Abstract: The purpose of this study is to find out the evidence of volatility in selected stock markets, contagion effect of US sub-prime crisis on selected South Asian stock markets and contagion effect between emerging stock markets during sub-prime crisis of 2007-08. Chinese currency devaluation crisis of August 2015 are also observed in this study as a special case and this study also has tested that, Can China be another channel of contagion for Pakistan? ARCH family models (ARCH, GARCH, EGARCH and GJR-GARCH) are used as quantitative technique to find volatility in stock markets. Copulas (Clayton and Gumbel) are used to measure contagion effect between U.S. and 4 South Asian countries. After testing the normality and stationarity, ARCH family models are estimated. Best fitted models of volatility are selected on the basis of AIC. Best fitted model for Pakistan is EGARCH, for China is GARCH, for Sri-Lanka is EGARCH, for India is GJR-GARCH and for U.S. is ARCH. Selected models have “no ARCH effect” and “no serial correlation” left in their residuals. Copula results (two divisions of sample period) proved that Pakistan and India have contagion effect. China has shown weak contagion while Sri Lanka has no contagion effect. In three period divisions of sample period, Pakistan and India showed a quick response to U.S. sub-prime crisis. Dynamic Conditional Correlation Coefficient is also increased during crisis period in all the countries with the exception of China. Emerging to emerging stock market transmission of contagion effect test results show that there is a contagion effect between Pakistan and India but there is no contagion effect between Pakistan and China and, between Pakistan and Sri-Lanka during the U.S. sub-prime crisis of 2007-08. Special case of Pakistan and China for “Chinese currency devaluation” results has proved that China can transmit negative shocks to KSE. This is a new channel of contagion for Pakistan.

1. Introduction

Today, when the world is becoming global village, the different markets of the world are more interlinked to each other and are more vulnerable to each other. These interlinks are may be real or financial. When a negative or positive shock occurs in one market that moves to other markets due to these interlinks. Negative shock here means the crisis. Crisis may also be defined as “A time of danger or difficulty”. In recent era the financial markets have witnessed a financial depression. This financial depression was named Subprime crises or Global Financial Crises of 2007-08. These crises originated from U.S. The crisis spread across the financial markets very quickly, initially in developed and then to emerging markets due to interdependence of these markets. Participants of these markets bear a severe cost due to movement of crises from one market to another. There are several theories of depression which explain the movement of these crises and are well supported by different depression models e.g. [12] E. Baumohl et al (2001), they used the data of three Central and Eastern European (CEE-3) countries to find a shift in contagion. They used breaks in DCCs (Dynamic Conditional Correlations) and MV-GARCH model and concluded that there is a shift contagion between the CEE-3 countries.

These shocks spread across the countries very quickly and investors of those markets suffered losses. So therefore the interdependence of these markets needed to be calculated. The interdependence of financial markets has received a considerable attention in recent era and prolific literature is written on it. A lot of evidences are found in literature that the correlation between stock returns is higher in turmoil period than in stable period. [35] Wang and Thi (2006) found that the there is a significant increase in means of correlation coefficient between pre-crisis and post-crisis period. For this purpose upper tail dependence (when stock returns are extremely positive) and lower tail dependence (when stock returns are extremely negative) are helpful to estimate increase in positive or negative correlation. This correlation is time varying and it cannot be calculated by simple correlation technique. Simple correlation is used when stock returns are normally distributed. But mostly the finance data is not normally distributed. To capture this time varying correlation DCC (Dynamic Conditional Correlation) is used. During
crisis period, negative shocks are followed by negative shocks for a prolong period of time. This phenomenon is called volatility clustering. Simple regression models are not well supported to capture this volatility. So, volatility factor is captured by ARCH family models.[17] Min and Hwang 2012, [25] Nieh, Yang and Kao (2012), they all used ARCH family models. The interdependence and this increasing correlation of these markets during and after the crisis were given a name “Contagion”. A series of crisis have been seen in last two decades with roughly a difference of three years such as in 1987 the US stock market was crashed, in 1990 a loan and saving collapse, in 1994 Mexican peso crisis arises and then Asian crisis of 1997 then Long Term Capital Implosion and Russian default in 1998, Brazilian currency was devalued in 1999 which had bad effects on other financial markets, Burst of technological bubble in 2000, then a deflationary pressure was seen in credit markets in post-Enron period of 2002 and then world became witnessed of US sub-prime crisis of 2007.

As the crises were occurring, financial analysts were analyzing the phenomenon of spreading these crises to other markets and new methods (e.g. simple correlation, cross-market correlation, ARCH, GARCH, GJR-GARCH, APGARCH, DCC-MGARCH, CCC-MGARCH, BEKK, HAC and Copulas) to measure Contagion are evolved.

The purpose of this study is to estimate the dependence between US stock market returns and 4 South Asian stock market returns (Pakistan, India, Sri-Lanka and China). This dependence structure can help deferent departments of sample countries to formulate policies to save them from movement of crisis. For this purpose, Copula models are used as these are flexible to model the conditional dependence structure of stock returns. Crisis selected for the study are US sub-prime crisis 2007-08. Dependence between stock return series is modeled by Copula models. To check the dynamic volatility of stock return series ARCH family models (ARCH, GARCH, EGARCH and GJR-GARCH) are used. To check the dependence of stock returns Clayton and Gumbel copulas are used in this study.

A special case of Pakistan and China is also discussed in this study. China has devalued its currency in August 2015 due to which Chinese stock market faced a short term crisis. This crisis has negative impact on Pakistani stock market as well.

Dependence of stock markets has important implications for financial investors and policy makers. It can help to reduce the losses that occurred during crisis.

The term contagion can be defined as “The change in transmission mechanism that takes place during or after turmoil period” and it can be seen as a significant increase in cross-market correlation (According to very restrictive definition of World Bank)

In social sciences the term contagion used by[21] King and Wadhwani (1990), they found increased correlation in financial markets in turmoil period by cross-market correlation technique and they give a name “Contagion” to this phenomenon.

In Economic times contagion is referred to as a situation where a shock of one market or country spreads out to others and affects other markets and associated countries.

