CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Return & Volatility Transmission from Exchange Rate-to-Industries and Industries-to-Industries in Pakistan: An Evidence from ARMA & DCC-ADCC GARCH Models

by

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This thesis is dedicated to my parents & teachers, who are always a light for me in the dark and their unwavering support guided my Unfocused words into Coherent ideas.

CERTIFICATE OF APPROVAL

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Abstract

The purpose of this study is to investigate the return & volatility transmission from exchange rates-to-industries and industries-to-industries in Pakistan. The study employs the daily data of PKR/USD and average industrial indices of 14 industries for the period of 6/2000 to 6/2018. Return and volatility spillover is measured by using ARMA (1,1) GARCH (1,1)-M model for both exchange rates-to industries and industries-to-industries specifications. Moreover, the time-varying nature of conditional correlation is further explored by using DCC-ADCC models for both aspects as well. The findings of the study provide strong evidence of volatility transmission from exchange rate to various industries but limited evidence is found regarding return spillover. However, there found return and volatility spillover across different industries for the given time period which indicates the limited evidences of diversification. In addition, DCC GARCH also reveals the time-varying nature of conditional correlation. The results also show the presence of asymmetric behavior among different industries.

Keywords: Return & Volatility Spillovers, DCC, ADCC & Industrial Interdependencies.

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Abbreviations

EMH	Efficient Market Hypothesis
VAR	Vector Autoregressive
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
MV-GARCH	Multivariate GARCH
ARMA-GARCH	Autoregressive Moving Averages GARCH
GARCH-M	Generalized Autoregressive Conditional Heteroscedasticity In Mean
GJR-GARCH	Glosten-Jagannathan-Runkle GARCH
CCC	Constant Conditional Correlations
DCC	Dynamic Conditional Correlations
ADCC	Asymmetric Dynamic Conditional Correlations

Chapter 1

Introduction

Stock market behavior is assessed by the role of information either it is macroeconomic or firm-specific. Because investment in different securities or other financial assets is based on the information that different market participants use. Efficient Market Hypothesis (EMH) states that at a given point of time, any change occurs in the securities prices is fully reflected in the prices of other securities. But, the major issue for all people including insiders, outsiders, stakeholders and other market participants (including regulator) is the asymmetry of information in the market. To protect investors, the main objective of the regulator has always been the reduction of information asymmetry by using firm fundamentals. It is argued that, mandatory disclosure, controlling of financial information and effective corporate administration can reduce the information asymmetry (Frankel and Li, 2004). But the point is still there that, all information concerned with the industry factors, market factors, and firm-specific factors is fully uncovered by stock prices of a firm.

Over the last few years, it has been observed that stocks, industries, and markets are becoming more and more synchronized. In recent times of global economic uncertainty, it has been confirmed that stock markets are operating no more in isolation and have gone beyond their fundamental linkage. This is just because of the quick transmission of information from one market to another and the linkage of the global financial system, that turns the coordinated actions a reality in modern financial markets. Investment in different asset classes either across sectors or investing abroad gives the benefits of portfolio diversification. This strategy provides a clear theoretical and empirical framework to the investors, that the correlation between sectors is not only constant, as it can be changed (dynamic) at any time on the happening of certain events. In the times of global financial crises, it is seen that the stock markets generally show a system-wide movement that reflects the benefits of diversification when it is most.

Exchange rates fluctuation (appreciation or depreciation) has also been a matter of concern for many economists and policy practitioners (Wesseh Jr and Niu, 2012). Some authors argue that long run trade can be improved when the currency depreciates and some argue otherwise (Bahmani-Oskooee and Alse, 1994). A number of researchers have conducted studies to explore the dynamic connection between industrial returns and exchange rate movements. This linkage is further debated in the literature of financial economics on two potential theoretical backgrounds. Firstly, the pioneer study by Dornbusch and Fischer (1980) describes from a flow-oriented model, that firm competitiveness is strengthened by the depreciation of domestic currency which in turn leads to increase their exports and future expected cash flows that ultimately affect the industry as a whole. Secondly, the stock-oriented models of exchange rate determination (also called the portfolio balance approach) established a relationship between prices and exchange rates (Branson, 1983; Frankel, 1992). The profitability of domestic industries is directly related to the fluctuations in exchange rates. Any change occurred in the prices with the fluctuations in exchange rate may be due to (a) change the terms of rivalry with outside firms for local exporters and import competitors, (b) change the input costs for industries that use internationally priced input, and (c) modify the estimation of advantages designated in foreign currency standards. Due to these adverse arrangements of impacts, exchange rate movements influence few industries directly than others, while the effect of exchange rate variations on an industry ought to depend fundamentally on the industrys connection with the rest of the world economy.

Understanding what normally compares to magnified exchange rates explicit and industry-specific relationships and transmission could furnish financial specialists and investment institutes with important experiences for the optimization of the portfolio to reduce the risk i.e. diversification techniques. Investors, who rely on the past estimates of correlations can get benefits to use the guidance from the portfolio diversification and make efficient decisions. This study focused on analyzing the impact of exchange rate fluctuations in recent years on the industries of one of the important emerging markets, Pakistan. Moreover, the study also focuses specifically on the dynamic nature of such fluctuations or transmission in the domestic market across the main industries of Pakistan. A solid connection between them would have critical implications for monetary approaches and international capital budgeting choices since negative shocks influencing one market might be transmitted rapidly to another through contagious impact either pretty much or less.

1.1 Theoretical Background

1.1.1 Efficient Market Hypothesis

In modern finance, a lot of attention has been given to the Stock market efficiency from different economists and practitioners. Modern financial markets assume that the market are effective. The term efficiency creates a link between information and stock prices. In this context, the EMH proposed that there exists timely and rapid incorporation of information to the stock prices. So, every investor gets the desired returns from the investment (Reilly and Brown, 2011). According to Malkiel and Fama (1970) the allocation of resources is based on the decision of fair price discovery that can only be done when markets are efficient and reflect all relevant information. So, the assessment of the behavior of the stock market is considered very important.

Dyckman and Morse (1986) state that, "***An efficient security market is a market if (a) the price of the traded security fully shows the all available information (b) these prices react immediately and in an***

un-bias form to new information". On the other hand, there is a chance that prices can mislead the investors and will further effect the decision making process of the selection of securities. So, the element of market inefficiency can prevail in the market and reject the EMH (Aumeboonsuke and Dryver, 2014).

