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DOCTORAL THESIS
Doctor of Philosophy (PhD)

VOLATILITY SPILLOVER EFFECTS FROM G7 STOCK MARKETS TO E7 STOCK MARKETS

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THESIS APPROVAL PAGE

DECLARATION

I hereby declare that this doctoral thesis titled as "Volatility Spillover Effects from G7 Stock Markets to E7 Stock Markets" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

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ABSTRACT

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Volatility Spillover Effects from G7 Stock Markets to E7 Stock Markets

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Dokuz Eylül University

Graduate School of Social Sciences

Department of Business Administration

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The objective of this study is to examine volatility spillover from G7 to E7 stock markets by applying the VAR-GARCH model to daily data from 01 September 1995 to 15 March 2016. Further, the study examines the volatility spillover from US stock market to E7 stock markets before and after the Global Financial Crisis. Finally, this study calculates optimal weights and hedge ratios for the portfolios, including E7 and US stocks.

The findings show significant evidence of volatility spillover from G7 stock markets to E7 stock markets in most cases. In particular, a close inspection of constant conditional correlations reveals that the most of the G7 stock markets are strongly correlated with Brazil, Mexico and Russia. This result suggests that the geographical proximity should be taken into consideration while examining the volatility spillovers of stock markets. The empirical results show that the stock markets of China, Indonesia and India are less affected by the volatility spillovers from G7 stock markets. The findings further show that constant conditional correlations have rapidly increased among the US and Brazilian, Mexican and Russian stock markets after the Global Financial Crisis. Moreover, the findings of optimal weights and hedge ratios suggest that investors should invest more proportion of their portfolios in the US stock market than the E7 stock markets to minimize the risk.

Keywords: Volatility Spillover, Global Financial crisis, E7, G7, VAR-GARCH Model, Hedge Ratios

ÖZET

Doktora Tezi

G7 Hisse Senedi Piyasalarından E7 Hisse Senedi Piyasalarına Oynaklık Yayılma Etkisi

Muzammil KHURSHID

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İngilizce İşletme Yönetimi Programı

Bu çalışmanın amacı, 1 Eylül 1995 ten 15 Mart 2016'a kadar G7 hisse senedi piyasalarından E7 hisse senedi piyasalarına oynaklık yayılma etkisini VAR-GARCH modeli uygulayarak incelemektir. Ayrıca, bu çalışma Küresel Mali Kriz öncesi ve sonrası ABD hisse senedi piyasalarından E7 hisse senedi piyasalarına oynaklık yayılma etkisini araştırmaktadır. Son olarak, bu çalışma E7 ve G7 hisse senetlerini içeren portföyler için optimal ağırlıkları ve korunma oranlarını hesaplamaktadır.

Bulgular, çoğu durumlarda G7 hisse senedi piyasalarından E7 hisse senedi piyasalarına oynaklık yayılma etkisi olduğuna dair önemli kanıtlar göstermektedir. Özellikle, yakından incelenen sabit koşullu korelasyonlar G7 hisse senedi piyasalarının Brezilya, Meksika ve Rusya ile güçlü bir şekilde ilişkili olduğunu ortaya koymaktadır. Bu sonuç, hisse senedi piyasalarında oynaklık yayılımı incelenirken coğrafi yakınlığın dikkate alınması gerektiğini önermektedir. Ampirik sonuçlar Çin, Endonezya ve Hindistan hisse senedi piyasalarının G7 hisse senedi piyasalarının oynaklık yayılmalarından daha az etkilendiğini göstermektedir. Bulgular ayrıca sabit koşullu korelasyonların Küresel Mali Kriz sonrası ABD ve Brezilya, Meksika ve Rusya hisse senedi piyasalarında hızla arttığını ortaya koymaktadır. Ayrıca, optimal ağırlıkları ve korunma oranlarına ilişkin sonuçlar yatırımcıların risklerini en aza indirmek için portföylerinin daha büyük bölümünü E7 hisse senedi piyasalarından ziyade ABD hisse senedi piyasasına yatırmaları gerektiğini göstermektedir.

Anahtar Kelimeler: Oynaklık Yayılma Etkisi, Küresel Mali Kriz, E7, G7, VAR-GARCH Modeli, Korunma Oranları

VOLATILITY SPILLOVER EFFECTS FROM G7 STOCK MARKETS TO E7 STOCK MARKETS

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ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroskedasticity
CCC	Constant Conditional Correlation
E7	Emerging 7
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedastic
G7	Global 7
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
GJR-GARCH	Glosten-Jagannathan-Runkle- Generalized Autoregressive Conditional Heteroscedasticity
IMF	International Monetary Fund
MICEX	Moscow Interbank Currency Exchange
NYSE	New York Stock Exchange
PP	Phillips–Perron
PWC	Pricewaterhouse Coopers
QFII	Qualified Foreign Institutional Investor
SSE	Shanghai Stock Exchange
TSE	Tokyo Stock Exchange
UK	United Kingdom
US	United States
VAR-GARCH	Vector Autoregressive- Generalized Autoregressive Conditional Heteroscedasticity

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INTRODUCTION

Over the last three decades, financial globalization and integration among the stock markets have increased the availability of funds and accelerated the transmission of information across the financial markets. International trade, foreign direct investment and capital inflows have increased the linkages among the stock markets (Chan et al., 1997). The free cross-border flow of capital, new economic blocks, and linkages among stock markets have reduced the problems of asymmetric information and increased the co-movements of international capital markets. Moreover, the stock markets are becoming more open to international investors. The financial integration and globalization have also offered potential benefits in the shape of capital accumulation. As a consequence, emerging markets benefited from the increasing capital inflows.

Inspite of some advantages, financial integration and globalization also carry some risks. Volatility spillover is one of the most dangerous threats of increased interdependence. Volatility spillover is referred to as the transmission of volatility from one stock market to another. It applies to the spread of market disturbances from one to another (Akca and Ozturk, 2016). In response to the transmission of volatility, the stock markets have experienced a sharp decline in stock returns, especially during the financial crisis and still continue. Additionally, contagion of the financial crisis severely affects the global and emerging markets. Therefore, the noteworthy aspect for investors and portfolio managers is to realize the significance of volatility spillover due to its crucial role across markets. This has resulted in a growing interest in examining the volatility spillover between the global and emerging markets in recent years and provides a suitable reason to investors and portfolio managers for diversifying their investments. The transmission of volatility in stock markets is important for the asset pricing, hedging strategies, trading strategies and regulatory strategies.

The primary objective of this study is to examine volatility spillover from G7 stock markets to E7 stock markets. The study employed generalized VAR-GARCH approach, developed by Ling and McAleer (2003), to analyze daily data on the stock prices of national indices over the period from 1995 through 2016. Since the recent financial crisis originated from US and spread to other countries, it is a particular interest of this study to inspect the volatility spillover from US stock market to E7 stock markets before and after the Global Financial Crisis. There exist some studies investigating the volatility spillover between US and other stock markets including BRIC (Syripolous et al., 2015), some European (Singh et al., 2010) and Asian stock markets (Majdoub and Mansour, 2014). However, there has been yet no study investigating the volatility spillover between the US and E7 stock markets. Poised to address this lacuna, this study is a first step to check the volatility spillover between US and E7 stock markets. Detecting volatility spillover between the US and E7 stock markets is of great importance. If there exists a spillover effect, knowing the direction and magnitude of spillover can help the investors of emerging markets to adjust their asset allocations to reduce their risk exposures.

The current study contributes to the literature in many ways. The foremost of the contributions is that while the existing studies focus mostly on one or two developed countries and few emerging markets (Miyakoshi, 2003; Li, 2007; Demiralay and Bayraci, 2015; Li and Giles, 2015), the current study specifically focuses on the E7 and G7 countries. The main focus of the current study is to investigate the volatility spillover from each G7 stock market to E7 stock markets. These stock markets have not been examined jointly in the literature. To the best of author's knowledge, this is the first study, which investigates the volatility spillover from each G7 stock markets to E7 stock markets. Another contribution is the data set used in this study. While most of the studies use either weekly or monthly data, the current study uses daily data, which covers an extended period from 1995 to 2016.

Moreover, the current study contributes particularly to the existing literature, since it considers the pre- and post- global financial crisis. Surprisingly, there has been no study investigating the shock and volatility transmission between the US and E7 stock markets with respect to the global financial crisis. Furthermore, this study also contributes to the existing literature by computing optimal weights and hedge ratios of E7-US stock portfolio holdings in terms of portfolio management and hedging strategies. Lastly, the current study employs the most recent and sophisticated volatility spillover model to examine the national indices of E7 and G7 stock markets.

To the best of author's knowledge, this study becomes the first study to run VAR-GARCH model to examine the national indices of the E7 and G7 stock markets.

This study is beneficial for academicians, individual investors, portfolio managers, and policy makers. It is crucial not only for an individual investor but also for portfolio managers to know how the international stock markets are interlinked with each other and how to reduce the severe effects of uncertainty on the expected stock returns. So, it provides a better understanding of diversification benefits to the investors and portfolio managers to protect their investments.

This study is organized as follows; Chapter I provides the overview of the E7 and G7 stock markets. Chapter II describes literature review. Chapter III depicts data and methodology used in this study in order to analyze the volatility spillover effects between the G7 and E7 countries. Chapter IV highlights the empirical results and discussion. The contribution and concluding remarks are given at the end.

CHAPTER I

OVERVIEW OF E7 AND G7 COUNTRIES AND STOCK MARKETS

This chapter describes the overview of E7 and G7 economies and stock markets.

Over the last 20 years, the appearance of a series of financial crises has shown how emerging economies can play a vital role in the world economy, and they have presented themselves as a better opportunity against global economies for investors during the financial crisis. For instance, the sub-prime financial crisis devastated not only US stock market but also other major global stock markets and emerging stock markets. The devastating results from the crisis brought a decline in the market capitalization of emerging markets from $ 14.5 trillion to $ 6.2 trillion (Hale, 2012).

In fact, the 2007-2009, Global Financial Crisis has led investors to understand the vulnerability of emerging markets. In the past few decades, the emerging markets have become increasingly integrated with the international financial system and thus more dependent on external financing. Deepening financial integration has come at a price for many emerging economies, and it increased the vulnerability of these countries to external shocks and crises.

It was particularly obvious in the advent of the recent global crisis, during which vulnerability of both developed and developing markets increased. Recently, we have experienced the sub-prime financial crisis originated from the US but spread all over the world like an invisible virus and slowed down the growth of the advanced and emerging markets.

Among the emerging markets, in particular, E7 countries have attracted considerable attention due to high economic growth. E7 countries have long been in the radar of investors with the expectations that E7 economies will surpass the G7 economies and account for a greater share of world output in the near future, explicitly by 2020 (Pricewaterhouse Coopers, 2015).

Understanding the behavior and mechanism of E7 stock markets, their reaction against shocks and volatility spillovers relative to global stock markets, such as G7 stock markets, remains vital for investors, portfolio managers and policy makers. The investigation of volatility spillovers can help investors to have proper asset pricing process and volatility forecasting between E7 and G7 stock markets.

Moreover, investors would be able to anticipate fluctuations in their portfolio values due to stock price shocks. Foreign investors always seek the high returns by diversifying the portfolios and find alternate markets to invest during the crisis. From the portfolio diversification perspective, the analysis of spillover effects can be helpful in constructing the optimal weights and hedge ratios for portfolio holdings. Therefore, the linkages between global stock markets and emerging stock markets have become a hot topic of debate.

1.1 FINANCIAL STATISTICS OF E7 AND G7 COUNTRIES

The recent financial crisis not only hit the global financial markets but also enhanced the shift in economic power from developed to emerging countries. While the emerging economies weathered the storm well, the developed economies suffered and remained vulnerable even for a long time after the crisis. During this period, the emerging economies proved themselves as true competitors to the developed economies, and they reinforced an argument that the global economic axis will be shifted from G7 to E7 countries in the following decades (Pricewaterhouse Coopers, 2011). Over the past two decades, the share of emerging economies has increased to 38% in global GDP (Global Financial Stability Report, 2016).

Table 1 presents the key financial statistics from International Monetary Fund for the G7 and E7 countries in 2015. International Monetary Fund (2015) reports G7 countries as the most advanced economies all over the world and these countries contribute 64% of the global wealth. G7 economies are the biggest players of the world economy with the GDP of $34,975 billion. The US economy is the biggest contributor in the global economy with a GDP of $ 17,968 billion, which is approximately 22.4% of the gross world economy.

Table 1: Financial Statistics for E7 and G7 Countries

Panel A: Financial Statistics for E7 Countries

Country	Nom. GDP (Bil. $)	Nom. GDP per capita	PPP GDP (Bil. $)	PPP GDP per capita	PPP GDP world share	Population (Millions)
Brazil	1,799.612	8,802.168	3,207.861	15,690.127	2.835	204.451
China	11,384.763	8,280.086	19,509.983	14,189.522	17.241	1,374.957
India	2,182.577	1,688.378	8,027.031	6,209.477	7.093	1,292.707
Indonesia	872.615	3,415.834	2,838.643	11,111.815	2.508	255.462
Mexico	1,161.483	9,592.116	2,220.134	18,334.990	1.962	121.087
Russia	1,235.858	8,447.423	3,473.780	23,744.224	3.070	146.300
Turkey	722.219	9,290.425	1,576.293	20,276.988	1.393	77.738

Panel B: Financial Statistics for G7 Countries

Country	Nom. GDP (Bil. $)	Nom. GDP per capita	PPP GDP (Bil. $)	PPP GDP per capita	PPP GDP world share	Population (Millions)
Canada	1,572.781	43,934.814	1,628.414	45,488.895	1.439	35.798
France	2,422.649	37,728.412	2,646.948	41,221.473	2.339	64.213
Germany	3,371.003	41,267.310	3,842.004	47,033.231	3.395	81.687
Italy	1,819.047	29,847.382	2,173.597	35,664.911	1.921	60.945
Japan	4,116.242	32,480.660	4,842.395	38,210.626	4.279	126.729
UK	2,864.903	44,117.802	2,659.728	40,958.227	2.350	64.938
US	17,968.195	55,904.295	17,968.195	55,904.295	15.878	321.410

Source: Author's compilation based on data from the International Monetary Fund (2015) website.

Table 1 also shows that the E7 economies are producing $19,359 billion GDP. However, it is important to note that major portion of GDP of the E7 countries comes from China. China is the second biggest economy in the world with a GDP of $ 11,385 billion, but it is not considered as a developed economy by IMF and World Bank. Further, China is not among the countries with high per-capita GDPs. From the population's point of view, E7 economies are highly populated as compare to G7 economies. That's why the GDP per capita is very low in the E7 economies.

Table 2 represents the real GDP growth (%) for the E7 and G7 countries from 2007 to 2016. According to the World Economic Outlook (2016), the real GDP growth rate of India was 7.3% in 2015 and it is expected to reach at 7.5% in 2016. There was a considerable abatement in real GDP of China in 2015 and it is projected to further decrease in 2016. It is evident that the E7 countries are more volatile with respect to their GDP growth but they have considerably higher GDP growth than the G7 countries.

The real GDP growth rate of G7 countries is given in Panel B. The real GDP growth of G7 economies is low as compared with E7 economies. The GDP growth in US remained stable in 2015 and it is projected to remain same in 2016. Most of the G7 economies are expected to be stable in 2016. A detailed inspection of E7 and G7 countries shows that E7 and G7 economies have observed a sharp decline in real GDP growth rate in 2009 in response to the Global Financial Crisis. However, E7 countries started to recover sharply in 2010. An important aspect while comparing the GDP of E7 and G7 is that during Global Financial Crisis all G7 countries dealt with significant negative GDP growth but China, India and Indonesia experienced 9.2, 8.5 & 4.7% growth in their GDP growth respectively in 2009.

Table 2: Real GDP Growth(%) for E7 and G7 Countries

Panel A:Real GDP Growth (%) for E7 Countries

Country	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 (Proj.)**
Brazil	3.0	5.1	-0.1	7.5	3.9	1.9	3.0	0.1	-3.8	-3.8
China	9.9	9.6	9.2	10.6	9.5	7.7	7.7	7.3	6.9	6.5
India	7.1	3.9	8.5	10.3	6.6	5.6	6.6	7.2	7.3	7.5
Indonesia	2.7	7.4	4.7	6.4	6.2	6.0	5.6	5.0	4.8	4.9
Mexico	2.9	1.4	-4.7	5.1	4.0	4.0	1.3	2.3	2.5	2.4
Russia	5.8	5.2	-7.8	4.5	4.3	3.5	1.3	0.7	-3.7	-1.8
Turkey	4.0	0.7	-4.8	9.2	8.8	2.1	4.2	2.9	3.8	3.8

Panel B: Real GDP Growth (%) for G7 Countries

Country	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016 (Proj.)**
Canada	3.2	1.0	-2.9	3.1	3.1	1.7	2.2	2.5	1.2	1.5
France	2.4	0.2	-2.9	2.0	2.1	0.2	0.7	0.2	1.1	1.1
Germany	1.7	0.8	-5.6	3.9	3.7	0.6	0.4	1.6	1.5	1.5
Italy	1.5	-1.1	-5.5	1.7	0.6	-2.8	-1.7	-0.3	0.8	1.0
Japan	1.0	-1.0	-5.5	4.7	-0.5	1.7	1.4	0.0	0.5	0.5
UK	3.0	-0.5	-4.2	1.5	2.0	1.2	2.2	2.9	2.2	1.9
US	3.0	-0.3	-2.8	2.5	1.6	2.2	1.5	2.4	2.4	2.4

Source: Author’s compilation based on World Economic Outlook (2016)

Table 3 represents the market characteristics of E7 and G7 stock markets. According to the Table 3, G7 stock markets have experienced remarkable growth from 2010 to 2015. In general, the statistics show that the G7 stock markets are larger in size than those of E7 stock markets. During the sampling period, E7 stock markets except China have experienced a downward trend in terms of market capitalization.