The World Bank defined it in three ways:

“First approach is termed as Broad Definition: Contagion is the cross-country transmission of shocks or the general cross-country spillover effects.” Second is Restrictive Definition: “Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks.” This definition is usually referred as excess co-movement, commonly explained by herding behavior. Third Very Restrictive Definition: “Contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "normal times".”


In study, Forbes and Rigobon (2002) definition of contagion is used. That is “High increase in co-movements of stock markets during crisis period.”

[20] Ionescu et al (2009) when negative shocks of one financial market spread to other developed and emerging markets, the emerging markets are affected more than developed markets, this transmission of shocks is due to interdependence of the countries and interdependence is due to real and/or financial linkages. If two countries are more interlinked then the effect of negative shocks (contagion) can be more sever. So, it is important for all the countries to know the effect and intensity of contagion so that the sound internal and international policies can be developed.

In this study the volatility and contagion effect is estimated in U.S. and 4 South Asian countries during Global financial crisis of 2007-2008. Also, contagion effect is estimated from emerging to emerging stock markets during the same crisis.

Objectives of this study are:

1. To test the volatility in selected stock markets,
2. To test the existence of contagion effect between U.S. and 4 South Asian stock markets.

restriction: in the social sciences, the term contagion is used to describe situations where a shock in one market is transmitted to other markets, beyond any fundamental link among the countries or beyond common shocks. This definition is usually referred to as excess comovement, commonly explained by herding behavior. A third, very restrictive definition states that contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "normal times".

In this study, Forbes and Rigobon (2002) defined contagion as "high level increase in market co-movements during crisis period." They defined contagion as the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred to as excess co-movement, commonly explained by herding behavior. A third, very restrictive definition states that contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "normal times".

In this study, Forbes and Rigobon (2002) defined contagion as "high level increase in market co-movements during crisis period." They defined contagion as the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred to as excess co-movement, commonly explained by herding behavior. A third, very restrictive definition states that contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "normal times".

In this study, Forbes and Rigobon (2002) defined contagion as "high level increase in market co-movements during crisis period." They defined contagion as the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred to as excess co-movement, commonly explained by herding behavior. A third, very restrictive definition states that contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "normal times".
3. To test the existence of contagion from emerging to emerging stock markets.

4. To check those stock markets which have shown quick response to US sub-prime crisis (Three period divisions).

5. To test the conditional correlation in stable and turmoil period.

6. To test the contagion effect transmitted from China to Pakistan.

This study is contributing to existing pool of knowledge by adding the dependence structure of 4 South Asian markets on US stock market. A class of ARCH family models and Copula family is used to model volatility and dependence. Asian markets are now becoming more attractive to investors so this study will help them to understand the dynamic linkages of 4 Asian stock markets and US stock market. Dependence of stock markets has important implications for financial investors and policy makers. It can help to reduce the losses that occurred during crisis.[11] Claessens and Forbes (2004) have found that Argentine crisis of 2001-2002 and Turkish crisis of 2001 did not have a severe effect on other countries and also they have found that Banks have reduced short term loans to developing countries, investors have withdrawn their investments in foreign markets and they have reduced exposure to foreign markets. They said, investors and governments are, now, not surprised about crisis and they have formed policies to protect themselves from crisis contagion.

This study is different from existing literature in five ways. First, countries selected for this study are given less attention, as a group, to test contagion effect. Second, DCC-MGARCH model with copulas is new technique applied on these sample countries. Third, a new Channel of contagion (China) for Pakistan is found during Chinese stock market crash in August 2015. Fourth, emerging to emerging stock market results are estimated for selected sample countries. Fifth, Three divisions (pre-crisis, crisis and post-crisis) of sample period is applied on US and 4 South Asian countries to test quick response of stock markets to crisis.

2. Literature Review

To understand the impact of US crisis on stock prices it is important to understand the contagion first. Therefore firstly the theory of financial contagion is reviewed here. In literature numerous researches has been conducted on contagion and various results witnessed from the past studies.

[33] Aharony and Swary (1983) have taken all banks working in America as population and their sample were all the banks listed in New York Stock Exchange (NYSE). They analyzed three bank failures in history of America. United States Bank of San Diego (USNB) and Hamilton National Bank of Chattanooga (HNB) and the failure of Franklin Bank of New York (FNB). They found that USNB and HNB were failed due to internal problems such as frauds and irregulations. While FNB was failed due to heavy foreign exchange losses. Overall results show that there is no contagion effect on banking sector performance. The decrease in stock prices of solvent banks was due to negative signals in the market. [8] Thomas C. and Chiang (2007) have investigated contagion effect in 8 Asian countries and two industrial countries Japan and US. They used DCC-GARCH model in their study. They found that there is an increase in correlation in different pairs of countries after the crisis which confirms the contagion effect. [26] Liu and Pan (1997) Have used daily returns US and Japan to find the influence of these two markets on four Asian markets. They used ARMA model with GARCH in two stages. First they used these models on each stock return to find serial correlation and in second stage they found standard residuals and squared of standard residuals in mean and volatility equations to capture volatility. They found that US market is more influential on Asian markets than Japan and these markets are more integrated after 1987 crash. [4] Taimurbaig and IlanGoldfajn (1998) Have taken the data from equity markets, foreign exchange, interest and sovereign debt markets. They estimated cross-country correlations and found that currencies and sovereign spread show increased correlation during crisis while after controlling for country news and some other fundamentals, equity and currency market also showed significant contagion effect. To estimate contagion in markets they used Vector Auto Regression (VAR) model to check that either negative returns are moved to other countries or not? And their final results showed the evidence of contagion in selected four markets. [21] Yilmaz (1999) has raised two issues in their study related to global financial system. First was, global financial system will transfer the volatility from one country to other countries and the second one was the movement of contagion effects that moves from one market to other market. He took equity returns of 19 countries and used correlation, simple rolling regression and goodness of fit measures to find volatility in stock markets. Then he used GARCH model to measure volatility and contagion in Istanbul. Final results showed the increased correlation in markets and presence of contagion effect in Istanbul. The carriers of contagion effect are New York Stock Exchange and Hong Kong Stock Exchange. [27] Forbes and Rigobon (2002) have
investigated the three crisis that are occurred in 1987 (US market crash), 1994 (Mexican devaluation) and 1997 (Asian crisis). According their findings there is no contagion effect, there is only interdependence in market. They made some assumptions and said that increased correlation in crisis period is conditional on volatility of certain market. If this volatility is adjusted then there is no any increase in unconditional correlation and hence no contagion.