On the basis of the theoretical framework of EMH, Bachelier (1900) argued that the variations in commodity prices are random in nature. The study shows that all periodic events are covered by market prices however, it doesn't indicate a clear association with price changes. Samuelson et al. (1965) expanded the work of Bachelier and started a new debate in modern economics. It states that, if one could make certain that a price would rise, it would have effectively risen.

The criticism on the idea of EMH was presented by Malkiel in (2003) that stock prices cannot be predicted; and gave his argument about the partial prediction of the stock prices (Malkiel, 2003). In response to Famas study that states ***"prices adjust with the arrival of new information and spread speedily without any delay"***. Malkiel argues that ***"if information flow is speedily reflected in the stock prices then there is no link between todays price and tomorrows price because they are totally independent"***. In this manner, technical analysis just examines the past price change to anticipate future prices and fundamental analysis just helps the investors to make the comparison based on profit, cash flows and other attributes of a firm. It doesnt support the argument that markets are fully efficient, because of the presence of lesser rationality in some market participants. The quick incorporation of information in stock prices cannot be uncovered by professionals and experts (Grossman and Stiglitz, 1980).

The theory of market efficiency strongly supports this study. Efficient market hypothesis (EMH) talks about the precise reflection of information from the prices at any point of time in the same way. On the basis of this information, when market participants and professionals predict that the prices will increase in near future, they will adjust their costs appropriately so that there will not be a huge effect on the firm's market value. On the other hand, if there found a high level of probability in the world market, it is very hard to modify their costs adequately.

So, if information arises in the prices of any market, then ultimately it will transmit the effects in the prices of other markets.

1.2 Gap Analysis

A number of studies have been investigated extensively in the literature of financial economics on spillover effects in financial markets. Most of the studies illuminate on analyzing return and volatility linkage across countries but for identical assets. However, there exists a contextual gap that the spillover effect across industries of Pakistan is still unexplored. Similarly, the spillover transmission from the exchange rate to the market is available but the evidence on the transmission of information from the exchange rate to industries is also missing in Pakistan. Moreover, with the passage of time if its becoming the part of emerging markets or frontier markets and there is an interest of people then the insight of this phenomenon can be increased. So this research provides a gateway to future researchers in a new domain.

1.3 Statement of Problem

Understanding the link between exchange rates and various industries has become critical since the cooperation between them will influence both the import and export of a country. In previous studies, most of the researchers showed that information created in one market immediately transmits to the other market through contagion effect. So, any information raised in one market influences the mean and volatility of other markets (Hamao et al., 1990; King and Wadhwani, 1990; Engle and Susmel, 1993; Lin et al., 1994; Karolyi, 1995; Nieh and Lee, 2001; Franck and Young, 1972; Pan et al., 2007). Apart from this, with the passage of time, industries are also no more in isolation and getting closer to each other. This phenomenon is widely seen in emerging markets that indicates, there also exists a relationship between mean and volatility linkage across different industries. Most of the previous literature shows that the information about the co-movement between different markets is already studied. Moreover, the past literature also tells that the spillover effects are mostly seen across different countries or regions. Information about exchange rate-to-market and industry-to-market is available but the evidence on exchange rate specific and industry-specific information is inconclusive especially in emerging markets i.e. Pakistan. So, the debate on the response of these types of transmission of information is still unexplored.

1.4 Research Questions

This research will answer the following questions:

Research Question 1

How information created in the exchange market transmit to the various industries in Pakistan?

Research Question 2

How information created in one industry transmits to the other industries in Pakistan?

Research Question 3

Is correlation among exchange rate and different industries time-varying?

Research Question 4

Is correlation among different industries time-varying?

Research Question 5

Does the correlation between exchange rate and different industries show asymmetric behavior?

Research Question 6

Does the correlation among different industries show asymmetric behavior?

Research Question 7

Is there any interdependence of industries in Pakistan?

1.5 Research Objectives

Objectives of the study are as follows:

Research Objective 1

To explore the return and volatility spillover from the exchange rate to various industries in Pakistan.

Research Objective 2

To analyze the return and volatility spillover across different industries in Pakistan.

Research Objective 3

To explore the possibility of dynamic conditional correlation between exchange rate and various industries.

Research Objective 4

To analyze the possibility of dynamic conditional correlation across different industries.

Research Objective 5

To explore the asymmetric behavior of conditional correlation between exchange rate and different industries.

Research Objective 6

To analyze the asymmetric behavior of conditional correlation across different industries.

Research Objective 7

To facilitate the market participant about the inter-dependencies of different industries in Pakistan.

1.6 Significance of the Study

The purpose of this research is to examine the return and volatility spillover effect from exchange rate to various industries and across different industries as well. The importance of this study is mentioned below:

As we know, Pakistan is an emerging market. From the last previous years, it has been again included in the category of emerging markets. Due to this, the interest of foreign investors to invest in the Pakistani stock markets is increasing. Moreover, most of the shares of the stock market are owned by China that also encouraged a huge amount of investment from many international investors because they foresee many international activities in this market. So, this situation demands that the information about the dynamics of this emerging market must be provided to potential investors for the purpose of efficient decision making.

Moreover, when investment from China will come then there will be a huge increase in the economic activities in various industries of Pakistan. The expectations related to different industries are that their future expected cash flows will also increase. So, either these industries work in isolation or one industry is connected with other industries, this study will explore these phenomena.

In addition, when we talk about an emerging market like Pakistan, then a higher volatility is seen in Pakistani currency market. Unfortunately, a sharp decline is followed in the currency market of Pakistan from previous 10 to 15 years. In recent years, a trend of 20% to 30% depreciation is found in this market. This variation in currency market is also integrated with all macroeconomic dynamics and prices. So, this high volatile period demands to revisit the pattern of this currency market once again.

Finally, when we talk about investors of the market, then the main objective of every investor is diversification. As diversification demands the cross industries investments, so it is important to see that which industries are providing diversification benefits with each others. The opposite direction of spillover can be used to determine that, which industries are better for diversification.

1.7 Plan of the Study

Chapter 1 provides the introduction, Theoretical Background, Gap Analysis, Problem Statement, Questions, Objectives and Significance of the Research. Chapter 2 includes the literature reviews of the past studies and hypotheses for the study. Chapter 3 covers the research methodology of the current research study. Data analysis and results are covered in Chapter 4. Finally, Chapter 5 covers the conclusion, recommendations and limitation of the current research study.

