January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

Spillover Effect between Stock and Currency Markets: An Empirical evidence from Developed and Developing Economies

Rabia Luqman (Corresponding Author)
PhD Scholar, Department of Commerce, BZU Multan.
Lecturer, Department of Management Sciences, COMSATS University Islamabad, Vehari Pakistan
Email: rabia@ciitvehari.edu.pk

Dr. Rehana Kousar
Professor, Department of Commerce,
BahauddinZakariya University Multan, Pakistan
Email: rehankousar@bzu.edu.pk

Mariashams Khakwani
Lecturer, Institute of Management Sciences, The Women University, Multan, Pakistan

Shanza Tabasum
Lecturer, Department of Management Sciences, COMSATS University Islamabad, Vehari Pakistan

Article Info
Volume 82
Page Number: 5004 - 5020
Publication Issue:
January-February 2020

Article History
Article Received: *18 May 2019*
Revised: *14 July 2019*
Accepted: *22 December 2019*
Publication: *25 January 2020*

Abstract:

Volatility Spillover between currency and equity markets has gained much attention for academicians and policy makers in recent era. Many studies has been conducted on this relationship in developed economies. But in this study, we use daily time series data from G8+5 countries and Pakistan for the 2000-2016 and apply DCC-GARCH to check the sign and magnitude of spillover effect between currency and equity markets. Results have shown that Brazil, Germany, USA, UK, Russia, South Africa, Pakistan, Japan, Italy, India, France and Canada has positive spillover between these two markets. Mexico and China reported no spillover between these two markets.

Keywords: *Volatility Spillover; Currency and Equity Markets; DCC GARCH*

1. Introduction

The global financial crisis has raised many questions concerning the future of global economic growth. One of the major global challenges is to find out possible ways to avoid such crisis in future. This challenge is further exacerbated because of the integration and interdependence of financial markets.Financial crisis in one economy creates similar results in other economies.Due to these high interdependence, markets have to suffer because such crisis are widely spread, among the economies of developed and under-developed regions. As a result of this volatility transmission between stock markets and exchange rates, financial markets are facing higher fluctuations in asset prices due to asymmetric

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

information in emerging markets than those of developed markets. To know about the transmission mechanism among the financial markets, studies have been conducted (Kumar, 2013; Dimitrova, 2005). According to (Ebrahim, 2000), it is important to know about how shocks are transmitted across financial markets (stock exchange market and foreign exchange market) and also to explore the magnitude of their effect. Studies has been conducted to identify the future financial crisis and to find out the ways to reduce such crisis (Aydemir&Demirhan, 2009;Kutty, 2010; Kumar, 2013; Zhao, 2010).Theories related to this relationship among the stock market and exchange rate markets are micro-economic theory and macro-economic theory.Micro-economic theory suggests that exchangeratechanges have dynamic effects on stock prices (Dornbuschand Fisher, 1980).According to later approach, stock price changes will affect the exchange rates (Kumar, 2010).

2. Literature Review

Volatility leads towards high risk in different securities and it becomes difficult to manage portfolio at international level. Due to shock in US economy in 2008 leads towards the drastic decline in other economies financial markets and create negative returns, liquidity becomes very low at global platform. As markets are getting more interdependent over the time so if there come shock in one economy it will spread to all over the globe and this effect known as spill-over and extreme amplifications of spill-over leads towards the contagion effect. A study conducted by Kaur (2002) to check the volatility changes among the markets and concluded that there is great impact of equity market on the economic stability of any country and equity market gets affected by changes in currency market and interest rates. As exchange rate changes it will create positive or negative impact on equity market based on the nature of economy. Developing economies also play an important role for managing the portfolio at international level as they are also growing and contributing the overall growth at the global level. So, if there is change in foreign exchange rate then it will affect the performance of all related countries (Kim 2003). Changes in the currency create different impacts on the export-oriented countries or at import-oriented countries, if a country has export orientation then, currency decline will lead to increase in sale of goods and leads towards the increased wealth of the country. But if country has import-orientation then decline in currency value will lead to decrease in sale of goods and will lead towards the decrease in equity markets (Kao 1990).

