LUNDS UNIVERSITET
Ekonomihögskolan

Department of Economics
NEKN02 Economics:
Master Essay I - Finance Programme
June 2013

Estimation of Volatilities and Spillover Effects Between Developed and Emerging Market Economies

Master Thesis: NEKN02 (15 credits ECTS)

Supervisor:

Hans Byström

Authors:

Iryna Kharchenko

Plamen Tzvetkov

Abstract

This study focuses on establishing the existence of volatility spillover effects between stock indices that represent developed and emerging markets. We employ a CGARCH(1,1) model, which distinguishes between the short-term (transitory) and long-term (permanent) conditional variance, allowing us to simultaneously examine the time trends of changes in volatility and spillover effects between developed and growing economies. Our data sample covers a period from January 1995 to April 2013 and is further broken down into two subsamples from January 1995 to January 2008 and from January 2008 to April 2013, which respectively represent periods before and after the global financial crisis. We find some evidence that volatility spillover moves in a uni-directional way from the developed to the emerging markets when examining the whole period. In our full sample, we conclude spillover from the USA to China, as well as from France and Germany to Russia. Although, when we break our data into the subsamples, volatility before the crisis exhibits a flow from the emerging market of India to the USA. Our subsample after the crisis determines volatility spillover from all developed markets to India. Through testing the standardized residuals of the model as well as examining information criterion parameters we concluded that the CGARCH(1,1) has captured the ARCH effects and is sufficient for the purposes of the study.

Keywords: *Volatility of stock returns, CGARCH, Spillover effects, Emerging markets*

Table of Contents

1. Introduction

When we take a look at the history of financial diversification we can see that it has been only since the late 1960s that international investors have started to look into diversification as a way to manage the volatility risk of their portfolio. With developing closer ties between the countries came capital flows, followed by more liberal financial market relations. Over time all these factors coupled with technological advances have led to growing interdependencies between countries, as well as their financial markets. Investors have the freedom of trading on the global market. Reducing idiosyncratic risk helps maximize returns in the long run, which explains why a large number of research articles have been devoted to the benefits of diversification.

However, it is also important to address potential drawbacks of this increased interdependence, which may not be as obvious as the apparent benefits. In particular, the exposure to cross-border spillover effects can transfer shocks from one region to another, which can lead to greater economic volatility. Such developments become of even greater significance during times of economic instability. Therefore, this paper examines the effect and levels of volatility contagion between several stock indices. By using three developed and three developing indices, we form a hypothesis that spillovers are transferred from the developed to the developing markets. Given the recent economic growth of the emerging nations under consideration in our data, it will be of a particular interest to determine if the volatilities of their markets tend to exhibit any significant influence on the developed countries.

Significant number of studies suggest that models accounting for ARCH effects, and some variations of GARCH models are capable of evaluating variance more precisely than the basic historical variance (unconditional variance). Based on this research, estimation of spillover effects with a GARCH model, or its variation, becomes an important area for further academic study. Volatility of some geographical regions has been examined more frequently, such as Asian stocks and their short and long term relationships, influence of the USA on India and interdependence of European stocks. However, little interest is devoted to the study of volatility of Brazil, Russia, India and China (BRIC countries) and their relationships with developed countries. Our study focuses on the emerging markets of China, India and Russia and the developed markets of France, Germany and the USA, which are among the top ten world economies according to their gross domestic products. Therefore, the purpose of this Master Thesis is to extend the literature in this area by researching the trends in volatility evolution within the two groups of countries, as well as shining the light on spillover effects, evidence of which is quite inconsistent and inconclusive. We focus on the period starting December of 1994 until April of 2013, which attempts to fill in the gaps in the existing research and bring it up to date. We examine the relationships between volatilities of the chosen indices during the whole period, as well as the sub-periods before and after the global financial crisis of 2008.

The value of our research lies first and foremost in accurate estimation of volatilities, which can be used in financial decision making such as portfolio management, measurement of diversification benefits, risk management, and value-at-risk estimation to name a few. Secondly, GARCH models have proven to be a robust method for capturing the effects of financial time-series, as well as being sufficient for the modeling of conditional volatility and spillover effects. The results presented in this thesis should be relevant for researches, who are focused on the global financial crisis and its implications, those who are interested in spillover effects, investors that hold stocks of the companies that belong to the indices under the examination, as well as the general audience that attempts to grasp relatively new financial phenomena.

Our research paper is divided into six main parts. In Section 2 we present our literature review. In this section, we show previous theoretical background and empirical studies that relate to our topic in general, as well as those that use data comprised of some or all of the stock indices in our respective research. In Section 3, we provide our data with a historical analysis of the specific importance for choosing certain countries in our study. Section 4 consists of our methodology. Here, we explain the steps that will be undertaken, their significance, as well as all the models that will be used in our analysis. In Section 5 we interpret our empirical results and define what the outcomes represent. Final remarks and conclusion is presented in Section 6.

We should note that there are some limitations to the undertaken study. First of all, the estimated CGARCH models are of (1,1) order, although the model specifications proved to be sufficient for capturing ARCH effects in the chosen time-series. Secondly, only weekly volatility is analyzed. We have not attempted to employ daily data that may provide more insight into volatilities, but at the same time poses such challenges for the estimation as asynchronous trading. Finally, the data series sample was arbitrary divided into two subsamples of before and after the global financial crises of 2008. It might have been beneficial to determine subsamples through an application of a methodical approach, for example, iterated cumulative sums of squares (ICSS) algorithm. This method detects sudden changes in the variance of the returns and the length of the variance shift, which can be used for identifying subsamples, which in turn reduces the degree of volatility persistence that might be otherwise overestimated (Wang et al., 2007).

2. Literature Review

2.1. Previous Empirical Findings on Volatility Spillovers

The recent financial and credit crises have shifted focus on the interdependence level of financial markets, as well as volatility spillovers (Gatfaoui, 2012). International stock markets, under ever-expanding globalization, have been experiencing an increasing interdependency or interaction with one another as a result of information spillovers among stock markets. Morana and Beltratti (2008) reveal the increasing co-movements of prices, returns, volatilities and correlations between the developed markets of the USA, UK, Germany and Japan. Understanding these links is very important for determining asset allocations, pricing domestic securities, implementing global hedging strategies, (Ng, 2000). Gunasinghe (2005) concluded that the Indian stock market had a low volatility spillover effect on other regional markets, like Sri Lanka and Pakistan. Abraham and Seyyed (2006) found an asymmetric volatility spillover from the more accessible, but smaller, Bahirini market to the less accessible Saudi market.

The existence of volatility spillovers implies that one large shock increases the volatilities not only in its own asset or market, but also in other assets or markets as well. Volatility and its changes signal the flow and arrival of new information (Ross, 1989). If information comes in clusters, asset returns or prices may exhibit volatility even if the market perfectly and instantaneously adjusts to the news. Thus, study on volatility spillover can help understanding how information is transmitted across equity markets. As a consequence, current literature has increasingly focused on the spillover effect and volatility (Like Kim, 2009; Beirne, et.al., 2010; Mukherjee and Mishra, 2010; Park, et.al., 2010; Kumar and Pandey, 2011 among others). An important issue in asset allocation and risk management is whether financial markets become more interdependent during financial crises. This issue has acquired great importance among academics and practitioners, especially since the appearance of several emerging market crises of the 1990s (Kenourgios and Padhi, 2012). Until then, financial crises models were developed with regard to crises as events occurring in individual countries. However, those crises episodes focused the empirical research on the examination of contagion effects and the inter-regional or intercontinental nature of the shocks.

The main concern is to choose a reliable and consistent volatility measure. The volatility of financial markets represents the magnitude of the movement between the current and previous returns. The error terms (also referred to as residuals or innovations) illustrate the uncertainty over time and represent the risk measure in the financial markets. Kyle (1985) suggests that volatility of stock prices contains more information than the actual price. Since volatility is a time-varying risk measure (volatility clustering effects of large (small) changes followed by other large (small) changes) the relationship of the stock indices movements across the markets allows for estimation of conditional variance that is present in time-series data (Mukherjee and Mishra, 2010). Chuang et al. (2007) found significant interdependence among the conditional variance of six East Asian markets when studying volatility transmissions. They conclude that Japan is the most influential market in their study group, which is also supported by Gebka and Serwa (2007). Time-variation in the conditional variance of financial time-series is also important when attempting to calculate risk and other hedging strategies (Hansen and Lunde, 2001).

2.2. Empirical Findings on Volatility Spillovers from Developed to Developing Markets

The above findings clearly indicate that volatility spillover contributes a significant effect on interdependent markets. This explains the increasing studies toward identifying any trends and directional volatility transmissions. However, most of these studies seem to focus on the impact between developed markets, or alternatively between local and regional markets. In our research, we try to establish any potential volatility spillovers specifically from developed to developing markets and identify the directional co-movements of the volatility.

Researchers have conducted studies on volatility spillover between the US and other emerging markets and determined a unidirectional transmission of volatility from the US to the other countries (Kumar and Pundey, 2011). This finding appears quite intuitive and supports our hypothesis. Al-Zeaud and Alshbiel (2012) state that researchers have examined volatility spillovers between mature and emerging markets and determined that mature markets do indeed influence the conditional variances and returns of other regional markets. Chittedi (2007) used a Granger Causality test and concluded that the developed markets of the US, Japan and France have an influence on the developing market of India. However there was no evidence that the developed markets had an effect on the other BRIC nations. Kenourgious (2007) examined the relationships between the developed markets of the US and UK with the emerging BRIC markets and found an increase in the correlations and volatilities during crisis periods as opposed to stable times. Bhar and Nikolova (2009) analyzed the interaction of the BRIC nations with the rest of the world. Their research concludes that India exhibits the highest regional and global interdependence, followed by Brazil, Russia and lastly China. To our knowledge there are no other researches that extensively focus on spillover contagion from the developed to the emerging markets of the BRIC nations. Therefore, our paper focuses on contributing further findings of volatility linkages precisely between those two specific groups.

2.3. Volatility Models

The vast research on volatility spillovers has stirred an enormous interest amongst researchers and practitioners to develop models that can accurately forecast volatility. Despite this enthusiasm, establishing which models are superior in forecasting volatility is very much a matter of debate. There has been a lot of theoretical research on measuring volatility based on models of the (Generalized) Autoregressive Conditional Heteroskedasticity ((G)ARCH) family, and their respective extensions. Bollerslev's 1986 development of GARCH can be seen as a modified version of Engle's 1982 ARCH that takes care of some of the drawbacks that the model has. In a GARCH model the conditional variance is presented as a weighted function of the long-term average value of the variance, the volatility during the previous period and the fitted variance from the model during the previous period. By allowing the current variance to depend on its own previous lags the model is able to include all the necessary information into a much simpler and more parsimonious equation than is often the case with ARCH. GARCH is also less likely to breach the non-negativity constraint for all parameters in the conditional variance equation to be higher than zero. GARCH provides a reliable volatility measure since both the market trend and its corresponding volatility pattern are simultaneously accounted for over time (Gatfaoui). Alternatively, Tse and Tung (1992) conclude that exponentially weighted moving average (EWMA) models deliver better volatility forecasts than GARCH models.

However, it is important to note that GARCH models enforce symmetric response to positive and negative volatility shocks. This occurs due to the squaring of the lagged residuals in the conditional variance equation, and therefore losing the signs (Brooks, 2008). Since there is a general consensus that a negative shock is likely to increase the level of volatility more than a positive shock of the same magnitude, a symmetric GARCH may not account for potential leverage effects (Brooks, 2008). This limitation has led to the development of further extensions of the GARCH model. Nelson's 1991 EGARCH and Glosten, Jagannathan and Runkle's GJR-GARCH, developed in 1993, are two popular extensions of the univariate GARCH model that address potential asymmetries. Empirical results vary on which of these models provides the best volatility forecasts. According to the research done by Liu and Hung (2010) GJR-GARCH achieves the most accurate volatility forecasts with EGARCH just slightly behind. Alternatively, in 2010 Mukherjee found that EGARCH was a better model compared to the TGARCH (also referred as GJR-GARCH) model for the SENSEX because there was an indication that there was a considerable amount of asymmetry in the series. Kanas (1998) used an EGARCH model to evaluate the volatility spillover between the European stock markets of London, Frankfurt and Paris. In 1999 Engle and Lee developed the component GARCH (CGARCH) model that distinguishes between short (temporary) and long-term (permanent) conditional volatility. This allows CGARCH to separate the effect of spillovers on stock price volatility in the short and long term (Égert and Kocenda, 2005). The research conducted by Kang, Kang and Yoon (2009) concluded that CGARCH is better equipped to capture volatility persistence and provides superior volatility forecasts than GARCH.