[34] Bae, Karolyi, and Stulz (2003) have used daily returns of indices of Asian and Latin American countries, including those of this study. They used same day data and lagged or previous day data as well. They conducted this study to find contagion in above said markets during Mexican peso devaluation (1994), Asian crisis (1997) and Russian crisis (1998). They used a technique in which they found number of coincidences of occurrence of negative returns and positive returns in markets. They also used GARCH model to find volatility. They concluded that there is a contagion in markets. Contagion is less important in Asian countries than Latin American. Also, there are lesser chances of contagion from Asian countries to American than American to Asian and US is less responsive or not affected by Asian contagion. They also concluded that contagion is predictable and it depends or related with interest rates of the region, change in currencies rates and conditional volatility of stock prices in that region. [6] Boschi (2005) has tested the contagion effect of Argentine crisis on six countries (Argentina, Brazil, Mexico, Russia, Turkey, Uruguay, and Venezuela). He has taken data of three markets, stock markets, foreign exchange market and sovereign debt market of these countries. He used VAR and “instantaneous correlation coefficient corrected for hetroscedasticity” to find the contagion. He found that there is decrease in correlation coefficients in crisis and hence there is no contagion effect of Argentine crisis on above said countries. His results are in accordance of Forbes and Rigobon’s theory of non-crisis-contingent contagion. [35] Wang and Thi (2006) have taken data of stock returns of Thiland and Chinese economic area. They used DCC-MGARCH model to test the existence of contagion in above said markets during Asian crisis of (1997). They found that the mean correlation of DCC-MGARCH is increased in post-crisis period than pre-crisis stable period. They concluded that Chinese economic area is affected by Asian flu.[18] Imer (2007) has taken the data of Turkey, Russian Federation and other seven developing countries. He used granger causality model to find out contagion effect. The data was taken from Bloomberg from 1995 to 2004 including the period of Asian crisis. He used daily closing stock returns of indices. He ignored the closing timings of stock exchanges and also implicitly and incorrectly ignored the non-trading effects. His findings include that there is increase in caulsilities during crisis period and hence there is contagion effect in Turkey and RF. [16] horta, mendes, and Vieira (2008) have used copulas to test the contagion effect in developed countries during US subprime crisis of 2008. They also calculated Kandal’s Tau and spearman’s rho. They found that coefficients of copulas and Kandal’s tau and spearman’s rho increased during crisis showing contagion effects of crisis in selected countries. But two countries of their sample (Portugal and Germany) showed weak results of contagion. They also claimed that tail dependence cannot be used as the indicator of contagion as they may show incorrect results. According to them, contagion is increase in co-movement during crisis.

[21] Min and Hwang applied DCC (Dynamic Conditional Correlation) model on daily stock returns from 2006 to 2010. The study conducted on four OECD countries: Japan, UK, Australia, and Switzerland. The results concluded that contagion impact increased in the last three counties due to US crisis while opposite impact witnessed in Japan. They also used a new technique by combination of DCC and MGARCH models. They held that US crisis began from failure of Lehmann Brothers in September 2008. And many economists expecting that the US market crisis will affect the world adversely. The main purpose of this study is to analyze the transfer of US market crisis to four OECD countries and to check the degree of volatility between US and the four OECD countries. They used stock exchange variables to measure these objectives as daily sovereign Credit Default Swap (CDS) spread, the VIX index, the relative stock market capitalization to the US, and the TED spread. CDS technique is used to analyze the risk of countries, TED spread identified the difference between the 3-month London Interbank Offered Rate (LIBOR) and the yield on the US Treasury bills with the same maturity and the third variable is VIX index that measured the stock market uncertainty. They witnessed direct relationship between VIX Index and Contagion i.e., increase in VIX stock market index increases the contagion impact on the OECD countries while there is inverse relationship found between TED spreads and contagion i.e., TED spreads and relative stock market capitalization decrease the conditional correlations of the four OECD countries with the US.[11] Dimitriou and Simos (2013) have used the data of four major countries namely US, EMU, China and Japan to find contagion during subprime crisis of US 2008. VECH representation of MGARCH is used to model volatility. Results show high volatility in all the countries except for China. China is not directly influenced by US market volatility rather it is indirectly affected by Japan. They found that there is contagion effect in all countries. Japan and EMU countries are directly affected by subprime crisis of
It has the following null and alternative hypothesis.

Jarque-Bera test values can be calculated as;

\[(3.3)\]

The Latin American and European countries taking the US as condition, they found that some of applied this method on their selected countries by find the original channel of contagion. When they can also be checked. This method is very useful to variate interdependence, the effect of third country given a new technique to test contagion effect. According to their method, while calculating bi-countries. [40] Abbara and Zevallos (2014) have given a new technique to test contagion effect. According to their method, while calculating bivariate interdependence, the effect of third country can also be checked. This method is very useful to find the original channel of contagion. When they applied this method on their selected countries by taking the US as condition, they found that some of the Latin American and European countries’ contagion effect vanished. [23] Changqing, Chi, Cong, and Yan, (2015) took the stock market data for 42 countries covering a large horizon from 1997 to 2015. They used Markov Regime Switching Copula to investigate contagion effect on China. They also claim tail dependence for contagion effect. According to their findings, contagion exists in markets during US subprime crisis but they also confirmed the low contagion effect of US crisis of 2007 on China. Mainly their study was conducted to investigate the channels of contagion for China so that they may help policy makers to manage the flow of financial risk to their country.

3. Research Methodology

In this study contagion effect of global financial crisis is checked. As this crisis affected the stock markets of almost all over the world so the population of this study is stock markets of all over the world. Sample period is of 10 years started from January 01, 2005 to December 31, 2014. This duration includes pre-crisis period, crisis and post crisis period. Sample of countries selected for this study includes stock markets of America, China and south Asian countries. But due to non-availability of data of Nepal, Bhutan and Maldives’s stock indices are not included in sample, remaining south Asian countries are included that are Pakistan, India, Sri Lanka and China. Reason to include China is that, Pakistan has a large trade with it and China is investing in Pakistan in different projects so in near future the financial markets may become more integrated with each other and it is possible that economies of both countries may affect to each other more strongly than today. So, vulnerability of China’s stock exchange to financial crisis will help the investors of both countries to develop some strategies for their investments. Portfolio managers can also develop policies regarding their portfolio development. New York stock exchange index (S&P 500) is taken because crisis is originated from America.