There are number of factors that will affect the stock price of a country and these are dividends offered by the firm will affect the changes in stock price and exchange rates changes will also affect the sales of the firm and hence equity market will also get affected (Kurihara 2006). Another study conducted by Apergis and Rezitis (2001) on the volatility among the equity and currency market and concluded that in case of London and New York there are no volatility relationship among the markets that if there come change in one market will not affect the other market. They found no evidence of volatility in case of London and New York by applying the GARCH method.Badrinath and Apte (2005) conducted the study on the volatility among the markets by using the EGARCH in case of India and found evidence of significant volatility Spill-over among the currency and equity markets of India. By applying the same methodology EGARCH, Buguk et al. (2003) conducted another study by using the agriculture data and found strong evidence of spill-over among the markets. Aloui (2007) concluded that there exists strong evidence of volatility spill-over among the markets. Kemal (2006) conducted a study by using the sample of Pakistan and supported the existence of spill-over among the markets.In case of India, study also find the existence of volatility spill-over among

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

the markets (Mishra et al. 2007).In case of European economies, study concluded that there is less evidence of volatility spill-over among the markets (Morales 2008). Study concluded the uni-directional relationship from equity market to currency market by using the EGARCH and sample countries of study was New Zealand (Choi et al. 2009). Bhar and Nikolova (2009) concluded that there exists volatility spill-over among the markets in case of BRIC markets and applied the EGARCH to test the relationship among the variables. Study found evidence of strong spill-over effect among the markets by using the sample of Hong Kong, Singapore, India, Korea and Thailand (Mukherjee and Mishra 2008). Omrane and Christian (2015) found the spill-over among the currency markets of sample economies. Study concluded with the strong evidence of spill-over among the markets by using the sample of India and applied the GARCH model to test the spill-over effect among the currency and equity markets (Saha and Chakrabrati 2011). By using the sample of South African markets, study concluded that there exists spill-over effect from equity to currency market (Bonga and Hoveni 2013). Study found evidence of strong spill-over effect at the time of crisis or after the crisis period between the currency and equity markets in case of India (Ghosh 2014). Another study conducted to check the spread of shocks and volatility among the currency markets of different countries that if there comes decline in one country currency then it will affect the other related country currencies and study found the strong evidence of transmission of shocks among different countries (Sahoo 2012). Study used the sample of commodity markets to check the spill-over effect of the current and future return among the currency and equity markets and found the two-way spill-over effect among the markets (Dey 2011).

In case of different stock markets, there is evidence of strong volatility spill-over effect among the markets (Miralles-Marcelo, &Miralles-Quiros, 2013; Kenourgios&Dimitriou, 2015; Coudert, Herve, &Mabille, 2015; Li & Giles, 2015; Hemche, Jawadi, Maliki, &Cheffou, 2016). Due to crisis, spill-over effect among the markets increased in case of emerged and emerging markets, integration among the financial markets also increased at this time and transmit the changes more rapidly as if there come crisis in one economy then it will transfer to other economy at higher rate (Engle 2011). If markets are not interdependent then there is less evidence of spill-over effect because each market is working at difference economy and other economies do not create any impact on it so if there is crisis in one economy then there will be less tendency that it will transmit to other economies (Li and Giles 2015).

To efficiently manage the risk of portfolio, investors will use the interactions among the markets so they can minimise the risk and increased the return on their investments (Sadorsky, 2012). Trade linkages in the markets are the main cause to transmit the changes among the markets as changes in the equity market in China in 2015, as China is emerging economy but other economies are also related to Chinese economy so they also get affected by the changes in Chinese equity market (Guimar~aes-Filho& Hong, 2016).

3. Research Methodology

Dynamic Conditional Correlation (DCC) model has the benefit of univariate GARCH but doesn't involve the complexity of multivariate GARCH. In this model, there are two steps to estimate the DCC GARCH. Firstly, univariate GARCH is estimated and then secondly, correlations are predicted. In this model number of parameters to be predicted are independent of the series to be correlated. An analysis of the performance of Dynamic Conditional Correlation methods for large covariance matrices is considered in Engle

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

and Sheppard (2001, 2002). Covariance matrix is divided in two components as 1) conditional standard deviation 2) a correlation matrix and these components are time-varying.Dynamic Conditional Correlation (DCC-) GARCH model is described as:

$$r_t = \mu_t + a_t$$
$$a_t = H_t^{1/2} z_t$$
$$H_t = D_t R_t D_t$$

Notation:

$\boldsymbol{r_t}$: n × 1 vector of log returns of n assets at tim

$\boldsymbol{a_t}$: n × 1 vector of mean-corrected returns of n a
Cov [a_t] = H .