Interestingly enough there is some evidence to suggest that these better models do not always provide better volatility forecast than a standard GARCH (1,1) model (Hansen and Lunde, 2001). In 2010, Guidi found that while indices were better forecasted using asymmetric GARCH models, the simple symmetric GARCH models with the normal distribution actually performed better in volatility forecasting of five Asian stock markets and were good enough to be used for forecasting purposes. Dimson and Marsch (1990) conclude that simple models perform better than exponential smoothing models. Liu and Hung (2010) point out that a GARCH model with normal distribution is more desirable than the more sophisticated error distribution models when asymmetries are ignored. However, they also emphasize that modeling asymmetric components is more important than specifying error distribution, in order to improve volatility forecasts of financial returns in the presence of fat-tails, leptokurtosis, skewness and leverage effects. Therefore, ignoring asymmetries and assuming a normal distribution is not likely to consistently deliver the most reliable volatility forecasts.

Lastly, it is important to mention that there are other univariate GARCH model extensions that are not addressed in this research. In addition, there are multivariate GARCH models that include VECH, the diagonal VECH and the BEKK. Li (2007) used a BEKK model and concluded that there is a weak interdependence between the stock markets of China and Hong Kong. These multivariate GARCH models are quite related to their univariate counterparts, aside that the former allow for equations that specify how the covariances move with time (Brooks, 2008). Wang and Wang (2010) used a multivariate GARCH model to investigate volatility spillover and found weak interdependence from the developed markets of the USA and Japan to the developing market of China.

3. Markets and Data

3.1. Market Characteristics

It is important to understand the history of market exchanges, because some of the aspects relating to the historical development define the relationships between the indices. The established links between the markets, targeted investors and legal regulations, along with other factors might restrict the freedom of movement of financial funds from one market to the other.

The number of years of existence, as well as trends of the economy in the particular country might influence the number of players or the level of trust and interest in the particular economy. With that in mind, we examine how and when the indices of emerging countries came into existence, since they are less seasoned than those of developed countries and have been a subject of research for a fairly short period of time.

3.1.1. Chinese Stock Exchange

The history of stock exchange in China dates back to 19th century, with Shanghai Stock exchange opening and closing for periods of time during activities of war. With the establishment of a social market economy in the 1980s, Shanghai stock exchange re-opened for business later in 1990. While Shanghai is the main stock exchange of China, Shenzhen and Hong Kong are targeting the technology sector, as well as market securities. Hong Kong stock exchange was incorporated into the Chinese stock exchange infrastructure in 1997, requiring new legislation to be drafted. Unlike Shanghai and Shenzhen, the Hong Kong exchange is for-profit business, which makes it quite unique. With establishing a presence in three locations, China has increased its grip on the world economy. In addition to the A-shares available for local investors, both Shanghai and Shenzhen stock exchanges have introduced B-shares to be traded in US or Hong Kong dollars. The B-shares were intended to attract foreign capital and were only available to foreign investors. Furthermore, after 1993 the government introduced H-shares in Hong Kong and N-Shares in New York. Both of these share categories were once again targeting foreign capital. The government recognized the growing importance of stock exchanges as a mechanism for effective resource allocation, which is why it accumulated fast growth by improving the infrastructure and trading systems, as well as ensuring smooth operations and increasing number of listed companies and trading volume. Market capitalization in China, from the time of re-opening the Shanghai stock exchange, has been through some turbulent times. Reaching its peak in 2007 with 71.3 million investors, 860 listed companies and more than 6 trillion USD in market capitalization, the exchange took a sharp dip right after the global financial crisis and lost almost 60 percent of its market capitalization (Shu et al., 2010). In 2011, the Shanghai stock exchange was the sixth largest stock exchange in the world with 2,794 billon USD in market capitalization and 3,658 billion USD in trading value, while Hong Kong stock exchange was the seventh, making China into a powerful financial force that has to be accounted for and considered when addressing international financial challenges (World Bank report, 2011).

3.1.2. Indian Stock Exchange

Bombay Stock Exchange or BSE was established in 1875 and was the first stock exchange in Asia. In terms of number of listed members, it is the world's number one stock exchange accounting for more than 5000 members as of 2011. In 2007, it was the tenth largest stock exchange in the world, but after the widespread financial crisis it experienced a drop and has so far not been able to return to the top ten stock exchanges list. Similarly to China, India is heavily dependent on trading partners and some Indian enterprises have preferred to list their shares on the international exchanges of the US and UK. Ten major Indian companies are listed on the New York Stock Exchange and account for 19 percent weight in the benchmark 30-scrip stock price index of the BSE (Raj et al., 2009). BSE made a transition to electronic trading only in 1995, but at the same time it became the world's first internet trading system, which enabled investors in any part of the world to trade on the BSE platform (BSE India, 2013). As of October 31, 2012, BSE reached market capitalization of 1,200 billion USD. In terms of number of transactions, the Bombay Stock Exchange is the world's fifth most active and third largest. This makes it a world leading among exchanges for index options trading (Indiazetzone, 2013).

3.1.3. Russian Stock Exchange

We can say that Russia is relatively new to the stock exchange arena. Since, the country has been under a command rule for almost a century, Russian stock exchange took its roots only after the breakup of the Soviet Union and with the beginning of perestroika. With initial movements towards private ownership and the establishment of financial institutions that are a commonplace in the developed countries of the west, Russia has taken a step towards establishing a stock exchange system too. Nowadays, there are several stock exchanges operating in Russia, two main being RTS and MICEX. Both stock exchanges have been open since 1995, but in their short history have experienced significant drops during world financial crisis, which no market remained completely immune to. MICEX closed its operations for a day in 2008, due to a daily drop of more than 10 percent, which illustrates that Russian stock exchanges were some of the most sensitive to the worldwide financial crisis. As Russia is so overwhelmingly dependent on the prices of natural resources, which are themselves very dependent on growth, it is not very surprising that it has been adversely affected by the increasing weakness of the global economy (Adomanis, 2012). Put together the RTS and MICEX make the largest stock exchange in Eastern Europe, approaching in size the Deutsche Börse stock exchange, which is currently the tenth largest in the world. Russian market capitalization was about 796 billion USD according to the World Bank data report of 2011, while in 2008 it comprised to half of its current size. Given the Russian stock exchange is growing and gaining noticeable size in recent years, it is logical to expect for it to become increasingly influential and play an important role in the near future as one of the countries to offset the rising power of Chinese economy.

3.1.4. Importance of BRIC Countries

The BRIC countries, a term first introduced by then the Head of Global Economics for Goldman Sachs, Jim O'Neill, are being paid more attention to since their growing importance in the global economy. The acronym stands for the members of the group, in particular Brazil, Russia, India and China. The newest addition to the group has been South Africa, with a smaller weight in the world economy, but high ambitions.

The economies of these emerging countries represent 25.9 percent of the world's land mass, 43 percent of the global population and are accountable for 17 percent of the total global trade. The group holds one quarter of the world's purchasing power, which makes it a valuable player with the growing leading potential. According to the United Nations Development Programme "by 2020, the combined economic output of the three leading developing countries alone – Brazil, China and India – will surpass the aggregate production of Canada, France, Germany, Italy, the UK and the United States." (United Nations Development Report, 2013).

Goldman Sachs believes that the decade starting in 2010 will introduce the re-distribution of influence and leadership and therefore the players, pointing out that the BRIC countries will become hugely attractive to international investors. Historically, when the countries reach a stage of industrialization and GDP per capita reaches a level of 1000 to 3000 USD it drives the amount of savings and investments. Russia, India and China can be characterized by low consumption and high savings. Some analysts argue that with the financial crisis of 2008 came the expedited shift in economic power away from the US. India is expected to not only overtake Japan by purchasing power parity, but it is also expected to grow faster after 2020. Not so long ago, China was believed to become the world's largest economy only by 2041, while nowadays it appears like it will happen as early as 2020, some 20 years earlier (Goldman Sachs, 2013).

If anyone had any doubts about the rising power of the BRIC nations, they would probably become convinced of it due to the recent agreement of the group's members to establish a new financial institution to counterweigh World Bank and IMF. Members are still discussing the lending power of the Reserve Fund, but currently it is planned that all five members will contribute 10 billion USD each.

The need to establish its own financial institution arose from the suspicion of the World Bank and IMF being biased towards the developed nations. Given that the five countries hold 4.4

trillion of foreign currency reserves they are capable and in need of shielding this wealth. The reserve will have a protective function and ensure a short-term liquidity in volatile times, as well as offer support with balance-of-payments problems (RT, 2013).

These factors combined, make Russia, China and India an attractive target for research. If the projections are correct, we will witness a shift of economic powers and it is essential to understand where we are in this particular moment in time, in order to recognize the change in the pattern.

3.2. Data

In this thesis we analyze weekly returns of six stock indices, calculated from stock price indices of six countries that include the USA, France, Germany, Russia, India and China. Our study has chosen a major national index to represent each country. Thus, the data is comprised of the SASHR (China), DAX30 (Germany), CAC40 (France), BOMBSE (India), RUSSL (Russia) and NASDAQ (United States) indices respectively. Stock indices are strong market indicators and their subsequent returns illustrate directional market moves (Gatfaoui, 2012). Considering our purpose of trying to obtain the directional movement of volatility spillovers, we are confident that stock indices are the most suitable data for our particular aim. Our data is taken on a weekly basis from DataStream and all indices are converted into USD ($) currency to maintain consistency. Furthermore, we used Yahoo Finance to double check and ensure the validity of the collected numbers. Using weekly data frequency for our indices rather than daily data avoids the representation bias of some thinly traded stocks, i.e., the problem of non-trading or non-synchronous trading. In addition, weekly data also avoids any abnormal big/ask spreads that can occur in daily data (Bodkhe, Kamaiah and Sakthivel, 2012). The returns where calculated using the formula (3.2.1.):

$$R_t = (PI_{t+1} - PI_t)/PI_t \qquad (3.2.1.)$$

where R_t ia the return and $PI_{t,t+1}$, are the price indices of the two subsequent days.

Note, a large number of studies use log-returns, but since the calculated returns are stationary, it is not necessary to further transform returns into log returns.

The total number of observations in the period covered in our research is 955 for each index, summing up to 5730 number of observations in total, with the first observation being on 1994-12-30 and the last one being on 2013-04-19. Our sample is further divided into two subsamples that illustrate the period before and after the global financial crisis of 2008, from 1994-12-30 to 2008-01-06 and from 2008-01-07 to 2013-04-19 respectively (Table 3.2.1). CGARCH model is applied twice to both the entire sample period and two subsample periods in order to identify the relationships between conditional variances and respective spillover effects. In order to capture the difference between and after the crisis observations for 2008 were kept as a part of after the crisis subsample.

Table 3.2.1 - Specification of Samples

Sample	Period
Entire sample	1994-12-30-2013-04-19
Subsample1	1994-12-30-2008-01-06
Subsample2	2008-01-07-2013-04-19

Note: the whole period sample consists of 955 observations, the first subsample consists of 680 observations and the second subsample consists of 275 observations of index returns.

The purpose of the thesis is to analyze the level and direction of volatility spillover effects between several developed and developing nations. In our developed group, we include France, Germany and USA. The developed economies of the US and European countries have become more interdependent, and therefore more exposed to shocks from each other's respective financial markets (Gatfaoui, 2012). The intention of estimating the model with the given data is to establish if there are similar volatility behaviors and market trends between our group of developed countries and the major emerging economies of China, India and Russia. It is important to clarify that the focus is strictly on determining the direction of volatility spillovers between the developed and developing countries. Therefore, we do not address any specific linkages between members of each specific group.