As exhibited in Table 3, most of the G7 stock markets witnessed a significant increase in market capitalization, a measure to assess stock market strength. For G7 stock markets, the highest market capitalization is recorded for the US stock market with $ 25,067,540 million. With the exception of Italy, G7 stock markets are generally high in size in relation to their GDP. The US stock market is also recorded the largest market in terms of GDP with a growth of 139.7%, followed by Japan 118.7% and Canada 102.8% respectively.

Table 3; Market Characteristics of G7 and E7 Stock Markets

Panel A: *Statistics for G7 Stock Markets*

	Market Cap. $ millions		Market Cap. % of GDP		Turnover Ratio % of Mar. Cap		No. Of Listed Companies	
Country	2010	2015	2010	2015	2010	2015	2010	2015
Canada	2,171,195	1,593,399	134.6	102.8	64.7	68.8	3,771	3,799
France	1,911,515	2,088,317	86.2	73.7	70.6	56.0	617	490
Germany	1,429,719	1,715,800	41.8	51.1	104.5	84.2	690	555
Italy	535,059	587,312	25.2	27.5	124.4	350.0	290	290
Japan	3,827,774	4,894,919	69.6	118.7	111.6	113.8	2,281	3,504
UK	1,868,153	....	66.9	....	146.4	....	2,105	1,858
US	17,283,452	25,067,540	115.5	139.7	208.4	165.1	4,279	4,381

Panel B: *Statistics for E7 Stock Markets*

	Market Cap. $ millions		Market Cap. % of GDP		Turnover Ratio % of Mar. Cap		No. Of Listed Companies	
Country	2010	2015	2010	2015	2010	2015	2010	2015
Brazil	1,545,566	490,534	70.0	27.6	58.8	85.6	373	345
China	4,027,840	8,188,019	66.7	75.4	205.0	480.3	1,036	1,081
India	1,631,830	1,516,217	95.5	73.1	66.2	50.9	5,034	5,835
Indonesia	360,388	353,271	47.7	41.0	29.0	21.2	420	521
Mexico	454,345	402,253	43.2	35.2	24.5	25.8	130	136
Russia	951,296	393,238	62.4	29.7	53.3	29.8	556	251
Turkey	302,443	188,862	41.4	26.3	133.3	185.2	263	392

Source: Author’s compilation based on the World Bank’s World Development Indicators; Stock markets (2015)

Japanese stock market (from 2281 to 3504) has recorded significant increase, followed by the US stock market (from 4279 to 4381) and Canada (from 3771 to 3799), while France (from 617 to 490), Germany (from 690 to 555) and UK (from 2105 to 1858) have recorded negative growth. Overall, there is an increase in the number of listed companies in G7 countries. On the whole, it could be concluded that stock markets of G7 economies experienced more growth as compared to those of E7 economies.

A detailed inspection of E7 stock markets shows that the Chinese stock market has the highest market capitalization. Apart from China, E7 stock markets are generally small in size in relation to their GDP and generally they have experienced a downward trend. The Chinese stock market is recorded the largest market in terms of

GDP with a growth of 75.4%, followed by Indian stock market (73.1%) while Turkish stock market is recorded the smallest. With respect to the number of listed companies, the Indian and Chinese stock markets are recorded significant growth.

It could be concluded that stock markets of G7 economies are much bigger in comparison with those of E7 economies. The only exception is China. From 2010 to 2015, stock markets of G7 economies have experienced a higher growth as compared with the E7 economies. China is again an exception in the E7 markets as it has experienced the highest stock market growth. Overall, these facts motivate to choose the E7 and G7 countries for examining the volatility spillover effects and linkages among them.

1.2 OVERVIEW OF E7 AND G7 STOCK MARKETS

This section describes the brief overview of E7 and G7 stock markets.

1.2.1 Stock Market of Brazil

The Brazilian stock market was established on August 23, 1890 as a state-owned company. Brazilian stock market is the largest stock exchange in Latin America. In 1990, all the exchanges had been merged under the name of Bovespa to make a national stock market. It was demutualized in 2007 and now it is regulated as a private company. The benchmark indices of Brazilian stock market is BOVESPA. Brazilian Stock Exchange and Brazilian Mercentile and Futures Exchange merged in 2008, creating BM & FBOVESPA. It provides trading of stocks, bonds and derivatives. It also acts as a central counterparty that helps in cash settlement in its environments. By the end of 2015, there were 345 listed firms on the Brazilian Stock Exchange and its market capitalization was 490,534 million dollars. The market capitalization to GDP ratio was 70% in 2010, which decreased to 27.6% in 2015. However, the turnover ratio increased from 58.8% to 85.6% (World Bank Development Indicators, 2015).

Historically, Brazilian financial markets were not developed due to the political uncertainty, and they were unable to provide sufficient capital to firms. The regulations were not suitable for the investors. In 1960s, military government took some steps for the revival of the stock markets. However, these steps were not enough to generate considerable results due to the family-owned businesses. In 1976, corporate law was passed for legal structure for capital markets. This law resolved many problems and granted rights to individual investors. The present success of Brazilian Stock Exchange is due to Novo Mercado regulations. Brazilian Stock Exchange introduced these three new listing sections in 2000, the Novo Mercado, level 2 and level 1 of corporate governance standards. These regulations are based on a contractual agreement of the listed company, its management and shareholders. The main theme of the Novo Mercado is to secure the rights of shareholders. In 2006 and 2011, Novo Mercado regulations were reviewed and at present 128 companies are listed under Novo Mercado (Brazilian Stock Exchange, 2016).

1.2.2 Stock Market of China

There are a couple of stock exchanges in China those are Shanghai Stock Exchange and Shenzen Stock Exchange. The Chinese stock exchange is the second largest stock exchange in Asia and partially open to foreign investors. There are 1081 listed companies with a market capitalization of 8,188,019 million dollars. The benchmark indices of Shanghai Stock Exchange is SSE Composite index. Shanghai Stock Exchange performs a number of functions like trading place and facilities in trading, formulation of business rules, listings of companies, and monitoring securities trading and disseminating market information (World Bank Development Indicators, 2015).

During 26 years, Shanghai Stock Exchange has emerged as an exchange with a strong market structure and deals in four securities categories: equities, bonds, funds and derivatives. For the efficient trading, Shanghai stock market has installed the world’s leading exchange system and infrastructure. There are 4538 listed bonds on the bond market with the outstanding value of 3.44 trillion RMB, and the annual turnover standing at 122.85 trillion RMB by the end of 2015 (Shanghai Stock Exchange, 2016).

In recent years, the world markets view the Chinese economy as a barometer of the world economy rather than an indicator of China's domestic economy itself. News about the Chinese economy affect the economies of other countries significantly (Baum et al., 2014). Although the Chinese financial markets are relatively isolated from the international markets, regulatory reforms over the last decade have done much to improve the functioning of the financial markets. In recent years, the Chinese stock markets gradually become more integrated with other markets as a result of relaxation of restrictions on capital controls such as the unlocking of state-owned shares, Qualified Foreign Institutional Investor (QFII) program, minority shareholder protection, dividend policy and disclosure.

Recently, the role of the Chinese stock market has been increased due to its large economic scale and impressive economic growth. In Asian region, the Chinese stock market has become a leading Asian market by market value. In 2009, the value of the China's A-share market increased 100.88 percent year-on-year to 3.57 trillion dollar, overtaking Japan's 3.53 trillion dollar (Kang and Yoon, 2011).

1.2.3 Stock Market of India

Stock market of India is known as Bombay Stock Exchange, located in Mumbai, India. It was established on 9th July, 1875. Bombay Stock Exchange is the 11th largest market throughout the world with a market capitalization of 1,516,217 million dollars. The turnover ratio for Bombay Stock market was 50.9% in 2015 (World Bank Development Indicators, 2015).

Bombay Stock Exchange is the oldest stock market in Asia. The Indian stock market holds sophisticated and advanced technology for trading. With the reopening of Indian economy in early nineties, Bombay stock market got a boom and installed an efficient and effective system. To overcome the volatility in the stock market, the 'badla' system has been closed. Necessary changes were made in the corporate governance rules to bring companies at a uniform level. On the global scale, flow of international capital has increased and Bombay stock market is preferred globally after China (Mukherjee, 2007).

By the end of 2015, there were 5,835 listed companies on Bombay Stock Market. It is world number one stock exchange in terms of listed companies. In 1992, Bombay stock exchange was opened to foreign investors. Foreign portfolio investment regulations were relaxed to attract global investors. In 2014, the foreign portfolio investment regulations have eased the entrance of foreign investors. With new foreign portfolio investment regulations, BSE has been engaged in many foreign portfolio investments related initiatives last year (Bombay Stock Exchange, 2016).

1.2.4 Stock Market of Indonesia

Stock market of Indonesia is located in Jakarta, Indonesia. It came into being in 1912 by the name of Jakarta stock exchange. In Indonesia, there were two exchanges; namely Jakarta Stock Exchange and Surabaya Stock Exchange. In 2007, Surabaya Stock Exchange merged with Jakarta Stock Exchange. Subsequently, Jakarta Stock Exchange renamed its name into the Indonesia Stock Exchange. It facilitates equities, fixed incomes, and derivative instruments trading. Jakarta Composite Index is the benchmark index. It has also Jakarta Islamic Index to measure the market activities under Sharia (Indonesia Stock Exchange, 2016). By the end of 2015, there were 521 listed companies with a market capitalization of 353,271 million dollars (World Bank Development Indicators, 2015).

In 1988, the Indonesian Stock Exchange was opened to foreign investors. By 1996, foreign investors have become dominant players in Indonesian Stock Market by holding over 27% of the total market capitalization and participating in 80% of daily trading value on the Indonesian Stock Exchange (Wang, 2007). However, the recent global financial crisis affected the economy of Indonesia. A sharp decline in stock prices was observed after the global financial crisis. It affected the foreign capital inflows severely in the Indonesia stock market (Bank of Indonesia, 2008).

1.2.5 Stock Market of Mexico

The Mexican Stock Exchange is also known as Bolsa Mexicana de Valores (BVM). It was founded on September 5, 1933. It is located in Mexico City. Mexican Stock Exchange stands second largest stock market in Latin America and the fifth in the Americas. Its benchmark stock index is the IPC. By the end of 2015, there were only 136 listed companies with a market capitalization of 402,253 million dollars. The market capitalization to GDP ratio was 43.2% in 2010, which decreased to 35.2% in 2015. However, the turnover ratio had increased from 24.5% to 25.8% (World Bank Development Indicators, 2015).

In 1990s, the Mexican government made some reforms to facilitate the foreign capital and to follow the present trends around the world. After deregulation, the Mexican stock market experienced boom, and a high foreign investment came into the Mexican economy. Commercial banks were also privatized under these reforms, and they also observed a boom in the shape of foreign capital. However, in 1994, these reforms created some problems for the survival of Mexican economy. During this period, the Mexican economy passed through Peso crisis. Due to the Peso crisis, banking system collapsed and the economy experienced a sharp devaluation that destabilized the economy severely (Haber 2005).

In 2008, Mexican Stock Exchange was demutualized. The Mexican Stock Exchange facilitates in organizing securities, transaction process and equal opportunities for all investors. It provides monetary resources to companies to perform their operations (Mexican Stock Exchange, 2016).

1.2.6 Stock Market of Russia

Russian Stock Exchange was established in 1995. The benchmark index of Russian Stock Exchange is RTS, which was established in 1995. RTS was comprised of 50 most liquid listed stocks on Russian stock market. Moscow Stock Exchange was established in 2011 in the result of merging the Moscow Interbank Currency Exchange (MICEX) and the Russian Trading System (RTS). Moscow Stock Exchange mainly deals with Equity, Bond, Derivatives, Commodities and Forex. As of December 2015, there were 251 listed companies on the Russian Stock Exchange with a market capitalization of 393,238 million dollars (World Bank Development Indicators, 2015).

Moscow stock exchange is considered as a very young stock market in comparison with the matured and developed countries that have established developed stock markets in the beginning of the 19th century. The rating of Moscow Stock Exchange was upgraded to investment grade by Standard & Poor rating agency in 2005 due to the opportunities for the long-term development. The upgradation in rating attracted many foreign investors despite of high volatility reputation (Moscow Interbank Currency Exchange, 2010).

Russian economy is based on the production of oil, and it is one of the leading oil exporter countries. By the end of 2009, the Russian stock market recovered from the global financial crisis as oil prices increased globally that increased the capital inflow to Russia. However, unrest in Europe and USA slowed down the developments and financial markets experienced a decline in the beginning of 2011 (Tregub and Posokhov, 2011).

1.2.7 Stock Market of Turkey

Istanbul Stock Exchange was established in 1986 as an autonomous organization in Istanbul to provide trading in equities and bonds. The benchmark index of the Turkish stock exchange is BIST 100. By the end of 2015, there were 392 listed companies with a market capitalization of 188,862 million dollars. The market capitalization to GDP ratio was 41.4% in 2010, which decreased to 26.3% in 2015. The turnover ratio had increased from 133.3% to 185.2% (World Bank Development Indicators, 2015).

Diverse range products are traded on Borsa Istanbul like equities of companies, exchange-traded funds, warrants and certificates and preemptive rights. It also offers a secure and transparent trading system to domestic and foreign investors. At the end of 2015, the Borsa Istanbul was ranked the 4th among 56 members of the World Federation of Exchanges with a turnover of 212% that indicates the liquidity of Borsa

Istanbul. In the recent decade, the share of foreign investors in the Borsa Istanbul has increased gradually, and they have a share of 62.36% of the free-float market capitalization (Borsa Istanbul, 2016).

Turkey observed a political unrest in late 1990s. Turkish stock market passed through two economic crises in the form of a liquidity crisis and banking crisis in 2001, and Borsa Istanbul collapsed by 63% in two days (Marois, 2012). IMF issued severe restructuring targets for Turkey. The restrictions on overseas investment were lifted and Turkish Stock Exchange was opened for overseas investors. Borsa Istanbul emerged as an alternative for investors who provides them diversification benefits (Tasan-Kok, 2004). A long political stability in last decade gave a sharp recovery to the economy of Turkey.

1.2.8 Stock Market of Canada

Toronto Stock Exchange was established on October 25, 1861 in Toronto. Toronto Stock Exchange is considered as the eighth biggest stock market all over the world by market capitalization. The S&P TSX Composite index is commonly used. It shares 70% of the market capitalization for all listed companies. The number of listed companies in Toronto Stock Exchange were 3799 in 2015 with a market capitalization of 1,593,399 million dollars. The market capitalization to GDP ratio was 134.5% in 2010, which decreased to 102.8% in 2015. However, the turnover ratio increased from 64.7% to 68.8% (World Bank Development Indicators, 2015).

There are four stock exchanges in Canada namely the Montreal Exchange, the Toronto Stock Exchange, the Alberta Stock Exchange and the Vancouver Stock Exchange. The Toronto Stock Exchange offers trading through Toronto Stock Exchange Index. Corporate shares were offered through a public offering in 2002, and S&P/TSX Composite Index was introduced by Toronto Stock Exchange. In the beginning, the S&P/TSX included 223 stocks with more than 1,500 listed companies on the Toronto Stock Exchange (Toronto Stock Exchange, 2016).

1.2.9 Stock Market of France

Stock market of France is known as Paris Bourse that is located in Paris. Paris Bourse is the second biggest stock market in Europe after UK. In September 2000, it was merged with the Amsterdam, Brussels and Lisbon stock exchange. The CAC 40 index is the benchmark index of the French Stock Market. The number of listed companies in French Stock Exchange were 490 in 2015 with a market capitalization of 2,088,317 million dollars. The market capitalization to GDP ratio was 86.2% in 2010, which decreased to 73.7% in 2015. Furthermore, the turnover ratio decreased from 70.6% to 56.0% (World Bank Development Indicators, 2015).

In 2000, Paris Stock Exchange was renamed as Euronext Paris. A large number of financial instruments are traded on Paris Stock Exchange as Equities, indices, bonds, commodities and derivatives. The CAC 40 index is a “free float market-capitalization-weighted index. CAC 40 index shows the performance of the 40 largest and most actively traded shares listed on Euronext Paris. CAC 40 reflects the 20% of market capitalization in the euro (Paris Bourse, 2016).

According to Banque (2016), European investors hold 45% of CAC 40 shares, and more than 25% of CAC 40 shares are held by non-Euro area investors. Since the Global Financial Crisis, the French stock market has observed a decline, and this caused a decrease in the foreign investment. Global financial crisis continued to affect the economy of France.

1.2.10 Stock Market of Germany

Stock market of Germany was set up in 1585. It is situated in Frankfurt and operated by Deutsche Börse AG and Börse Frankfurt Zertifikate AG. In construction of overall stock index, the returns of 30 blue chips German companies were used due to their active trading in Frankfurt stock exchange. Index was constructed by using free floating methodology. The DAX 30 has a base value of 1,000 as of December 31, 1987. As of June 18, 1999 only XETRA equity prices were used to calculate all DAX indices. There were 555 listed companies in German Stock Exchange in 2015 with a market capitalization of 1,715,800 million dollars. The market capitalization to GDP ratio was 41.8% in 2010, which increased to 51.1% in 2015. However, the turnover ratio decreased from 104.5% to 84.2% (World Bank Development Indicators, 2015).