$\boldsymbol{\mu_t}$: n × 1 vector of the expected value of the co

$\boldsymbol{H_t}$: n × n matrix of conditional variances of a_t a

$\boldsymbol{H_t}^{\frac{1}{2}}$: Any n × n matrix at time t such that H_t is the
$H^{1/2}_t$ may be obtained by a Cholesky factoriza

$\boldsymbol{D_t}$: n × n, diagonal matrix of conditional standarc

$\boldsymbol{R_t}$: n × n conditional correlation matrix of $\boldsymbol{a_t}$ at ti

$\boldsymbol{z_t}$: n × 1 vector of iid errors such that E[z_t]=0 aı

4. Analysis and Findings

Engle (2001, 2002)gave the DCC GARCH model to check the spillover between the variables as two variables are correlated and impact of one variable volatility on the other variable volatality. If one variable is going to change then how other variable will react to the changes. Variables of the study are stock indices of all 14 countries and exchange rate of all sample countries and DCC GARCH model is applied to each country to check the existence of volatility within the series and volatility clustering among the variables.

Table 4.1. Brazil DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	5.3715e+04	606.956703	88.4987	0.000000
Ω 1	7.9524e-01	0.247052	3.2189	0.001287
α 1	-3.6795e-02	0.015517	-2.3713	0.017726
β1	9.4587e-01	0.014518	65.1508	0.000000
γ1	1.1749e+00	0.113459	10.3555	0.000000
Constant 2	2.1434e+00	0.007669	279.4963	0.000000
Ω2	-3.1041e-01	0.043008	-7.2176	0.000000
α2	1.6140e-02	0.006283	2.5687	0.010209
B2	9.6541e-01	0.007096	136.0418	0.000000
γ2	1.2251e+00	0.198157	6.1827	0.000000

Dcca1	2.6717e-01	0.014228	18.7775	0.000000
Dccb1	7.3197e-01	0.014324	51.1020	0.000000

In case of Brazil Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of Brazil depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the Brazil stock market and Brazil exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of Brazil. There is positive spillover between these two markets. High correlations indicate the existence of extreme spillovers effect called the contagion effect.

Table 4.2. Canada DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	1.2171e+04	91.945683	132.3751	0.000000
Ω 1	5.2255e-01	0.205413	2.5439	0.010962
α 1	-1.7000e-02	0.011671	-1.4566	0.145234
β1	9.5034e-01	0.014799	64.2149	0.000000
γ1	1.1517e+00	0.100342	11.4775	0.000000
Constant 2	1.0337e+00	0.000607	1701.7032	0.000000
Ω2	-3.7448e-01	0.052942	-7.0733	0.000000
α2	3.7667e-02	0.012968	2.9047	0.003676
B2	9.6277e-01	0.007035	136.8625	0.000000
γ2	1.0613e+00	0.124038	8.5562	0.000000
Dcca1	1.8475e-01	0.015929	11.5981	0.000000
Dccb1	8.1504e-01	0.015961	51.0629	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of Canada Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and one parameter is significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices and exchange rate of Canada depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the Canada stock market

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

and Canada exchange rate market. There is positive spillover between these two markets.

Table 4.3 China DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	2107.082296	57.42720	36.691363	0.00000
Ω 1	0.519379	1.32432	0.392186	0.69492
α 1	0.038110	0.05922	0.643525	0.51988
β1	0.938428	0.12638	7.425517	0.00000
γ1	1.319307	1.29034	1.022448	0.30657
Constant 2	6.818824	0.85472	7.977797	0.00000
Ω2	-0.098825	7.11395	-0.013892	0.98892
α2	0.016588	1.65855	0.010001	0.99202
B2	0.980576	1.68354	0.582448	0.56027
γ2	0.398288	25.36060	0.015705	0.98747
Dcca1	0.395216	1.87526	0.210753	0.83308
Dccb1	0.596573	1.99353	0.299255	0.76475

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of China Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are insignificant that shows that ARIMA model cannot applied to data. It indicates that current values of stock indices of China don't depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are insignificant than GARCH model cannot be applied. The coefficient of GARCH shows the inexistence of volatility within the series. Dcca1 and dccb1 are insignificant that shows the no conditional correlations between the China stock market and China exchange rate market. If stock indices are going to changed then this will not lead to change in exchange rate of China. There is no spillover between these two markets.