4. Methodology

This section of the thesis discusses the steps involved in modeling of the conditional variance with GARCH models. If a reader is familiar with the methodology, its purpose and advantages of using GARCH models, CGARCH(1,1) in particular, this section could be skipped.

4.1. Unit Root Tests and Stationarity

Our analysis follows a multi-stage approach. As a starting point, we test our data for stationarity by running several unit root test statistics. We would like to establish that the series of data we will be examining are stationary. If the series are not stationary, it would mean that the previous values of error terms would not be time-decaying, meaning that old error terms will be influencing current values as much as, or more than current ones. Since we consider financial data this principle would be counter-intuitive. Regression of two non-stationary data series may give spurious relationships as an output, while in reality there is no real relationship between the variables. Another reason we need to make sure that our data is stationary is the fact that distributions associated with various tests will no longer apply. For example, a non-stationary data tested with F-statistic will not be f-distributed. Therefore, if data is not stationary it poses a problem of not being able to perform valid hypothesis testing, because the results will be valueless.

We have chosen an Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. The objective of ADF test is to establish whether ϕ=1 in the following equation:

$$y_t = \phi * y_{t-1} + u_t \tag{4.1.1}$$

We reject null hypothesis that our data series contains a unit root if test statistic is larger in absolute value than the critical value.

PP test is slightly different from an ADF test since it includes an automatic correction to allow for autocorrelation between the residuals. We apply both the price and return levels for each index to test for stationarity.

4.2. Cointegration Tests

In univariate models, the stochastic trend can be addressed by generating the first difference series, which then can be estimated using univariate Box-Jenkins methodology. In the multivariate model, stationarity can be a result of linear transformation of a number of non-stationary variables, which altogether removes the need to transform the data series. If this happens to be the case, such variables are said to be cointegrated. Most research on the subject of cointegration looks at variables with a single unit root, since for the most part traditional regression and time-series analysis is used when variables are non-stationary in the order of containing only one unit root, *I(1)*. Integration of variables of an order higher than unity is a rare occurrence.

Financial time-series data tends to be non-stationary, but its movement has a binding factor that does not let the relationship drift far from the “equilibrium.” In other words, time-series data series may be moving together. Variables may deviate from the common trend in the short run, but inevitably will return to the equilibrium in the long run. If we have a model with two variables only, then there can be at most one cointegrating vector. On another hand, if we have a multivariate model then we should use a system approach for cointegration, which allows defining more than one cointegrating relationship. One method that allows testing for multiple cointegrating vectors is the Johansen test.

We need to test whether the chosen stock indices are cointegrated. We test for cointegration of all indices as a group. In order to apply the Johansen cointegration test we need to make sure that our data is non-stationary at the level, but stationary when it is transformed.

4.3. Granger Causality Tests

When we are testing a model that includes a number of lags in each of the variables, it would be difficult to establish a particular relationship and its significance between each given lag and a dependent variable.

For example, if we examine a bivariate vector autoregressive model (VAR(3)):

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_{10} \\ \alpha_{10} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} * \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix} * \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{pmatrix} * \begin{pmatrix} y_{1t-3} \\ y_{2t-3} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \tag{4.3.1}$$

Individual equations for this VAR can be written in the following form:

$$y_{1t}=\alpha_{10}+ \beta_{11*}\, y_{1t-1}+ \beta_{12*}\, y_{2t-1}+\gamma_{11*}\, y_{1t-2}+ \gamma_{12*}\, y_{2t-2}+\delta_{11*}\, y_{1t-3}+ \delta_{12*}\, y_{2t-3}+u_{1t} \tag{4.3.2}$$

$$y_{2t}=\alpha_{20}+ \beta_{21*}\, y_{1t-1}+ \beta_{22*}\, y_{2t-1}+\gamma_{21*}\, y_{1t-2}+ \gamma_{22*}\, y_{2t-2}+\delta_{21*}\, y_{1t-3}+ \delta_{22*}\, y_{2t-3}+u_{1t} \tag{4.3.3}$$

To solve this problem we can run tests in a restricted setting where we assume all lags of a given variable equal to zero. If all the variables in the system are stationary, the joint hypothesis for a system of equations can be tested using a standard F-test methodology. Then the equations are estimated separately by OLS in order to find the unrestricted RRS. In the next step we would impose the restrictions and the model would be estimated one more time to find the restricted RRS. Then we can apply a standard F-statistics test. Basically the significance of given variables is tested on the basis of joint significance of the lags of a given variable in the equation. These tests were introduced by Granger back in 1969, slightly altered by Sims in 1972, and establish whether changes in one variable causes changes in another variable.

Mathematically speaking if y_1 causes $y_{2,}$ then the lags of y_1 should have a significant weight when defining changes in y_2 variable, in other words we can state that y_1 “Granger-Causes” y_2 or that we established univariate causality. If both lag of y_1 and y_2 were significant then we could say that there is a bi-directional causality. If the relationship is uni-directional, then we can say that the variable that causes the changes is strongly exogenous in the equation.

In our case we would like to examine the relationship between stock indices in our study. We need to refer back to stationarity. Granger causality test can be run only if both variables are stationary. Therefore, if our data series are stationary at levels we can apply the Granger causality technique, but if the series are non-stationary then the testing will be done on the transformed return series. At the same time, we have to keep in mind that we need to correct for cointegration, otherwise testing on cointegrated variables may illustrate spurious causality.

4.4. ARCH/GARCH Model Estimation

Since we are interested in spillover effects from developed countries to emerging, we need to estimate volatility of stock indices. Since volatility is one of the most important topics in finance modeling, the accurate forecasting of volatility holds a great importance. We know that volatility is measured by standard deviation or variance of returns. These are often used as a rough measure for the total risk of financial assets. The easiest method for deriving volatility estimates is the historical estimate. This method involves calculating standard deviation of returns over a specified period of time and then applying (forecasting) volatility over some period in the future. According to research (Akgiray, 1989; Chu and Freund, 1996) historical estimate is a weaker model for deriving volatility in comparison with the more robust time-series models. In order to estimate volatility, we need to test the relationships of our interest using an appropriate model, in order to generate volatility vectors and establish whether the relationship of the data series is linear or non-linear.

Volatility modeling began with a research done by Engle in (1982) where the author suggested to examine conditional variance as a distributed lag of previous squared returns in an Autoregressive Conditional Heteroscedasticity model (ARCH). The model assumes that the returns are not correlated serially, but their volatility (conditional variance) is dependent on previous returns behaving as a quadratic function. The model can de defined as the following:

$$R_t = \sqrt{\sigma_t^2}\ \varepsilon_t \tag{4.4.1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\ R_{t-i}^2 \tag{4.4.2}$$

Where R_t is the return and $\varepsilon_t$is IID N(0,1). A few years later the model was extended by Bollerslev (1986) to include on top of past squared errors past values of conditional variance, which he summarized in a Generalized ARCH (GARCH). The GARCH (p,q) model can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\ R_{t-i}^2 + \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^2 + \nu_t \tag{4.4.3}$$

where ω is a constant and ν_t is white noise with N(0,1).

GARCH (1,1) is the most widely used model for testing conditional variance. This is a useful method for the testing of financial data since volatility shocks are persistent in financial data series.

To determine whether using ARCH/GARCH models in our analysis is the most appropriate for our data set, we need to find out whether there is heteroscedasticity in the variance of the error terms of our indices over time. The easiest way to do this is to perform an ARCH test. The test is done by regressing the squared residuals on a constant and a predetermined number of lags. The null hypothesis of the test is that the data is homoscedastic, that volatility over time is constant. Its rejection means that the variance of the errors changes over time and that the data cannot be estimated using simple OLS, since one of the basic assumptions of homoscedasticity will be violated. If we reject the null hypothesis of homoscedasticity, it would mean that there is statistically significant evidence that the volatility of the returns of the stock returns is changing randomly over time. This outcome would confirm the fact that ARCH and GARCH are an appropriate choice for analyzing this particular data set and provides us with the basis for further analysis.

We will be evaluating a number of ARCH/GARCH models to identify the best fitting model for our data. Below you will find a brief description of different ARCH models.

The Exponential GARCH (EGARCH) model was proposed a few years later by Nelson (1991) introducing an exponential effects in variance shocks rather than quadratic

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(a_i \left(\left| \frac{R_{t-1}}{\sigma_{t-1}} \right| - E\left| \frac{R_{t-1}}{\sigma_{t-1}} \right| \right) + \gamma_i \frac{R_{t-1}}{\sigma_{t-1}} \right) + \sum_{j=1}^{q} \left(\beta_i ln\left(\sigma_{t-j}^2\right) \right) \quad (4.4.4)$$

where γ_i is the coefficient that allows for asymmetrical effect.

Threshold ARCH (TARCH) or GJR-GARCH model can be viewed as a special case of non-linear ARCH model.

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \; R_{t-i}^2 + \gamma R_{t-i}^2 d_{t-1} + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 + \nu_t \quad (4.4.5)$$

Where d_{t-1} is a dummy variable that takes a value of one if $R_{t-1} < 0$ in case of bad news and zero if $R_{t-1} > 0$ in case of good news.

In our research we will be using a component GARCH (CGARCH) model in order to generate short and long term volatility, as well as illustrate spillover effects. The mean and variance equations are defined as

$$R_t = \beta_1 + \beta_2 \, R_{t-1} + \varepsilon_t \quad (4.4.6)$$

$$q_t = \gamma_0 + \gamma_1 (q_{t-1} - \gamma_0) + \gamma_2 (\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (4.4.7)$$

$$\sigma_t^2 = q_t + \gamma_3(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma_4(\sigma_{t-1}^2 - q_{t-1}) \tag{4.4.8}$$

In our research we will expand CGARCH to include long term volatilities of the countries that will be treated as exogenous variables, making the formula for long-term volatility look like:

$$q_t = \gamma_0 + \gamma_1(q_{t-1} - \gamma_0) + \gamma_2(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \gamma_j \hat{h}_{j,t-1}^2 \tag{4.4.9}$$

While mean equation can be defined as:

$$R_t = \beta_1 + \varepsilon_t \tag{4.4.10}$$

CGARCH makes a distinction between short-term and long-term conditional variance. q_t, which represents long-term component of conditional volatility, is allowed to vary over time unlike it being constant in traditional GARCH model. $(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$ drives the movement of permanent component through time. $(\sigma_{t-1}^2 - q_{t-1})$ represents a short-term (transitory) component of conditional variance. The sum of γ_3 and γ_4 measures the short-term shock persistence generated by the shock to a short-term component represented by γ_3, while γ_1 measures the long-term shock persistence generated by the shock to a long-term component represented by γ_2. Short-term conditional volatility follows a mean-reverting process. CGARCH allows running models of the short and long-term spillover effects on stock volatility. Optimal lag length is determined by estimating the number of lags in unrestricted VAR model using lag length criteria, which is later applied in the CGARCH model.

5. Empirical Analysis

5.1. Descriptive Statistics

The first part of our analysis is to get a better understanding of our time-series data. The descriptive statistics table underneath provides a snapshot of some specific properties and characteristics of our stock indices.