Majority of the trade in Frankfurt Stock Exchange is executed by international investors. Deutsche Börse Group manages one of the biggest cash markets in the Europe with its members being Xetra and Börse Frankfurt and Deutsche Börse Cash Market. Not only these are involved in cash management but also they are responsible for the inflow of the foreign investment due to their transparency and the integrity in this cash handling process. This also encourages the other companies to raise their level of investment in the German stock market. One of the main reasons of this maintained transparency is the role of sustained regulations and strict supervision by the regulatory authorities. One of the outstanding feature of Börse Frankfurt is that it offers more than one million securities of German and international companies. All these opportunities presented to the individual and institutional investors are made possible with the timely and best possible execution of the investors' orders. This amazing environment definitely makes the Börse Frankfurt as one of the leading stock trading places in the world (Deutsche Boerse, 2016).

1.2.11 Stock Market of Italy

The Borsa di commercio di Milano was founded in 1808 by Eugène de Beauharnais in Milan. In 1997, it was re-opened after the privatization with its new name the Borsa Italiana. The well-known index of Borsa Italiana is FTSE MIB, which is comprised of 40 most liquid stocks. There were 290 listed companies in the Italian Stock Exchange in 2015 with a market capitalization of 587,312 million dollars. The market capitalization to GDP ratio was 25.2% in 2010, which increased to 27.5% in 2015. However, the turnover ratio decreased from 104.5% to 84.2% (World Bank Development Indicators, 2015).

Milan Stock Exchange being the sole Italian stock Exchange is basically owned by the London Stock Exchange. Since it is not one of the biggest trading places in the Europe, it is just being housing the lesser than 300 companies. Being such a small scaled stock exchange, it is very hard to be a financing source for the investors and the Italian firms. That's why Italy has the bank based economy, but Italy's governing bodies and central bank are trying to change this situation by encouraging the companies to take the alternative financing sources. They have also initiated some programs to increase the awareness regarding the venture capital and corporate bonds form of financing (Borsa Italiana, 2016).

The late 20th century is marked with the great deal of change in the Italian economy. Part of the change was due to the “Tangentopoli", the corruption scandal, and it was due to the inability of the Italian economy to handle the corruption in politics. This corruption led recession adversely affected the Italian economy progress. (Miniaci and Weber 1999).

1.2.12 Stock Market of Japan

Tokyo Stock Exchange (TSE) was established in 1878 in Tokyo, Japan. Tokyo Stock Exchange is the fourth biggest stock market in the world in respect of market capitalization. The numbers of domestic listed firms were 3504 in 2015 with a market capitalization of 4,894,919 million dollars. The benchmark indices of Japanese Stock Exchange are Nikkei 225 and TOPIX, which are commonly used. The market capitalization to GDP ratio was 69.7% in 2010, which increased to 118.7% in 2015 (World Bank Development Indicators, 2015). Tokyo Stock Exchange serves as central equities marketplace in Japan. Tokyo Stock Exchange consists of four equities markets: 1st Section, 2nd Section, Mothers (Market of High Growth and Emerging Stocks) and the JASDAQ (Japan Exchange Group, 2016).

Over the last three decades, the Japanese economy has experienced three financial crises. Bubble economic crisis took place in 1991. Tokyo Stock Market observed a sudden boost in stock prices, agitated economic activity and increased money supply. As a result, the Central Bank of Japan tightened the monetary policy to control it. By the end of 1991, stock prices began to settle at their actual levels (Okina et al., 2001).

Another financial crisis occurred in the late 1990s due to the collapses of the financial institutions. The spillover effect was obvious in the Japanese economy through stock market and economic relationship. In the beginning of the crisis, US and European markets went into recession. Later, the Japanese economy also observed large negative terms of trade due to the crisis (Bosworth and Flaaen 2009; Wyplosz, 2009). However, the Japan has continued to maintain its position in the regional and global economies.

1.2.13 Stock Market of UK

London Stock Exchange (LSE) is one of the historical financial institutions and its history can be related back to 300 years ago. London stock market was founded in 1801 in London, UK. It is the largest stock market in Europe. There were 1858 listed companies in 2015 (World Bank Development Indicators, 2015). The benchmark index of UK Stock Exchange is FTSE 100, which is most commonly used and it represents the top 100 listed companies on the London stock market.

London Stock Exchange is not only the leading stock market of the Europe but also it is the most influential stock exchange in the Europe. LSE group was created in 2007, when it merged with the Italian Stock Exchange (Borsa Italiana, 2016). Its importance can also be linked with the fact that it represents 98% of the market capitalization of the listed shares in the UK. London Stock Exchange is a source of financing for the local, international individuals and institutional investors. Moreover, it provides many products to foreign investors.

This is one of the main reasons of LSE's progress over the time as it always continues to evolve in terms of innovation and investor's protection by bringing the new guidelines and regulations. In this regard, it provides Sponsored Access to the non-members which allow them a direct technical connection to order books. LSE feels much obliged for its success towards the untiring efforts of the regulatory authorities, who try to maintain the consistent transparency and liquidity to ensure the smooth trading (London Stock Exchange, 2016).

1.2.14 Stock Market of US

New York Stock Exchange (NYSE) is located in New York City, New York, United States. It was incorporated on May 17, 1792. NYSE is considered as one of the earliest stock markets in the world and the most influential in US and other economies. NYSE is the largest stock exchange in the world by market capitalization of 25,067,540 million dollars as of December 2015. The numbers of domestic listed firms were 4381 in 2015. The market capitalization to GDP ratio was 115.5% in 2010, which increased to 139.7% in 2015 (World Bank Development Indicators, 2015).

The benchmark index of New York Stock Exchange is S&P 500. It is comprised of major 500 listed companies on the New York Stock Exchange. The S&P 500 is free-float capitalization-weighted. The S&P 500 is also used as an indicator to measure the performance of the US market. The diverse range of companies makes the S&P 500 a trustable and popular tool for the economic outlook.

The New York Stock Exchange has a transparent mechanism to raise the capital for listed companies which circulate this capital into the US economy. Five stock markets are regulated under the New York Stock Exchange, including the New York Stock Exchange, Archipelago and American Stock Exchange Options. Medium and large-sized companies are listed on NYSE and smaller companies on American Stock Exchange. A large range of asset classes: equities, options, exchange-traded funds and bonds are traded on NYSE (New York Stock Exchange, 2016).

CHAPTER II

LITERATURE REVIEW

This chapter provides the literature review on the linkages and volatility spillover effects between different types of stock exchanges. This chapter is divided into three sections. Section 2.1 focuses on the volatility spillover effects among developed stock markets. Section 2.2 provides the literature overview of volatility spillover effects between developed and emerging stock markets. Section 2.3 insights volatility spillovers between different types of markets.

2.1 VOLATILITY SPILLOVERS FROM DEVELOPED TO DEVELOPED STOCK MARKETS

Understanding the nature and extent of volatility spillover between different financial markets is important for investors. When the stock markets are integrated with each other, external shocks can have substantial influence on the stock markets and hence, it becomes difficult to reduce portfolio risk through diversification. Since the financial market integration is led by the developed markets, a large body of existing literature address volatility transmission among major stock markets in the developed countries (Hamao et al, 1990; Theodossiou and Lee, 1993; Bae and Karolyi, 1994; Wei et al., 1995; Baele, 2005; Giannellis et al, 2010; Xiao and Dhesi, 2010).

The study by Hamao et al. (1990) is considered as one of the foremost studies to measure the transmission of volatility among the stock exchanges of US, UK and Japan. By adopting GARCH-M model, they found volatility spillover from stock markets of US and UK to the stock market of Japan. Theodossiou and Lee (1993) measured the volatility spillover effects among stock markets of Canada, Germany, Japan, UK and US. Using the multivariate GARCH-M model, they reported significant volatility spillover effects between the stock exchange of US, UK, Canada, Germany and Japan.

Moreover, Bae and Karolyi (1994) studied the return and volatility spillover between the stock markets of US and Japan. They used a data from 1988 to 1992 and found a significant magnitude of volatility spillover effects between stock market of US and Japan. They also extended the GARCH model to examine asymmetric effects of positive and negative shocks.

Karolyi (1995) also examined the New York and Toronto stock exchanges to measure the volatility spillover by employing a multivariate BEKK-GARCH model over a period of between 1981 and 1989. Their study exhibited unidirectional volatility spillover from the New York and Toronto Stock Exchange. Booth et al. (1997) investigated the four Scandinavian stock markets by applying EGARCH model over a period of between 1988 and 1994. The findings showed that there are unidirectional volatility spillovers between Swedish-Norwegian stock markets. The findings also show the evidence of bidirectional volatility spillovers between Swedish-Finnish and Finnish-Danish stock markets.

Similarly, Kanas (1998) employed multivariate EGARCH model on major European stock exchanges (Frankfurt, London and Paris) and identified the bidirectional volatility spillovers among these stock markets. In the Western Europe, Baele (2005) made a study to examine the volatility spillover by modeling a multivariate regime switching framework. The study covered a period from 1980 to 2001 and came to the conclusion that past shocks of US stock exchange significantly transmit to the European stock markets. The findings also show the evidence of contagion from US stock market to EU stock markets during high volatility in world stock markets.

Similarly, Xiao and Dhesi (2010) examined four G-7 equity markets (France, Germany, UK and US) to measure volatility spillover effects over a period of 2004 to 2009. They employed multivariate GARCH-BEKK and DCC time-varying model. Using the multivariate GARCH-BEKK model, they identified the volatility spillover effects from the stock market of UK and US to the stock markets of France and Germany.

2.2 VOLATILITY SPILLOVERS FROM DEVELOPED TO EMERGING STOCK MARKETS

In recent years, emerging markets have received a great attention due to high risks associated with high returns in these markets. In the existing literature, the linkages between developed and emerging markets have been noticed after the 1997 Asian crisis. The linkages among global and emerging markets are considered very important, especially from the perspective of portfolio management and international diversification. Many studies shed light on volatility spillover effects from developed equity markets to emerging equity markets. For instance, Wei et al. (1995) studied volatility spillover effect among three global (Japan, UK and US) and two emerging equity markets (Taiwan and Hong Kong). They employed a univariate GARCH model over a period between 1991 and 1992 and they reported existence of volatility spillover effects from the stock market of US to the stock markets of Hong Kong and Taiwan.

2.2.1 Asian Region

In Asia-Pacific region, Ng (2000) ran a bi-variate GARCH model to examine the magnitude and volatility spillover effect among two global (US and Japan) and six Asia Pacific emerging stock markets. The results of the study revealed a strong volatility spillover effects from global to emerging equity markets as compare with regional equity markets.

On the other hand, Miyakoshi (2003) investigated the volatility spillover among the stock markets of US, Japan and seven Asian stock markets. She employed a bi-variate EGARCH model over a period between 1998 and 2000 and showed a significant volatility spillover from the stock market of US to other Asian stock markets. More importantly, the study exposed that the stock market of Japan (regional market) significantly influences the Asian markets.

Among the Asian-Pacific equity markets, Worthington and Higgs (2004) examined the transmission of volatility spillover among developed and emerging

Asian equity markets by applying a MV-GARCH model to find out the degree of volatility spillover by gathering data over a period of 1988 to 2000. They reported a positive and significant volatility spillover effects from mature Asian markets to emerging Asian equity markets.

Li (2007) investigated the stock markets of China, Hong Kong and US to measure the linkages and volatility spillover. He arranged a data set over a period of 2000 to 2005 and concluded that there is no direct linkage between the Chinese Stock Exchange and the US Stock Exchange. The outcomes of the study also suggested the low volatility spillovers between the Chinese Stock Market and Hong Kong Stock Exchange.

Moreover, Lee (2009) examined the volatility spillover effects among six Asian stock markets (Japan, Singapore, Hong Kong, India, South Korea and Taiwan). The study showed significant volatility spillover effects within these stock markets. Excluding India, the geographically close five countries (Hong Kong, Japan, Singapore, South Korea and Taiwan) are more linked with each other.

Furthermore, Moon and Yu (2010) investigated spillover effects by employing symmetric and asymmetric GARCH models between the stock market of China and US. They used a sample period from 1999 to 2007 and found a strong evidence of symmetric and asymmetric volatility spillover effects from the stock market of US to China. Sok-Gee and Karim (2010) conducted a study of a volatility spillover effect among 5 ASEAN stock markets (Malaysia, Indonesia, Philippine, Singapore, Thailand, Japan) and the stock market of US. They employed multivariate EGARCH model and reported significant volatility spillover effects between the stock markets of US and Japan. They concluded that Indonesian stock market is affected by US Stock Market.

Additionally, Johansson and Ljungwall (2009) tried to explore the linkages among the different stock markets of Greater China. Their study revealed that volatility spills over from Hong Kong to Taiwan, which further affects the volatility in China. Most recently, Syriopoulos et al. (2015) investigated the sectors of BRICS stock markets by using VAR-GARCH model from 2005 to 2013. Their findings showed a significant volatility spillover between US and BRICS countries and negative correlation between US and China.

Moreover, Abidin and Zhang (2011) studied major Asian markets to investigate the volatility spillover effect over a period of 2004 to 2010 by applying AR-GARCH model and they found significant volatility spillover effects among the Australian and Chinese stock markets. Li and Giles (2015) attempted to measure volatility spillover effects among 6 developing stock markets and two developed the stock markets (Japan and US). They used a data from 1993 to 2012 and employed GARCH-BEKK model. Their findings show that there is a significant volatility spillover from US to other Asian countries. Further, the findings suggest that there exists a bidirectional volatility spillover during the Asian financial crisis.

2.2.2 GCC and MENA Region

Awartani et al. (2013) recently conducted a study on the stock markets of GCC (Gulf Cooperation Council) countries to examine the directional volatility spillover effect employing a GARCH-DCC model over a sample period of 2004 to 2012. They found a unidirectional flow of information from the stock market of US and Saudi Arabia to other stock markets of GCC countries during the subprime crisis. Almost the same results were found by Al-Deehani and Moosa (2006) employed stochastic volatility approach to investigate volatility spillover effects among stock markets of Saudi Arabia. Kuwait and Bahrain. The empirical results of the study reveal that the stock market of Kuwait is more influential than others. However, the findings document that there is weak relationship among three markets in terms of volatility spillover effects.

In MENA region, Abou-Zaid (2011) conducted a study among the stock markets of Egypt, Israel, Turkey and US by using daily data over a period of between 1997 and 2007. The results of GARCH model report significant volatility spillover effects from the US stock market to the stock markets of Egypt, Israel and Turkey. Diebold and Yilmaz (2009) have also made a study on twelve emerging and seven developed stock markets and gathered a data from 1992 to 2007. They proposed a spillover model to measure linkages in returns and volatilities. The findings show a clear evidence of volatility spillover effect during the crisis episodes.

Giannellis et al. (2010) ran multivariate EGARCH model to investigate volatility spillover effects between two sectors of the stock market of US and UK. They used data from 1970 to 2002 and found significant reciprocal volatility spillover effects between stock market and real activity within a country. Beirne et al. (2013) employed tri-variate VAR-GARCH model to examine volatility spillover effects among 41 emerging and 6 mature stock markets. They distributed emerging stock markets among four geographic. They took a time period from 1993 to 2008 and found significant volatility spillover effects from mature to emerging stock market.

2.2.3 European and Latin America Region

In his recent study, Alikhanov (2013) examined the volatility spillover effects for the stock market of US and 8 European stock markets. He applied GJR-GARCH model and his findings showed significant volatility spillover effects from the stock market of US to the other European stock exchanges. Demiralay and Bayraci (2015) analyzed the stock markets of US, Germany, Russia and CEE in order to investigate volatility spillover effects by employing Diebold and Yilmaz approach. The findings of the study suggest that there is a significant volatility spillover from developed stock markets to Central and Eastern European stock markets.

Most recently, Akca and Ozturk (2016) explored the effect of subprime financial crisis on the volatility spillovers among three developed (US, UK and Germany) and three emerging (Greece, Spain and Turkey) stock markets by combining Diebold and Yilmaz model with stochastic volatility model over a period between 2003 and 2014. They claimed a high volatility spillover from the stock market of US to others.

2.3 VOLATILITY SPILLOVERS BETWEEN DIFFERENT TYPES OF MARKETS

The researchers not only investigated equity markets to examine transmission of volatility but also oil and foreign exchange markets. The relationship between oil price fluctuations and stock market returns has gained much attention in energy finance literature. A large body of literature addresses the relationship between crude oil prices and stock market returns in the major developed countries. Many studies have documented volatility spillover between oil price changes and stock markets. Most of the studies focused on the developed stock markets and reported a significant volatility spillover from oil price fluctuations to the developed stock markets. (Huang et al., 1996; Sadorsky, 1999; Hamilton, 2003; Park and Ratti, 2008; Apergis and Miller, 2009; Fayyad and Daly, 2011).

The earliest study in this field was carried out by Hamilton (1983) who studied the impact of oil prices on US economy and argued that changes in the oil prices considerably influence the US economy. In another early study, Jones and Kual (1996) investigated the effect of oil prices on the stock markets of Canada, Japan, UK and US. They employed a standard present value model which showed a negative impact of oil prices on stock returns.

On the contrary, Agren (2006) documented a strong evidence of volatility spillover from oil price fluctuation to US stock market where he employed asymmetric BEKK model. Furthermore, Malik and Ewing (2009) investigated the volatility spillover between oil prices and five US equity sector indices. They applied the BEKK-GARCH model and found a significant volatility spillover from oil prices to different sectors of US stock market.

Among the developing countries, some studies have paid attention to a particular region such as GCC countries. In this context, Hammoudeh and Eleisa (2004) investigated oil prices and six stock markets of Gulf Cooperation Council. They found a negative relationship between oil prices and GCC stock exchanges. In another study, Hammoudeh and Choi (2006) investigated the long-run links between oil prices and stock indices of five GCC countries (Bahrain, Kuwait, Oman, Saudi Arabia and

UAE). Their findings show that oil price changes have no direct effects on the GCC markets.