Chapter 2

Literature Review

International financial markets are the result of enhanced globalization and financial markets players are more conscious about that, how mean and volatility spillover or the transformation of shocks from one market to another market takes place over time. This transmission mechanism is also highlighted in some important paper that includes Hamao et al. (1990), King and Wadhwani (1990), Engle and Susmel (1993), Lin et al. (1994), Karolyi (1995). However, there exists a lack in the previous literature that most of these studies are done on some particular financial markets but dont provide the information regarding mean and volatility spillover or shocks transmission across industrial returns. As due to more globalization, the financial markets are coming more closer to each other, so it demands that there must exist some studies or research on how information about the movement of stocks and stock markets transmits from one market to other markets. These studies are being further used by different policymakers and practitioners to make the process of decision making regarding asset pricing, strategies for trading and hedging more effectively.

Globalization results in the linkage of emerging markets that further improves the accessibility to the capital markets at an international level. Strong global linkage diminishes the protection of the emerging securities exchanges from outside shocks, in this manner restricting the degree for fair financial policies (Li and Majerowska, 2007). From the international investors point of view, weak stock market linkage in the structure of considerably less than the best relationship between their profits gives conceivable additions from worldwide portfolio expansion, whereas advantages of diversification are eliminated through strong market linkage or co-movement in the returns. It is believed that an unwanted event in any market influences the return and volatility of the other markets either more or less. Sometimes the shocks created in one market transfers in only one aspect to the other markets i.e. mean or volatility. As the volatility spillover is often used as a proxy for risky assets, so the analysis of volatility is particularly important than mean or return spillover.

2.1 Return & Volatility Relationship Between Exchange Rate and Industries

An exchange rate is the price of a nation's currency in terms of another currency (Oxford dictionaries online, 2017). The change in the exchange rates is linked with the conversion of the currency and it continues to fluctuate until it reaches an equilibrium point. These movements are known as risk variation and risk associated with exchange rates deals with the fluctuations in the appreciation or depreciation of foreign currencies, which further impacts the stability and performance of a country. An exchange rate is affected by various macroeconomic factors such as prices of stock, treasury bill rates, discount rate, an increase or decrease in the general price levels and oil prices. In previous literature, numerous studies are conducted to explain the linkage between exchange rates and other macroeconomic variables or factors.

According to traditional theories, there exists a lead-lag relationship between the exchange rate and stock prices. But on the other side, the portfolio balance approach states that market mechanism determines exchange rates. It means exchange rate movements are being affected by the changes in stock prices. According to this approach, stock prices lead the exchange rates having a negative association because lower the domestic money demand and interest rates are caused by the reduction in domestic wealth and a decrease in the stock prices as well. The demand of the different investors for domestic assets and domestic currencies also becomes lower due to a decrease in domestic stock prices. So as a result, variations in the mechanism of demand and supply cause the domestic currency to depreciate and capital outflow takes place. In contrast, the willingness of foreign investors to invest in a countrys equity securities rises because of the increase in security prices. Thus, the international diversification takes place and investors get benefits from it. In result, these types of mechanism cause the currency to appreciate and capital inflows take place as well (Granger et al., 2000; Caporale et al., 2002; Stavarek, 2005; Pan et al., 2007).

Stock prices of the various firms either multinational, domestic or export-oriented also affected by the exchange rates. Changes in exchange rates immediately affect all of the financial statements like; statement of cash flow, statement of changes in owners equity, statement of financial position and statement of income of a multinational company in foreign countries. Thats why the stock prices get influenced by the change in the value of a firms foreign operations. There also exists a relationship between domestic firms and exchange rates as their particular portion of the output is based on the inputs that they import from other countries.

Most of the previous studies provide evidence on the relationship between exchange rates and stock market returns. In prior studies, the relationship between two variables is only discussed by using the basic statistical models e.g. Regression and Correlation analyses. Using monthly data of effective exchange rates and stock market indices of the U.S., a study done by Soenen and Hennigar (1988) for the period of 1980 to 1986 shows that, these two variables are negatively related to each other or they have a strong negative correlation between them. These authors argue that the competitiveness of the international firms and operational activities of businesses are negatively related to the volatility in the exchange rates. The link between exchange rates and stock prices is further explored by Pan et al. (2007) in 7 countries of East Asian during the period of 1988 to 1998. Using a VAR model, their results show a significant relationship between FX and other stock markets. The results of the direction of the causality from last to the previous are the same for some countries like Hong Kong, Korea, and Singapore and previous to the last for all other countries except Malaysia.

Nieh and Lee (2001) use the daily data of stock market indices and currency rates for the period of 1993 to 1996 and discuss the relationship between exchange rates and stock market indices for G-7 countries. They show that stock prices and exchange rates dont exhibit any long-run relationship in G-7 countries. While they also argue that some of these G-7 countries show a one days short run significant relationship, there exists no correlation in the U.S. These results are dependent on each countrys specific demographics and political environment and conditions that tend them to change after some time. In other words, these results or conclusions are flexible and influenced by the arrival of the new information in the market.

Using the daily data from 1985 to 1991, another work done by Ajayi and Mougouė (1996) in which they show a significant link between exchange rates and other stock market indices in 8 advanced countries. The results reveal that there exists a short run and long-run relationship between the currency market and stock indices. Domestic currency value reflects a positive long run as well as a negative short-run effect by an increase in the price of stocks. Also, the stock markets reflect both the long run and short rum effects by the devaluation of the currency. The difference between the nature of economies and the orientation of import and export dominant countries is discussed by Ma and Kao (1990). They argue that the stock market has a negative relationship with the depreciation of currency only for the export dominant country. While on the other side, this effect is totally vice versa between the exchange rates and stock market indices in an import dominant country.

Chiang et al. (2000) in their study find that there exists a direct association between the value of the national currency and stock returns of national firms of Asian countries. Similarly, the characteristics of emerging stock markets are being evaluated by Rashid Sabri (2004) to use as an indicator of stock return volatility and instability in emerging markets. The study reveals that a positive correlation to the change in the prices of emerging stocks is the representation of currency exchange rates and stock trading volume. The scope of the research in terms of volatility spillover is gone beyond the boundaries of stock markets. Also, a lot of work is being done in other domains of financial markets like foreign exchange, futures markets, and cash markets.