Data is consisting of daily closing values of KSE 100 index (Pakistan), BSE 100 index (India), SSE 180 index (China), CSE all-share price index (Sri Lanka) and S&P 500 index (US). Pares are made of each country with US. Returns of same date are taken for every country with respect to US. It means returns of same date are taken in each pair.

First of all normality of the data is checked. There are many tests to check the normality of the data. But two tests are famous to test the normality of large sample (large sample means more than 2000 observations) are used in this study. One of them is test of skewness. Skewness tells us the distribution of the data about mean. If the data is normally distributed then its skewness will be zero and if the data is distributed towards right from mean then it is called positively skewed and it will be called negatively skewed if distributed left to the mean. Skewness is defined as

\[ S = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^3 \]

\[ \text{Where,} \]

\[ \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \]

(3.1)

We use Kurtosis to check that, how thick the tails of distribution of data are? Kurtosis is given by the formula;

\[ K = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^4 \]

(3.2)

Here,

K = Kurtosis

Normal distribution will always have K=3. Excess kurtosis can be calculated as;

\[ \text{Excess Kurtosis} = K - 3 \]

Excess kurtosis for a normal distribution will always be zero. If K is greater than 3 then distribution is called Leptokurtic and is it is less than 3 then distribution is called platykurtic. Second test of distribution is Jarque-Bera test. This test follows \[ \chi^2 \] distribution with two degrees of freedom.

It has the following null and alternative hypothesis.

\[ H_0 = \text{Normal distribution} \]

\[ H_1 = \text{non-normal distribution} \]

Jarque-Bera test values can be calculated as;

\[ \text{Jarque-Bera} = n \left( \frac{\hat{\gamma}^2}{6} + \frac{\text{Excess Kurtosis}}{24} \right) \]

(3.3)
Null hypothesis will not be accepted if the calculated test statistics are greater than critical values. 

After normality tests, Stationarity test is done to check that the data used in the study is stationary or not? This test is very important in time series data. If the data is non-stationary and we treat it as stationary then it will give misleading results. To test the stationarity, there are three tests used in this study. Augmented Dickey Fuller (ADF) Test, Philips Peron (PP) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. This is first test of stationarity, Validity of the test is dependent on the condition that $\mu_t$ is white noise. If the data is auto correlated then the null hypothesis may not be accepted incorrectly. 

To avoid this reason another version of Dickey Fuller (DF) test is used which is called Augmented Dickey Fuller (ADF) test. ADF model is given below:

$\Delta y_t = \gamma_{t-1} + \sum_{i=2}^{\infty} \alpha_i \Delta y_{t-i} + \mu_t$ (3.4)

This is second test of stationarity used in this study. This test is similar to ADF test but the difference is that PP test contained an automatic correction method to ADF test. This method allow for auto correlated residuals. PP test is applied only on return series because in further working return series will be used for analysis. 

This is another test for stationarity. It is reverse of ADF and PP tests. It has different null hypothesis than the ADF and PP tests. 

$$H_0 = \text{The series is stationary}$$

$$H_1 = \text{The series is non-stationary}$$

Decision criteria are the same. As the test statistics becomes greater than the critical value, the null hypothesis will be rejected or vice versa. This test is used to confirm the data analysis that is obtained earlier. That is why it is also called “confirmatory data analysis”. KPSS is only run on return series of selected countries, reason for this is already explained above. 

After normality and stationarity tests the data is ready for estimation of volatility and dependence models. Models for volatility and dependence are overviewed below.

### 3.1. An Overview of ARCH family models

#### 3.1.1. Estimation of ARMA (p, q) process:

Before estimation of ARCH family models, ARMA order is required. ARMA (p,q) is the combination of AR (p) and MA (q). AR stands for Autoregressive with order “p” and MA stands for Moving Average with “q” order. AR means the series “$y_t$” depends linearly on its past value “$y_{t-1}$”, MA means the error term (white noise) “$\mu_t$” depends (linearly) on its previous value “$\mu_{t-1}$”. So ARM (p,q) tells us the series $y_t$ depends on its past value $y_{t-1}$ combined with the error term $\mu_t$ which depends on its previous value $\mu_{t-1}$. 

Following table shows the results for ARMA (p,q) to select the order of ARMA. After estimation of ARMA order, heteroskedasticity test and obtaining justification of existence of volatility, ARCH family models are estimated.

### 3.1.2. Autoregressive Conditionally Heteroscedastic (ARCH) models

There is an important assumption of CLRM is that the error term is constant over the time, $\{u_t \sim N(0, \sigma^2)\}$. If the error term has constant over time, it is said homoscedasticity. If the variance of the error term is not constant over time, it is called heteroscedasticity and if the variance of the error term is not constant and we assume it constant then the results obtained are may be misleading. Most of the time in finance, the data have heteroscedasticity. So, there was a need of such type of model that covers heteroscedasticity. Another reason for these models was “volatility clustering” which states that large changes will follow large changes (positive or negative) and small changes will follow small changes (positive or negative). ARCH model capture above said problems.


$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

In ARCH model variance $\sigma^2$ is depending on immediately previous error term $u_{t-1}$, so we can say the autocorrelation volatility is modeled. This is an ARCH (1) model as it depends on one lag squared value of error.

#### 3.1.3. Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

[5] Bollerslev and Taylor (1986) developed this model independently. In GARCH model the conditional variance not only depends on previous error squared but also on lag of conditional variance.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

It is a GARH (1, 1) model. It is more parsimonious and avoids over fitted. There are less chances of violation of non-negativity constraint.

