive power.

The first chapter contributes new findings to the existing literature in the following aspects. The first one of finding is the much more volatile FTQ and CI indicators found in European markets, and obvious decline in dynamic conditional correlation between stock markets and sovereign bond markets due to the onset of global financial crisis. The European sovereign debt crisis tends to give rise to positive dynamic conditional correlation for European markets, which indicates contagion based on the definitions set at the beginning. In addition, we find that contagion generally appears at least four months before the time when the Greek sovereign debt crisis was announced by the IMF. This suggests that investors may be able to reduce their portfolio risk through predicting possible contagion across different markets. Therefore, we further apply the multinomial logistic regression model to identify the predictive variables for contagion. We document the strong predictive power of conditional volatility, moderate power of exchange rate and weak power of interest rate. Finally, increasing copula coefficients denote the contagion found for the European sovereign debt markets, from the end of the tranquil period to the duration of crisis.

We additionally show that the dependence structure measured by Student-t copula is heightened most in the duration of crisis as GJR-normal model enters into the copula estimations, it means that Student-t copula is able to reflect the changes of dependence structure better after adding asymmetry information into structure.

In the second chapter, we examine the relationships between stock returns and trading volume, and those between trading volume and conditional volatility. Specifically, this chapter investigates linear and nonlinear Granger causalities between stock returns, trading volume and volatility with detrend process. We model the conditional volatility with Nelson's EGARCH model that includes the counterparts, which allows both positive and negative shocks rather than simple GARCH model with positive restrictions. This actually gives much more realistic assumption. With the linear Granger causality model, only a few countries see linear causal relations between the volume and return and between volatility and return, and the relations are mainly uni-directional. However, with the tests of nonlinear Granger causality model, we observe significant bi-directional causal relations in all of the 24 studied countries, proving that nonlinear Granger causality model is better in exploring the nonlinear relations between variables, as Hiemstra and Jones (1994) assert.

The tests for the tranquil period produce some interesting stories. When the data sample is restricted to the tranquil period, linear test results are much more significant compared with the results obtained when the data sample includes the volatile period after the 2008 Financial crisis; the response from stock returns to trading volume is clearly more significant than the other way round, so is the feedback from conditional volatility to trading volume. This finding is confirmed by a nonlinear test when the data sample contains only the relatively tranquil period. All in all, our research shows that trading volume is very sensitive to changes of stock returns and conditional volatility.

In the third chapter, we estimate the predictive power of the fundamental factors of valuing returns, which has been one of the most debated research topics in stock markets. The three driving factors that we consider in this chapter are: dividend, earnings and interest rate. In the VAR structure, we decompose the rate of returns into risk premium and interest rate, and evaluate the interest rate endogenously in a 4-variable VAR structure with nonlinear Wald tests, based on the theories of Shiller (1981), Kanas (2005), Campbell and Shiller (1988) and Jiang and Lee (2005).

Our results confirm the predictive power of dividend discount model and earnings discount model to stock prices. We observe dividend has the predictive power in 10 stock markets, and earnings has the explanatory power in 12 stock markets. However, we cannot find any predictive power for dividend or for earnings in some countries such as Norway, Chile, Colombia and Argentina. The dividend and earnings discount models are therefore estimated again without the endogenous variable of interest rate. This change improves the goodness of fit for Norway and Colombia, but does not improve the predictive power of dividend or earnings. Taken together, the third chapter finally estimates the relationships between basic driving factors, and finally contributes to the existing literature in the analysis of interest rate in structure, and in better observing the relationships between stock returns and fundamental factors, by plotting both fundamental and actual prices. This research still has a limitation and leaves an unanswered questions. For example, we cannot exactly observe the effect of interest rate and other driving factors on stock prices with only the dynamic present value model, therefore we are not able to accurately answer the question of whether other factors can predict the changes of stock prices, just like dividend and earnings. This problem may be solved in the future with another appropriate approaches.

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