Furthermore, Hammoudeh and Li (2008) investigated five GCC countries and employed a GARCH (1, 1) model to detect the volatility spillover from oil price fluctuations to GCC countries. They concluded that GCC stock returns are affected more by global than domestic events. More recently, Awartani et al. (2013) also examined the volatility spillover between the oil market and the GCC stock markets over the period of 2004 to 2012. They employed a spillover index proposed by Diebold and Yilmaz (2009) and found bi-directional volatility spillovers between oil prices and GCC countries.

In their paper, Basher and Sadorsky (2006) investigated the impact of oil price changes on the stock markets of 21 emerging countries. Using an international multi-factor model, they found significant evidence of volatility spillover from oil price fluctuations to stock markets. Furthermore, Bhar and Nikolova (2010) examined the oil price fluctuations in the Russian stock market by employing EGARCH model over a period of 1995 to 2007. Their findings show significant volatility spillover between oil and the Russian stock market returns.

Furthermore, some other studies have analyzed the volatility transmission between oil stock markets in Africa. Fore example, in a recent study, Lin et al. (2014) conducted a study to examine the volatility spillover between oil and the stock markets of Ghana and Nigeria. In addition to this, they computed the optimal weights and hedge ratios by using VAR-GARCH, VAR-AGARCH and DCC-GARCH results between 2000 and 2010. Their findings show significant unidirectional volatility spillover from oil to the stock markets of Ghana and Nigeria.

In their study, Narayan and Narayan (2010) tested the oil prices and stock exchange of Vietnam and found a positive significant impact on stock prices from oil price changes. Using vector error correction model, Masih et al. (2011) examined the oil prices and stock market of South Korea from 1988 through 2005. They determined the significant impact of oil prices on Korean stock market returns.

Recently, Demiralay and Gencer (2014) used VAR-AGARCH model to check the volatility spillover between oil and five sector indexes of 21 emerging stock markets from 1995 to 2013. They showed a significant volatility spillover from oil prices to the sectors. For the Chinese stock exchange, Caporale et al. (2015) suggested that oil price fluctuations affect sectoral stock returns significantly in China during the period of 1997 and 2014.

Most recently, Diaz et al. (2016) studied volatility transmission between oil and G-7 stock markets from 1970 through 2014. Their empirical results show negative response of past oil shocks to G-7 stock markets. For the opposite direction, Park and Ratti (2008) found significant and positive correlation between oil price fluctuations and 13 European stock markets over the period from 1986 to 2005. Ciner (2001) employed a non-linear causality model to examine the impact of oil shocks on US stock market and found significant relationship between oil shock and US stock market.

This chapter has reviewed existing empirical literature on the volatility spillover effect and linkages among stock markets. The literature reveals that many studies have been done using different time spans and different methods to investigate volatility spillover effects. The majority of the studies reveal that there is a significant and positive volatility spillover effects among stock markets. On the other hand, some studies argue that there is a negative volatility spillover effects among stock markets.

As noted in this chapter, the existing literature sheds light on different regions and economic blocks such as Asia-Pacific region, Euro Zone, MENA region, ASEAN countries and GCC countries. However, the empirical literature is lacking with regard to the volatility spillover effect from G7 stock markets to E7 stock markets. Hence, this study attempts to fulfill this gap in the literature.

To examine the volatility spillover effects in equity markets, the empirical literature focuses on a variety of methodologies and econometric techniques like AR-GARCH model, bi-variate GARCH model, GARCH-BEKK model, Multivariate GARCH-BEKK model, EGARCH model, GJR-GARCH model, GARCH-M model, Diebold and Yilmaz approach etc. However, a controversy still exists among the researchers regarding to the methodologies to examine the transmission of volatility from one country to another. These controversies signify that the ball is still wandering among the courts. Therefore, this study intends to resolve this controversy by employing a recent econometric model.

Table 4: Tabulated Previous Studies

Volatility Spillovers from Developed to Developed Stock Markets			
Year	**Author(s)**	**Model**	**Findings**
1990	Hamao et al.	GARCH-M	Found volatility spillover from stock markets of US and UK to the stock market of Japan.
1993	Theodossiou and Lee	Multivariate GARCH-M	Significant volatility spillover effects between the stock exchanges of US, UK, Canada, Germany and Japan.
1994	Bae and Karolyi	GARCH	Found a significant magnitude of volatility spillover effects between stock market of US and Japan..
1995	Karolyi	Multivariate BEKK-GARCH	Exhibited unidirectional volatility spillover from the New York and Toronto Stock Exchange.
1997	Booth et al.	EGARCH	Showed unidirectional volatility spillovers between Swedish-Norwegian stock markets.
1998	Kanas	Multivariate EGARCH	Identified the bidirectional volatility spillovers among stock markets of Frankfurt, London and Paris
2005	Baele	Multivariate regime switching framework	Past shocks of US stock exchange significantly transmit to the European stock markets.
2010	Xiao and Dhesi	Multivariate GARCH-BEKK	Identified the volatility spillover effects from the stock market of UK and US to the stock markets of France and Germany.

Volatility Spillovers from Developed to Emerging Stock Markets			
1995	Wei et al.	univariate GARCH	Reported existence of volatility spillover effects from the stock market of US to the stock markets of Hong Kong and Taiwan.
2000	Ng	bi-variate GARCH	Strong volatility spillover effects from global to emerging equity markets as compare with regional equity markets.
2003	Miyakoshi	bi-variate EGARCH	Significant volatility spillover from the stock market of US to the Asian stock markets.
2004	Worthington and Higgs	MV-GARCH	Significant volatility spillover effects from mature Asian markets to emerging Asian equity markets.
2006	Al-Deehani and Moosa	Stochastic volatility approach	The empirical results of the study reveal that the stock market of Kuwait is more influential than others.
2007	Li	MV GARCH	Concluded that there is no direct linkage between the Chinese Stock Exchange and the US Stock Exchange.
2009	Lee	bi-variate GARCH	Significant volatility spillover effects within Hong Kong, Japan, Singapore, South Korea and Taiwan.
2009	Johansson and Ljungwall	MV EGARCH	Their study revealed that volatility spills over from Hong Kong to Taiwan, which further affects the volatility in China.

2009	Diebold and Yilmaz	Diebold and Yilmaz Model	The findings show a clear evidence of volatility spillover effect during the crisis episodes.
2010	Moon and Yu	GARCH	Found a strong evidence of symmetric and asymmetric volatility spillover effects from the stock market of US to China.
2010	Sok-Gee and Karim	Multivariate EGARCH	Significant volatility spillover effects between the stock markets of US and Japan. They concluded that Indonesian stock market is affected by US Stock Market.
2010	Giannellis et al.	Multivariate EGARCH	Significant reciprocal volatility spillover effects between stock market and real activity within a country.
2011	Abidin and Zhang	AR-GARCH	Significant volatility spillover effects among the Australian and Chinese stock markets.
2013	Beirne et al.	tri-variate VAR-GARCH	Found significant volatility spillover effects from mature to emerging stock market.
2013	Awartani et al.	GARCH-DCC	Found a unidirectional flow of information from the stock market of US and Saudi Arabia to other stock markets of GCC countries during the subprime crisis.
2013	Alikhanov	GJR-GARCH	Significant volatility spillover effects from the stock market of US to the other European stock exchanges.

2015	Li and Giles	GARCH-BEKK	Significant volatility spillover from US to other Asian countries. Further, the findings suggest that there exists a bidirectional volatility spillover during the Asian financial crisis.
2015	Syriopoulos et al.	VAR-GARCH	Significant volatility spillover between US and BRICS countries and negative correlation between US and China.
2015	Demiralay and Bayraci	Diebold and Yilmaz approach	Significant volatility spillover from developed stock markets to Central and Eastern European stock markets.
2016	Akca and Ozturk	Diebold and Yilmaz model with stochastic volatility model	Claimed a high volatility spillover from the stock market of US to UK, Germany,Greece, Spain and Turkey.
Volatility Spillovers between Different Types of Markets			
1983	Hamilton	Granger Causality	Argued that changes in the oil prices considerably influence the US economy.
1996	Jones and Kual	standard present value model	Showed a negative impact of oil prices on stock returns.
2006	Agren	asymmetric BEKK	Documented a strong evidence of volatility spillover from oil price fluctuation to US stock market
2006	Basher and Sadorsky	multi-factor model	Found significant evidence of volatility spillover from oil price fluctuations to stock markets

2008	Hammoudeh and Li	GARCH	They concluded that GCC stock returns are affected more by global than domestic events.
2010	Bhar and Nikolova	EGARCH	Findings show significant volatility spillover between oil and the Russian stock market returns.
2011	Masih et al.	Vector Error Correction Model	Determined the significant impact of oil prices on Korean stock market returns.
2014	Demiralay and Gencer	VAR-AGARCH	Showed a significant volatility spillover from oil prices to the sectors.
2015	Caporale et al.	VAR-GARCH in mean	Suggested that oil price fluctuations affect sectoral stock returns significantly in China during the period of 1997 and 2014.
2016	Diaz et al.	VAR	empirical results show negative response of past oil shocks to G-7 stock markets.

CHAPTER III

DATA AND METHODOLOGY

This chapter presents the data and methodology. This chapter is organized as follows; Section 3.1 demonstrates data description of the study. Section 3.2 consists of methodology used for this study.

3.1 DATA DESCRIPTION

The data include daily closing prices of market indices for G7 (Canada, UK, Germany, Italy, France, Japan, US) and E7 (Brazil, China, India, Indonesia, Mexico, Russia, Turkey) stock markets. The data is gathered from Thomson Reuters DataStream over a period between 01.09.1995 and 15.03.2016 except for Italy due to non-availability of earlier 3 years data. The choice of this sampling period is made on the basis of the availability of data of all concerned stock markets. It is important to note that the sampling period starts from 1995. Among the E7 countries, Russian stock market was established in 1995. Therefore, the sampling period starts from 1995 and covers more than twenty years.

Furthermore, the sample period is divided into two subsamples to investigate before and after the Global Financial Crisis period (Louzis, 2015; Akca and Ozturk, 2016). Before the Global Financial Crisis period starts from January 8, 2002 to June 29, 2007 and after the Global Financial Crisis period begins from July 4, 2007 to December 28, 2012 to investigate the volatility spillover between US and E7 stock markets. The study covers only the days for which all indices have been available.

The stock market indices of E7 stock markets include Shanghai Composite index of China, S & P BSE 100 index of India, BOVESPA index of Brazil, IPC BOLSA index of Mexico, RTS index of Russia, JSX Composite index of Indonesia and BIST 100 index of Turkey. The G7 stock indices include S&P/TSX Composite Index of Canada, CAC 40 index of France, DAX 30 index of Germany, FTSE MIB index of Italy, Nikkei 225 of Japan, and FTSE ALL SHARE index of UK and S&P

500 index of US. The stock market indices of G7 and E7 countries are presented in Table 5.

Table 5: Stock Indices of G7 and E7 Countries

E7 Countries	Stock Index	G7 Countries	Stock Index
Brazil	BOVESPA	Canada	TSX
China	SSEC	France	CAC 40
India	BSE 100	Germany	DAX 30
Indonesia	JSX	Italy	FTSE MIB
Mexico	IPC BOLSA	Japan	Nikkei 225
Russia	RTS	UK	FTSE ALL SHARE
Turkey	BIST 100	US	S&P 500

3.2 METHODOLOGY

The daily returns are computed by using the following equation**:**

$$R_t \;=\; (P_t - P_{t-1}) / P_{t-1} \tag{1}$$

Where,

Pt = current closing price of index

P_{t-1}= previous closing price of index

Moreover, descriptive statistics are used to describe the important features of data quantitatively. Descriptive statistics assist to simplify the data in a sensible and manageable form. Descriptive statistics consist of Mean, Standard deviation, Skewness and the Kurtosis analysis.

Many methods are employed to capture volatility spillover and linkages among the stock exchanges such as VAR, ARCH-GARCH, EGARCH, and MGARCH with extended approaches as BEKK and DCC (Theodossiou and Lee, 1993; Bae and Karolyi, 1994; Wei et al., 1995; Li, 2007; Giannellis et al., 2010; Xiao and Dhesi, 2010; Padhi and Lagesh, 2012). Vector Autoregressive Model is employed on multiple time series data to find out linear interdependence. According to Fama (1965) and Mandlbort (1963) volatility clustering has been observed from the returns which leads to the time varying second order moments. ARCH model (Engle, 1982) and GARCH models (Bollerslev, 1986) are employed to handle volatility clustering. VAR model is used to find the mean equation for the subsamples and the full sample.

3.2.1 VAR-GARCH (1, 1) Model

In the existing literature, CCC-MGARCH model of Bollerslev (1986), the BEKK-GARCH model of Engle and Kroner (1995) are commonly used models in order to investigate the volatility spillover between different time-series. However, these models do not consider VAR as they use excessive parameters. VAR-GARCH (1, 1) model provides less excessive parameters for more meaningful and interpretable estimates (Hammoudeh et al., 2009).

This study employs a bivariate VAR-GARCH (1, 1) model, proposed by Ling and McAleer (2003), to explore volatility spillover effects among E7 and G7 equity markets. The VAR-GARCH model is based on the CCC-GARCH model of Bollerslev (1990). This method combines a multivariate GARCH process and a VAR model.

The strength of the model rests on its flexibility to explore the conditional volatility and conditional correlation cross effects with meaningful estimated parameters. This model also enables to capture the impact of past shocks. The VAR-GARCH model is also easy to use and it avoids the computational complications in estimating the unknown parameters. The ability of the VAR-GARCH model to capture cross-market volatility interactions has been tested and confirmed in the recent studies of oil, stock markets and agricultural commodities (Hammoudeh et al, 2009; Arouri et al, 2011; Mensi et al, 2014).

In VAR-GARCH model, the conditional mean and variance are as follows:

$$R_t = \mu + \Phi R_{t-1} + \varepsilon_t \tag{2}$$

$$\varepsilon_t = H_t^{1/2} \eta_t \tag{3}$$

Where;
R_t = the return of stock market index
ε_t= the residual terms of the mean equation
η_t = random vectors
H_t = conditional variances

Bollerslev's (1986) constant conditional correlation (CCC) model assumes that the conditional variance for each return, h_{it}, i = 1,…,m, follows a univariate GARCH process:

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} \tag{4}$$

Where α_{ij} represents the ARCH effects, or the short-run persistence of shocks to return *i*, and β_{ij} represents the GARCH effects, or the contribution of shocks to return *i* to long-run persistence, namely $\sum_{j=1}^{r} \alpha_{ij} + \sum_{j=1}^{s} \beta_{ij}$.

The conditional correlation matrix of CCC is $\Gamma = E\left(\eta_t \eta_t' \mid F_{t-1}\right) = E\left(\eta_t \eta_t'\right)$, where Γ = {p*ij*} for *i*, *j* = 1,…,*m*. From (3), $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, $D_t = (diag Q_t)^{1/2}$, and $E\left(\varepsilon_t \varepsilon_t^{'} \mid F_{t-1}\right) = Q_t = D_t \Gamma D_t$, where Q_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1} Q_t D_t^{-1}$, and each conditional correlation coefficient is estimated from the standardized residuals. In order to accommodate interdependencies, Ling and McAleer (2003) proposed a VARMA specification of the conditional mean and the following specification for the conditional variance:

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \tag{5}$$

where $H_t = (h_{1t},...,h_{mt})'$, $\vec{\varepsilon} = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)'$, and W, A_i for i = 1,…,r and B_j for i = 1,…,s are $m \times m$ matrices defined as:

$$A = \begin{pmatrix} \alpha_{(G7)1}^2 & \alpha_{(G7)2}^2 \\ \alpha_{(E7)2}^2 & \alpha_{(E7)1}^2 \end{pmatrix} \qquad B = \begin{pmatrix} \beta_{(G7)1}^2 & \beta_{(G7)2}^2 \\ \beta_{(E7)2}^2 & \beta_{(E7)1}^2 \end{pmatrix}$$

$$h_t^{E7} = C_{E7} + \alpha_{E7}(\varepsilon_{t-1}^{E7})^2 + \beta_{E7}h_{t-1}^{E7} + \alpha_{G7}(\varepsilon_{t-1}^{G7})^2 + \beta_{G7}h_{t-1}^{G7} \tag{6}$$

$$h_t^{G7} = C_{G7} + \alpha_{G7}(\varepsilon_{t-1}^{G7})^2 + \beta_{G7}h_{t-1}^{G7} + \alpha_{E7}(\varepsilon_{t-1}^{E7})^2 + \beta_{E7}h_{t-1}^{E7} \tag{7}$$

The above mentioned equations depict how the transmission of volatility takes place from one country to another country over the time. The error terms report the return innovation in corresponding stock markets at time (t-1) and check the effect of direct influence of shock transmission. The volatility interdependence is realized by h_{t-1}^{G7} and h_{t-1}^{E7}. In order to check the stationarity, the roots of the equation [I_2-AL-BL] = 0 must be outside the unit circle.