#### 3.1.4. GJR GARCH model

This model was proposed by [14] Glosten, Jagannathan and Runkle (1993). GJR was named after the authors. A basic requirement of GARCH is the volatility is symmetric. But leverage effect in equity market says that negative shocks affects with high magnitude than positive shocks. This is an asymmetry and it is not covered by GARCH as lagged residuals are squared and this square removes the sign. We can say that conditional variance used
in GARCH depends upon lagged residuals but not on their signs. Authors proposed GJR GARCH model to overcome this asymmetry problem.

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1} I_{t-1} \]  

(3.7)

Where \( I_{t-1} = 1 \) if \( \varepsilon_{t-1} < 0 \)

\[ = 0 \] Otherwise.

If \( \gamma \) is greater than zero then leverage effect is present. For non-negativity constraint, \( \alpha > 0, \alpha_1 > 0, \beta \geq 0 \) and \( \alpha_1 + \gamma \geq 0 \).

3.1.5. Exponential GARCH (EGARCH)

This model was proposed by [24] Nelson (1991). This model allows for negative returns and hence removed the condition of non-negativity which was artificially imposed. The model is defined as

\[ \ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \epsilon \]  

(3.8)

This is another way to explain conditional variance. Since \( \ln(\sigma_t^2) \) is used in model so, even the parameters will be negative the conditional variance will not be negative, it will remain positive.

3.1.6. Dynamic Conditional Correlation MGARCH

DCC model contains conditional correlation which is time varying. DCC model of [36] Tse and Tsui (2002) is defined as;

\[ H_t = D_t R_t D_t \]  

(3.9)

Here, \( D_t \) is conditional variance matrix and \( R_t \) is defined as under,

\[ R_t = (1 - \theta_1 - \theta_2) \bar{R} + \theta_1 \Psi_{t-1} + \theta_2 R_{t-1} \]  

(3.10)

Here, \( \theta_1 \) and \( \theta_2 \) are non negative parameters and sum of these two is less than one. \( \bar{R} \) is correlation matrix of \( \varepsilon_t \) where \( t = t - M, t - M + 1, ..., t - 1 \).

ARCH family models have captured the volatility of sample stock markets. Best fitted model for each stock market is selected on basis of AIC values. After volatility estimation, the copulas are estimated to model the dependence of sample stock markets. Copulas are overviewed here.

3.2. An overview of copulas

In finance, modeling dependence is getting more attraction day by day. If the distribution of the returns is elliptical then linear correlation coefficient can be used to find the dependence between returns. But financial markets returns are mostly non-elliptically distributed and are non-linearly correlated so, linear correlation coefficient will not give accurate results. Financial markets returns are mostly dependent on each other and have non-linear dependence [1] Kjersti, Aas (2006). In multidimensional distribution the dependence of variable is captured by copula models. The advantage of using copula-based models is that, in multivariate system, we can find appropriate marginal distribution for variables of the system and then a suitable copula can be selected.

Following are copulas that are used in this study.

3.2.1. Clayton Copula

This copula introduced asymmetries unlike of student’s t-copula which only includes joint extreme events. Clayton copula shows more dependence in negative tail as compared to positive. So this may be better choice to check the dependence during crisis. It is stated as

\[ C_\theta(u,v) = \left( u^{-\theta} + v^{-\theta} - 1 \right)^{-1/\theta} \]  

(3.11)

Here,

\[ \theta \] Should be less than \( \infty \) and should be greater than 0 OR \( 0 < \theta < \infty \). It is dependence controlling parameter. As its value goes to zero, it will show independence and as it goes to \( \infty \) it shows perfect dependence.

3.2.2. Gumbel Copula

This copula also incorporates asymmetric. The difference is that, it shows more dependence in positive tail.

\[ C_\delta(u,v) = \exp \left( -\left[ \log u \right]^\delta + \left( -\log v \right]^\delta \right) \]  

(3.12)

\( \delta \) is the parameter and it represents the dependence. If \( \delta \rightarrow 0 \) it means u and v perfectly depends each other. But if \( \delta \rightarrow 1 \), it means u and v do not have dependence. It measures positive tail dependence by taking the negative tail dependence as zero.

4. Data Analysis

Results of all the models applied and their explanations are discussed in this part.

4.1. Normality test and Descriptive statistics:

The basic test statistics and normality tests of selected indices return are given below.
Table 4.1: Group Statistics of all selected indices returns

<table>
<thead>
<tr>
<th></th>
<th>KSE</th>
<th>S&amp;P</th>
<th>SSE</th>
<th>BSE</th>
<th>CSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.059132</td>
<td>0.019829</td>
<td>0.036955</td>
<td>0.043964</td>
<td>0.065091</td>
</tr>
<tr>
<td>Median</td>
<td>0.101469</td>
<td>0.077103</td>
<td>0.041515</td>
<td>0.152452</td>
<td>0.043495</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1.351128</td>
<td>1.290971</td>
<td>1.638294</td>
<td>1.502911</td>
<td>0.982957</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.399804</td>
<td>-0.301944</td>
<td>-0.295396</td>
<td>-0.264095</td>
<td>-0.189248</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>5.867348</td>
<td>14.18174</td>
<td>6.805923</td>
<td>11.29527</td>
<td>11.20998</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>876.1371</td>
<td>12680.68</td>
<td>1526.056</td>
<td>6736.328</td>
<td>6225.592</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>Sum</td>
<td>4330.200</td>
<td>48.12610</td>
<td>91.24134</td>
<td>102.8753</td>
<td>143.9807</td>
</tr>
<tr>
<td>Sum Sq. Dev.</td>
<td>2373</td>
<td>2427</td>
<td>2469</td>
<td>2340</td>
<td>2212</td>
</tr>
</tbody>
</table>

Table 4.1 contained a comparative statistics of selected indices returns. Highest mean return is shown by CSE (RSL) and lowest mean return is shown by S&P (RUS). Maximum return is shown by BSE (RIND) during the sample period of 10 years starting from January 01, 2005 and ending on December 31, 2014. Lowest return is also shown by BSE (RIND) during such period. Highest standard deviation is shown by SSE. Highest skewness is shown by KSE (RPK) while lowest skewness is shown by CSE (RCHINA). That is KSE (RPK) is most negatively skewed during above said period in selected indices but Sri-Lanka has not depicted negative returns. S&P (RUS) has been most leptokurtic among selected sample indices during sample period. Jarque Bera test statistics proved that all the indices returns are non-normally distributed.