Table 5.1.1 - Descriptive statistics of stock returns

	R_China	R_France	R_Germany	R_India	R_USA	R_Russia
Mean	0.002083	0.001175	0.001872	0.002419	0.002121	0.004582
Median	0.000000	0.002067	0.004495	0.005041	0.003228	0.004686
Maximum	0.480787	0.132380	0.161162	0.164378	0.189781	0.567003
Minimum	-0.206964	-0.221592	-0.216097	-0.168971	-0.253047	-0.271652
Std. Dev.	0.039837	0.030839	0.032948	0.036296	0.034436	0.071987
Skewness	1.855442	-0.452467	-0.365579	-0.143538	-0.529758	0.834055
Kurtosis	26.24573	6.795758	6.915657	4.932269	8.233247	12.07039
Jarque-Bera	22049.94	605.8950	631.3728	151.8481	1134.438	3384.465
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	955	955	955	955	955	955

Note: descriptive statistics of the entire period of stock returns from 1994-12-30 to 2013-04-19

In Table 5.1.1, we present the skewness, kurtosis, Jarque-Bera statistic and probability values for the returns of each respective index. Skewness measures the probability distribution's deviation on either side of the mean, while kurtosis examines whether the data peaks or is flat relative to normal distribution. As we can see, the market returns for China and Russia are positively skewed, unlike all other indices that exhibit negative skewness. This indicates that the tails for China and Russia are longer or fatter on the right side of the probability density function, while all other countries have longer or fatter tails on the left side. Furthermore, the kurtosis values for the returns of all indices follow the leptokurtic distribution aside from India that is almost at that threshold too. Given these properties, we can determine that we do not have a normal distribution, which implies zero skewness and coefficient of kurtosis of three. This is also supported by the Jacque-Bera statistic test for normality of the distribution. As can be observed by the probability values for each variable, the null hypothesis cannot be accepted even at the 1% level. Thus, rejection means that we do not have a normal distribution, which indicates inefficiencies in the markets. Further illustration of the lack of normality in our index returns is illustrated by Figure 1 in the Appendix.

5.2. Correlations

Given our interest in the volatility transmissions between the developed and developing countries in our data, it is useful to examine the correlations of each market relative to the others. In Table 5.2.1, we present the correlation matrix summarizing the relationship between the chosen group of countries.

Table 5.2.1 -Correlation matrix

	R_China	R_France	R_Germany	R_India	R_USA	R_Russia
R_China	1.000000					

R_France	0.030231	1.000000				
	0.3507	-----				
R_Germany	0.060146	0.880733	1.000000			
	0.0632	0.0000	-----			
R_India	0.142604	0.375006	0.396401	1.000000		
	0.0000	0.0000	0.0000	-----		
R_USA	0.045872	0.669386	0.686624	0.352014	1.000000	
	0.1566	0.0000	0.0000	0.0000	-----	
R_Russia	0.054089	0.402093	0.436775	0.270966	0.360222	1.000000
	0.0948	0.0000	0.0000	0.0000	0.0000	-----

Note: the top number represents correlation between two stock returns while the bottom number represents the the p-value

It is interesting to see from Table 5.2.1 that the developed countries appear to be extremely highly correlated with each other. A high positive correlation implies that if one variable increase, so will the other. Alternatively, a negative correlation represents an inverse relationship, where an increase in one variable leads to a decrease in the other. As can be seen from Table 5.2.1, the pair of Germany–France has a very high positive correlation of almost 0.9, while USA has fairly high correlations with both developed countries in the range of 0.669-0.687. The table also demonstrates that the correlations between the developed and developing countries are not too high and range from levels of 0.03 between France and China, up to 0.43 between Germany and Russia. It is important to note that correlation indicates a co-movement, which is not sufficient to demonstrate dependence. Therefore, we cannot deduce that one variable causes an effect on the other given the correlation. Dependency is illustrated in our Granger Causality test further down in our analysis.

Table 5.2.1 also shows that all developed countries appear to have very low correlations with China. This can partly be explained by representing China with the stock index of Shanghai (which attracts significantly less foreign investment) than the other main index associated with China, the Hong Kong stock exchange. Lastly, the probabilities under the correlations show that at the 5% level of significance, we cannot reject the null hypothesis for the correlations of all countries with China, except for India.

5.3. Unit Root Statistics

The next part of our analysis is meant to determine if we have stationarity in our data. Ensuring that our variables are stationary is very important. This is because conducting our analysis with non-stationary variables may result in us researching a spurious relationship, effectively a nonsense relationship with no adequate validity and/or reliability. In other words, the variables can appear very strongly related when, in fact, it is simply a coincidence.

Table 5.3.1 - Unit root test statistic

	Augmented Dickey-Fuller Test			
	T_Statistic at Index Level	P-value	T-Statistic at Returns' Level	P-value
R_China	-1,976838	0,2973	-30,6679*	0,0000*
R_France	-2,054426	0,2636	-33,6996*	0,0000*
R_Germany	-1,846226	0,3581	-32,14494*	0,0000*
R_India	-0,542991	0,8801	-18,9132*	0,0000*
R_Russia	-1,443075	0,5621	-28,89288*	0,0000*
R_USA	-2,095845	0,2465	-31,41581*	0,0000*
	Phillips-Perron Test			
R_China	-1,890216	0,3371	-30,6876*	0,0000*
R_France	-2,037632	0,2707	-33,66094*	0,0000*
R_Germany	-1,907004	0,3292	-32,1252*	0,0000*
R_India	-0,466339	0,895	-28,36591*	0,0000*
R_Russia	-1,652225	0,4554	-28,94548*	0,0000*
R_USA	-2,148207	0,2259	-31,42059*	0,0000*

Note: Test Critical Value at 5% is -2.864361
*values represent rejection of null hypothesis that data contains a unit root

Table 5.3.1 illustrates our implementation of the Augmented Dickey-Fuller and Phillips-Perron tests for unit roots in the data. Both tests conclude the there are no unit roots in our data series. Each index at the price level is non-stationary. This is demonstrated by accepting the null hypothesis at the 5% significance level, as well as examining that the critical value for all indices is greater than the respective t-statistic. Coming across non-stationarity is quite common in practice. This is because financial time-series data often has properties that propel it as a random walk. Please refer to Figure 2 in the Appendix. One reason for this outcome is that if all available information is reflected in the price of a stock, then the best estimate for tomorrow's price of each stock in the given index will simply be the price of today. In addition, a random walk in financial time series can occur when the data is driven from its long-term trend due to mispricing of information, bubbles, shocks and other cyclical and/or temporary developments.

Therefore, in order to ensure that our variables are stationary we transform them into returns. Please refer to Figure 3 in the Appendix. This process ensures that each index is stationary, which can further be observed by Table 5.3.1, as we reject the null hypothesis of the data containing a unit root in all returns. We acknowledge that by transforming our data into returns may lead to the loss of some information that relates to the trend of movement in our indices, but given our assumption of a random walk at the price level it is a necessity to obtain stationarity and proceed with our analysis.

5.4. Cointegration

Having established that the indices are non-stationary at the price level and when transformed to returns become stationary, we proceed with investigating whether any cointegration exists. The purpose of testing for cointegration is to determine if two variables that are non-stationary, *I(1)*, share the same stochastic trend, so that a linear combination of them will lead those variables to convert to *I(0).* In our analysis we apply Johansen's Cointegration test and the Maximum Eigen statistic. In all scenarios we conclude that there is no cointegration between our indices. Please refer to Tables A1 and A2 in the Appendix.

In order to move forward with our analysis in this circumstance is to continue with using our stationary returns. This will avoid any spurious relationships, which is essential to our analysis. However, this approach also means that we can only analyze the short-term relationships between the returns, as any long-term information will be lost. In other words, having obtained no cointegration between our variables assumes that there is no influence between the variables in the long-term. This outcome is a bit surprising given that many researchers establish some level of interdependence between stock markets. On the other hand, there is also evidence to support our analysis. Chan *et al*. (1997) tested 18 stock markets over the span of 32 years using Johansen's Cointegration test and discovered that only a small number of the markets showed signs of cointegration. Menon, Sagaran and Subha (2009) also conclude no cointegration between the US and Indian stock markets.

Having described the relatively recent market activities of our developing countries in our data characteristics, it seems plausible to conclude that that there simply have not been observable trends to establish any long-term relationships yet. Further in our analysis we will use our CGARCH model to examine if there are short and long-term relationships between the volatilities of the indices.

5.5. VAR Model Procedure

After ensuring that our stock returns are stationary, we proceed with running a Vector Autoregressive Model (VAR) between the indices. VARs are particularly useful and practical when used for time-series data. One strong advantage of a VAR over traditionally restricted models is the flexibility to not specify which variables are endogenous. In addition, variables can depend on more than just own lags or previous disturbances making the process quite general. However, one obstacle that needs to be overcome when dealing with VARs is choosing the appropriate number of lags to use in the model. The number of lags can have a significant impact on the results and should be considered carefully. There are different methods of trying to determine the optimal lag selection. In our analysis, we choose to follow the Information Criterion (IC) when it comes to selecting the number of lags. Table 6 below shows our obtained results of the optimal number of lags under the Akaike Information Criterion (AIC), Schwartz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ).

Table 5.5.1 - Optimal choice of lags tests

		Optimal Number of Lags		
Developed Countries	Developing	**AIC**	**SC**	**HQ**
USA, Germany, France	China	2	0	1
USA, Germany, France	India	2	0	1
USA, Germany, France	Russia	2	0	1
Developing Countries	Developed	**AIC**	**SC**	**HQ**
China, India, Russia	France	2	0	0
China, India, Russia	Germany	2	0	0
China, India, Russia	USA	2	0	1

Note: AIC: Akaike Information Criterion; SC: Schwartz Information Criterion; HQ: Hannan-Quinn Information Criterion

Having established the optimal number of lags, we proceed to determine the causal effect relationships between our stock indices. Establishing causality is important because it provides us with an understanding of which variables affects which in the system. Table 5.5.2 below shows our results from running a Granger Causality test on the returns. Rejecting the null hypothesis of no causality indicates that there is a significant dependency of one index on another. From this we can conclude some interesting observations. Both markets of China and India appear to be dependent on the developed countries of our data at the 5% significance level. This uni-directional effect is consistent with our hypothesis that the developed markets will influence the developing markets. However, the developing market of Russia is not dependent upon any of the others.

Table 5.5.2 - Granger causality on returns between developed and developing countries

Null Hypothesis:	F-Statistic	Prob.
R_France does not Granger Cause R_China	15.1423	0.0001*
R_China does not Granger Cause R_France	0.90412	0.3419
R_Germany does not Granger Cause R_China	13.0540	0.0003*
R_China does not Granger Cause R_Germany	0.83070	0.3623
R_USA does not Granger Cause R_China	4.53621	0.0334
R_China does not Granger Cause R_USA	0.94950	0.3301
R_India does not Granger Cause R_France	0.04637	0.8296
R_France does not Granger Cause R_India	4.78517	0.0289*
R_Russia does not Granger Cause R_France	0.60327	0.4375
R_France does not Granger Cause R_Russia	0.30606	0.5802
R_India does not Granger Cause R_Germany	0.10591	0.7449
R_Germany does not Granger Cause R_India	7.52286	0.0062*
R_Russia does not Granger Cause R_Germany	0.05520	0.8143
R_Germany does not Granger Cause R_Russia	0.02246	0.8809
R_USA does not Granger Cause R_India	14.4020	0.0002*
R_India does not Granger Cause R_USA	0.39652	0.5290
R_Russia does not Granger Cause R_USA	3.63272	0.0570
R_USA does not Granger Cause R_Russia	0.06857	0.7935

Note: *values represent rejection of null hypothesis that the is no causality between the variables

There can be several reasons for the absence of dependence on developed markets. Russia is the largest country in the world with the ninth largest economy measured by its GDP and sixth largest according to purchasing power parity. The stability of the economy can be evaluated by middle class percentage compared with the total population. Among BRIC countries, Russia is the leader of middle class citizens that make up 68 percent, followed Brazil with 31 percent, China with 13 percent and finally India with only six percent. If we look at the dependency on consumer loans, we have to point out that it is the lowest among BRIC nations. Looking closely on composition of home mortgage loans, we can notice that they make up only two percent of Russia's GDP, while in EU the number reaches 51.4 percent. At the same time the US is outstanding home mortgage loans leader with an unprecedented 81.4 percent. These numbers make us believe that the population has more healthy financial habits, saving money, which in their turn contributes to the amount of funds inflowing into the Russian banking system.

Another factor that can explain the lack of dependency might be the level of debt. Among BRIC countries, Russia has the lowest level of debt amounting to 12 percent of its GDP, followed by China with 20 percent, Brazil with 65 percent and India with 69 percent. (Milldahl, 2012). These numbers are considerably lower that the debt level of the US (70 percent) and EU (90 percent).

At the same time Russia's currency reserves are the fourth largest in the world after China, Japan and Saudi Arabia. If we look at resources and international trade, Russia has the largest gas reserves in the world, second largest coal reserves and eighth largest oil reserves. When it comes to trade, the European Union is Russia's biggest trading partner accounting for 46.8 percent of overall trade in 2010 and the most important investor accounting for 75 percent of direct investments in the Russian economy.