Where

L = lag polynomial

I_2 = indentity matrix

The conditional covariance was modeled as;

$$h_t^{E7,\ G7} = \rho \times \sqrt{h_t^{E7} \times h_t^{G7}} \tag{8}$$

Where ρ= conditional correlation coefficient

This model allows both the conditional mean and volatilities between E7 and G7 stock markets to capture the interdependence and spillover effect. The log likelihood function *L* was optimized by the (Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; and Shanno, 1970) algorithm for a sample of T observations.

$$L = \sum_{t=1}^{T} L_t \ , \quad L_t = \ln(2\pi)n/2 - 1/2\ln\left|H_t\right| - 1/2\varepsilon_t^{'} H_t^{-1}\varepsilon_t \tag{9}$$

3.2.2 Portfolio Management

The study also computes the optimal weights and optimal hedge ratios of E7-US for the purpose of portfolio management and hedging strategies. Suppose that an investor wants to construct a portfolio of two assets E7-US to offset the risk in adverse situations. According to Kroner and Ng (1998), the optimal weight of E7 stocks in one dollar portfolio of *US-E7* at time t is given as:

$$W_t^{US,E7} = \frac{h_t^{US} - h_t^{US,E7}}{h_t^{US} - 2h_t^{US,E7} + h_t^{E7}} \tag{10}$$

and

$$\begin{cases} 0 \ if \ W_t^{US,E7} < 0 \\ W_t^{US,E7} \quad if \ 0 \leq W_t^{US,E7} \leq 1 \\ 1 \ if \ W_t^{US,E7} > 1 \end{cases}$$

Where $W_t^{E7,US}$ refers to the weight of stocks of E7 stocks in one US dollar portfolio of the two stocks portfolio of US-E7 at time t. The terms h_t^{US} and h_t^{E7} are the conditional variances of US and E7 stocks. The value of $h_t^{E7,US}$ shows the conditional covariance between US and E7 stocks at time t. The weight of US stocks in supposed portfolio is 1- $W_t^{US,E7}$.

3.2.3 Hedging Strategies

In order to calculate the optimal hedge ratios, we followed Kroner and Sultan (1993) who constructed optimal hedge ratios to minimize risk.As to the optimal hedge ratios, it is important to know how much a long position of one dollar on the index returns of US can be hedged by short position of $\beta_t^{E7,US}$ dollar on the E7 stocks. Kroner and Sultan (1993) proposed the hedge ratio as follows:

$$\beta_t^{US,E7} = \frac{h_t^{US,E7}}{h_t^{E7}} \tag{11}$$

CHAPTER IV

EMPIRICAL RESULTS AND DISCUSSION

This chapter reveals the empirical results and discussion. This chapter is organized as follows; Section 4.1 represents descriptive statistics. Section 4.2 demonstrates the figures of prices and returns of E7 and G7 stock markets. Section 4.3 describes the results of unit root tests. Section 4.4 reports the empirical results of VAR-GARCH model for E7 and G7 stock markets. Section 4.5 exhibits the summary statistics for the portfolio weights and hedge ratios.

4.1 DESCRIPTIVE STATISTICS

Table 6 describes the summary statistics of the stock returns for E7 and G7 countries. The average returns are generally positive. In general, the findings show that the stock returns of E7 stock markets are higher than those of G7 stock markets. The unconditional volatility, as measured by standard deviations, is higher for the E7 stock markets in comparison with G7 stock markets. The findings imply that emerging markets are riskier but provides higher returns than developed economies. The kurtosis of all countries are greater than 3, indicating that all stock return series are leptokurtic. The Jarque-Bera test rejects the null hypothesis of normality for both E7 and G7 stock return series. The L-B test results indicate evidence of autocorrelation in return series of E7 and G7 stock markets.

The detailed inspection of developing and developed countries is given in Panel A and in Panel B, respectively. For E7 stock markets, the Russian stock market has the highest volatility, as approximated by a standard deviation of %3.30, followed by the Turkish stock market (%3). The negatively skewed returns are found in China, while the positively skewed returns are found in other stock markets. For G7 stock markets, the Italian stock market provides the lowest return with the highest volatility of %1.8. The markets of France, Italy and UK are positively skewed, while the markets of Canada, Germany, Japan, and US are negatively skewed.

Table 6: Descriptive Statistics for E7 and G7 Countries

Panel A: Statistics for E7 Countries

Country	Brazil	China	India	Indonesia	Mexico	Russia	Turkey
Mean	0.0009	0.0005	0.0007	0.0008	0.0009	0.0011	0.0018
Std. Dev.	0.025	0.020	0.019	0.019	0.017	0.033	0.030
Min	-0.170	-0.196	-0.112	-0.155	-0.150	-0.326	-0.019
Max	0.520	0.138	0.174	0.206	0.136	0.343	0.331
Skewness	2.267	-0.138	0.370	0.401	0.309	0.727	0.796
Kurtosis	53.350	6.477	8.089	13.785	9.250	17.201	11.933
J-B	44379.43	6507.34	10214.93	29514.55	13305.64	46129.49	22438.24
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
ARCH-LM	44.095	190.397	166.401	162.338	194.720	148.088	107.801
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LB- Q (12)	33.262	27.385	32.969	90.022	40.395	46.190	28.092
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LB- Q (24)	56.412	38.455	43.771	109.297	60.607	72.925	65.902
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
# of Obs	3715	3715	3715	3715	3715	3715	3715

Panel B: Statistics for G7 Countries

Country	Canada	France	Germany	Italy	Japan	UK	US
Mean	0.0003	0.0004	0.0005	0.0001	0.0001	0.0002	0.0004
Std. Dev.	0.012	0.016	0.017	0.018	0.017	0.0130	0.013
Min	-0.156	-0.108	-0.111	-0.124	-0.119	-0.097	-0.128
Max	0.110	0.119	0.122	0.147	0.125	0.111	0.098
Skewness	-0.553	0.160	-0.09	0.108	-0.119	0.031	-0.326
Kurtosis	13.421	4.746	4.292	5.664	4.856	6.785	6.748
J-B	28072.63	3503.41	2857.35	4407.13	3660.22	7127.03	7114.57
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
ARCH-LM	212.861	394.766	387.571	310.437	379.784	478.423	467.540
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LB-Q (12)	34.794	52.339	33.900	31.275	9.193	46.253	45.104
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LB-Q (24)	60.948	67.068	54.712	48.863	16.221	73.763	58.053
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
# of Obs	3715	3715	3715	3291	3715	3715	3715

Note: *P-values are in parentheses. JB is the empirical statistics of the Jarque–Bera test for normality based on skewness and excess kurtosis. ARCH refers to the empirical statistics of the statistical test for conditional heteroskedasticity of order 6. LB is the empirical statistics of the Ljung–Box tests for autocorrelations.*

4.2 RESULTS OF UNIT ROOT TESTS

Table 7 reports the results of unit root tests with trends and without trends. Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) tests were employed to check the unit root. The null hypothesis was rejected for ADF and PP tests. The results indicate that all return series are having a stationary process at the 1% significance level.

Table 7: Results of Unit Root Test for E7 and G7 Countries

Panel A: *Statistics for E7 Countries*

	With Trends		Without Trends	
Country	ADF	PP Test	ADF	PP Test
Brazil	-61.894***	-62.028***	-61.860***	-61.981***
China	-61.070***	-61.110***	-61.070***	-61.102***
India	-56.421***	-56.438***	-56.428***	-56.438***
Indonesia	-55.861***	-55.720***	-55.867***	-55.718***
Mexico	-57.812***	-57.757***	-57.803***	-57.740***
Russia	-56.446***	-56.436***	-56.415***	-56.400***
Turkey	-60.233***	-60.266***	-60.127***	-60.156***

Panel B: *Statistics for G7 Countries*

	With Trends		Without Trends	
Country	ADF	PP Test	ADF	PP Test
Canada	-59.435***	-59.449***	-59.430***	-59.435***
France	-62.465***	-62.667***	-62.457***	-62.647***
Germany	-62.125***	-62.181***	-62.129***	-62.176***
Italy	-59.201***	-59.250***	-59.203***	-59.243***
Japan	-62.328***	-62.417***	-62.323***	-62.402***
UK	-62.310***	-62.446***	-62.315***	-62.443***
US	-63.303***	-63.487***	-63.307***	-63.481***

*Note: ***, ** and * denotes coefficients are significant at 1%. 5% and 10% level respectively. The P-values with trends for ADF and PP are -3.966, -3.413 and -3.128 respectively. The P-values without trends for ADF and PP are -3.435, -3.862 and -2.567 respectively.*

Figure 1 and 2 exhibit stock return behaviors for E7 and G7 countries. In general, the sampling period is characterized by high volatility. It is obvious in Figure 1 that while the volatility increased in Indian and Indonesian markets during the Asian crisis, the stock returns of Brazil and Mexico were affected from the 1994 Mexican financial crisis.

In addition, the Turkish and Russian stock markets have experienced highly volatility during the 1990s that both economies were characterized by severe currency devaluations in 1994 and 1998, respectively. It is noteworthy that all stock markets exhibit high volatility during the 2007-2009 financial crisis, which originated from the US and spread over the other countries. It appears that the recent global financial crisis has asymmetric impact on the stock returns of G7 and E7 countries. While Russia, India and Brazil experienced large spikes in their return series, the other markets had relatively small spikes in respond to the recent financial crisis.

Figure 1: Daily Stock Returns for E7 Stock Markets

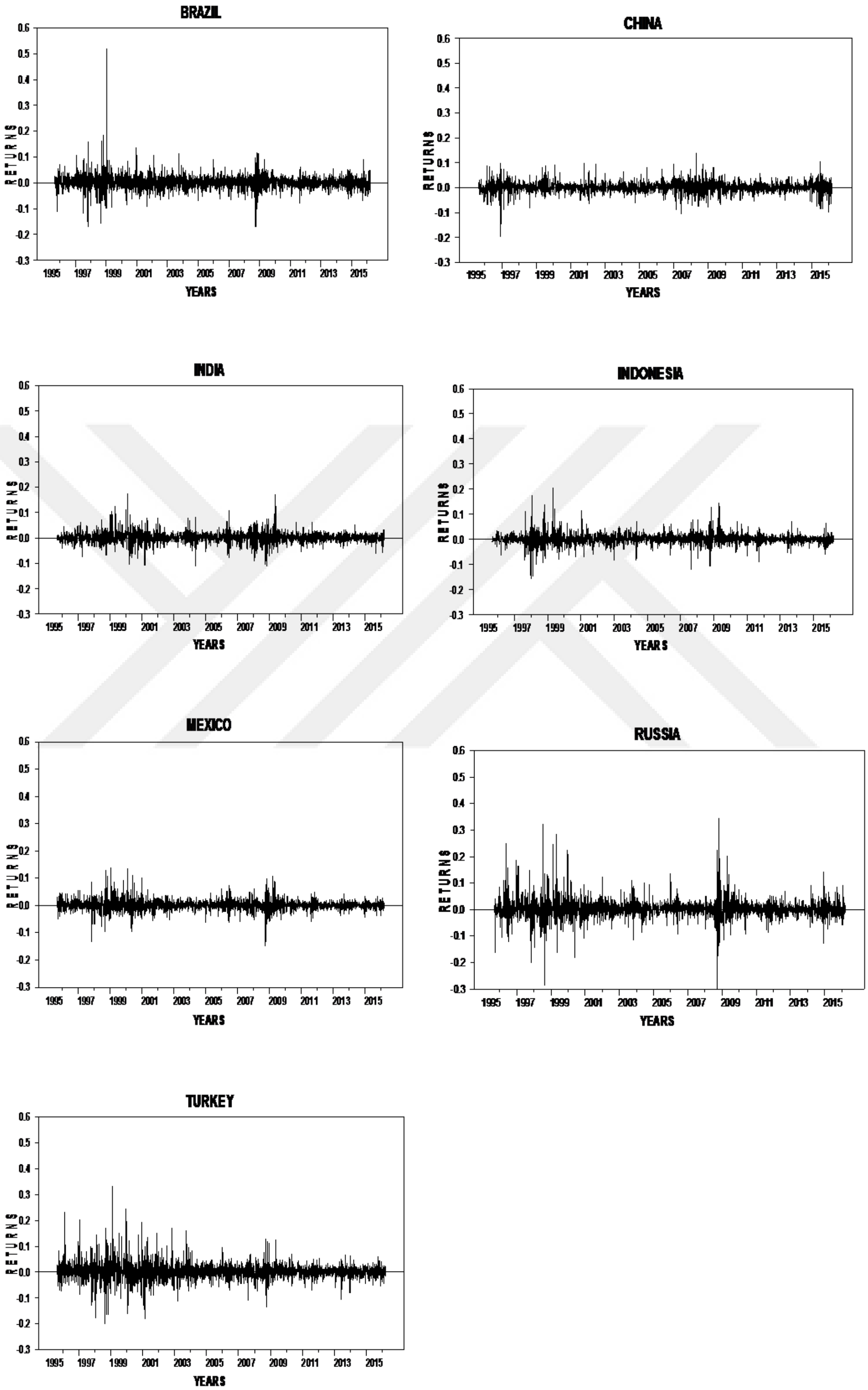
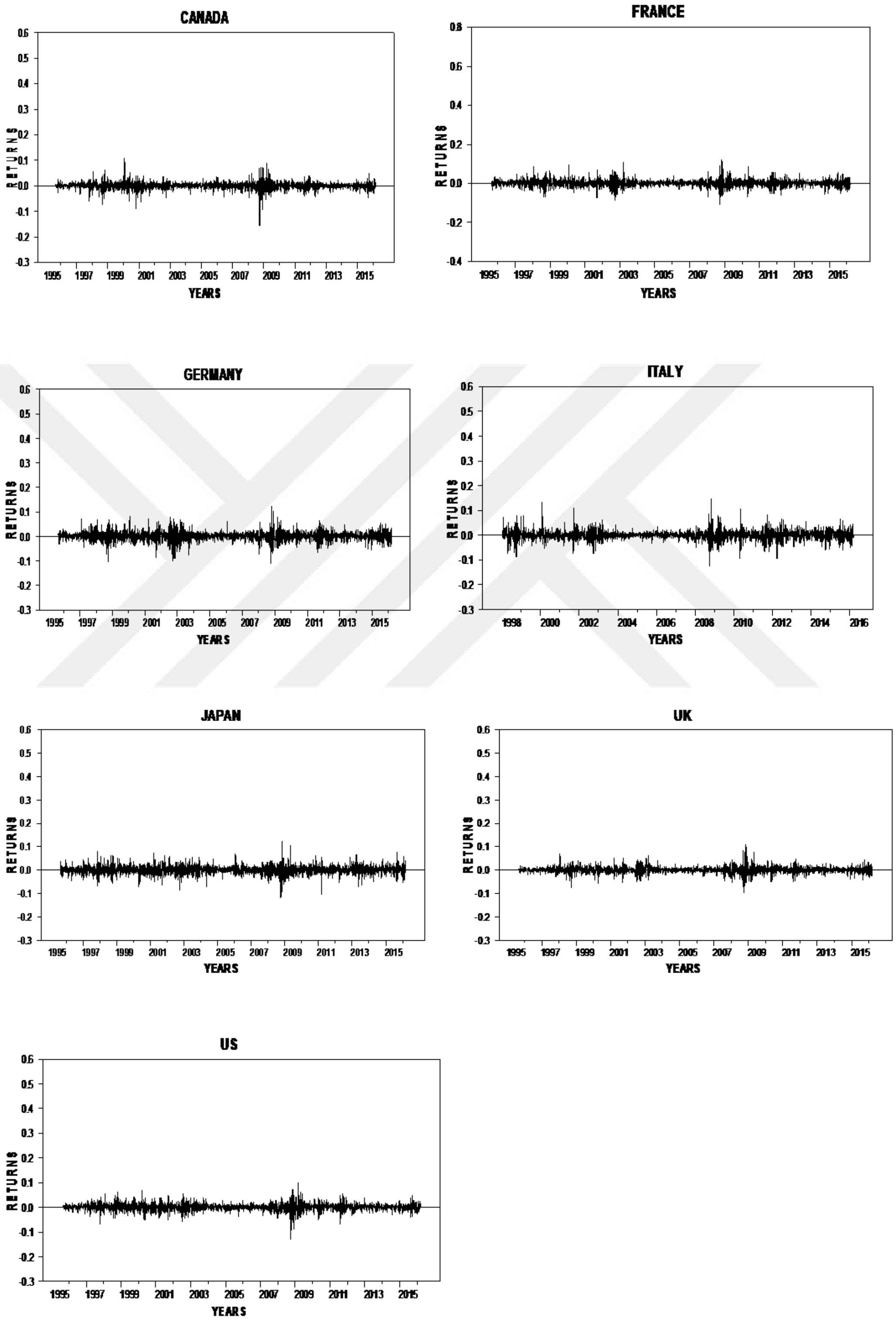


Figure 2: Daily Stock Returns for G7 Stock Markets



4.3 EMPIRICAL RESULTS OF VAR (1)–GARCH (1) MODEL

Tables 8 to 16 summarize the empirical outcomes of the estimated VAR(1)–GARCH(1) model. The term h_{t-1}^{G7} describes the conditional variances of the G7 stock markets at time t respectively. h_{t-1}^{E7} describes the conditional variance for the E7 stock markets. The error terms $(\varepsilon_{t-1}^{E7})^2$ and $(\varepsilon_{t-1}^{G7})^2$ refer the impact of shocks on the indices of the E7 and G7 stock markets at time t−1 respectively.

4.3.1 Estimates of VAR (1)-GARCH (1) model for Canada and E7

Table 8 documents seven bivariate VAR-GARCH (1, 1) models for testing the volatility spillover between the Canadian stock market and E7 stock markets. According to the mean equation, the one-period lagged returns of the Canadian stock market significantly affect the current returns of the most of E7 stock markets except China and India. More importantly, the coefficients of the Chinese and Indian stock markets are found insignificant, which implies that stock market of Canada does not affect the current returns of the Chinese and Indian stock market. On the contrary, the Chinese and Indian stock markets significantly affect the current returns of the Canadian stock market. Brazil and Mexico are reported as the most influenced markets with the coefficients of 0.002 and 0.010 respectively. Moreover, the past stock returns of Indonesia, Russia and Turkey seem to be affected negatively by the Canadian stock market.