Table 4.4. France DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	4020.349823	33.419527	120.2994	0.000000
Ω 1	0.473662	0.169102	2.8010	0.005094
α 1	0.020503	0.007922	2.5880	0.009653
β1	0.945908	0.015221	62.1431	0.000000

TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

γ1	1.157253	0.183630	6.3021	0.000000
Constant 2	1.296492	0.011553	112.2213	0.000000
Ω2	-0.559154	0.146280	-3.8225	0.000132
α2	-0.029743	0.024846	-1.1971	0.231278
B2	0.931688	0.023992	38.8340	0.000000
γ2	1.339393	0.320197	4.1830	0.000029
Dcca1	0.292186	0.011887	24.5804	0.000000
Dccb1	0.706247	0.011883	59.4345	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of France Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of France depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the France stock market and France exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of France. There is positive spillover between these two markets.

Table 4.5 Germany DCC GARCH

Optimal Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Constant 1	6198.324765	81.619910	75.9413	0.000000
Ω 1	0.399631	0.144822	2.7595	0.005790
α 1	0.012228	0.006461	1.8927	0.058393
β1	0.955613	0.011468	83.3304	0.000000
γ1	1.283834	0.214665	5.9806	0.000000
Constant 2	1.296492	0.011375	113.9808	0.000000
Ω2	-0.559154	0.138977	-4.0234	0.000057
α2	-0.029743	0.023706	-1.2546	0.209609
B2	0.931688	0.022525	41.3624	0.000000
γ2	1.339393	0.321560	4.1653	0.000031
Dcca1	0.321377	0.016950	18.9605	0.000000
Dccb1	0.676903	0.017047	39.7087	0.000000

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of Germany Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of Germany depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the Germany stock market and Germany exchange rate market. If stock indices are going to change then this will lead to change in exchange rate of Germany. There is positive spillover between these two markets.

Table 4.6India DCC GARCH

Optimal Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Constant 1	2649.266900	202.175697	13.1038	0.000000
Ω 1	-8.366665	0.433423	-19.3037	0.000000
α 1	10.000000	0.032072	311.7965	0.000000
β1	0.988080	0.043787	22.5656	0.000000
γ1	-6.978562	0.998939	-6.9860	0.000000
Constant 2	45.851876	0.401549	114.1874	0.000000
Ω2	-0.142873	0.032239	-4.4317	0.000009
α2	0.026437	0.011971	2.2084	0.027214
B2	0.971312	0.010362	93.7343	0.000000
γ2	1.131558	0.112125	10.0919	0.000000
Dcca1	0.237415	0.019166	12.3874	0.000000
Dccb1	0.762057	0.019245	39.5971	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of India Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of India depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the India stock market and India exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of India. There is positive spillover between these two markets.

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

Table 4.7 Italy DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	2.1669e+04	1.2130e+03	17.8638	0.000000
Ω 1	4.9286e-01	3.5186e-01	1.4007	0.161303
α 1	2.1995e-02	1.2043e-02	1.8263	0.067802
β1	9.5928e-01	2.2879e-02	41.9291	0.000000
γ1	1.0641e+00	1.8871e-01	5.6386	0.000000
Constant 2	1.2965e+00	1.1326e-02	114.4680	0.000000
Ω2	-5.5915e-01	1.4361e-01	-3.8936	0.000099
α2	-2.9743e-02	2.3650e-02	-1.2576	0.208537
B2	9.3169e-01	2.3384e-02	39.8427	0.000000
γ2	1.3394e+00	3.2082e-01	4.1750	0.000030
Dcca1	3.4362e-01	2.0624e-02	16.6614	0.000000
Dccb1	6.5332e-01	2.0926e-02	31.2205	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of Italy Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of Italy depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the Italy stock market and Italy exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of Italy. There is positive spillover between these two markets.