We see that there are significant ties between Russia and European Union, but lack of debt, considerable purchasing power, significant currency reserves as well as its position as a leading economic power allows Russia to stay fairly independent from the US influence that China and India are under. These results are in large supportive of our hypothesis. There appears to be uni-directional causality from the developed to the developing markets. The only exception is Russia, where we cannot conclude any causality. Some drawbacks of the Granger causality that need to be pointed out include the sign and size of the effect. The test indicates that there is a statistical significance at a given confidence level, but whether this effect is positive or negative, or the magnitude of its size cannot be deduced from this type of test. For that purpose the next stage of our analysis involves the development of a CGARCH model, in order to capture the levels of volatility between the groups of developed and developing countries.

5.6. CGARCH(1,1)

Before we begin to implement our CGARCH models for each respective index, we need to test of heteroscedasticity in our data. This can be done by performing a simple ARCH test. Table 5.6.1 shows our results. Accepting the null hypothesis indicates that we have homoscedastic data where the variance is constant over time. Alternatively, rejection of the null hypothesis illustrates heteroscedasticity as the variance in the residuals changes over time. As we can see from our outcomes, we cannot accept the null hypothesis even at the 1% significance level for all indices. This allows us to conclude that the returns of our data are suitable for an ARCH type regression, since the constant variance assumption needed for OLS is not applicable.

Table 5.6.1 - Heteroscedasticity test

Country	**China**	**Russia**	**India**	**France**	**Germany**	**USA**
F-Statistic	10,2101	41,465	23,4924	20,6611	42,6258	34,5701
Probability F-Stat	0,0014*	0,0000*	0,0000*	0,0000*	0,0000*	0,0000*
Obs*R-squared	10,123	39,8178	22,9748	20,2647	40,8847	33,4289
Probability Chi-Square	0,0015*	0,0000*	0,0000*	0,0000*	0,0000*	0,0000*

Note: *we reject a null hypothesis of time-series data having homoskedasticity (constant variance)

In order to examine the volatility spillover across our countries and analyze any bi-directional contagion effects between the developed and developing nations, we need to test a univariate GARCH model. Thus, we can estimate the volatility for each stock index. In particular, we choose to employ a CGARCH model because its properties allow us to extract the permanent component of volatility, as well as the total volatility (Égert and Kocenda, 2005). Having established that our variables are not normally distributed, running a CGARCH with a Student's t-distribution consistently provides a better fit across all indices by yielding lower AIC and SC values.

A univariate CGARCH enhancement would not require the estimation of as many coefficients, as the multivariate GARCH counterparts. The VEC model of Bollerslev, Engle and Wooldridge (1988), working with six series would require the estimation of so many coefficients that the significance of the coefficient estimates would be extremely reduced. This problem can be partly overcome in more restricted multivariate specifications, such as the BEKK model proposed by Engle and Kroner (1995). However, the resulting specification is unlikely to be robust to the ordering of the series, resulting in still fairly large number of coefficients (Pramor and Tamirisa, 2006). As a result, for the purposes of our research we are giving the preference to a univariate CGARCH model over multivariate GARCH models, since we are interested in estimating the relationships between the returns and their respective volatilities that satisfy five percent significance level. If a multivariate GARCH model significantly reduces the significance of the estimated coefficients to the point of not being able to satisfy the significance level of five percent, it would make the research redundant.

CGARCH decomposes conditional volatility into long and short term conditional volatility. Long-term component of conditional volatility represents time-varying volatility that converges to γ_0 and is driven by coefficient $\gamma_{1.}$ In practice most of the time the value of γ_1 falls somewhere between 0.9 and 1, which means that permanent component of conditional volatility approached the unconditional variance very slowly. If it ever reached one, then the volatility would not be time varying any more and would be represented by unconditional and therefore constant variance. Coefficient γ_2 that belongs to the following part of conditional variance equation $(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$ drives the movement of permanent component through time. The difference between the previous lag of conditional variance and permanent component stands for a short-term component of volatility that dies out with time. The Coefficient that corresponds to the short-term volatility persistence is $\gamma_{4.}$ The long-term volatility component is determined by current expectation of the short-term volatility, which is represented by the sum of coefficients γ_3 and γ_4, which equals to less than one. CGARCH model defines conditional variance using two equations. The variables in the transitory equation drive short-term volatility, while the variables of the trend equation affect long-term component of volatility of indices.

Table 5.6.2 - CGARCH model for the entire sample covering the period from 1994-12-30 to 2013-04-19

CGARCH Model				Coefficients											
	Regression Output and Parameter Estimates								Information Criterion		Standardized residuals stat. and diagnostics				
	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	AIC	SC	Skewness	Kurtosis	Corr.	Corr.	ARCH
China	0.001422*	0.925758*	0.126361*	-0.007444	-0.938606*	-0.020765*	0.044637	-0.014328	-3.920737	-3.854502	1.624182	19.52840	0.093	0.999	0.932581
z-Statistic	(3.610003)	(34.16105)	(3.948301)	(-0.498385)	(-10.61668)	(-2.852862)	(0.689633)	(-0.329646)							
Probability	0.0003	0.0000	0.0001	0.6182	0.0000	0.0043	0.4904	0.7417							
India	0.001101*	0.940505*	0.161379*	-0.056179	-0.044439	0.045479	-0.056756	0.023374	-3.943821	-3.877530	-0.072413	3.805853	0.100	0.337	0.866152
z-Statistic	(2.261867)	(30.02693)	(4.077342)	(-1.081845)	(-0.048979)	(1.455688)	(-1.324830)	(0.676178)							
Probability	0.0237	0.0000	0.0000	0.2793	0.9609	0.1455	0.1852	0.4989							
Russia	0.015659	0.995737*	0.075997*	0.112863*	0.651295*	0.005314	-0.156241*	0.096379*	-2.945749	-2.864092	0.070504	5.055015	0.802	0.827	0.938786
z-Statistic	(0.489827)	(116.6268)	(2.779948)	(2.307251)	(4.034687)	(0.183925)	(-3.393973)	(2.899045)							
Probability	0.6243	0.0000	0.0054	0.0210	0.0001	0.8541	0.0007	0.0037							
France	0.000693	0.970503*	0.129558*	-0.074403	-0.256172	0.000430	0.001497	0.001618	-4.319791	-4.268883	-0.555271	5.225019	0.224	0.987	0.845392
z-Statistic	(1.345766)	(46.26503)	(4.372259)	(-1.514114)	(-0.385721)	(0.040979)	(0.761257)	(0.354064)							
Probability	0.1784	0.0000	0.0000	0.1300	0.6997	0.9673	0.4465	0.7233							
Germany	0.000747	0.956070*	0.157665*	-0.017262	-0.724615	0.012838	0.000794	-0.002443	-4.261568	-4.210660	-0.815990	6.397824	0.925	0.979	0.614946
z-Statistic	(1.700824)	(36.84902)	(4.196087)	(-0.377289)	(-0.785853)	(0.820000)	(0.401082)	(-1.108136)							
Probability	0.0890	0.0000	0.0000	0.7060	0.4320	0.4122	0.6884	0.2678							
USA	-0.000492	0.984940*	0.029071	0.108179*	0.775362*	0.016031	0.000118	0.001482	-4.234835	-4.183927	-0.433288	4.072534	0.724	0.998	0.760785
z-Statistic	(-0.877440)	(129.5802)	(1.043435)	(2.526818)	(8.455033)	(1.561147)	(0.144155)	(0.706412)							
Probability	0.3802	0.0000	0.2967	0.0115	0.0000	0.1185	0.8854	0.4799							

Notes: Method of estimation: ML - ARCH (Marquardt) – Student t-distribution, with Bollerslev-Wooldridge robust standard errors & covariance. The first row of the γ_i columns shows the estimated parameter values. The second and third rows show the corresponding z-statistics and the p-values (respectively). The skewness and kurtosis indicate appropriate usage of student t- distribution. In the Corr and $Corr_2$ column are p-values based on a Ljung-Box joint test for autocorrelation in the standardized residuals and squared standardized residuals respectively. Stability of all the models was tested using 12 lags of the respective residuals. The values in the ARCH column are p-values based on from F-statistic from an Engel's (1982) test for ARCH effects with one lag. AIC: Akaike's Information Criterion. SC: Schwarz's Bayesian Information Criterion. γ_5, γ_6, γ_7 in case with China, India and Russia stand for USA, Germany and France respectively, while in case with France, Germany and USA these coefficients stand for India, Russia and China respectively.

Table 5.6.3 - CGARCH model for subsample one covering the period from 1994-12-30 to 2008-01-06

CGARCH Model	**Coefficients**														
	Regression Output and Parameter Estimates								Info. Criterion		Standardized residuals stat. and diagnostics				
	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	AIC	SC	Skewness	Kurtosis	Corr.	Corr.^{2}	ARCH
China	0.001575*	0.906066*	0.022456	0.126075	0.641967*	-0.031320*	0.093859	-0.049858	-3.960120	-3.860024	2.219399	27.07128	0.383	0.999	0.932939
z-Statistic	(3.928350)	(18.43906)	(0.271728)	(1.431037)	(3.749073)	(-2.094021)	(0.802765)	(-0.699133)							
Probability	0.0001	0.0000	0.7858	0.1524	0.0002	0.0363	0.4221	0.4845							
India	0.001374*	0.712484*	0.107879	0.063196	-0.814437*	0.081649	-0.215028	0.086875	-3.725774	-3.570467	0.199591	3.491416	0.052	0.746	0.694504
z-Statistic	(3.661536)	(3.313952)	(1.454922)	(1.385554)	(-5.148241)	(1.084137)	(-1.106562)	(0.778594)							
Probability	0.0003	0.0009	0.1457	0.1659	0.0000	0.2783	0.2685	0.4362							
Russia	0.032742	0.999699*	0.019838	0.114254*	0.700476*	-0.016293	-0.115956*	0.086180*	-2.634383	-2.687489	0.121839	4.666977	0.360	0.987	0.813123
z-Statistic	(0.747824)	(4167.736)	(1.670402)	(2.431419)	(5.569024)	(-1.718041)	(-2.252276)	(2.508711)							
Probability	0.4546	0.0000	0.0948	0.0150	0.0000	0.0858	0.0243	0.0121							
France	0.000541	0.977822*	0.102143*	-0.071863	-0.339889	-0.003383	0.001521	0.001167	-4.472516	-4.385866	-0.259985	3.141175	0.428	0.367	0.469008
z-Statistic	(0.954085)	(51.73824)	(3.735486)	(-1.391333)	(-0.550265)	(-0.391498)	(0.972803)	(0.356910)							
Probability	0.3400	0.0000	0.0002	0.1641	0.5821	0.6954	0.3307	0.7212							
Germany	0.000713	0.972884*	0.124566*	-0.019843	-0.870199*	0.004060	0.001048	-0.001908	-4.334055	-4.247405	-0.404394	3.417250	0.603	0.994	0.728572
z-Statistic	(1.204800)	(48.26442)	(3.923892)	(-0.637511)	(-3.637046)	(0.313443)	(0.706572)	(-0.989197)							
Probability	0.2283	0.0000	0.0001	0.5238	0.0003	0.7539	0.4798	0.3226							
USA	-0.001231*	0.984072*	0.029170*	0.004871	-1.002753*	0.027893*	-0.000218	0.001798	-4.240313	-4.153663	-0.473782	4.515167	0.619	0.782	0.993278
z-Statistic	(-1.962429)	(141.3276)	(2.062008)	(1.107524)	(-1349.015)	(2.413551)	(-0.276784)	(1.078576)							
Probability	0.0497	0.0000	0.0392	0.2681	0.0000	0.0158	0.7819	0.2808							

Notes: Method of estimation: ML - ARCH (Marquardt) – Student t-distribution, with Bollerslev-Wooldridge robust standard errors & covariance. The first row of the γ_i columns shows the estimated parameter values. The second and third rows show the corresponding z-statistics and the p-values (respectively). The skewness and kurtosis indicate appropriate usage of student t- distribution. In the Corr and Corr2 column are p-values based on a Ljung-Box joint test for autocorrelation in the standardized residuals and squared standardized residuals respectively. Stability of all the models was tested using 12 lags of the respective residuals. The values in the ARCH column are p-values based on from F-statistic from an Engel's (1982) test for ARCH effects with one lag. AIC: Akaike's Information Criterion. SC: Schwarz's Bayesian Information Criterion. $\gamma_5, \gamma_6, \gamma_7$ in case with

China, India and Russia stand for USA, Germany and France respectively, while in case with France, Germany and USA these coefficients stand for India, Russia and China respectively.