From the variance equation perspective, the ARCH and GARCH coefficients which are used to estimate shocks and volatility independence in the conditional variance equations are highly significant in most cases. The past shocks of the Canadian stock market, $(\varepsilon_{t-1}^{G7})^2$, affect the return dynamics of most of the E7 stock markets negatively. The past volatility of the Canadian stock market, represented by h_{t-1}^{G7}, has significant impact on the E7 stock markets. The only exception is stock markets of China and India with insignificant coefficients. The past volatility of the Canadian stock market has no impact on the Chinese and Indian stock return volatility. As for the opposite direction, the impact of past conditional volatility of most of the emerging markets, h_{t-1}^{E7} on the conditional volatility of the Canadian stock market is negatively significant. The reported outcome indicates that past conditional volatility of E7 countries can be modeled to estimate future volatility. To capture persistence in conditional variance of stock returns, GARCH (1.1) is sufficient.

Turning out to the constant conditional correlation, the findings report that E7 stock returns are positively correlated with Canadian stock returns. The magnitudes of the correlations are generally high. The study reports low correlation between Canadian and Chinese stock market that implies the opportunities for diversification. The implication of this finding for portfolio diversification is that the addition of the Chinese stocks would minimize the risk. However, the highest constant conditional correlation between Canada and E7 stock market returns occurs in Mexico (0.570), followed by Brazil (0.550) and Russia (0.379) respectively, which implies that Mexican, Brazilian and Russian stock markets are integrated with Canadian stock market. The geographical position and trading relations among these countries would be the reason of high correlation among these stock markets.

Table 8: Estimates of VAR (1)-GARCH (1) model for Canada and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	Canada	Brazil	Canada	China	Canada	India	Canada	Indo	Canada	Mexico	Canada	Russia	Canada	Turkey
G7(1)	0.055***	0.002***	0.059***	-0.005	0.060***	-0.013	0.065***	-0.019***	0.036*	0.010*	0.056***	-0.009***	0.048***	-0.005***
	(0.000)	*(0.000)*	*(0.001)*	*(0.455)*	*(0.002)*	*(0.215)*	*(0.000)*	*(0.000)*	*(0.053)*	*(0.080)*	*(0.005)*	*(0.002)*	*(0.000)*	*(0.000)*
E7(1)	0.109***	-0.047***	0.112***	-0.002	0.206***	0.060**	0.278***	0.037**	-0.014	0.054***	0.345***	0.016**	0.259***	-0.047***
	(0.000)	*(0.000)*	*(0.000)*	*(0.870)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.020)*	*(0.486)*	*(0.000)*	*(0.000)*	*(0.056)*	*(0.000)*	*(0.009)*
Variance Equation														
C (10) [4]	0.030***	0.141***	0.019***	0.073***	0.023***	0.067***	0.019***	0.070***	0.037***	0.009*	0.031***	0.249***	-0.140***	2.569***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	(0.059)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon^{G7}_{t-1})^2$	0.110***	-0.0008***	0.086***	0.0003	0.088***	0.002	0.097***	-0.003***	0.114***	-0.011***	0.121***	-0.0007	0.225***	-0.001***
	(0.000)	*(0.000)*	*(0.000)*	*(0.675)*	*(0.000)*	*(0.146)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon^{E7}_{t-1})^2$	0.058**	0.085***	-0.010**	0.092***	0.054***	0.088***	0.067***	0.117***	-0.049***	0.098***	0.108***	0.109***	-0.136***	0.207***
	(0.012)	*(0.000)*	*(0.016)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
h^{G7}_{t-1}	0.868***	0.001***	0.904***	-0.0004	0.897***	-0.002	0.885***	0.005***	0.847***	0.016***	0.854***	0.001***	0.618***	0.060***
	(0.000)	*(0.000)*	*(0.000)*	*(0.665)*	*(0.000)*	*(0.424)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
h^{E7}_{t-1}	-0.065***	0.896***	0.003	0.896***	-0.033*	0.888***	-0.037***	0.857***	0.080***	0.893***	-0.123***	0.876***	1.831***	0.150***
	(0.004)	*(0.000)*	*(0.571)*	*(0.000)*	*(0.053)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
CCC G7	0.550***		0.092***		0.271***		0.250***		0.570***		0.379***		0.217***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	21238.68		21268.05		21700.68		21836.68		22627.56		20024.36		19680.73	
AIC	10.738		10.880		11.088		11.058		11.563		10.065		10.150	
H-Q	10.722		10.873		11.079		11.045		11.556		10.054		10.137	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.3.2 Estimates of VAR (1)-GARCH (1) model for France and E7

The parameters of the VAR-GARCH model which demonstrates the seven pairs of return and volatility spillover from the stock market of France to stock markets of E7 stock markets are shown in Table 9. Analyzing the mean equation, it has been estimated that there exists significant return spillovers from the stock market of France to stock markets of Brazil, Indonesia and Mexico. The one-period lagged returns of the French stock market significantly affect the current returns of Brazil, Indonesia and Mexico. This finding violates the weak form of the efficient market hypothesis that states that past returns have no effect on future returns. It is interesting to note that there are bi-directional return spillovers between France and Indonesia. Importantly, the coefficient of Indonesia is negative that implies that past returns of French stock market reduce current returns of Indonesian stock market.

Looking in the opposite direction, the most of the coefficients of E7 stock markets are found insignificant. In order to examine the variance equation, most of the coefficients are recorded significant. The estimates of past shocks of the French stock market, $(\varepsilon_{t-1}^{G7})^2$, affect the return dynamics of Indian and Indonesian stock markets. It implies that E7 stock markets are not affected by the past shock of French stock market.

The reported estimates of past shocks of E7 stock markets significantly affect the stock market of France which suggest that E7 stock markets are more influential. Examining the variance equation minutely, it is found that the past volatility of French stock market, represented by h_{t-1}^{G7}, has no significant impact on most of the E7 stock markets. The only exception is stock markets of India and Indonesia with significant coefficients. On the other direction, the past volatility of most of E7 stock markets have negative significant impact on the stock market of France which implies that increase in the volatility of E7 stock markets reduces the volatility of the French stock market.

The constant conditional correlations (CCC) of France and E-7 countries are positive. The positive and significant correlations between France and E-7 stock returns imply that investors can gain potential returns by investing in E-7 stock markets. The highest constant conditional correlation between France and E7 stock market returns occurs in France- Mexico (0.498), followed by France-Brazil (0.435) and France-Russia (0.417) respectively. It suggests that there are limited global diversification opportunities available for investors. However, there exists the lowest correlation between stock markets of France and China suggesting that investors may take benefits from diversification.

Table 9: Estimates of VAR (1)-GARCH (1) model for France and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	France	Brazil	France	China	France	India	France	Indo	France	Mexico	France	Russia	France	Turkey
G7(1)	-0.063***	0.068***	-0.021	-0.005	-0.028	-0.004	-0.018	-0.053***	-0.091***	0.111***	-0.029	0.002	-0.027	-0.002
	(0.000)	*(0.000)*	*(0.251)*	*(0.618)*	*(0.110)*	*(0.718)*	*(0.209)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.108)*	*(0.795)*	*(0.130)*	*(0.751)*
E7(1)	0.027	-0.030	0.059***	*0.0003*	0.086***	0.066***	0.122***	0.049**	-0.017	0.050**	0.004	0.072***	0.046	-*0.005*
	(0.248)	*(0.163)*	*(0.000)*	*(0.983)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.013)*	*(0.291)*	*(0.011)*	*(0.869)*	*(0.000)*	*(0.102)*	*(0.762)*
Variance Equation														
C (10) [4]	0.042***	0.125***	0.036***	0.071***	0.042***	0.070***	0.034***	0.062***	0.037***	0.024***	0.035***	0.049***	0.030***	0.035***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{G7})^2$	0.084***	0.001	0.090***	*0.0001*	0.081***	*0.005**	0.103***	*-0.005****	0.080***	*0.0006*	0.078***	*0.00002*	0.078***	*0.0006*
	(0.000)	*(0.557)*	*(0.000)*	*(0.918)*	*(0.000)*	*(0.060)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.848)*	*(0.000)*	*(0.974)*	*(0.000)*	*(0.510)*
$(\varepsilon_{t-1}^{E7})^2$	0.009	0.079***	-0.005*	0.092***	0.009**	0.091***	0.028***	0.063***	0.0008	0.072***	0.011	0.042***	0.028***	0.044***
	(0.398)	*(0.000)*	*(0.095)*	*(0.000)*	*(0.034)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.814)*	*(0.000)*	*(0.171)*	*(0.000)*	*(0.007)*	*(0.000)*
h_{t-1}^{G7}	0.897***	0.0002	0.898***	0.0003	0.905***	-0.006**	0.878***	0.014***	0.903***	0.001	0.902***	0.001	0.901***	0.002
	(0.000)	*(0.894)*	*(0.000)*	*(0.847)*	*(0.000)*	*(0.048)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.638)*	*(0.000)*	*(0.117)*	*(0.000)*	*(0.114)*
h_{t-1}^{E7}	-0.013	0.902 ***	0.004	0.894***	-0.011**	0.894***	-0.017***	0.905***	-0.003	0.925***	-0.015*	0.955***	-0.034***	0.956***
	(0.350)	*(0.000)*	*(0.354)*	*(0.000)*	*(0.014)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.486)*	*(0.000)*	*(0.076)*	*(0.000)*	*(0.007)*	*(0.000)*
CCC G7	0.435 ***		0.108***		0.311***		0.273***		0.498***		0.417***		0.348***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	19768.31		20058.49		20514.92		20554.53		21251.09		18867.91		18964.29	
AIC	10.063		10.308		10.520		10.470		10.844		9.506		9.603	
H-Q	10.051		10.298		10.512		10.459		10.836		9.496		9.596	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectiv*

4.3.3 Estimates of VAR-GARCH model for Germany and E7

Table 10 reveals the results of the bivariate VAR-GARCH (1, 1) model for the seven pairs of Germany-E7 stock markets returns. Taking a closer look at first part of the table, the empirical findings document that the one lagged returns of German stock market significantly affect current stock returns of Brazilian and Mexican stock market. Rests of the stock markets are found insignificant that implies that the current returns of most of the E7 stock markets are not affected by the past returns of the German stock market. On the other side, most of the E7 stock markets affect the current returns of the German stock market except Brazil and Russia. The past returns of E7 stock markets have a greater effect on the stock market of Germany.

The coefficients of ARCH and GARCH terms in the conditional variance equation are found significant in most of the cases. The past own volatility spillovers are statistically significant for the stock markets of German and E7 stock markets. There are bidirectional volatility spillovers between the German stock market and stock markets of Brazil, India and Turkey. The negative sign implies that 1% increase in the volatility of the German stock market reduces the volatility in the stock markets of Brazil, India and Turkey. Analyzing the past shocks from the German stock market to E7 stock markets, there is no evidence of significant effect of past shocks from German stock market to E7 stock markets except Turkish stock market. On the contrary, past shocks of E7 stock markets significantly affect the current returns of German stock market.

At the end, table 10 represents the conditional correlations between the German stock market and E7 stock markets. The lowest correlation is found between stock market of China and Germany with a coefficient of (0.101) and the highest correlation occurs between Germany-Mexico with a coefficient of (0.498). The important implication of this finding is that investors should be aware of the highly correlated stock markets since they provide limited diversification benefits.

Table 10: Estimates of VAR (1)-GARCH (1) model for Germany and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	Germany	Brazil	Germany	China	Germany	India	Germany	Indo	Germany	Mexico	Germany	Russia	Germany	Turkey
G7(1)	-0.050**	0.067***	-0.007	0.004	-0.013	0.004	-0.008	-0.008	-0.051***	0.103***	-0.038**	-0.002	-0.013	0.0001
	(0.011)	*(0.000)*	*(0.680)*	*(0.609)*	*(0.499)*	*(0.762)*	*(0.621)*	*(0.546)*	*(0.000)*	*(0.000)*	*(0.023)*	*(0.218)*	*(0.460)*	*(0.984)*
E7(1)	0.021	-0.024	0.058***	*-0.00005*	0.092***	0.064***	0.133***	0.062***	0.030***	0.032*	-0.004	0.082***	0.053**	-0.003
	(0.370)	*(0.211)*	*(0.000)*	*(0.997)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.083)*	*(0.880)*	*(0.000)*	*(0.049)*	*(0.858)*
Variance Equation														
C (10) [4]	0.042***	0.126***	0.032***	0.069***	0.044***	0.070***	0.037***	0.077***	0.034***	0.107***	0.097***	0.415***	0.029***	0.038***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{G7})^2$	0.079***	*0.005***	0.088***	*-0.002***	0.083***	*0.003****	0.089***	*-0.003*	0.056***	*0.008****	0.240***	-0.002***	0.071***	*0.004****
	(0.000)	*(0.033)*	*(0.000)*	*(0.053)*	*(0.000)*	*(0.009)*	*(0.000)*	*(0.381)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{E7})^2$	0.046***	0.072***	-0.004**	0.091***	0.006**	0.095***	0.013**	0.118***	-0.024***	0.113***	-0.052***	0.198***	0.045***	0.035***
	(0.000)	*(0.000)*	*(0.013)*	*(0.000)*	*(0.051)*	*(0.000)*	*(0.024)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
h_{t-1}^{G7}	0.903***	-0.002	0.901***	0.003**	0.902***	-0.008**	0.900***	0.003	0.935***	-0.009***	0.704***	0.020***	0.913***	-0.002**
	(0.000)	*(0.233)*	*(0.000)*	*(0.037)*	*(0.000)*	*(0.018)*	*(0.000)*	*(0.385)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.015)*
h_{t-1}^{E7}	-0.048***	0.908***	0.003	0.897***	-0.008**	0.890***	-0.005	0.860***	0.036***	0.847***	0.132***	0.762***	-0.052***	0.964***
	(0.000)	*(0.000)*	*(0.219)*	*(0.000)*	*(0.022)*	*(0.000)*	*(0.393)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
CCC G7 and E7	0.439***		0.101***		0.306***		0.260***		0.498***		0.409***		0.335***	
	(0.000)		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	19674.51		19952.20		20407.12		20471.37		21053.38		18616.05		18863.33	
AIC	9.973		10.220		10.427		10.370		10.756		9.398		9.516	
H-Q	9.962		10.212		10.421		10.359		10.748		9.391		9.512	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.3.4 Estimates of VAR (1)-GARCH (1) model for Italy and E7

The results from VAR(1)-GARCH(1) model for Italy and E7 are reported in Table 11. Initially, the coefficients of stock markets of Brazil, Mexico and Turkey are positive and significant, indicating that the one period lagged returns of Italian stock market affect the current returns of stock markets of Mexico (0.081), Brazil (0.059) and Turkey (0.015) respectively. On the other hand, cross-mean spillovers from E7 stock markets to Italian stock market exist indicating one period lagged returns of Italian stock market are affected from the past returns of the stock market of Indonesia (0.113), India (0.109), China (0.077) and Turkey (-0.092). The negative sign indicates that 1% increase in the stock returns of Turkish stock market decreases the stock returns of the Italian stock market.

According to the conditional variance equation, there is a negative bi-directional volatility spillover between the stock markets of Italy, Brazil, India and Turkey. Negative volatility implies that 1% increase in the volatility of one stock market leads to a decrease in volatility of other stock markets. Continuing the analysis, there is significant effect of past shocks from Italian stock market to Turkish stock market. There is no evidence of significant effect of past shocks from Italian stock market to rest of the E7 stock markets.

On the other hand, past shocks of most of the E7 stock markets are transmitted to the stock market of Italy. The constant conditional correlations between Italy and E7 stock markets are positive in general. The lowest conditional correlation is found between the Italian and Chinese stock markets. This outcome ensures that the Chinese stock market is less correlated with the Italian stock market. This result implies that a combination of securities from Chinese stock market can be picked to diversify the portfolio.

Table 11: Estimates of VAR (1)-GARCH (1) model for Italy and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	Italy	Brazil	Italy	China	Italy	India	Italy	Indo	Italy	Mexico	Italy	Russia	Italy	Turkey
G7(1)	-0.054**	0.059 ***	-0.024	0.010	-0.036*	0.014	-0.017	-0.023	-0.068***	0.081***	-0.026	0.004	-0.054***	0.015*
	(0.010)	*(0.000)*	*(0.191)*	*(0.376)*	*(0.073)*	*(0.286)*	*(0.425)*	*(0.147)*	*(0.000)*	*(0.000)*	*(0.192)*	*(0.668)*	*(0.008)*	*(0.093)*
E7(1)	0.028	-0.042	0.077***	*0.005*	0.109***	0.037*	0.113***	0.043**	-0.015	0.044**	0.001	0.068***	-0.092***	-0.024
	(0.257)	*(0.063) **	*(0.000)*	*(0.792)*	*(0.000)*	*(0.081)*	*(0.000)*	*(0.031)*	*(0.246)*	*(0.033)*	*(0.964)*	*(0.001)*	*(0.000)*	*(0.000)*
Variance Equation														
C (10) [4]	0.031***	0.086***	0.025***	0.074***	0.040***	0.069***	0.031***	0.086***	0.026***	0.023***	0.026***	0.091***	0.037***	0.782***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{G7})^2$	0.083***	*0.002*	0.096***	*-0..0002*	0.090***	*0.003*	0.093***	-0.001	0.086***	-0.005	0.087***	*0.002*	0.120***	0.011***
	(0.000)	*(0.178)*	*(0.000)*	*(0.905)*	*(0.000)*	*(0.176)*	*(0.000)*	*(0.624)*	*(0.000)*	*(0.152)*	*(0.000)*	*(0.204)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{E7})^2$	0.025***	0.067***	-0.003	0.100***	0.009**	0.096***	0.012***	0.113***	0.006*	0.057***	0.005	0.068***	-0.086***	0.278***
	(0.002)	*(0.000)*	*(0.170)*	*(0.000)*	*(0.024)*	*(0.000)*	*(0.004)*	*(0.000)*	*(0.059)*	*(0.000)*	*(0.540)*	*(0.000)*	*(0.000)*	*(0.000)*
h_{t-1}^{G7}	0.913***	-0.003*	0.900***	0.001	0.906***	-0.006**	0.904***	0.0002	0.911***	0.003	0.899***	0.001	0.869***	-0.003***
	(0.000)	*(0.083)*	*(0.000)*	*(0.511)*	*(0.000)*	*(0.013)*	*(0.000)*	*(0.940)*	*(0.000)*	*(0.364)*	*(0.000)*	*(0.569)*	*(0.000)*	*(0.000)*
h_{t-1}^{E7}	-0.027***	0.922***	0.003	0.883***	-0.010***	0.891***	-0.014***	0.870***	-0.007**	0.937***	-0.010	0.926***	0.107***	0.690***
	(0.000)	*(0.000)*	*(0.281)*	*(0.000)*	*(0.009)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.016)*	*(0.000)*	*(0.292)*	*(0.000)*	*(0.000)*	*(0.000)*
CCC G7	0.424***		0.119***		0.339***		0.247***		0.493***		0.422***		0.353***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	17323.94		17691.60		17952.12		17915.63		18639.84		16682.59		16457.50	
AIC	9.883		10.226		10.307		10.278		10.662		9.410		9.464	
H-Q	9.878		10.222		10.302		10.271		10.655		9.406		9.463	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.3.5 Estimates of VAR (1)-GARCH (1) model for Japan and E7

Table 12 reports the results of seven bivariate VAR(1)-GARCH (1) pairs for examining the volatility spillover between Japanese stock market and E7 stock markets. According to the mean equation, most of the estimates are found statistically significant at different levels except China. Surprisingly, in the case of Chinese stock market, the coefficient of the Chinese stock market is insignificant, which implies that one-period lagged returns of the Japanese stock market do not affect the current returns of the Chinese stock market even though Japan and China are geographically closer to each other.