4.2. Stationarity Test Results:

Table 4.3 shows that all the return series are stationary as all the test statistics are more negative than the critical values for all given levels of significance that is 1%, 5% and 10%.

Table 4.3: ADF test Results

<table>
<thead>
<tr>
<th></th>
<th>KSE (RPAK)</th>
<th>SSE (RCHINA)</th>
<th>S&amp;P (RUS)</th>
<th>CSE (RSL)</th>
<th>BSE (RIND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significance</td>
<td>Critical values</td>
<td>Test statistics</td>
<td>Critical Value</td>
<td>Test Statistics</td>
<td>Critical Value</td>
</tr>
<tr>
<td>5%</td>
<td>2.8626</td>
<td>-2.863</td>
<td>-49.9228</td>
<td>-2.863</td>
<td>-2.86276</td>
</tr>
</tbody>
</table>

4.3 Results Philip-Peron (PP) test:

This test is similar to ADF test but the difference is that PP test contained an automatic correction method to ADF test. This method allow for auto correlated residuals.

In table 4.4 Overall results of PP test are significant at all the given levels of significance. In each case the test statistics are more negative than the critical values given in the test.

Table 4.4: PP test Results

<table>
<thead>
<tr>
<th></th>
<th>KSE (RPAK)</th>
<th>SSE (RCHINA)</th>
<th>S&amp;P (RUS)</th>
<th>CSE (RSL)</th>
<th>BSE (RIND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significance</td>
<td>Critical values</td>
<td>Test statistics</td>
<td>Critical Value</td>
<td>Test Statistics</td>
<td>Critical Value</td>
</tr>
</tbody>
</table>
4.4 Results of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test:

Table 4.5 contains the results of KPSS test. In all the results obtained for KPSS test, the test statistics have lesser values than the critical values. So the test is not significant and the null is not rejected. All the series are stationary at 1%, 5% and 10% levels of significance.

Table 4.5: KPSS test Results

<table>
<thead>
<tr>
<th>Significance Level</th>
<th>KSE (RPAK)</th>
<th>SSE (RCHINA)</th>
<th>S&amp;P (RUS)</th>
<th>CSE (RSL)</th>
<th>BSE (RIND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>0.739000</td>
<td>0.739000</td>
<td>0.739000</td>
<td>0.739000</td>
<td>0.739000</td>
</tr>
<tr>
<td>5%</td>
<td>0.463000</td>
<td>0.463000</td>
<td>0.463000</td>
<td>0.463000</td>
<td>0.463000</td>
</tr>
<tr>
<td>10%</td>
<td>0.347000</td>
<td>0.347000</td>
<td>0.347000</td>
<td>0.347000</td>
<td>0.347000</td>
</tr>
</tbody>
</table>

4.5 ARMA (p, q) Order Results:

Table 4.7 showing summary of ARMA process of Pakistan, India, Sri Lanka, America and China. Statistics of Pakistan show that Critical values of Ljung-Box test are ±0.039 and in AC (Auto Correlation) 3 values are significant and in PAC (Partial Auto Correlation) 4 values are significant. In India 1 value is significant in AC and 2 values are significant in PAC and Critical value of values Ljung-Box test are ±0.0401. While for America, Critical value of Ljung-Box test is ±0.0391 and 3 values are significant in AC and 3 are significant in PAC of America. Last column statistics are of China here 1, 1 proportion found and it is witnessed that in AC and PAC 1 value is significant, while Critical value of values Ljung-Box test are ±0.0384.

Table 4.7: ARMA test Results

<table>
<thead>
<tr>
<th>DESCRIPTION</th>
<th>ARMA RESULTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>COUNTARIES</td>
<td>PAK</td>
</tr>
<tr>
<td>CRITICAL VALUES</td>
<td>±0.03948</td>
</tr>
<tr>
<td>AC</td>
<td>4</td>
</tr>
<tr>
<td>PAC</td>
<td>3</td>
</tr>
<tr>
<td>ARMA (p,q)</td>
<td>(4,3)</td>
</tr>
</tbody>
</table>

Note: AC stands for Auto correlation, PAC stands for Partial Auto Correlation, and ARMA stands for Auto Correlation Moving Average.
4.6 Results of ARCH test:

A simple regression is run with a constant and residuals are taken from regression and a test is run on residuals to get confident justification about the presence of ARCH effect. This test is heteroskedasticity test of ARCH.

This test has two hypothesis i.e. Null and alternative.

\[ H_0 = \text{No ARCH effect} \]

Results are presented in table 4.8 Probability value of F-statistics for all the countries is less than 5%. It means ARCH test of Heteroskedasticity for all the countries is significant so, the null hypothesis “No ARCH effect” is not accepted and alternative hypothesis “there is ARCH effect” is accepted in all the cases. Now we can run the ARCH family models.

<table>
<thead>
<tr>
<th>COUNTARIES</th>
<th>PAK</th>
<th>INDIA</th>
<th>S.L</th>
<th>USA</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.3856</td>
<td>0.1742</td>
<td>0.2811</td>
<td>0.2049</td>
<td>0.1562</td>
</tr>
<tr>
<td>p-value</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
</tbody>
</table>