Table 5.6.4 - CGARCH model for subsample two covering the period from 2008-01-07 to 2013-04-19

CGARCH Model	Coefficients														
	Regression Output and Parameter Estimates								Info. Criterion		Standardized residuals stat. and diagnostics				
	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	AIC	SC	Skewness	Kurtosis	Corr.	Corr.^{2}	ARCH
China	0.004394	0.997989*	0.009943	0.034056	-0.697067	-0.019010	-0.018882	0.023909	-3.890328	-3.707165	0.220961	3.031494	0.569	0.418	0.616156
z-Statistic	(0.276746)	(125.3893)	(0.649879)	(0.643031)	(-1.245329)	(-0.519243)	(-0.447236)	(1.159873)							
Probability	0.7820	0.0000	0.5158	0.5202	0.2130	0.6036	0.6547	0.2461							
India	-3.98E-06	0.938153*	-0.149311	0.179067	0.674920*	0.285362*	-0.263293*	0.078400*	-4.032125	-3.822795	0.048680	3.061197	0.817	0.778	0.579609
z-Statistic	(-0.015110)	(1355.659)	(-1.014597)	(1.195549)	(6.677854)	(5.539309)	(-4.185435)	(2.464484)							
Probability	0.9879	0.0000	0.3103	0.2319	0.0000	0.0000	0.0000	0.0137							
Russia	0.039027	0.997152*	0.155133*	0.053379*	-0.935674*	-0.038583	-0.140836	0.104127	-3.479684	-3.348853	-0.357800	4.648039	0.361	0.461	0.715544
z-Statistic	(0.157703)	(55.16132)	(3.371436)	(2.174977)	(-50.23609)	(-0.267616)	(-0.969405)	(1.164038)							
Probability	0.8747	0.0000	0.0007	0.0296	0.0000	0.7890	0.3323	0.2444							
France	0.000535	0.715248*	0.209519	-0.123813	-0.060459	-0.087177	0.072558	0.065431	-3.910418	-3.727254	-0.715212	5.381045	0.084	0.977	0.859454
z-Statistic	(1.518191)	(3.428268)	(1.048087)	(-0.579930)	(-0.052333)	(-0.843440)	(1.206363)	(0.564164)							
Probability	0.1290	0.0006	0.2946	0.5620	0.9583	0.3990	0.2277	0.5726							
Germany	0.000637*	0.613915*	0.273695	0.062837	-0.857391*	-0.044418	0.111221	-0.040710	-4.051824	-3.855577	-0.621533	4.899453	0.123	0.943	0.983080
z-Statistic	(2.234469)	(3.172967)	(1.839337)	(1.456335)	(-9.151906)	(-0.323119)	(1.806111)	(-0.452054)							
Probability	0.0255	0.0015	0.0659	0.1453	0.0000	0.7466	0.0709	0.6512							
USA	0.000333	0.847076*	0.423123*	0.031320	-0.446506	-0.052271	0.030342	0.086694	-4.198776	-3.989447	-0.115190	2.916137	0.730	0.710	0.942082
z-Statistic	(0.680326)	(6.983978)	(3.283800)	(0.338061)	(-0.325598)	(-0.698285)	(1.002514)	(0.982040)							
Probability	0.4963	0.0000	0.0010	0.7353	0.7447	0.4850	0.3161	0.3261							

Notes: Method of estimation: ML - ARCH (Marquardt) – Student t-distribution, with Bollerslev-Wooldridge robust standard errors & covariance. The first row of the γ_i columns shows the estimated parameter values. The second and third rows show the corresponding z-statistics and the p-values (respectively). The skewness and kurtosis indicate appropriate usage of student t- distribution. In the Corr and Corr2 column are p-values based on a Ljung-Box joint test for autocorrelation in the standardized residuals and squared standardized residuals respectively. Stability of all the models was tested using 12 lags of the respective residuals. The values in the ARCH column are p-values based on from F-statistic from an Engel's (1982) test for ARCH effects with one lag. AIC: Akaike's Information Criterion. SC: Schwarz's Bayesian Information Criterion. $\gamma_5, \gamma_6, \gamma_7$ in case with China, India and Russia stand for USA, Germany and France respectively, while in case with France, Germany and USA these coefficients stand for India, Russia and China respectively.

Table 5.6.2 above summarizes the values and significance of the coefficients for each index. Excluding the US, for all countries we can observe the forecasting error term γ_2 is found to be significant due to the probability of it being lower than the 1% threshold. Therefore, we can state that there is an initial effect of the shock to the permanent component of conditional variance for all indices other than USA. In addition, all indices are significant in the persistence of the trend component (γ_1) at 1% level, which means that any shocks to the long-run component will have a long-term effect and a high degree of memory. The value of γ_3 is only significant for Russia and USA at the 5% level, which indicates that there is impact of the shock to the short-term component only to those markets. The coefficient γ_4 stands for the level of memory of the short-term component and indicates whether the memory of the transitory component affects the conditional volatility. We find significance at the 1% level only for China, Russia and USA. The sum of coefficients γ_3 and γ_4 illustrate significance of the short-term components. Therefore we can conclude that for France, India and Germany the impact of the shock on the short-term volatility component does not drive conditional variance.

The spillover coefficients for each index are portrayed by γ_5, γ_6 and γ_7. In the case for China, the only significant spillover occurs from USA (represented by γ_5 and value -0.020765). The negative sign represents that the volatility of USA will actually reduce the volatility of China. For Russia, we can also observe a spillover at the 1% significance level coming from France and Germany (represented by the values of γ_6 and γ_7 in Table 5.6.2 respectively). These results show some spillover effects in a uni-directional movement from the developed to the developing countries. Lack of further significant coefficients at the 5% level in our research allows us to conclude no observation of bi-directional spillovers, or uni-directional flow from the emerging to the developed markets.

The next step of our analysis was to divide our data into two subsamples and analyze any spillovers that occurred before and after the global financial crisis of 2008. Table 5.6.3 shows our results for the subsample before the crisis. We observe similar findings as our full sample when we evaluate the spillover coefficients γ_5, γ_6 and γ_7. At the 5% significance level volatility spillover occurs from USA to China, as well as France and Germany to Russia. The only additional spillover in this case occurs from India to USA at the 5% significance level. Lastly, when we evaluate our subsample that takes place after the financial crisis of 2008, we can observe some considerable differences. In this scenario, the only volatility spillover occurs from all developed markets into India. For USA and France this takes place at the 1% significance level, while with Germany at the 5% respectively. This is a particularly interesting finding given the lack of spillover coming into India from the full sample, as well as the subsample before the crisis. Table 5.6.4 shows our results for the after crisis subsample.

Our last analysis focuses on the short-term volatility between the indices. By subtracting the long-term component from the conditional volatility of our CGARCH, we were able to generate the short-term volatility for each index. After running a Granger Causality test, we find dependencies that occur from the developed markets of France, Germany and the USA to Russia for our full sample. This illustrates that USA exhibits some influence on Russia in a shorter horizon than France and Germany. In our subsample before the financial crisis, we establish a uni-directional causality only from Germany to Russia, which is also captured by CGARCH model. In our subsample after the financial crisis, we observe significant differences compared to our CGARCH results. There are bi-directional dependencies between the markets of France with both India and China. In addition, there are uni-directional dependencies occurring from Germany to Russia, China to Germany, as well as India, China and Russia to the USA. Tables 5.6.5 – 5.6.7 below show our results.

The Granger causality tests show that there appears to be a rising significance of the emerging economies, particularly post the financial crisis era. However, it is important to note that we cannot deduce the sign or magnitude of these relationships, unlike estimating spillover coefficients extracted using the CGARCH models. Therefore, relationships established by CGARCH are considered to be more comprehensive.

Table 5.6.5 - VAR Granger Causality/Block Exogeneity Wald Tests for short-term volatility for the entire sample from 1994-12-30 to 2013-04-19

	China	Russia	India	France	Germany	USA
China	N/A	0.7058	0.4932	0.8110	0.9369	0.8809
Russia	0.1023	N/A	0.0000*	0.0000**	0.0001**	0.0178**
India	0.7048	0.0250	N/A	0.0052	0.2289	0.0103
France	0.9249	0.7188	0.8751	N/A	0.1497	0.5937
Germany	0.7519	0.4007	0.1167	0.0063	N/A	0.3743
USA	0.7684	0.0963	0.5982	0.5453	0.8815	N/A

Note: a row represents independent variables, while a column represents dependent variable; the values represent p-values for the causality between two variables; *indicates the causality at 5% significance level; **the causality relevant to our research subject

Table 5.6.6 - VAR Granger Causality/Block Exogeneity Wald Tests for short-term volatility for the subsample of observations before financial crisis of 2008, from 1994-12-30 to 2008-01-06

	China	Russia	India	France	Germany	USA
China	N/A	0.5158	0.9727	0.3523	0.4874	0.9823
Russia	0.8770	N/A	0.0568	0.7370	0.0026**	0.8132
India	0.5209	0.5328	N/A	0.3600	0.1885	0.8634
France	0.7114	0.7579	0.9325	N/A	0.3749	0.5809
Germany	0.7625	0.6020	0.8247	0.1371	N/A	0.5867
USA	0.8148	0.4885	0.1756	0.1735	0.2293	N/A

Note: a row represents independent variables, while a column represents dependent variable; the values represent p-values for the causality between two variables; *indicates the causality at 5% significance level; **the causality relevant to our research subject

Table 5.6.7 - VAR Granger Causality/Block Exogeneity Wald Tests for short-term volatility for the subsample of observations after financial crisis of 2008, from 2008-01-07 to 2013-04-19

	China	Russia	India	France	Germany	USA
China	N/A	0.0004*	0.2393	0.0085**	0.8206	0.2817
Russia	0.6233	N/A	0.4961	0.0000**	0.0000**	0.1171
India	0.0020*	0.4897	N/A	0.0001**	0.4939	0.2264
France	0.0022**	0.4424	0.0039**	N/A	0.8147	0.0000*
Germany	0.0137**	0.2359	0.0092**	0.0000*	N/A	0.0000*
USA	0.0436**	0.0126**	0.0013**	0.0000*	0.3270	N/A

Note: a row represents independent variables, while a column represents dependent variable; the values represent p-values for the causality between two variables; *indicates the causality at 5% significance level; **the causality relevant to our research subject

6. Conclusion

In our study, we focused on determining potential volatility spillover effects between several developing and emerging countries. By using a major stock index to represent each country, we applied several econometric techniques to evaluate the dependencies and relationships of France, Germany and USA with China, India and Russia. Our Granger causality for returns provided a significant uni-directional influence coming from the developed markets to China and India. We further establish no causality between the developed markets and Russia, which after further research we explain this independence due to the country’s large middle class, as well as low levels of debt holdings. After conducting Johansen’s test for cointegration, we observe that there are no long-term relationships between any of the indices. We attribute this finding to the fact that there have not been any observable trends to establish long-term relationships between our chosen developed and emerging markets.

Our study employed a CGARCH model to estimate the volatility and spillover coefficients between the indices. The properties of CGARCH that differentiate between the short-term (transitory component) and long-term (permanent component) conditional variance make it a desirable model for the purpose of our study. Furthermore, its flexibility of not having to estimate so many parameters as the multivariate GARCH models is another motivation for its preference. After estimating the spillover coefficients for our full data sample between the developed and developing indices, we find significance coming from USA to China, as well as from France and Germany to Russia. This outcome is fairly supportive of our initial hypothesis that volatility spillover will move from the developed to the emerging markets. Interestingly enough, in the cases of USA and China and France and Russia we observe a volatility spillover that results in the volatility decrease in the relative emerging market.