Kanas (2000) study the interrelationship between exchange rates and stock market returns of six industrialized group of countries i.e. U.S., U.K., Japan, Germany, Canada, and France. His study concludes the following points: (i) exchange rate and stock market returns co-move with each other; (ii) the spillover is found significant in all countries from stock market returns to exchange rates except Germany; (iii) there exists a asymmetric behavior of the spillover from stock market returns to exchange rates; (iv) the shocks of volatility from one market to other markets (i.e. stock market returns to exchange rates) is found insignificant for all countries; (v) when the model of EGARCH is applied on these two series, then there found a significant negative coefficient of correlation for all countries, which shows that there exist a contagion effects between these two series of returns i.e. stock market returns and exchange rates.

In another study, it is seen that the diversified portfolio of the U.S. stock market is being affected by both first and second order effects of exchange rates (Alaganar and Bhar, 2007)In their study, they use the data of weekly returns of 16 World Equity Benchmark Series (WEBS) in which each WEBS represents a diversified portfolio of foreign stock market rather than the U.S. share market. They use two techniques in their study in which the diversification technique is applied on each WEB series while the tracking performance of a foreign country through WEBS in only traded in U.S. Dollars by using Morgan Stanley Capital International (MSCI) index. Alaganar and Bhar check the dependence of diversified country index portfolios on exchange rates volatility by using GJR & GARCH-M models. They find that the uncertainty in the exchange rate is derived from the WEBS returns as a pricing factor. They also report that the stock market diversification is triggered by the information of the second moment of exchange rates.

Bodart and Reding (2001) study the linkage between exchange rates and expected sectoral returns. They find that there exists a positive mean and volatility spillover from exchange rates to sectoral returns but the intensity of this effect is quite less. They also report that the exchange rate regime, the intensity and the direction of the transmission of information has a significant influence on the spillover of exchange rates. The individual firms returns are explained in a study by Chen et al. (2004) in which they use exchange rate changes and market returns as factors in a two-factor model approach. The empirical findings of this study show that exchange rate exposure has a significant impact on the returns of the firms in the sample. This paper is quite different from a previous study done by Chen et al. in which they focus the volatility spillover between the currency market and stock market returns of New Zealand.

The study of Wenshwo and Miller (2002) covers the empirical findings for the era of financial crises of 1997 to 2000 in the Korean stock market. Their study concludes the following points: (i) Korean stock market and Korean foreign exchange market operate in a bi-directional causal relationship; (ii) there exists a negative relationship between the stock market returns and the level of exchange rate depreciation; a positive relationship is also found between the volatility of the exchange rate depreciation and stock market returns; and the volatilities of these both markets are interconnected and responds to each other.

In some Asian countries, Chiang et al. (2007) find a positive connection between these two variables i.e. exchange rates and stock market returns. Using the recent Asian data, they use two basic models to check the Granger Causality between these two variables; the first one is the basic unit root test and second is the cointegration approach. By employing the impulse response technique they show that exchange rates Granger Cause the stock prices for South Korea. On the other side, the results or findings for the Philippines, seem to be totally opposite but consistent with a portfolio approach, as the stock prices Granger causes the exchange rates with a negative correlation (Granger et al., 2000) A strong linkage is also attained by the data from Hong Kong, Malaysia, Singapore, Thailand, and Taiwan.

A study based on 5 major European countries is conducted by Aloui (2007) in which he examines the relationship between equity and currency markets. The model that is used in this study is the EGARCH model in which he finds the bi-directional flow of volatility spillover between equity and currency market. In this study, he also finds the evidence about the persistence of the volatility that is more in equity prices as compared to the currency market. Moreover, his study uses the EGARCH model to determine the movement of these two series on the basis of two periods e.g. pre and post euro periods. However, the influence of the exchange rates on the stock market is found less in both periods.

Similarly, in India, Mishra et al. (2007) investigate the same relation between two financial markets that is currency and equity markets. Their analyses also reveal that there exists a flow of bi-directional shocks from one financial market (currency market) to another financial market (equity returns). In the past recent years, the same findings are also reported by various authors e.g. (Kumar, 2013; Panda and Deo, 2014). in their studies with special reference to India. In New Zealand, Choi et al. (2009) also empirically reports the same transmission mechanism between exchange rates and stock market returns. Their results are also consistent with the findings reported by (Kumar, 2013; Panda and Deo, 2014) that, there exists a bi-directional flow of shocks of volatility from one market to other markets.

Bernanke and Kuttner (2005) study the relationship dynamics between monetary policy and stock prices that reveal the conceivable financial sources of the complete effect. Their study finds that an unforeseen 25 basis points cut in the government funds target rate give an expansion generally stock indices by 1%. Their study also discusses the effects of monetary policy on other industries in which they conclude that the effect of monetary policy is more on the individual stocks as more as compared to the broad indices.

For the period of 1990 to 2003, the study done by Mun (2007) documents that, how the variations in exchange rates influence the correlation in stock markets and volatility. He finds that local stock market volatility is more affected by the variations in the high FX rate but this effect is seen less in the U.S. stock markets. Furthermore, if the variations in the exchange rates are more, then there will be less correlation between the U.S. and the local stock market. Yang and Doong (2004) use a Multivariate Exponential GARCH model to examine the volatility transmission between exchange rates and stock prices in G-7 countries for the period of 1979 to 1999. A direct relationship is found between these two variables from the reported results of this study.

Lin et al. (1994) resemble this transmission of volatility from one market to another market as a meteor shower, while Ross (1989) argues that volatility in stock returns is derived from the rate of information flow. Since the time required for the process of information and the rate of information flow is different for each sector or market, so one should be clear that the different pattern of the volatility can be observed over the time. With the passage of time, as the globalization and financial integration is becoming more vital in the financial markets, so there found a keen interest between different market participants to understand the transmission mechanism of the volatility across different markets, regions, and countries. These changes in the volatility of one market transmitted to the other market also alter the expectations of the different people across different markets.

In previous literature, the Granger causality analysis gives some mixed evidence on the interaction between stock prices and exchange rates. A study is done by Abdalla and Murinde (1997) in India, Pakistan, Korea, and the Philippines reveals that there exists a lead-lag connection between exchange rates and stock prices. Their results show that exchange rates Granger causes the stock prices or in other words, exchange rates lead the stock prices. In contrast, a unidirectional causality relationship is found by Pan et al. (2007) between these two variables. Moreover, using the data of 4 countries; Indonesia, Philippines, Singapore and Thailand, Harjito and McGowan Jr (2007) examines the causal relationship between exchange rates and stock prices. Their results also conclude that exchange rates lead the stock prices or exchange rates Granger causes the stock prices in the following countries.