In contrast, the returns of the Indonesian and Russian stock markets exert negative influence on the Japanese stock returns. These findings are inconsistent with Sok-Gee and Karim (2010) who concluded that the Japanese stock returns negatively influence the Indonesian stock returns. This also indicates that E7 stock markets are not influential in terms of returns.

Furthermore, the estimates of variance equation are found highly significant in most cases. The findings illustrate that past shocks of the Japanese stock market significantly and positively affect the return dynamics of most of the E7 stock markets. At the same time, the past shocks of E7 stock markets significantly influence the return dynamics of the Japanese stock market except India and Mexico.

The findings further report the significant conditional volatility spillovers from the Japanese stock market to most of the E7 stock markets. An interesting point is that the coefficients of conditional volatility of India and Turkey are insignificant. This finding implies that there is no significant volatility spillovers from Japanese stock market to the Indian and Turkish stock markets. This result is consistent with the study by Lee (2009), but differs with Li and Giles (2014) who found significant volatility spillovers from the stock market of Japan to the stock market of India. The estimates of the conditional volatility spillovers from Japan to Indonesia coincide with Sok-Gee and Karim (2010). As for the opposite direction, the impact of past conditional volatility of most of the emerging markets h_{t-1}^{E7}, on the conditional volatility of the Japanese stock market is statistically insignificant which reveals that E7 countries have no volatility spillover to Japan.

Turning out to important examination of the constant conditional correlations, the findings show that E7 stock markets are positively correlated with Japanese stock market. The highest correlation between the Japanese stock market and E7 stock market returns occurs in Indonesia (0.338), followed by India (0.301) respectively. These countries are situated in Asian region and it can be a reason of high correlations between Japan-Indonesia and Japan-India. The findings also suggest that E7 stock markets are closely integrated with the stock market of Japan. The empirical literature is evident that Japanese stock market is integrated with Asian stock markets (Ng, 2000; Caporale et al, 2006).

Table 12: Estimates of VAR (1)-GARCH (1) model for Japan and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	Japan	Brazil	Japan	China	Japan	India	Japan	Indo	Japan	Mexico	Japan	Russia	Japan	Turkey
G7(1)	-0.064***	0.173***	-0.008	-0.018	-0.036*	0.072***	-0.006	0.017*	-0.066***	0.247***	-0.085***	0.064***	-0.025	0.036***
	(0.000)	*(0.000)*	*(0.642)*	*(0.152)*	*(0.054)*	*(0.000)*	*(0.634)*	*(0.073)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.172)*	*(0.000)*
E7(1)	0.019	-0.020	0.008	*0.002*	-0.001	0.088***	-0.020***	0.113***	-0.012	0.051***	-0.034***	0.074***	0.011	-0.0004
	(0.392)	*(0.300)*	*(0.590)*	*(0.883)*	*(0.938)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.495)*	*(0.009)*	*(0.000)*	*(0.000)*	*(0.673)*	*(0.982)*
Variance Equation														
C (10) [4]	0.085***	0.169***	0.117***	0.079***	0.094***	0.064***	0.658***	0.122**	0.089***	0.027***	0.225***	0.142***	0.095***	0.056***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.039)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{G7})^2$	0.079***	0.016***	0.106***	*0.008****	0.090***	0.014***	0.260***	-0.002***	0.083***	0.024***	0.229***	*0.004****	0.097***	*0.003***
	(0.000)	*(0.000)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.003)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.022)*
$(\varepsilon_{t-1}^{E7})^2$	0.042***	0.087***	-0.007***	0.090***	-0.006	0.094***	-0.019***	0.263***	0.005	0.077***	-0.046***	0.146***	0.026*	0.046***
	(0.007)	*(0.000)*	*(0.009)*	*(0.000)*	*(0.206)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.218)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.075)*	*(0.000)*
h_{t-1}^{G7}	0.883***	-0.011***	0.861***	-0.010***	0.873***	-0.009	0.512***	0.027***	0.874***	-0.013**	0.688***	0.005***	0.857***	0.001
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.115)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.028)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.378)*
h_{t-1}^{E7}	-0.048**	0.889***	0.002	0.898***	0.009	0.889***	0.052***	0.730***	-0.007	0.918***	0.230***	0.800***	-0.036	0.952***
	(0.021)	*(0.000)*	*(0.664)*	*(0.000)*	*(0.298)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.250)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.124)*	*(0.000)*
CCC G7	0.214***		0.159***		0.301***		0.338***		0.203***		0.288***		0.216***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	19276.57		19798.81		20214.23		20248.08		20610.27		18322.08		18536.03	
AIC	9.915		10.271		10.482		10.471		10.640		9.374		9.503	
H-Q	9.909		10.269		10.478		10.461		10.635		9.370		9.499	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.3.6 Estimates of VAR (1)-GARCH (1) model for UK and E7

Table 13 documents the results of the VAR-GARCH (1, 1) model for volatility spillover between UK and E-7 countries. In the mean equation, one period lagged UK stock returns significantly affect the stock returns in Brazil, Mexico and Russia that imply short-term predictability in UK stock returns fluctuations. The past UK stock returns help to predict the stock returns in Brazilian, Mexican and Russian stock markets. Conversely, most of the E-7 stock market returns have significant impact on UK stock returns except for Brazil, Mexico and Russia.

According to the conditional variance equation, most of the ARCH and GARCH coefficients of E-7 stock markets are statistically significant at different levels. The results exhibit that past shocks of UK stock returns significantly affect the volatility of stock returns of E7 stock markets except Brazil and India. It seems that a past shock from UK market leads to enhance stock market volatility of E-7 countries. However, the past shocks have a negative and significant impact on the stock markets of Indonesia, Mexico, Russia and Turkey.

Furthermore, the past conditional volatility of UK, h_{t-1}^{G7}, seems to be significant for most of the E-7 stock markets at 1% and 5% level respectively except Brazil and India. This finding suggests that the past volatility of UK is transmitted to the E-7 stock markets. Examining the E7 stock markets individually, the bi-directional volatility spillovers exist between UK and Turkey. This result is shared by Akca and Ozturk (2016) who found significant volatility spillover between UK and Turkey. As for the opposite direction, the volatility cross effects, h_{t-1}^{E7}, run from E-7 stock markets to UK stock market in most cases.

The constant conditional correlations of UK and E-7 countries are positive. The positive and significant correlations between UK and E-7 stock returns imply that investors can gain potential returns by investing in E-7 stock markets and UK stock market. The highest CCC occurs between UK-Russia (0.482), followed by UK-Mexico (0.479) and UK-Brazil (0.442) respectively. Interestingly, one thing that requires attention, the low conditional correlation between UK and China suggests that the Chinese stock market is suitable for portfolio diversification.

Table 13: Estimates of VAR (1)-GARCH (1) model for UK and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	UK	Brazil	UK	China	UK	India	UK	Indo	UK	Mexico	UK	Russia	UK	Turkey
G7(1)	-0.045**	0.049***	-0.004	-0.007	-0.019	0.014	-0.0005	-0.014	-0.048***	0.084***	-0.006	0.010***	-0.0006	-0.003
	(0.018)	*(0.000)*	*(0.809)*	*(0.316)*	*(0.307)*	*(0.140)*	*(0.974)*	*(0.142)*	*(0.000)*	*(0.000)*	*(0.695)*	*(0.000)*	*(0.973)*	*(0.103)*
E7(1)	0.047	-0.047**	0.082***	-0.002	0.107***	0.067***	0.178***	0.053***	-0.008	0.040**	0.032	0.081***	0.111**	-0.022
	(0.175)	*(0.027)*	*(0.000)*	*(0.885)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.006)*	*(0.527)*	*(0.034)*	*(0.345)*	*(0.000)*	*(0.029)*	*(0.275)*
Variance Equation														
C (10) [4]	0.027***	0.112***	0.026***	0.072***	0.025***	0.059***	0.023***	0.073***	0.042***	0.030***	0.039***	0.080***	0.139***	0.604***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{G7})^2$	0.094***	*0.0001*	0.102***	*0.001***	0.097***	*0.002*	0.106***	-0.003**	0.257***	-0.005***	0.120***	-0.001***	0.103***	-0.001***
	(0.000)	*(0.767)*	*(0.000)*	*(0.047)*	*(0.000)*	*(0.295)*	*(0.000)*	*(0.018)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{E7})^2$	0.047**	0.071***	-0.009	0.094***	0.019**	0.088***	0.034***	0.120***	-0.032***	0.093***	0.049***	0.054***	0.083***	-0.002***
	(0.022)	*(0.000)*	*(0.272)*	*(0.000)*	*(0.027)*	*(0.000)*	*(0.005)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
h_{t-1}^{G7}	0.882***	0.001	0.884***	-0.001**	0.883***	-0.0002	0.872***	0.006***	0.741***	0.017***	0.836***	0.003***	0.836***	-0.143***
	(0.000)	*(0.148)*	*(0.000)*	*(0.035)*	*(0.000)*	*(0.906)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
h_{t-1}^{E7}	-0.070***	0.918***	0.005	0.894***	-0.023**	0.901***	-0.013	0.857***	0.042***	0.890***	-0.075***	0.945***	-0.077***	0.340***
	(0.004)	*(0.000)*	*(0.586)*	*(0.000)*	*(0.012)*	*(0.000)*	*(0.427)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
CCC G7	0.442***		0.100***		0.326***		0.297***		0.479***		0.482***		0.315***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	20889.59		21161.55		21635.43		21727.94		22230.06		20069.33		19400.22	
AIC	10.599		10.833		11.047		11.011		11.367		10.078		10.155	
H-Q	10.582		10.821		11.040		10.997		11.357		10.066		10.148	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.3.7 Estimates of VAR (1)-GARCH (1) model for US and E7

Table 14 exhibits seven bivariate VAR-GARCH (1.1) models for testing the volatility spillover between the US stock market and E7 stock markets. The findings of mean equation show that with the exception of Indonesia, the other E7 countries' stock returns are not affected by one-period lagged returns of the US. There is a negative and significant impact of the US one-period lagged returns on the Indonesian current stock returns. This outcome is consistent with the findings of Sok-Gee et al. (2010), who concluded that the Indonesian stock returns are affected by the US stock returns. For the opposite direction, with the exception of the Mexican stock market, the past stock returns of E7 stock markets have significant positive influence on the US stock returns.

Turning out to the variance equation, the ARCH and GARCH coefficients are highly significant in most of the cases. Out of the seven stock markets, the past shocks of the US stock market, $(\varepsilon_{t-1}^{US})^2$, have significant impact on the markets of India and Russia with the coefficients of 0.006 and 0.001 respectively. As to E7-US, the past shocks of E7 stock markets, $(\varepsilon_{t-1}^{E7})^2$, are found positively significant. It implies that past shocks of E7 stock markets affect the US stock market.

The past volatility of US stock market, represented by h_{t-1}^{G7}, has insignificant impact on most of the E7 stock markets. The past volatility of US stock market significantly affect the volatility of stock markets of China, Mexico and Turkey with coefficients of 0.002, 0.005 and 0.001 respectively. This finding indicates that the volatility of stock markets of China, Mexico and Turkey increase when the volatility of the US stock market increases. Investigating the E7 stock markets individually, the past volatility of US stock market has a significant impact on the Turkish stock market. This result is consistent with the study of Akca and Ozturk (2016) who found significant volatility spillover between US and Turkey. The past volatility of US stock market has no impact on the Indonesian stock market. This result is significantly different than those of Miyakoshi (2003).

On the other side, the past volatility of E7 stock markets, represented by h_{t-1}^{E7}, has negatively significant impact on US stock market. The significant cross volatility effects indicates necessity for portfolio managers to calculate the optimal weights and hedging ratios to deal with risk in an E7-US stock portfolio. Focusing on the estimates of the constant conditional correlation, all the E7 stock markets are positively correlated with the US stock market. The highest constant conditional correlation between US and E7 stock market returns occurs in US-Mexico (0.635), followed by US-Brazil (0.568) and US-Russia (0.323) respectively. The high conditional correlations suggest that Mexican, Brazilian and Russian stock markets are not suitable vehicles of portfolio diversification for the investors and portfolio managers. These results are consistent with the study of Adrangi et al., (2014).

Table 14: Estimates of VAR (1)-GARCH (1) model for US and E7

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	US	Brazil	US	China	US	India	US	Indo	US	Mexico	US	Russia	US	Turkey
G7(1)	-0.024	-0.009	-0.024	0.0005	-0.022	-0.015	-0.020	-0.022**	-0.028	-0.012	-0.028	-0.010	-0.028	-0.007
	(0.219)	*(0.319)*	*(0.178)*	*(0.947)*	*(0.197)*	*(0.162)*	*(0.287)*	*(0.050)*	*(0.193)*	*(0.405)*	*(0.138)*	*(0.131)*	*(0.128)*	*(0.325)*
E7(1)	0.071**	-0.040*	0.117***	-0.0002	0.230***	0.058***	0.282***	0.059***	0.024	0.025	0.323***	0.024	0.296***	-0.032
	(0.026)	*(0.053)*	*(0.000)*	*(0.991)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.002)*	*(0.331)*	*(0.237)*	*(0.000)*	*(0.227)*	*(0.000)*	*(0.104)*
Variance Equation														
C (10) [4]	0.032***	0.136***	0.021***	0.070***	0.027***	0.059***	0.027***	0.063***	0.031***	0.032***	0.031***	0.089***	0.028***	0.032***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
$(\varepsilon_{t-1}^{G7})^2$	0.087***	*0.0004*	0.083***	-0.0009	0.083***	*0.006****	0.090***	-0.0009	0.077***	-0.001	0.087***	*0.001****	0.086***	*0.0009*
	(0.000)	*(0.632)*	*(0.000)*	*(0.223)*	*(0.000)*	*(0.009)*	*(0.000)*	*(0.625)*	*(0.000)*	*(0.538)*	*(0.000)*	*(0.009)*	*(0.000)*	*(0.149)*
$(\varepsilon_{t-1}^{E7})^2$	0.068***	0.076***	-0.004	0.090***	0.032***	0.087***	0.021**	0.131***	0.024***	0.048***	0.103***	0.043***	0.074***	0.015***
	(0.000)	*(0.000)*	*(0.497)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.056)*	*(0.000)*	*(0.006)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
h_{t-1}^{G7}	0.891***	0.0005	0.901***	0.002**	0.896***	-0.002	0.889***	0.003	0.896***	0.005*	0.889***	-0.0005	0.884***	0.001**
	(0.000)	*(0.541)*	*(0.000)*	*(0.039)*	*(0.000)*	*(0.283)*	*(0.000)*	*(0.169)*	*(0.000)*	*(0.078)*	*(0.000)*	*(0.517)*	*(0.000)*	*(0.044)*
h_{t-1}^{E7}	-0.084***	0.908***	-0.001	0.899***	-0.036***	0.902***	0.007	0.846***	-0.039***	0.950***	-0.134***	0.954***	-0.102***	0.986***
	(0.000)	*(0.000)*	*(0.869)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.633)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
CCC G7	0.568***		0.061***		0.227***		0.199***		0.635***		0.323***		0.251***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	20943.61		20912.91		21329.84		21443.34		22509.42		19637.49		19740.36	
AIC	10.644		10.742		10.931		10.891		11.518		9.885		10.013	
H-Q	10.630		10.734		10.923		10.878		11.511		9.877		10.005	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 15, 2016. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respective*

4.3.8 Estimates of VAR (1)-GARCH (1) model for US and E7 (Before Global Financial Crisis period):

Table 15 demonstrates the results of the bivariate VAR-GARCH (1, 1) model for the seven pairs of US-E7 stock markets over the pre-Global Financial Crisis period, January 8, 2002 to June 29, 2007. According to the mean equation, the findings show that the one lagged returns of US stock market significantly affect current stock returns of E7 stock markets. The only exceptions are India and Mexico. According to the Table 13, the findings show that US stock market affects the current returns of the E7 stock markets.