4.7 Results of ARCH family models:

Table 4.9 contains parameter values, probability value and the value of Akaike information criterion (AIC) and Schwarz information criterion (SIC). Guide line is that, lowest the value of AIC and SIC better the model is fitted. For Pakistan, EGARCH model has lowest AIC and SIC value. So it is best fitted for Pakistan. For China, GARCH model has lowest AIC and SIC values so GARCH model is best fitted for China. For Sri-Lanka, EGARCH model has lowest value of AIC and SIC so, this model is best fitted. For India, GJR-GARCH model has lowest values of AIC and SIC so, it is best fitted for India. All the models have captured the volatility of stock indices returns. And also, all the models, which are selected on the basis of AIC and SIC criteria, have “no ARCH effect” and “no serial correlation” left in their residuals. For US, GJR-GARCH model has lowest values of AIC and SIC but the residuals of this model has significant ARCH effect so this model has not captured all the volatility of S&P 500 index returns. Other ARCH family models have also the same results except ARCH model. But ARCH model has highest AIC and SIC values among these models. On the basis of AIC and SIC criterion ARCH model cannot be selected because it has lost highest information among all the selected models. So here we have assumed that the information lost is not so material as the sample size is so large and daily stock return data is taken. On the basis of this assumption and the assumption of CLRM that are given above at the start of this chapter, ARCH model is declared best fitted for US. Results for Lag variable for U.S. are also the same as that of ARCH model for levels of return.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>KSE-EGARCH</th>
<th>S&amp;P-ARCH</th>
<th>SSE-GARCH</th>
<th>BSE-GJR.GARCH</th>
<th>CSE-EGARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.9164</td>
<td>0.0318</td>
<td>0.497</td>
<td>0.0520</td>
<td>0.4044</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.3322</td>
<td>0.9443</td>
<td>0.1023</td>
<td>0.8800</td>
<td>-0.0352</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>-0.1236</td>
<td>0.0191</td>
<td>0.0002</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.000</td>
<td>0.0191</td>
<td>0.0002</td>
<td>0.0000</td>
</tr>
<tr>
<td>AIC</td>
<td>-6.1469</td>
<td>-6.4161</td>
<td>-5.6089</td>
<td>-5.9473</td>
<td>-6.7248</td>
</tr>
<tr>
<td>SIC</td>
<td>-6.1351</td>
<td>-6.3976</td>
<td>-5.5996</td>
<td>-5.9357</td>
<td>-6.7127</td>
</tr>
</tbody>
</table>

4.8 Copula Results with respect to US (Three divisions of sample period):

Now whole period is divided into three parts, i.e. pre-crisis period, crisis period and after crisis period. Division of whole period is as, pre-crisis period (from January 01, 2005 to October 09, 2007), crisis period (from October 10, 2007 to March 09, 2009) and post-crisis period (from March 10, 2009 to December 31, 2014). March 10, 2009 is the day when S&P 500 index again started recovery, so it is a valid day to separate the crisis period from normal period. This division is done to
find that which country showed to quick response towards the US stock market downfall.

Table 4.11 contains the results of Copulas. Main copula that measures the negative tail dependence and test the presence of contagion effect is Clayton copula. According to the results, the value of Clayton copula parameter is increased during the crisis period and after the crisis period. Hence there is contagion effect in KSE, transmitted by US stock market.

Shanghai stock exchange of China has not shown increase in co-movement during crisis period. Coefficients of Clayton and Gumbel copula are decreased during the crisis period. But after the crisis period, there is increase in tail dependence which proves that China is not affected quickly from US crisis but it has weak contagion effect after the crisis period.

Indian stock market is most affected among the selected stock markets of sample. There is decrease in tail dependence between India and US during the crisis and after the crisis period. India has shown a quick response to the US crisis. There is contagion effect in India transmitted from US to Bombay stock market of India.

DCC coefficient for KSE, CSE and SSE is decreased during the crisis period but there is increase in coefficient for BSE. It means BSE has shown quick response to US sub-prime crisis. After the crisis period, KSE and SSE has shown increased DCC coefficient while there is decrease in DCC coefficient for CSE and BSE.

Table 4.11: Results of copulas with respect to US

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-crisis</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crisis</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-crisis</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Intable 4.11, n, AIC, L.L., *, ‡, representativesof number of observations, Akaika information criterion, coefficient of Clayton copula, Log Likelihood, coefficient of Gumbel copula, respectively.

4.9 Emerging to emerging market results

There is decrease in tail dependence in Colombo stock exchange of Sri-Lanka during and after the crisis period. Hence there is no evidence of direct contagion in Sri-Lankan stock market triggered by US stock market.

Indian stock market is most affected among the selected stock markets of sample. There is increase in tail dependence between India and US during the crisis and after the crisis period. India has shown a quick response to the US crisis. There is contagion effect in India transmitted from US to Bombay stock market of India.

DCC coefficient for KSE, CSE and SSE is decreased during the crisis period but there is increase in coefficient for BSE. It means BSE has shown quick response to US sub-prime crisis. After the crisis period, KSE and SSE has shown increased DCC coefficient while there is decrease in DCC coefficient for CSE and BSE.
Pakistan during crisis period. DCC coefficient is also decreased and insignificant. After the crisis period, copulas and tail dependence has shown increased values. It means China has not affected Pakistan during the crisis period but after the crisis period these markets became correlated to each other and could not give the benefit of international diversification.

In case of Pakistan and Sri-Lanka, Tail dependence is decreased during the crisis period. Hence, there is no quick increase in co-movement between Pakistan and Sri-Lankan stock market, even after the crisis period there is decrease in tail dependence. So, there is no contagion between Pakistan and Sri-Lankan stock markets. DCC coefficient became negative during crisis period but remain insignificant. Investors can take benefits of international diversification by investing in these two stock markets.

Results of Pakistan and Indian stock markets show that there is decrease in Clayton and Gumbel copulas during the crisis period, so there is no quick contagion transmission from these two markets for each other. But after the crisis period, there is increase in tail dependence between these two stock markets. So, Indian stock market has no quick effect on Pakistani stock market but has transmitted contagion after the crisis period.

### Table 4.13
Emerging to emerging market results (With respect to Pakistan and three divisions of sample period): Special case of China and Pakistan