Apart from this, the relationship between stock returns and currency market is also discussed from another point of view. In some studies, this relationship is discussed through the impact on the currency market of capital inflows that are generated by the changes in global equity portfolio investments. Thus, Froot et al. (2001) and Richards (2005) documents that the capital inflows show a direct and significant positive relationship with stock returns - particularly in the emerging markets that further strengthen the link between stock and currency values in financial markets of these emerging economies. In recent years, Cho et al. (2015) report that the stock market characteristics and behavior depend upon the movement of capital inflows and outflows in emerging economies especially in the recessionary period.

The comparison of exchange rate sensitivity with respect to the banking sectors of two countries i.e. U.S. Bank and Japanese Bank is done by Chamberlain et al. (1997) in which they use both monthly and daily data. In their study, they found the partial co-movement of the banking companies with the changing exchange rates i.e. stock returns of a small portion of U.S. banking firms change with the exchange rate and only a few banks of Japan also move with the change in the exchange rates.

Using a three index model,Choi et al. (1992) and Wetmore and Brick (1994) assessed the effect of markets by bank stock returns, exchange rate and interest rate factors under the assumption of constant variance error terms. Even the results of Choi et al. (1992) give more focus on the sensitivity of interest rather than the exchange rates sensitivity, Wetmore and Brick (1994) examines the opposite and controversial results for U.S. banks. Additionally, when the same three index model is applied to the Korean banks for return generating process, Hahm (2004) also finds the sensitivity link between stock returns and those other factors.

Kasman et al. (2011) report that there exists a significant negative relationship of interest rates and exchange rates with conditional stock returns of banks. In addition, market returns are found to be more sensitive with bank stock returns as compared to the interest rates and exchange rates, which shows that the fundamentals of the bank stock returns are determined by the market returns. Their result also indicates that the volatility of the bank stock returns is determined by the volatility of interest rates and exchange rates. Hence, all the evidence that is presented in their study can help interested participants to examine the observable bank characteristics and diversify their risk exposure. Overall, the findings of their study are found to be strong and vigorous only in case of emerging markets like Turkey in which interest rate risk and exchange rate risk are not controlled by using derivative markets or hedging.

Using a multivariate Granger causality test, Darrat (1990) examines the efficiency of the Canadian stock market and finds that its expected returns are constant over time. This study reveals that the Canadian stock market makes some necessary adjustments with the arrival of new information regarding the monetary policy in the market. In addition, Kwon and Shin (1999) find that the stock market of Korea and other macroeconomic variables like; interest rates, inflation, exchange rate, production, the balance of trade co-move with each other. They use Granger causality and co-integration technique to observe the lead-lag relationship and co-movement of the series, respectively.

By employing the co-integration technique for the monthly time series data from 1987 to 2000, Maghayereh (2003) reports the long run relationship between the stock market and other macroeconomic variables in the Jordanian financial market. This study encompasses the effects of macroeconomic variables like; exchange rates, inflation, industrial production, discount rates on prices of the Jordanian stock market. The results show that there exists a significant positive relationship between these macroeconomic variables and the stock market as they can be used as a predicting factor for the forecasting of stock prices.

Using the Ljung-Box Q test, Breusch-Godfrey LM test, Unit root test, and Granger causality test, Tripathy (2011) documents the linkage between the Indian stock market and other macroeconomic factors such as discount rate, money supply, exchange rates etc. for the time period of 2005 to 2011. The test shows that the Indian stock market has a bi-directional relationship with exchange rates, discount rates, and international markets. Moreover, this study also confirms that there exists a significant relationship between exchange rates, interest rate and international markets on stock prices of India.

In another study, Naik and Padhi (2012) find that various macroeconomic variables like; risk-free rate, money supply, consumer price index and exchange rates are found to be positively linked with the Indian stock market (BSE SENSEX) from the period of 1994 to 2011. The results show that both series co-move with each other with an individual macroeconomic variable and also confirm the long run relationship between them.

Luthra and Mahajan (2014) examine the relationship between BSE BANKEX and other macroeconomic variables such as; GDP, inflation, metal prices and exchange rates. BSE BANKEX is a limited launch of Bombay stock exchange, mostly includes major private and public sector banks. The results of this study conclude that BSE BANKEX reflects a significant positive relationship with GDP, inflation and exchange rates, while there exists no relationship between BANKEX and metal prices.

In New Zealand, a study conducted by Gan et al. (2006) report the same relationship between the stock market and other macroeconomic variables. They use different macroeconomic variables like discount rate, inflation, circulation of money, WTI oil futures and exchange rates in the long and short run. In conclusion, they report that there exists a long term connection between stock prices and macroeconomic variables but only for some specific variables in New Zealand. However, the stock exchange of New Zealand proves a bad indicator for different macroeconomic variables, when Granger causality test is applied.

Keeping the above studies in concern, Islam (2003) conducts the same research to determine the short run and long-run equilibrium relationship between the Kuala Lumpur stock exchange (KLSE) index and 4 macroeconomic variables i.e. discount rate, exchange rate, inflation a sectoral production. He also reports the same results: KLSE stock returns and other macroeconomic variables exhibit a statistically significant relationship between them with respect to the short run (dynamic) and long rum (equilibrium).

Ibrahim (1999) extends the work of Islam (2003) by adding more macroeconomic variables in his study to investigates the dynamic linkage between the KLSE stock index and 7 other macroeconomic variables. He investigates the dynamic interactions between the KLSE Composite Index, and seven macroeconomic variables (industrial production, money supply M1 and M2, consumer price index, foreign reserves, credit totals, and exchange rate). Moreover, after analyzing these macroeconomic variables, he also confirms that the Malaysian stock market is an inefficient market.

Muhammad et al. (2002) use the monthly data from 1994 to 2000 and investigates the relationship between stock prices and exchange rates for Asian Markets including the following countries; Pakistan, Sri Lanka, India, and Bangladesh. Their results show a long-run bi-directional causal relationship between stock markets and exchange rates only in two countries, Bangladesh and Sri Lanka. While no significant relationship is found in sub-continent countries i.e. Pakistan and India.