Table 4.8 Japan DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	1.4945e+04	48.011328	311.28650	0.00000
Ω 1	6.4006e-01	0.477290	1.34103	0.17991
α 1	-2.4460e-02	0.022340	-1.09491	0.27356
β1	9.4249e-01	0.031427	29.99001	0.00000
γ1	1.4113e+00	0.128811	10.95611	0.00000

TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

Constant 2	1.0770e+02	0.753830	142.87672	0.00000
Ω2	1.6302e-02	0.058158	0.28031	0.77924
α2	-1.0314e-02	0.006709	-1.53746	0.12418
B2	9.3831e-01	0.013836	67.81814	0.00000
γ2	1.4102e+00	0.255390	5.52175	0.00000
Dcca1	2.4445e-01	0.020860	11.71899	0.00000
Dccb1	7.5499e-01	0.020907	36.11122	0.00000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of Japan Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are insignificant that shows that ARIMA model cannot be applied to data. It indicates that current values of stock indices of Japan don't depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the Japan stock market and Japan exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of Japan. There is positive spillover between these two markets.

Table 4.9 Mexico DCC GARCH

Optimal Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Constant 1	4.5083e+04	7.1904e+03	6.26990	0.00000
Ω 1	6.6983e+00	2.7925e+01	0.23987	0.81043
α 1	-2.8173e+00	8.9052e+00	-0.31636	0.75173
β1	5.9117e-01	2.0856e+00	0.28345	0.77683
γ1	3.8498e+00	2.3126e+01	0.16647	0.86779
Constant 2	1.0896e+01	2.5797e-02	422.37604	0.00000
Ω2	-1.9183e-01	1.7877e-02	-10.73031	0.00000
α2	2.8089e-02	6.3620e-03	4.41527	0.00001
B2	9.6544e-01	4.9500e-03	195.05417	0.00000
γ2	1.0338e+00	9.1641e-02	11.28039	0.00000
Dcca1	1.8847e-01	3.1797e-01	0.59273	0.55336
Dccb1	4.7945e-01	7.1546e-01	0.67013	0.50278

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

In case of Mexico Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are insignificant that shows that ARIMA model cannot be applied to data. It indicates that current values of stock indices of Mexico don't depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are insignificant than GARCH model cannot be applied. The coefficient of GARCH shows the inexistence of volatility within the series. Results have shown that there is high volatility within the series of exchange rate of Mexico.

Table 4.10 Pakistan DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	1.8057e+04	649.373571	27.807340	0.00000
Ω 1	3.4827e-01	6.278754	0.055469	0.95576
α 1	1.8514e-02	0.181652	0.101919	0.91882
β1	9.6474e-01	0.358484	2.691174	0.00712
γ1	1.5639e+00	2.053092	0.761724	0.44622
Constant 2	8.5060e+01	0.205432	414.052739	0.00000
Ω2	-1.6692e-02	0.054779	-0.304708	0.76059
α2	2.2680e-03	0.002798	0.810626	0.41758
B2	9.9040e-01	0.018892	52.424609	0.00000
γ2	3.5782e-01	0.819452	0.436653	0.66236
Dcca1	1.2850e-01	0.016258	7.904100	0.00000
Dccb1	8.7131e-01	0.016303	53.446603	0.00000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of Pakistan Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are insignificant that shows that ARIMA model cannot be applied to data. It indicates that current values of stock indices of Pakistan don't depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the Pakistan stock market and Pakistan exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of Pakistan. There is positive spillover between these two markets. High correlations indicate the existence of extreme spillovers effect called the contagion effect.

TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

Table 4.11 Russia DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	1430.360513	25.675137	55.7099	0.000000
Ω 1	0.294874	0.242814	1.2144	0.224594
α 1	-0.014316	0.005969	-2.3983	0.016473
β1	0.954536	0.008515	112.0939	0.000000
γ1	1.273393	1.009329	1.2616	0.207085
Constant 2	29.219986	0.667389	43.7825	0.000000
Ω2	-0.178699	0.126776	-1.4096	0.158668
α2	0.027972	0.011006	2.5415	0.011038
B2	0.965770	0.012761	75.6787	0.000000
γ2	1.335969	0.495106	2.6984	0.006968
Dcca1	0.331198	0.016630	19.9159	0.000000
Dccb1	0.666849	0.016778	39.7448	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of Russia Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of Russia depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series.