<table>
<thead>
<tr>
<th>Stock indices→</th>
<th>KSE-SSE</th>
<th>KSE-CSE</th>
<th>KSE-BSE</th>
<th>KSE-SSE</th>
<th>KSE-CSE</th>
<th>KSE-BSE</th>
<th>KSE-SSE</th>
<th>KSE-CSE</th>
<th>KSE-BSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clayton</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*</td>
<td>0.0416</td>
<td>0.0715</td>
<td>0.0530</td>
<td>0.0073</td>
<td>0.0622</td>
<td>0.0477</td>
<td>0.1041</td>
<td>0.0008</td>
<td>0.1657</td>
</tr>
<tr>
<td>n</td>
<td>722</td>
<td>722</td>
<td>722</td>
<td>369</td>
<td>369</td>
<td>369</td>
<td>1516</td>
<td>1516</td>
<td>1516</td>
</tr>
<tr>
<td>L.L</td>
<td>0.0561</td>
<td>-1.6694</td>
<td>-1.1070</td>
<td>0.0014</td>
<td>0.8131</td>
<td>-0.7500</td>
<td>6.9574</td>
<td>0.0221</td>
<td>10.9917</td>
</tr>
<tr>
<td>Gumbel</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*</td>
<td>1.0208</td>
<td>1.0358</td>
<td>1.0264</td>
<td>1.0037</td>
<td>1.0311</td>
<td>1.0238</td>
<td>1.0521</td>
<td>1.0004</td>
<td>1.0829</td>
</tr>
<tr>
<td>n</td>
<td>722</td>
<td>722</td>
<td>722</td>
<td>369</td>
<td>369</td>
<td>369</td>
<td>1516</td>
<td>1516</td>
<td>1516</td>
</tr>
<tr>
<td>L.L</td>
<td>-0.1374</td>
<td>-1.4840</td>
<td>-0.6220</td>
<td>-0.0325</td>
<td>0.3791</td>
<td>-0.7048</td>
<td>7.6632</td>
<td>0.0339</td>
<td>15.5404</td>
</tr>
<tr>
<td>DCC Coeff.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(p-value)</td>
<td>-0.0068</td>
<td>0.0166</td>
<td>0.0432</td>
<td>-0.0094</td>
<td>-0.0427</td>
<td>0.0042</td>
<td>0.0592</td>
<td>0.0367</td>
<td>0.1021</td>
</tr>
</tbody>
</table>

Note: Intable 4.13, n, AIC, L.L, , representatives of Log Likelihood number of observations, Akaika information criterion, parameter of Clayton copula, parameter of Gumbel copula, respectively.

### 4.10 China-Pak results for copulas:

This is actually the value of this study. In this study another channel of contagion is tested. For Pakistan, Chinese’s stock markets may affect more severely than US stock market. To test this hypothesis I have calculated copulas for Pakistan and China. A recent decline in Chinese stock market is occurred due to devaluation of their currency which has affected the Pakistani stock market badly. The results of this recent crisis are also calculated and are shown in a table below. These results help to explain my hypothesis “Chinese stock market affects more to Pakistan stock markets than US stock market”. The total period is again divided into two parts that is pre-crisis (from January 01, 2015 to August 09, 2015) and post crisis (from August 10, +2015 to March 31, 2016) period.

Table 4.14 contains the results of Pakistan and China. Both copula parameters are increased after the crisis period. China is an emerging market and this market can affect Pakistan more severely.
results confirm the hypothesis of the study that “China can affect severely to Pakistan”. So, international portfolio managers can get benefit from these results while managing their international portfolios. They will not get the benefits of international diversification by investing these two stock markets during crisis period. Moreover, if crisis occur in these markets, it can move from one stock market to other.

Table 4.14: China-Pak results for copulas

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Clayton δn AIC</td>
<td>0.0887</td>
<td>0.5663</td>
<td>538.44</td>
</tr>
<tr>
<td></td>
<td>141</td>
<td>153</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-270</td>
<td>17.51</td>
<td></td>
</tr>
<tr>
<td>Gumbel δn AIC</td>
<td>1.0443</td>
<td>1.2831</td>
<td>22.87</td>
</tr>
<tr>
<td></td>
<td>141</td>
<td>153</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-296</td>
<td>15.51</td>
<td></td>
</tr>
<tr>
<td>DCC Coeff. (p-value)</td>
<td>0.0148 (0.6418)</td>
<td>0.1385 (0.0000)</td>
<td>835.81</td>
</tr>
</tbody>
</table>

Note: Intable 4.14, n, AIC, δ, α, representatives of number of observations, Akaiika information criterion, parameter of Clayton copula, parameter of Gumbel copula respectively.

5 Discussion and results

This study is conducted in two parts. In first part volatility is calculated, in second part contagion effect between US and 4 south Asian countries, and between emerging stock markets is estimated. There are four ARCH family models (ARCH, GARCH, EGARCH and GJR-GARCH) are used to find the volatility and tow copula models (Clayton and Gumbel copulas) are used to find contagion effect during sub-prime crisis between US and 4 selected South Asian countries. Contagion effect is also tested between Pakistan and emerging countries during such period. A recent crisis occurred in Chinese stock market in August 2015 that has affected Pakistani stock market, is also the part of the study. This crisis was occurred in due to devaluation of Yuan (China’s currency). Best fitted models that have captured volatility is EGARCH for Pakistan, GARCH for China, EGARCH for Sri-Lanka, GJR-GARCH for India and ARCH for US. All the models are selected on the basis of AIC and SIC criteria and selected models have “no ARCH effect” and “no serial correlation” left in their residuals. Copula results (two divisions of sample period) for tail dependence proved that there is contagion in Pakistan and India. Sri Lanka has no contagion effect. China is showing weak contagion. This result for China is in accordance with [10] Chien-Chung Niehet al (2012). These stock markets can be used for international diversification. In three period divisions, Pakistan and India showed a quick response to US crisis. Negative tail dependence is increased as quickly as the crisis occurred in US. Emerging to emerging market transmission of contagion effect test results show that there is a contagion effect between Pakistan and India. But there is no contagion effect between Pakistan and China and, between Pakistan and Sri-Lanka during the US sub-prime crisis of 2007-08. Three division period results show that there is no quick response triggered by emerging sample countries to Pakistan but after the crisis period, after-shocks are transmitted to Pakistan by China and India. It means these two emerging stock markets can lately, directly or indirectly affect Pakistan. Special case of Pakistan and China for “Chinese currency devaluation crisis” results has proved that China can transmit contagion to Pakistani stock markets. Chinese stock exchange crash of August 2015 was weaker than US sub-prime crisis but despite of being weaker in effects;
it has transmitted strong contagion effect on Pakistan. So, in future, Chinese stock exchanges can affect severely to Pakistani stock exchanges.

Here are some suggestions for future researchers; the future research can be narrow down by selecting some sectors as Target population or by comparing contagion of listed and non-listed companies of stock exchange. Other models can also be used for calculating contagion effect by using other ARCH family models & copulas. In this research sample is based on five countries so future research can take some other group of countries. Here US subprime crisis are considered but in future contagion of some other crisis can be evaluated. Different channels of contagion can be tested for a single country.

5. References