Husain (2006) also reports a causal relationship between sectoral variables of the Pakistan economy and stock prices. The data set is divided into two halves; the first one is pre-liberalization and second is post liberalization for the period of 1959-60 to 2004-05. Using the annual data for both halves, he confirms the causal relationship between sectoral variables of the Pakistan economy and the stock market. In his study, he uses the various econometric and statistical models like; error correction model-ECM, Granger causality technique, and regression analyses and Augmented Dicky Fuller ADF Unit Root test. In the conclusion of his study, he also finds the long run relationship between stock prices and other sectoral variables.

Using the Johansen and Juselius JJ approach, Mukherjee and Naka (1995) examine the Vector Error Correction Model VECM linkage between the stock market and other macroeconomic variables (exchange rates, inflation, money supply, government bond rate and call rate) in Japan. They report that there exists a long run relationship between these two variables and stock market co-move with other macroeconomic factors. Maysami and Koh (2000) document the same relationship for the Singapore stock market. They found the evidence of co-integration relationship between the Singapore stock market and other variables such as; circulation of money, short term and long term interest rate, inflation and fluctuations in exchange rates. So, they also find the evidence of correlation between these prescribed variables used in their study.

In Cyprus, a study done by Tsoukalas (2003) investigates the relationship between the security market and other macroeconomic variables. The linkage between the security market and the exchange rate (taken as a macroeconomic variable) is found to be significant in Cyprus. The possible reason for these results can be the behavior of the Cyprus economy that totally depends on the services sectors like; tourism and offshore banking etc. In Japan, Kurihara (2006) uses the daily data of stock prices and exhibits a strong association between stock prices and other macroeconomic variables for the time period of 2001 to 2005. The variables that he employs in his study are as follows; (i) the Japanese stock prices, (ii) stock prices of U.S., (iii) exchange rate (/$), and (iv) the Japanese interest rate etc. The findings of his study show that stock prices are not affected by the change of the domestic interest rate. However, there exists a link between the exchange rate, U.S. stock prices and Japanese stock prices that the Japanese stock prices change if any fluctuations arise in the exchange rate and U.S. stock prices.

Doong et al. (2005) choose the time frame of 1989 to 2003 in which he examines the dynamic linkage between exchange rates and stock prices for six Asian countries (Indonesia, Malaysia, Philippines, South Korea, Thailand, and Taiwan). Their result s found no relationship between these variables. In other words, these both variable are not co-integrated with each other. A bidirectional Granger causality is found to be significant with respect to four countries; Indonesia, Korea, Malaysia, and Thailand. Additionally, the contemporaneous fluctuations in exchange rates are found to be negatively linked with stock returns for all countries except Thailand.

Another side of the literature also discusses the transmission of information or connection between the two most important macroeconomic variables i.e. Exchange Rates and Oil Prices. For the time period starting from 1996 to 2014, Li et al. (2016) use the daily data and examine the linkage between these two variables. The data set of this study is comprised on the 5 sample currencies, which include, Australia (AUD), Canada (CAD), Mexico (MXN), Russia (RUB), and South Africa (ZAR). They use the Multi-fractal detrended cross-correlation analysis (MF-DCCA) analysis in their study. They report that there exists a cross-correlation between these two macroeconomic variables. Novotnỳ et al. (2012) uses the monthly data set for the period of 1982 to 2010 and investigates a negative relationship between Brent Fuel prices and the U.S. exchange rate by using Granger causality technique in his research. The findings of his study reveal that the variations in the oil prices affect the exchange rates in a two-way flow of influence i.e. in both directions.

From the all above-mentioned studies, it is clear that there are no limits of literature on financial integration and relationships between different macroeconomic variables but, the studies on the behavior of emerging markets like Pakistan are scarce or limited. In addition, the previous studies on the emerging stock markets of Asia just only study about the co-movements between the series using Co-integration, Vector Auto-regression framework and Granger Causality (Ahmad et al., 2005; Bhattacharya and Samanta, 2003; Eun and Shim, 1989; Al Asad Bin Hoque, 2007; Voronkova, 2004; Wong et al., 2005; Yang et al., 2006). All of these studies do not explore the interactions of macroeconomic variables in terms of return and volatility spillover among the markets of a specific country. Moreover, there is also a lack of information regarding the impact of macroeconomic variables with the behavior of each industrial returns, individually.

2.2 Return & Volatility Relationship Across the Industries

The performance of stocks is grouped by some particular markets that is summarized by sectoral indices. Investors use these summarization as a benchmark to evaluate the performance of specific stock or market. Growth and development of a country is measured by using these sectoral indices. There are many factors that play a vital role in the development of Pakistani stock market such as; Pakistani stock exchange and other intermediaries, size, volume of trading, total number of listed stock at Pakistani stock exchange, stock indices and stock turnovers.

In past, the interaction between different markets and industries is documented by many researcher in their studies. Using the monthly time frequency of S&P stock indices from 1988 to 1997, Ewing (2002) studies the interdependent relationship between 5 industrial sectors (capital goods, financial, utilities, industrials and transportation) by employing the Vector Auto-regressive framework VAR and generalized forecast error variance decomposition techniques. In his study he reports that, any shocks or unexpected new in one sector significantly effect the mean and volatility of the other sectors. In addition, for the post crises period of 1987, Ewing et al. (2003) investigate the linkage between macroeconomic variables and other 5 major sectors listed at S&P 500 stock exchange. Moreover, they also find an influence of the unexpected macroeconomic variables on individual securities prices rather than some expected events.

In another study, the relationship across and within the sectors listed on two stock exchanges of China e.g. Shanghai and Shenzhen is reported by Wang et al. (2005) for the period chosen from 1994 to 2001. Mean and volatility spillover across sectors is also documented by Hassan and Malik (2007) in which they use a multivariate GARCH model on daily returns of the different U.S. industrial indices from the period of 1992 to 2005. The results of their study show that the transmission of shocks in terms of mean returns and volatility is significant from one industry to other industries. Li and Majerowska (2008) use BEEK GARCH estimation to investigate the relationship between the stock markets of emerging and developed countries. They conclude that, there exists return and volatility spillover from developed markets to emerging markets, proposing that the risk exposure of foreign investor can be reduced by extending their portfolio with the inclusion of stocks traded in emerging markets.