Table 4.12 South Africa DCC GARCH

Optimal Parameters	Estimate	Std. Error	t value	Pr(>|t|)
Constant 1	5.0613e+04	73.500896	688.5999	0.000000
Ω 1	7.6512e+00	0.014722	519.7097	0.000000
α 1	-3.5084e+00	0.008451	-415.1251	0.000000
β1	2.3594e-01	0.000566	416.5544	0.000000
γ1	-4.1032e+00	0.008017	-511.7981	0.000000
Constant 2	7.7418e+00	1.132313	6.8371	0.000000

Ω2	-2.0894e-01	0.070825	-2.9501	0.003177
α2	4.0189e-02	0.036067	1.1143	0.265149
B2	9.4344e-01	0.064682	14.5858	0.000000
γ2	1.1893e+00	0.700429	1.6979	0.089524
Dcca1	2.0954e-01	0.024369	8.5987	0.000000
Dccb1	7.0657e-01	0.085187	8.2943	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of South Africa Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of South Africa depend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series.

Table 4.13 UK DCC GARCH

Optimal Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Constant 1	5870.676510	28.664663	204.8054	0.000000
Ω 1	0.592953	0.159536	3.7167	0.000202
α 1	-0.017373	0.007384	-2.3528	0.018634
β1	0.938466	0.013548	69.2691	0.000000
γ1	1.061991	0.095346	11.1383	0.000000
Constant 2	1.574934	0.012181	129.2907	0.000000
Ω2	-0.640158	0.242249	-2.6426	0.008228
α2	0.028314	0.019754	1.4333	0.151765
B2	0.925067	0.034439	26.8614	0.000000
γ2	1.603269	0.428793	3.7390	0.000185
Dcca1	0.314970	0.014082	22.3672	0.000000
Dccb1	0.682991	0.014302	47.7565	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of UK Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of UKdepend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied.

TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series.

Table 4.14 USA DCC GARCH

Optimal Parameters	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Constant 1	1.0563e+04	49.520798	213.30284	0.000000
Ω 1	5.8966e-01	0.211245	2.79138	0.005248
α 1	4.2176e-02	0.013712	3.07589	0.002099
β1	9.4351e-01	0.016819	56.09797	0.000000
γ1	1.2619e+00	0.197339	6.39465	0.000000
Constant 2	8.4100e+01	1.956164	42.99231	0.000000
Ω2	-8.8960e-02	0.150494	-0.59112	0.554440
α2	4.4104e-02	0.012740	3.46201	0.000536
B2	9.3740e-01	0.024710	37.93682	0.000000
γ2	1.7134e+00	0.313107	5.47226	0.000000
Dcca1	2.8408e-01	0.016490	17.22695	0.000000
Dccb1	7.1432e-01	0.016619	42.98085	0.000000

(10% level is identified by * and at the 5% level by ** and 1% by ***)

In case of USA Dynamic conditional correlation GARCH, Omega and alpha 1 are the ARIMA parameters and both are significant that shows that ARIMA model can be applied to data. It indicates that current values of stock indices of USAdepend on its lagged terms. Beta 1 and gamma 1 are the GARCH parameters and if both parameters are significant than GARCH model can be applied. The coefficient of GARCH shows the existence of volatility within the series. Results have shown that there is high volatility within the series. Dcca1 and dccb1 are significant that shows the high correlation between the USA stock market and USA exchange rate market. If stock indices are going to changed then this will lead to change in exchange rate of USA. There is positive spillover *between* these two markets.

Conclusion & Discussion

There is high correlation between the Brazil stock market and Brazil exchange rate market. Germany,USA, UK, Russia,South Africa, Pakistan, Japan, Italy, India, France and Canada has positive spillover between these two markets. Mexico and China reported no spillover between these two markets.