In our subsample before the financial crisis, we conclude the same outcomes of volatility spillover, with the addition of a spillover occurring from the emerging market of India to USA. Our subsample after the financial crisis yields considerably different outcomes. The only spillover occurs between the developed markets and India implying that there are weaker dependencies between the developed and emerging economies. This finding shows that post financial crisis has lead to diminishing interdependencies of Russia and China on the developed markets, while raising significance of developed countries on India.

Lastly, our Granger causality test on short term volatility extracted from our CGARCH concludes dependency only from the developed markets to Russia for our full sample, as well as the influence of Germany on Russia for the subsample before the crisis. These findings are consistent with our CGARCH results. In the subsample after the crisis we observe significant differences between the relationships. The Granger Causality implies dependency of bi-directional nature between France with India and China, and a uni-directional movement from Germany to Russia, China to Germany and all three emerging countries to the USA.

The results of our research suggest that the financial crisis of 2008 was responsible for a major shift in interdependencies among developed and emerging markets. In some instances it led to diminishing interdependence, while in others it increased the ties between the countries illustrated by the example of India.

References

Adomanis, M. (2012). Russia's Stock Market in Comparative Perspective. *Forbes Online Edition.* Retrieved May 10, 2013, from http://www.forbes.com/sites/markadomanis/2012/06/09/russias-stock-market-in-comparative-perspective/

Abraham, A., & Seyyed, F.J. (2006). Information transmission between the Gulf equity markets of Saudi Arabia and Bahrain. *Research in International Business and Finance, 20*(3), 276–285.

Akgiray V. (1989). Conditional heteroscedasticity in time series of stock returns: evidence and forecasts. *Journal of Business 62*(1), 55-80.

Al-Zeaud, H. A., & Alshbiel, S. O. (2012). Multivariate Volatility and Spillover Effects in Financial Markets Case Study USA and Major European Stock Markets. *Interdisciplinary Journal of Contemporary Research Business, 4*(6), 901 – 911.

Beirne, J., Caporale, G.M., Schulze-Ghattas, M., & Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review, 11*(3), 250-260.

Bhar R., & Nikolova B. (2009). Return, Volatility Spillovers and Dynamic Correlation in the BRIC Equity Markets: An Analysis Using a Bivariate EGARCH Framework. *Global Finance Journal*, *9*(3), 203 – 218.

Bodkhe, N., Kamaiah, B., & Sakthivel, P. (2012). Correlation and Volatility Transmission across International Stock Markets: A Bivariate GARCH Analysis. *International Journal of Economics & Finance, 4*(3), 253 – 264.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*(3), 307–27.

Bollerslev, T., Engle R.F., & Wooldridge, J.M. (1988). A Capital Asset Pricing Model with Time-Varying Covariances. *Journal of Political Economy, 96*(1), 116–31.

Bombay Stock Exchange. (2013). *Indianetzone*. Retrieved May 10, 2013, from http://www.indianetzone.com/6/bombay_stock_exchange.htm.

BRICS Brochure. (2013). *Goldman Sachs*. Retrieved May 10, 2013, from http://www.goldmansachs.com/gsam/docs/funds/investor_education/investor_education/brics_brochure.pdf.

Brooks, C. (2008). Introductory Econometrics for Finance. Cambridge [England] ; New York: Cambridge University Press, 2008.

BSE Achievements. (2013). *BSE website*. Retrieved on May 10, 2013, from http://www.bseindia.com/static/about/achivements.aspx?expandable=0

Chan, C.K., Benton, G.E., & Min, S.P. (1997). International stock market efficiency and integration: a study of eighteen nations. *Journal of Business Finance & Accounting*, *24*(6), 803 – 813.

Chittedi, K.R. (2007). Stock Market Integration in India. *M.Phil dissertation, University of Hyderabad, Hyderabad, Andhra Pradesh.*

Chu, S.H., & Freund, S. (1996). Volatility Estimation for Stock Index Options: A GARCH Approach. *Quarterly Review of Economics and Finance*, *36* (4), 1996, 431-450

Chuang, I.-Y., Lu, J-R., & Tswei, K. (2007). Interdependence of international equity variances: Evidence from East Asian markets. *Emerging Markets Review*, *8*(4), 311–327.

Egert, B., & Kocenda, E. (2005). Contagion Across and Integration of Central and Eastern European Stock Markets: Evidence from Intraday Data. *William Davidson Institute Working Paper Number 798.*

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates for the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987–1008.

Engle, R.F., & Kroner, F.K. (1995). Multivariate Simultaneous Generalized ARCH *Econometric Theory*, *11*(1), 122–50.

Gartfaoui, H. (2012). Translating financial integration into correlation risk: A weekly reporting's viewpoint for the volatility behavior of stock markets. *Economic Modeling, 30*(1), 776–791.

Gebka, B., & Serwa, D. (2007). Intra- and inter-regional spillovers between emerging capital markets around the world. *Research in International Business and Finance,* 21(2), 203–221

Goodwin, D. (2012). Modeling and Forecasting Volatility in Copper Price Returns with GARCH Models. *Lund University Student Theses Database.*

Guidi, F. (2010). Modeling and forecasting volatility of East Asian Newly Industrialized Countries and Japan stock markets with non-linear models. *Munich Personal RePEc Archive, Working Paper n. 19851*.

Gunasinghe, W.I.C.S. (2005). Behaviour of stock markets in South Asia: An econometric investigation. *South Asia Economic Journal, 6*(2), 165–191.

Hansen, P.R., & Lunde, A. (2001). A forecast comparison of volatility models: does anything beat a GARCH(1,1)? *Journal of Applied Econometrics, 20*(7), 873 – 889.

Kanas, Angelo. (1998). Volatility Spillovers across Equity Markets: European Evidence. *Applied Financial Economics, 8*(2), 245-256

Kang, S. H., Kang, S-M., & Yoon, S-M. (2009). Forecasting volatility of crude oil markets. *Energy Economics 31*(1), 119 – 125.

Kenourgious, D., & Padhi, P. (2012). Emerging markets and financial crises: Regional, global or isolated shocks? *Journal of Multinational Financial Management, 22*(1-2) 24 – 38.

Kenourgios, D., Samitas, A., & Paltalidis, N. (2007). Financial Crises and Contagion: Evidence for BRIC Stock Markets. *EFMA Vienna Meetings 2007.*

Kim, B. J. (2009). Volatility Spillover Effect between Korea and China. *Journal of Knowledge Studies, 7*(2), 39-60.

Kumar, S. B., & Pandey, A. (2011). Volatility Transmission from Global Stock Exchanges to India: An Empirical Assessment. *Vision: The Journal of Business Perspective December, 15*(4), 347-360.

Kyle, A.S. (1985). Continuous auction and insider trading. *Econometrica*, 53(6), 1315–1335.

Li, H. (2007). International linkages of the Chinese stock exchanges: A multivariate GARCH analysis. *Applied Financial Economics, 17*(4), 285–297

Liu, H-C., & Hung, J-C. (2010). Forecasting S&P-100 stock index volatility: The role of volatility asymmetry and distributional assumption in GARCH models. *Expert Systems with Applications, 37*(7), 4928–4934.

Market Capitalization of Listed Companies (% of GDP). (2013). *World Bank Data*. Retrieved May 10, 2013, from http://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS

Milldahl, N. (2012). Risks and Returns in the Russian Stock Market: Is Russia any different? Retrieved on May 10, 2013, from http://brage.bibsys.no/umb/bitstream/URN:NBN:no-bibsys_brage_32166/1/2012.%20NataliaMillidahl.pdf.

Morana, C., & Beltratti, A. (2008). Co-movements in international stock markets. *Journal of International Financial Markets, Institutions and Money, 18*(1), 31–45.

Mukherjee, K., & R. K. Mishra (2010), Stock Market Integration and Volatility Spillover: India and its Major Asian Counterparts. *Research in International Business and Finance , 24*(2), 235-251.

N. Rajiv Menon, M.V. Subha, & S. Sagaran, (2009). Cointegration of Indian stock markets with other leading stock markets. *Studies in Economics and Finance, 26*(2), pp.87 - 94

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific-basin. *Journal of International Money and Finance, 19*(2), 207–233.

Park, J.-H., D.-S. Jung, T.-H. Kim, & Y.-T. Byun (2010). Price and Volatility Spillover between Korean Stock Market and Chinese Stock Market: Sub-prime Crisis. *Korean Journal of Financial Engineering, 9*(2), 29-51.

Pramor, M. & Tamirisa, N. T. (2006). Common Volatility Trends in the Central and Eastern European Currencies and the Euro. *IMF Working Paper* (European Department).

Raj, J., & Dhal, S. (2009). Is India's Stock Market Integrated with Global and Major Regional Markets?. ICFAI Journal Of Applied Finance, 15(2), 5-37.

Ross, S.A. (1989). Information and volatility: The no-arbitrage martingale to timing and resolution irrelevancy. *Journal of Finance, 44*(1), 1–17.

Shu Quan, L., & Takao, I. (2010). Testing and Analyzing Efficiency of Chinese Stock Markets. International Review Of Applied Financial Issues & Economics, 2(3), 528-539.

South Asia Driving Force in 'Rise of the South,' Says Human Development Report. (2013). *United Nations Development Programme*. Retrieved May 10, 2013, from http://hdr.undp.org/en/media/PR5-RBAPregional-SouthAsia-2013HDR-ENG.pdf

Tse, S.H., & Tung, K.S. (1992). Forecasting volatility in the Singapore stock market. *Asia Pacific Journal of Management*, *9*(1), 1–13.

Wang, P., & Moore, T. (2009). Sudden changes in volatility: The case of five central European stock markets. *Journal Of International Financial Markets, Institutions And Money*, 19(1), 33-46. doi:10.1016/j.intfin.2007.08.006

Wang, P., & Wang, P. (2010). Price and volatility spillovers between the Greater China markets and the developed markets of US and Japan. *Global Finance Journal*, *21*(3), 304 – 317.

World Bank Report 2011 (2011). *World Bank website*. Retrieved on May 10, 2013 from http://siteresources.worldbank.org/EXTANNREP2011/Resources/8070616-1315496634380/WBAR11_YearInReview.pdf

World Top 10 Stock Exchanges. (2013). *World Stock Exchanges*. Retrieved on May 10, 2013, from http://www.world-stock-exchanges.net/top10.html.

Under Construction: BRICS the Stage to Build Multi-Polar World. (2013). *RT website.* Retrieved May 10, 2013, from http://rt.com/news/order-world-brics-summit-836/.

Appendix: Figures and Tables

Figure 1 – Graphs below represent the QQ Plots for the stock return of each country. Lack of linearity in the graphs below illustrates that neither of the indices follows the N-distribution given the fatter tails, which justifies using student t-distribution while estimating CGARCH model.