Harrison and Moore (2009) use the co integration technique in their study to investigate the relationship between the stock markets of emerging countries of Central & Eastern Europe and developed countries of Western Europe. They employ the MGARCH models to determine the return and volatility spillover between the markets. In addition, Malik and Ewing (2009) chose the period of 1992 to 2008 to examine the mean and volatility spillover between 5 different

U.S. industries with a major macroeconomic variable i.e. oil prices. They use the weekly return data of oil prices with other 5 industrial indices and employ bi-variate GARCH models for their results estimation. Their results are found to be significant in a sense that, the transmission of information from oil prices effects the return and volatility of some other sectors or industries.

Using the Baba, Engle, Kraft, and Kroner BEKK & Asymmetric Baba, Engle, Kraft, and Kroner BEKK models, Karmakar (2010) examines the effects of mean and volatility spillover between small and large stocks in Indian market. Bubák et al. (2011) use the intraday data to determine the dynamic linkage of volatility spillover between the foreign exchange rate (/$) and Central European currencies by employing the model-free estimates of daily exchange rate volatility. The results of their study reveals that there exists a intra-regional volatility spillover across the markets of CE foreign exchange. Hammoudeh et al. (2009) investigate the transmission of shocks and volatility spillover across there sectors in Saudi Arabia, Qatar, Kuwait and U.A.E. by using multivariate VAR-GARCH model. Moreover, the effect spillover relationship across different sectors listed on Amman stock is assessed in the study of Al-Fayoumi et al. (2009) by using Error Correction Model ECM.

Scheicher (2001) applies the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) with a constant conditional correlation in his study to examine the effects of return and volatility spillover with respect to global and regional integration of stock markets in Hungary, Poland, and Czech Republic and Standard & Poor (S&P)s world index. He chooses the period of 1995 to 1997 and use daily return data of stock prices. The results show that there exists a link between emerging stock markets and global market in terms of only mean spillover proxies by S&Ps world index. Moreover, the international volatility exhibit no effect on the regional and global markets, while the estimation of MGARCH provide the evidence that the regional influences are reason of volatility of the market.

During 1991 to 1994, Chou et al. (1999) determine the relationship with respect to return and volatility between Taiwan stock exchange and U.S. stock market using; close-to-open, open-to-close, and close-to-close returns of indices of Taiwan probably known as Taikex and U.S.s S&Ps 500 index. The results show that the transmission of information regarding volatility flow from U.S. to Taiwan. Apart from this, some important linkage is also found from one market (United States) to other market (Taiwan) when MGARCH models is applied. There exists both spillover for Taiwan stock market i.e. mean and volatility spillover. In addition, the total daily volatilities of Taiwan stock markets are also effected by the volatility in the U.S. stock markets.

Using the time frame of 1987 to 1989, Karolyi (1995) investigates the dynamic linkage of short run returns and volatilities of the stock that are traded on New York stock exchange and Toronto stock exchange of Canada. In his study, he use the Vector Auto-regressive Model VAR and MGARCH for time series data (daily) of stock market indices with respect to both local currencies like; S&P 500 & TSE 300. He concludes that, the transmission mechanism reflects the flow of information or the spillover of shocks is from S&P 500 to TSE 300. For the measurement of the shocks effects from one market to another market is done by using MGARCH models that are less smaller and sustainable.

To examine the effect of means and volatility transmission between Financial Times Stock Exchange (FTSE) 100, FTSE 200, and FTSE small cap equity indices of U.K., Harris and Pisedtasalasai (2006) use Constant Conditional Correlation MGARCH models in their study by using daily returns for the sample period of 1986 to 2002. In their study, they apply Glosten et al. (1993) approach GJR-GARCH to capture the effects of any asymmetry between the series. In conclusion, they find the evidence of asymmetric behavior between the volatility transmission across small and large stocks in U.S. Moreover, the portfolio of large stock also exerts a significant positive impact on the portfolio of small stock.

In another study, Worthington and Higgs (2004) pick the sample period of 1988 to 2000 and also cover up the mechanism of transmission between stock returns and volatility among 3 developed and 6 emerging Asian market such as; Hong Kong, Japan, & Singapore and Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand, respectively. They use the specification of Baba, Engle, Kraft, and Kroner (BEKK) MGARCH model for the detection of source and intensity of volatility transmission. The study reveals the there exists a positive returns and volatility spillover between the series. Finally, Fujii (2005) exhibits a causal relationship with respect to both mean and volatility spillover, not only across the Asian and Latin American region but also beyond these two regions.

The issue of volatility transmission between Australian & New Zealand stock markets is highlighted in a study done by Brailsford and Faff (1996). The results show a two-way (bi-directional) flow of influence as; the volatility of the Australian stock market spillovers the volatility of the New Zealand stock market. Similarly, the volatility of the New Zealand stock market spillovers the volatility of the Australian stock market. Baele (2005) investigate the intensity and time varying nature of volatility transmission between 13 local European stock markets and aggregate European (EU) and U.S. markets.

Allen et al. (2013) use multivariate GARCH model to examine the transmission of volatility from Chinese stock market to Australian Stock market. They find the division of the spillover effects between these markets before and after the crises period i.e. pre and post GFC, since the GFC is started and triggered in U.S. Moon and Yu (2010) also report a bi-directional relationship with respect to transmission mechanism between Chinese and U.S. stock markets. They find the effects of good and bad news on the volatility of Chinas stock market. Moreover, they also talk about an increasing effect of Chinese stock exchange on growing world market as they are becoming more liquid and open since 2005.

Abbas et al. (2013) examine the comparison of volatility spillover among the stock markets of 4 regional countries; Pakistan, India Sri Lanka and China with the stock markets of 4 developed countries; USA, UK, Singapore, and Japan. The results show the presence of volatility among the regional countries as their economic boundaries are inter linked with each others. They also find some partial evidence of volatility transmission among other countries, beyond their economic linkage. Beirne et al. (2010) also investigate the spillover relationship between develop and emerging stock markets. The result of their study show that the emerging markets cover a large portion of spillover effects from global and regional markets. Moreover, Asian and Latin American markets only reflect the mean return spillover, while emerging markets of Europe is dominated by volatility spillover.