Understanding transmission mechanism among the financial markets of different economies are important from the perspective of investors.Investors are compensated against the risk that they bear in any security. This is the basic rule for all the models used for asset pricing. If investors bear the high risk then will earn the high profit. This risk is measured by the variation in the security’s return and if two securities are having the same variation then they provide the same

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

level of profit. But if one security variations are high among the other then it will provide the higher return as compared to other securities.

Policy makers are concerned about the transmission mechanism between these two markets because this may affect their decisions regarding the policies related to these markets. As stock price will rise, it may increase the value of currency and in turn exchange rate will be appreciated as compared to other economies. In some cases, policy makers depreciate the value of currency and it will result in increase in exports and in turn depreciate the exchange rate as compared to other economies. So, policy makers have to decide that which policy is better at the time of crisis and at normal times after knowing the transmission mechanism between these two markets (Dimitrova, 2005; Gavin, 1989).

It is very important to predict about the crisis in future for the regulator, because now crisis occur and spread all over the world and due to interdependence between countries. Every country become affected. But if one country knows about the future crisis then it may take steps to overcome the problems arises from the crisis and also make policies that help in time of crisis.

Now companies are also working at international levels and they suffer if there come crisis in one country and then spread all over the world. Multinational companies have to manage the sales from different countries and have to tackle the issues of capital budgeting, short term investment and long-term financing. They have to face the exposure from different economies and if they know about the mechanism that how shocks are transmitted and magnitude of their effect then it will be beneficial for them to earn the maximum profits.

The contribution of this study is that it will develop the understanding that how different countries are economically and financially integrated with each other and with Pakistan. The study is very important in the Asian context because of the shifting of global economic power towards China and India. Findings of the study will complement the macroeconomic and microeconomic approaches relating to foreign exchange market and stock market.In this study time period is from 2000-2016, so further research can be extended to longer period and sample countries may be taken more than included in this study.

References

[1]. Aloui, C. (2007). Price and volatility spillovers between exchange rates and stock indexes for the pre-and post-euro period. *Quantitative Finance*, *7*(6), 669-685.

[2]. Apergis, N., &Rezitis, A. (2001). Asymmetric Cross-market Volatility Spillovers: Evidence from Daily Data on Equity and Foreign Exchange Markets. *The Manchester School*, *69*(s1), 81-96.

[3]. Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International money and finance*, *30*(7), 1387-1405.

[4]. Aydemir, O., &Demirhan, E. (2009). The relationship between stock prices and exchange rates: Evidence from Turkey. *International Research Journal of Finance and Economics*, *23*(2), 207-215.

[5]. Badrinath, H. R., &Apte, P. G. (2005). Volatility spillovers across stock, call money and foreign exchange markets. *Department of Economics (San Diego, University of California)*.

[6]. 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*, *19*(3), 203-218.

[7]. Bonga-Bonga, L., &Hoveni, J. (2013). Volatility Spillovers between the Equity Market and Foreign Exchange Market in South Africa in the 1995-2010 Period. *South African Journal of Economics*, *81*(2), 260-274.

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

[8]. Buguk, C., Hudson, D., & Hanson, T. (2003). Price volatility spillover in agricultural markets: an examination of US catfish markets. *Journal of Agricultural and Resource Economics*, 86-99.

[9]. Choi, J. J., Laibson, D., Madrian, B. C., &Metrick, A. (2009). Reinforcement learning and savings behavior. *The Journal of finance*, *64*(6), 2515-2534.

[10]. Coudert, V., Hervé, K., &Mabille, P. (2015). Internationalization versus regionalization in the emerging stock markets. *International Journal of Finance & Economics*, *20*(1), 16-27.

[11]. Dey, K., Maitra, D., & Roy, S. (2011). Price Discovery, Market Efficiency and Volatility Revisited: Anecdotes from Indian Pepper Futures Markets. In *Conference on Interdisciplinary Business Research, Society of Interdisciplinary Business Research (SIBR)*.

[12]. Dimitrova, D. (2005). The relationship between exchange rates and stock prices: Studied in a multivariate model. *Issues in Political Economy*, *14*(1), 3-9.

[13]. Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *The American Economic Review*, *70*(5), 960-971.

[14]. Ehrmann, M., Fratzscher, M., &Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: measuring international financial transmission. *Journal of Applied Econometrics*, *26*(6), 948-974.