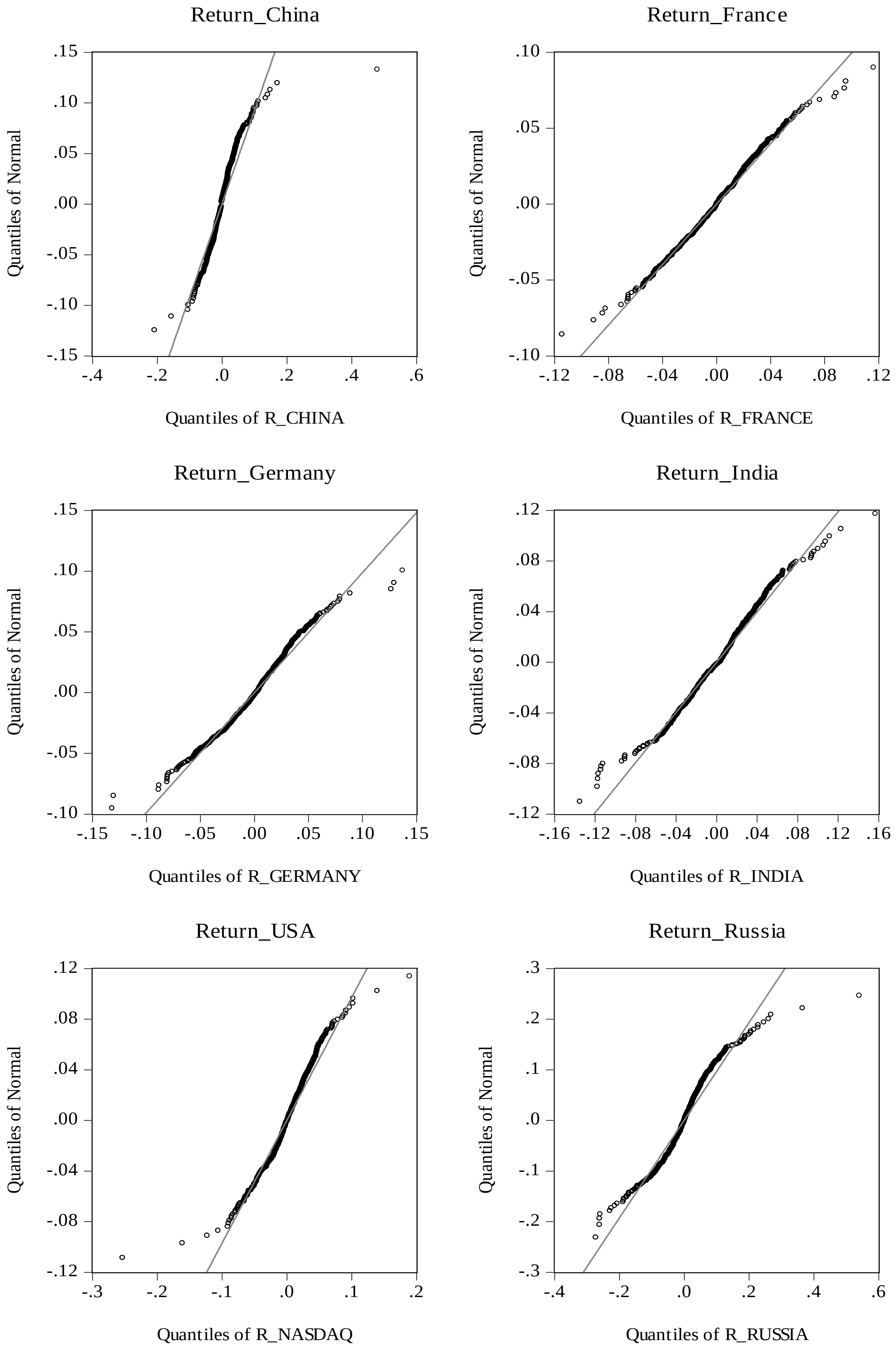

Figure 2 – Each graph represents the movements of stock indices for the respective country during the sample period from 1994-12-30 to 2013-04-19.

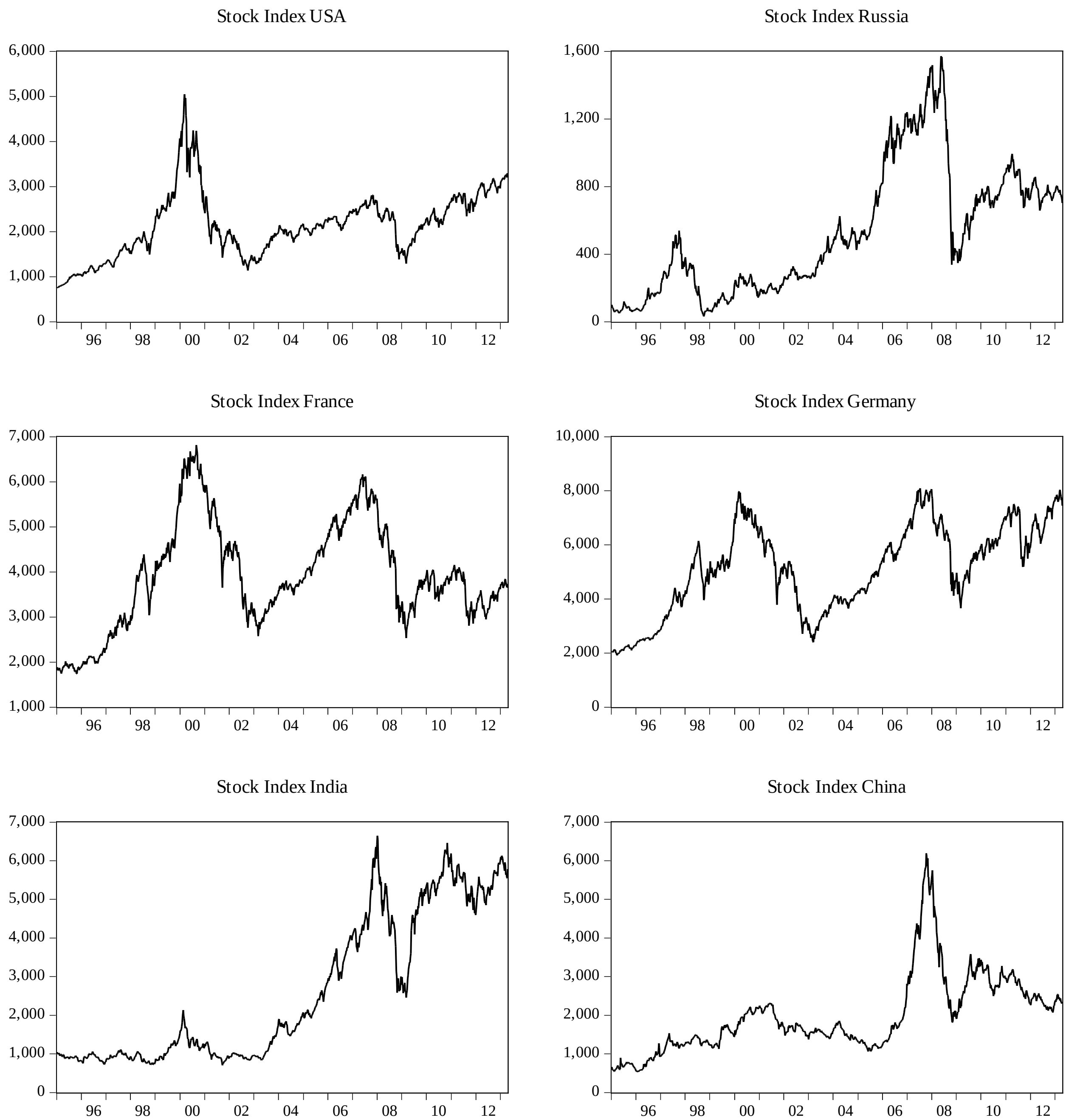

Figure 3 – Graphs below represent the movement of the stock returns for each index through the sample period from 1994-12-30 to 2013-04-19. These graphs clearly illustrate volatility clustering effect, which takes place particularly around former financial crises of 2000 (tech-bubble) as well as during 2008 widespread financial crisis.

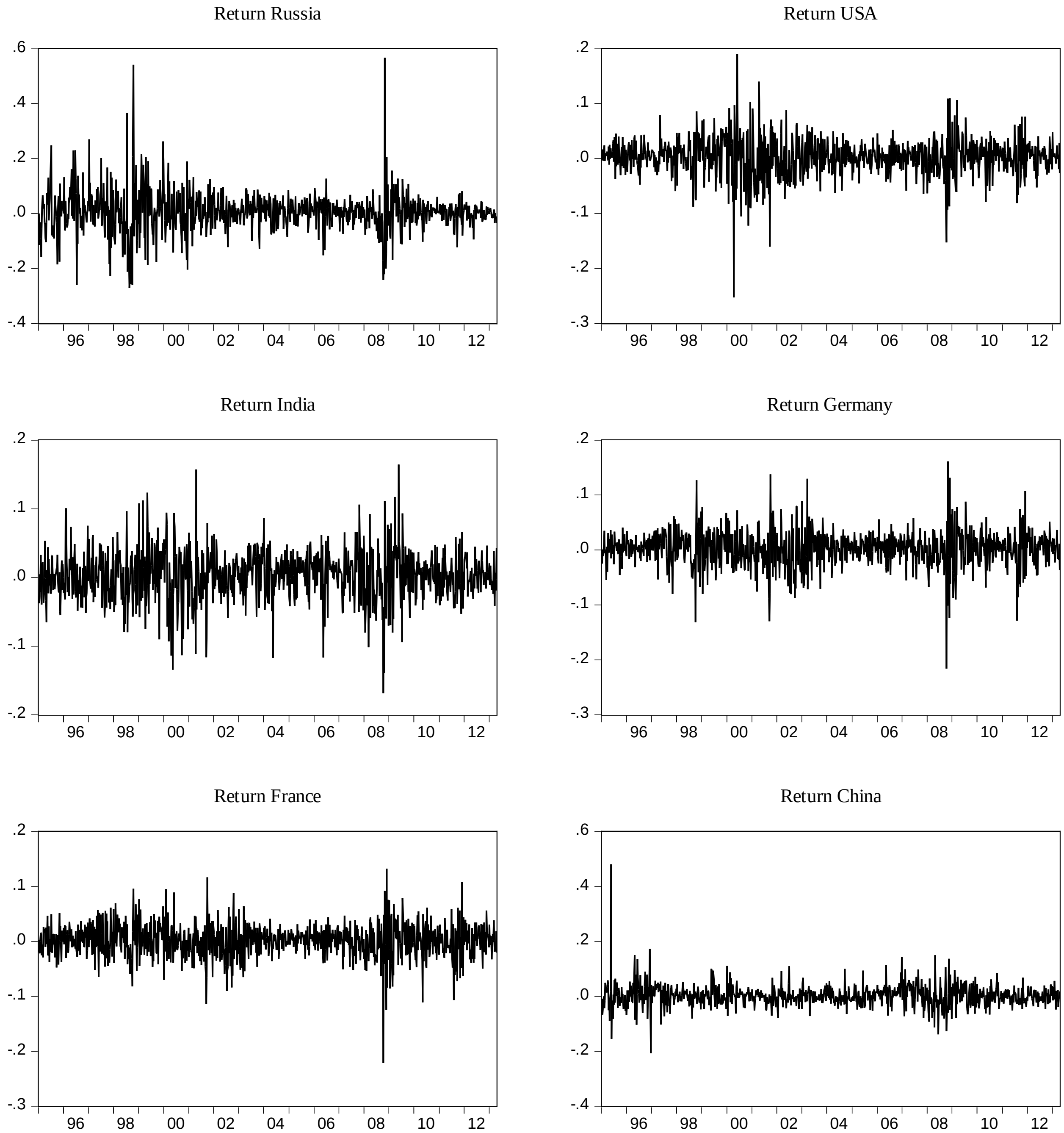

Table A1 and A2 – Two tables below summarize Johansen test for cointegration of stock indices of our sample. Both of these tests show that none of the variables are cointegrated and therefore there is no need to correct for cointegration in the model.

Table A1 - Unrestricted cointegration rank test (trace)

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.036037	86.99005	95.75366	0.1720
At most 1	0.019755	52.12309	69.81889	0.5439
At most 2	0.017497	33.16786	47.85613	0.5476
At most 3	0.009543	16.39857	29.79707	0.6840
At most 4	0.007139	7.289536	15.49471	0.5442
At most 5	0.000509	0.483256	3.841466	0.4869

Note: trace test indicates no cointegration at the 0.05 significance level; * denotes rejection of the hypothesis at the 0.05 level

Table A2 - Unrestricted cointegration rank test (maximum eigenvalue)

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.036037	34.86696	40.07757	0.1720
At most 1	0.019755	18.95523	33.87687	0.8247
At most 2	0.017497	16.76929	27.58434	0.5998
At most 3	0.009543	9.109031	21.13162	0.8235
At most 4	0.007139	6.806280	14.26460	0.5123
At most 5	0.000509	0.483256	3.841466	0.4869

Note: Max-eigenvalue test indicates no cointegration at the 0.05 significance level; * denotes rejection of the hypothesis at the 0.05 significance level; **MacKinnon-Haug-Michelis (1999) p-values