Moreover, the estimates show that E7 stock markets affect the current returns of the US stock market. The exceptions are Brazil and Mexico. Turning out to the conditional variance equation, the ARCH and GARCH coefficients are significant in most cases. Regarding to the volatility transmission between the US and E7 stock markets, the results represent significant bidirectional volatility spillovers. The only exception is the Mexican stock market. Moreover, the findings illustrate that the past shocks of US stock market significantly affect the return dynamics of most of the E7 stock markets. As far as transmission of past shocks of E7 stock markets are concerned, past shocks of the Brazilian, Chinese, Indonesian and Turkish stock markets significantly affect US stock market. Furthermore, the constant conditional correlations between the US and E7 stock markets are positive and small except Brazil (0.606) and Mexico (0.651).

Table 15: Estimates of VAR (1)-GARCH (1) model for US and E7 (Before Global Financial Crisis period)

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	US	Brazil	US	China	US	India	US	Indo	US	Mexico	US	Russia	US	Turkey
US (1)	-0.070*	-0.024**	-0.083***	0.010*	-0.076**	-0.003	-0.070***	-0.059***	-0.070*	-0.012	-0.062***	-0.026***	-0.030	-0.025**
	(0.054)	*(0.035)*	*(0.000)*	*(0.080)*	*(0.031)*	*(0.857)*	*(0.000)*	*(0.000)*	*(0.055)*	*(0.611)*	*(0.000)*	*(0.000)*	*(0.311)*	*(0.041)*
E7(1)	-0.027	-0.030	0.032***	-0.019	0.151***	0.080**	0.307***	0.134***	0.047	0.012	0.296***	0.041***	0.443***	-0.031
	(0.704)	*(0.359)*	*(0.001)*	*(0.565)*	*(0.000)*	*(0.017)*	*(0.000)*	*(0.000)*	*(0.248)*	*(0.743)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.311)*
Variance Equation														
C (10) [4]	-0.314***	0.245***	0.179***	1.160***	0.0211***	0.270***	0.022***	0.077***	0.032**	0.345***	0.544***	2.145***	-0.924	0.116***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.047)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.118)*	*(0.007)*
$(\varepsilon_{t-1}^{US})^2$	0.045***	-0.009***	0.113***	0.025***	0.047***	*0.007***	0.283***	0.030***	0.051***	*0.004*	0.105***	-0.004***	-0.017	-0.0005
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.029)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.560)*	*(0.000)*	*(0.000)*	*(0.234)*	*(0.727)*
$(\varepsilon_{t-1}^{E7})^2$	0.184***	-0.004	-0.028***	0.144***	0.004	0.181***	0.203***	0.199***	-0.026	0.148***	0.013	0.079***	0.828***	0.021
	(0.000)	*(0.192)*	*(0.000)*	*(0.000)*	*(0.682)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.222)*	*(0.000)*	*(0.410)*	*(0.000)*	*(0.004)*	*(0.248)*
h_{t-1}^{US}	0.740***	0.151***	0.855***	-0.071***	0.941***	-0.011**	0.713***	-0.103***	0.938***	-0.016	0.477***	-0.015***	0.758***	0.066**
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.025)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.315)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.026)*
h_{t-1}^{E7}	-0.085***	0.913***	-0.087***	0.488***	-0.040**	0.727***	-0.131***	0.433***	0.032	0.658***	-0.092***	0.441***	1.710***	0.283**
	(0.009)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.038)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.331)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.042)*
CCC US and E7	0.606***		0.108***		0.205***		0.203***		0.651***		0.201***		0.193***	
	(0.000)		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	6006.87		5929.43		6124.72		6119.31		6458.76		5679.53		5643.31	
AIC	11.486		11.419		11.588		11.798		12.351		11.067		10.812	
H-Q	11.482		11.416		11.577		11.779		12.342		11.056		10.801	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from January 8, 2002 to June 29, 2007. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.3.9 Estimates of VAR (1)-GARCH (1) model for US and E7 (After Global Financial Crisis period)

Table 16 covers the post-Crisis period, July 4, 2007 to March 15, 2016, to estimate the bivariate VAR-GARCH (1, 1) model. According to mean equation, one-period lagged US stock market returns significantly affect only the Chinese and Mexican stock markets. This implies that past US returns help to predict the stock returns in Chinese and Mexican stock markets. There is no significant evidence for the rest of the E7 stock markets. For the opposite direction, one-period lagged returns of E7 stock markets have a significant impact on the current returns of US stock market.

The findings show that most of the ARCH and GARCH coefficients of E7 stock markets are statistically significant at different levels. The estimates of ARCH and GARCH coefficients capture shock dependence and volatility persistence in the conditional variance equations. The results document that the past shocks of US stock market significantly affect the volatility of the Chinese, Mexican and Russian stock returns. It seems that past shocks of US stock market lead to enhance stock market volatility in these stock markets. The findings further present that the past conditional volatility of US stock market, h_{t-1}^{G7} , is significant only for China at 1% level. This implies that the past volatility of US stock market is transmitted to the Chinese stock market. As for the opposite direction, the volatility cross effects, h_{t-1}^{E7}, run from E7 stock markets to US stock market in most cases except Indonesia and Turkey.

Turning out to the constant conditional correlation, the findings represent that E7 stock returns are positively correlated with US returns. The magnitude of the correlations is generally high. The highest correlation between US and E7 stock market returns occurs in US-Mexico (0.750), followed by US-Brazil (0.727), US-Russia (0.516) and US-Turkey (0.472), respectively. These high correlations between US and E7 stock markets returns suggest that crisis period enhances the integration of E7 stock markets and their dependence on US stock market. It also implies that diversification benefits are limited in these stock markets during the Global Financial crisis. However, the low conditional correlation between US and China suggests that stock market of China is suitable for portfolio diversification during the Global Financial Crisis.

The empirical results document that there exists significant bidirectional volatility spillover between US and E7 stock markets before the Global Financial Crisis. Turning out to after Global Financial Crisis period, the results reveal that past shocks of US stock market significantly affect the volatility of Chinese, Mexican and Russian stock returns. Furthermore, it is observed that constant conditional correlations rapidly increase between US and E7 stock markets after the crisis. The implication of this finding is that the Global Financial Crisis has increased the integration of E7 stock markets with US stock market.

Table 16: Estimates of VAR (1)-GARCH (1) model for US and E7 (After Global Financial Crisis period)

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
Mean Eq	US	Brazil	US	China	US	India	US	Indo	US	Mexico	US	Russia	US	Turkey
US (1)	-0.110**	0.013	-0.084**	0.047***	-0.084**	-0.003	-0.074**	-0.039	-0.204***	0.107***	-0.118***	0.018	-0.092**	-0.005
	(0.013)	*(0.680)*	*(0.012)*	*(0.000)*	*(0.021)*	*(0.898)*	*(0.049)*	*(0.138)*	*(0.000)*	*(0.002)*	*(0.001)*	*(0.350)*	*(0.017)*	*(0.825)*
E7(1)	0.057	-0.040	0.250***	-0.021	0.354***	-0.027	0.368***	-0.076**	-0.090***	0.057	0.353***	-0.024	0.201***	-0.057
	(0.335)	*(0.352)*	*(0.000)*	*(0.439)*	*(0.000)*	*(0.389)*	*(0.000)*	*(0.028)*	*(0.000)*	*(0.125)*	*(0.000)*	*(0.515)*	*(0.000)*	*(0.115)*
Variance Equation														
C (10) [4]	0.061***	0.114***	0.063***	0.017**	0.056***	0.051***	0.063***	0.010	0.102***	-0.171***	0.051***	0.090**	0.067***	0.119***
	(0.003)	*(0.000)*	*(0.000)*	*(0.013)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.644)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.013)*	*(0.003)*	*(0.003)*
$(\varepsilon_{t-1}^{US})^2$	0.092***	0.011	0.117***	-0.012***	0.099***	*0.005*	0.115***	*-0.009*	0.073***	0.028***	0.095***	*0.006**	0.094***	*0.008*
	(0.000)	*(0.263)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.540)*	*(0.000)*	*(0.126)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.099)*	*(0.000)*	*(0.261)*
$(\varepsilon_{t-1}^{E7})^2$	0.087***	0.053***	0.013**	0.024***	0.059***	0.066***	0.016	0.180***	-0.079***	0.110***	0.109***	0.090***	0.066**	0.059***
	(0.004)	*(0.006)*	*(0.030)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.210)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.016)*	*(0.003)*
h_{t-1}^{US}	0.833***	0.018	0.848***	0.019***	0.871***	0.004	0.856***	0.012	0.848***	-0.001	0.881***	-0.004	0.874***	-0.005
	(0.000)	*(0.335)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.991)*	*(0.000)*	*(0.162)*	*(0.000)*	*(0.804)*	*(0.000)*	*(0.371)*	*(0.000)*	*(0.706)*
h_{t-1}^{E7}	-0.154**	0.960***	-0.014**	0.970***	-0.061**	0.923***	0.024	0.814***	0.603***	0.455***	-0.096**	0.900***	-0.053	0.907***
	(0.011)	*(0.000)*	*(0.039)*	*(0.000)*	*(0.023)*	*(0.000)*	*(0.353)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.028)*	*(0.000)*	*(0.165)*	*(0.000)*
CCC US	0.727***		0.133***		0.325***		0.290***		0.750***		0.516***		0.472***	
and E7	*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*		*(0.000)*	
Log Like	5714.02		5368.92		5516.16		5588.91		6042.60		5289.51		5437.87	
AIC	10.871		10.198		10.411		10.478		11.462		9.634		10.420	
H-Q	10.842		10.173		10.366		10.442		11.432		9.606		10.401	

*Note: The bivariate VAR(1)-GARCH(1, 1) model is estimated for each E7 country from July 4, 2007 to December 28, 2012. The p values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H-Q information criteria. ***. ** and * denote coefficients are significant at 1%. 5% and 10% level respectively.*

4.4 PORTFOLIO MANAGEMENT AND HEDGING STRATEGIES

Table 17 demonstrates the summary statistics for the portfolio weights, $W_t^{US,E7}$, and hedge ratios, $\beta_t^{US,E7}$, produced by the VAR(1)–GARCH(1) model. For the US-E7 portfolios, the average weight of E7 stocks ranges from 0.026 (Brazil-US) to 0.337 (Indonesia-US). For Indonesia-US portfolio, the optimal weight of the Indonesian stocks in a one dollar Indonesia-US portfolio should be 33.7%, the rest (66.3%) should be invested in the US stock market. For the Chinese stocks, the optimal holding is 31.4%, showing that the majority of the money (68.6%) should be invested in the US stocks. Overall, investors should invest more proportion of their portfolio in the US stocks than the E7 stocks to minimize the risk.

Table 17: Summary Statistics for the Portfolio Weights and Hedge Ratio

	$W_t^{US,E7}$	$\beta_t^{US,E7}$
Brazil-US	0.026	0.320
China-US	0.314	0.045
India-US	0.294	0.151
Indonesia-US	0.337	0.154
Mexico-US	0.244	0.486
Russia-US	0.090	0.132
Turkey-US	0.128	0.124

Note: The table reports average optimal weights and hedge ratios for all stock markets

Furthermore, the results show that in general, the hedge ratios are low. However, the hedge ratios are high for the portfolios including the stocks from US-Brazil and US-Mexico. The hedge ratios range from 0.045 (Chinese stock market) to 0.486 (Mexican stock market). The lowest hedge ratio implies that a short position in the Chinese stocks would be more effective to hedge the US stocks exposure.

Further, the highest hedge ratio of 0.486 suggests that a one-dollar long position in the US stock market should be hedged with a short position of 0.486 cents in the Mexican stock market. High hedge ratios of Mexican and Brazilian stock markets indicate that diversification opportunities are limited in these markets. These results are consistent with Adrangi et al., (2014). As a whole, these estimates support the view that adding US stocks in a well-diversified portfolio of E7 stocks reduces the risk.

CONCLUSION

The main purpose of this study is to investigate the volatility spillover between G7 stock markets and E7 stock markets over the period from 1995 to 2016. The sample countries for G7 are Canada, France, Germany, Italy, Japan, UK, US and for E7 countries are Brazil, China, India, Indonesia, Mexico, Russia and Turkey. This study also investigates the volatility transmission between US stock market and E7 stock markets before and after the Global Financial Crisis. The empirical analysis is based on the VAR–GARCH model, which enables us to investigate the spillover effects both in returns and conditional volatility. Using the findings of the VAR-GARCH model, the study also analyzes the optimal weights and hedge ratios for E7-US portfolio holdings.

In most of the stock markets studied, the results show significant return and volatility spillover from G7 stock markets to E7 stock markets. The empirical evidence reveals significant volatility transmission between the Canadian stock market and E7 stock markets except China and India. Since the highest constant conditional correlation occur between the Canadian-Mexican, Canadian-Brazilian and Canadian-Russian stock markets, investment in these markets offer low portfolio diversification opportunities for the investors. It also implies that stock markets of Mexico, Brazil and Russia are closely integrated with stock market of Canada. The geographical position and trading relations of these countries would be the reason of high correlation between these stock markets.

For stock market of France, most of the E7 stock markets appear to be unaffected by the volatility spillovers from the French stock market, while volatility spillovers from E7 stock markets have significant effect on the French stock market. Moreover, Mexico, Brazil and Russia appear highly correlated with France, which implies that investors have limited opportunities for diversification in these markets. The low constant conditional correlations are recorded in China, India and Indonesia among E7 stock markets. Geographically, these stock markets are situated in the Asian region. The implication of this findings is that investors should add stocks from the markets from the Asian region to reduce the risk.

This study emerges many conclusions. The empirical findings show bidirectional volatility spillovers between the German stock market and stock markets of Brazil, India and Turkey. Moreover, the elevated correlations appear between stock market of Germany and E7 stock markets, except China. The important implication of this finding is that investors should be aware of the towering correlation in these markets.

The empirical findings show negative bi-directional volatility spillover between stock market of Italy and stock markets of Brazil, India and Turkey, which implies that 1% increase in the volatility of the Italian stock market leads to a decrease in the volatility of these stock markets. The lowest conditional correlation is between the Italian and Chinese stock markets which ensure that Chinese stock market is less correlated with Italian stock market. It is suggested that portfolio managers should add stocks from the Chinese stock market to diversify their portfolios.

Additionally, the estimates show that the Japanese stock market seems to be more influential in terms of return spillovers to E7 stock markets. The findings reveal that the past shocks of Japanese stock market significantly affect the return dynamics of E7 stock markets. Interestingly, the coefficients of conditional volatility of India and Turkey are insignificant, which implies that there exists no significant volatility spillover from the Japanese stock market to the Indian and Turkish stock markets. The findings suggest that E7 stock markets are closely integrated with the stock market of Japan. The previous studies also confirm that the Japanese stock market is integrated with Asian stock markets (Bekaert and Harvey, 1997; Ng, 2000; Caporale et al., 2006).

The findings further show significant volatility spillover between UK and E7 stock market returns. The transmission of volatility is more apparent from past shocks to stock returns of E7 countries. The results suggest that past UK shocks have a significant impact in determining the future volatility for the E7 stock markets. Considering the estimated conditional correlation, all E7 stock markets exhibit significant and positive correlations with UK. However, the magnitude of the correlation is low for China-UK portfolio holdings. The low correlation implies that investors might gain substantial returns by investing in the Chinese stock market.

The empirical evidence regarding the US market reveals significant volatility transmission between the US and E7 countries. Among E7 countries, the Indian and Russian markets are sensitive to the US market shocks and instability. The highest correlation occurs between the US and Mexican stock market followed by the US and Brazilian stock market. The results of US market indicate that since US stocks highly co-move with the Mexican, Brazilian and Russian stocks, holding a portfolio that combines US-Chinese or US-Indian stocks may attain the goal of international portfolio diversification.

The study also covers the pre-Global Financial Crisis and post-Global Financial Crisis period to examine volatility spillovers between US and E7 stock markets. After the Global Financial Crisis period, the past shocks of the US stock market significantly affect the volatility of the Chinese, Mexican and Russian stock returns. The study further finds that constant conditional correlations have rapidly increased between the US and Mexican, Brazilian and Russian stock markets due to the crisis which implies that benefits of diversification are limited in these E7 markets. There is a slight increase in constant conditional correlations between the US and Chinese stock market after Global Financial Crisis. It makes the Chinese market more attractive during the recent Global Financial Crisis. The low correlation suggests portfolio diversification opportunities in these markets.

Moreover, the examination of optimal weights and hedge ratios suggests that investors should invest more proportion of their portfolios in the US stock market than the E7 stock markets to minimize the risk. The high hedge ratios of Mexican and Brazilian stock markets indicate that diversification opportunities are limited in these markets. As a whole, the results indicate that adding US stocks in a well-diversified portfolio of the E7 stocks reduces the risk.

Overall, the results show significant volatility spillover between G7 stock markets and E7 stock markets. It is prominent to note that correlations between stock exchanges become more significant within a same geographical region. Another striking finding is that the stock markets of China, Indonesia and India are less affected by G7 stock markets in terms of volatility spillover and correlations. The findings also support the fact that the geographic proximity, the absence of time difference and close cultural familiarity may help to disseminate investment opportunities and information.

Considering the investors, who hold US and stocks from E7 countries, the results suggest that investors should monitor the correlation levels. With regards to the diversification benefits among E7 countries, the study concludes that the Chinese, Indonesian and Indian stock markets are still partially integrated with G7 stock markets, which provide the opportunities to investors to diversify their portfolios. However, another important conclusion is that the stock markets of Brazil and Mexico are highly correlated with G7 stock markets and offer low diversification opportunities.

In light of the above-mentioned issues, the results are crucial for portfolio managers and policy makers for building an optimal portfolio and forecasting stock return volatility. For the future research avenue, it would be interesting to extend this study that allows examining the volatility spillover between G7 and other major emerging stock markets. This research can also be extended to close geographical region of US and G7 markets.

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