[15]. Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

[16]. Engle, R. F., & Sheppard, K. (2001). *Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH* (No. w8554). National Bureau of Economic Research.

[17]. Hemche, O., Jawadi, F., Maliki, S. B., &Cheffou, A. I. (2016). On the study of contagion in the context of the subprime crisis: A dynamic conditional correlation–multivariate GARCH approach. *Economic Modelling*, *52*, 292-299.

[18]. Hong, H., Li, F. W., & Xu, J. (2016). *Climate risks and market efficiency* (No. w22890). National Bureau of Economic Research.

[19]. Kenourgios, D., Papadamou, S., &Dimitriou, D. (2015). Intraday exchange rate volatility transmissions across QE announcements. *Finance Research Letters*, *14*, 128-134.

[20]. Kim, K. H. (2003). Dollar exchange rate and stock price: evidence from multivariate cointegration and error correction model. *Review of Financial economics*, *12*(3), 301-313.

[21]. Kumar, M. (2013). Returns and volatility spillover between stock prices and exchange rates: Empirical evidence from IBSA countries. *International Journal of Emerging Markets*, *8*(2), 108-128.

[22]. Kumar, M. (2013). Returns and volatility spillover between stock prices and exchange rates: Empirical evidence from IBSA countries. *International Journal of Emerging Markets*, *8*(2), 108-128.

[23]. Kurihara, Y. (2006). The relationship between exchange rate and stock prices during the quantitative easing policy in Japan. *International Journal of Business*, *11*(4), 375.

[24]. Kutty, G. (2010). The relationship between exchange rates and stock prices: the case of Mexico. *North American Journal of Finance and Banking Research*, *4*(4), 1.

[25]. Li, Y., & Giles, D. E. (2015). Modelling volatility spillover effects between developed stock markets and asian emerging stock markets. *International Journal of Finance & Economics*, *20*(2), 155-177.

[26]. Ma, C. K., & Kao, G. W. (1990). On exchange rate changes and stock price reactions. *Journal of Business Finance & Accounting*, *17*(3), 441-449.

[27]. Miralles-Marcelo, J. L., Miralles-Quirós, J. L., &del Mar Miralles-Quirós, M. (2013). Multivariate GARCH models and risk minimizing portfolios: The importance of medium and small firms. *The Spanish Review of Financial Economics*, *11*(1), 29-38.

January - February 2020
ISSN: 0193 - 4120 Page No. 5004 - 5020

[28]. Mishra, A. K., Swain, N., & Malhotra, D. K. (2007). Volatility spillover between stock and foreign exchange markets: Indian evidence. *International Journal of Business*, *12*(3), 343.

[29]. Morales, L. D. L. N. (2008). Volatility Spillovers between Equity and Currency Markets: Eviderice from Major Latin American Countries. *Cuadernos de economía*, *45*(132), 185-215.

[30]. Mukherjee, K. N., & Mishra, R. K. (2008). Stock market integrafion and volafility spillover: India and its major Asian counterparts (Munich Personal RePEc Archive paper, No. 12788).

[31]. Omrane, W. B., &Hafner, C. (2015). Macroeconomic news surprises and volatility spillover in foreign exchange markets. *Empirical Economics*, *48*(2), 577-607.

[32]. Panda, P., &Deo, M. (2014). Asymmetric and Volatility Spillover Between Stock Market and Foreign Exchange Market: Indian Experience. *IUP Journal of Applied Finance*, *20*(4).

[33]. Qayyum, A., & Kemal, A. R. (2006). Volatility spillover between the stock market and the foreign exchange market in Pakistan.

[34]. Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, *34*(1), 248-255.

[35]. Saha, S., &Chakrabarti, G. (2011). Financial crisis and financial market volatility spill-over. *The international journal of Applied Economics and Finance*, *5*(3), 185-199.

[36]. Sahoo, S. (2012). Volatility transmission in the exchange rate of the Indian rupee. *RBI Bulletin Publications, https://rbidocs. rbi. org. in/rdocs/Publications/PDFs/08WPT220612FL . pdf, Accessed on August*, *24*, 2014.

[37]. Zhao, H. (2010). Dynamic relationship between exchange rate and stock price: Evidence from China. *Research in International Business and Finance*, *24*(2), 103-112.