Sakthivel et al. (2012) examine the long-run relationship by using co integration analysis and volatility spillover between the series of the returns of stock indices in following countries; USA, India, UK, Japan and Australia. In addition, a bidirectional as well as a unidirectional transmission of volatility is found from U.S. to Indian market and Japan, United Kingdom to Indian market, respectively. In America, the relationship of mean and volatility spillover is found by Diebold et al. (2011) in which they use the stock markets of American region; Argentina, Brazil, Mexico, Chile and U.S. they report that there exists a wide variation with respect to mean and volatility spillover among the markets. Volatility spillover arises when some particular economic events occur, while mean spillover are found to occur gradually.

In et al. (2001) report the transmission of a unidirectional volatility from U.S. markets to both Asian and Japanese stock markets by using the sample of stock markets of U.S.A., Japan and other six emerging or developing economy countries such as; China, India, Indonesia, Malaysia, the Philippines, and Thailand. Additional effects of bidirectional volatility spillover is also found from U.S. market to other Asian markets during financial crises in Asian markets. Using univariate EGARCH model, Olbryś (2013) documents that volatility of U.S. and biggest emerging Central Eastern European countries CEEC-3 markets exhibit the asymmetric effect on innovations. The results show that negative innovations and volatility has a direct relationship rather than positive innovations.

Although there exists a lot of literature on the inter-dependencies of different stock markets and industries but most of the studies on the transmission of return and volatility are based on the spillover across different countries, regions and different financial markets. Most of the previous literature that discussed above shows that the flow of information vary from country to country and market to market according to their respective regions. While any return and volatility linkage between industries to industries of a particular region or any country is scarce. In short, the studies on the inter-dependencies of industries in terms of mean and volatility linkage is limited or near to missing in previous literature.

2.3 Time-Varying Conditional Correlations

Over the past two decades, there exists an extensive literature on different Multivariate GARCH models with respect to conditional variance-covariance and conditional volatility characteristics. First of all, Bollerslev et al. (1988) propose first multivariate GARCH model The VECH model, which is used to determine the conditional covariance matrix between the series. The VECH model is used when the estimated returns dimensions of large parameters grows to check the direct generalization of uni-variate approach. In addition, to make this model more precise and comprehensive, the earlier versions of Baba, Engle , Kraft & Korner's BEKK model is also used to determine the conditional covariance matrix and conditional constant correlation CCC with its other variants as well. Engle (2002) later provides the concept of Dynamic Conditional Covariance DCC GARCH model in which the assumption of time varying conditional correlation is introduced rather than Constant Conditional Correlation CCC.

The work of Engle (2002) is further extended by Cappiello et al. (2006) in which they provide another concept of Asymmetric Dynamic Conditional Correlation ADCC GARCH model that includes the underlying assumptions regarding positive and negative shocks of news. Mostly, it is seen that the market volatility of the same sample size reflects more effects of the negative shock rather than positive shocks. In uni-variate GARCH models proposed by Engle and Ng (1993) these asymmetric behaviors are broadly discussed. Nevertheless, there exists a limited literature on the behavior of asymmetric correlations among the stock markets but global financial crises give it more importance with respect to negative shocks and more turbulence.

There exists a huge body of literature on the co integration, international financial integration and spillover effects on stock markets returns. For the purpose of the benefits of portfolio allocation and diversification, the outcomes of volatility transmission specially in the financial crises has attained a considerable focus in the previous literature. It is also revealed in the previous literature that the effects of negative shocks tend to increase the volatility of high magnitude as compared to the positive shocks (Engle and Ng, 1993).

To emphasize the importance of portfolio diversification and allocation, Kalotychou et al. (2014) examine the volatility correlation across sectors using the sample of the stock markets of U.S., U.K. and Japan. Their indicate following two points; (i) there exists a benefit of portfolio management for time varying volatility. (ii) they also uncover the dynamics returns correlations. Using the time frame of 1995 to 1997, Scheicher (2001) uses Vector Auto-regression VAR CCC model to investigates the co-integration between three European developing markets i.e. The Czech Republic, Poland and Hungary. The results show that, there exists both regional and global transmission in returns but only volatilities transmission in regional market. This results suggest that, mean spillover of global shocks is found in Central Europe stock markets instead of volatility shocks.

Kasch-Haroutounian and Price (2001) chose the time frame of 1994 to 1998 and apply two different multivariate GARCH approaches the constant conditional correlation (CCC) and the BEKK models to examine the interrelationship among Central European markets; the Czech Republic, Poland, Hungary and Slovakia. The authors report that, Hungarian and Czech & Hungarian and Polish are positively related to each others with the values of 0.22 and 0.13, respectively. For the other pairs, correlations are found to be insignificant and vary small.

For the time frame of 1997 to 2008, Savva and Aslanidis (2010) examine the relationship between market and both among 5 Central and Eastern European countries (the Czech Republic, Poland, Hungary, Slovakia and Slovenia) and vis--vis euro area market by using CCC and smooth transition CC (STCC) models. The evidence of higher correlation is found between the largest CEE markets (the Czech Republic, Poland and Hungary) as compared to the Slovenia and Slovakia. The authors also find a strong inter linkage of the Czech Republic, Poland and Hungary in this region. Furthermore, the authors also report that there exists an increasing correlation vis--vis euro area among CEE markets and between Polish, Slovenian and Czech markets. However, there find a stability between the pairs of other stock markets.

Tse and Tsui (2002) examine the effects of time varying conditional correlation between stock and foreign exchanges markets by using time varying conditional correlation model VCC. Using Dynamic Conditional Correlation (DCC), Asymmetric Dynamic Conditional Correlation (ADCC), Generalized Dynamic Conditional Correlation (GDCC) and Asymmetric Generalized Dynamic Conditional Correlation (AGDCC) models, Cappiello et al. (2006) take the sample of 21 sectoral indices and 13 bond indices and investigate the asymmetric nature of volatility between them. To determine the dynamic effects of correlation between U.S. and Japanese markets, in comparison with U.S. and Hong Kong markets, McAleer et al. (2008) use Generalized Auto-regressive Conditional Correlation model (GARCC) in their study.

Using a DCC model, Wang and Moore (2008) also investigate the interdependent relationship between 3 emerging markets (the Czech Republic, Poland and Hungary) vis--vis the aggregate euro area market. The authors find a substantial increasing correlation between CEE and euro area market due to enlargement of E.U. and financial crises. Furthermore, they also find a direct relationship between financial depth and higher correlation. However, there exists no relationship or any influence on correlations between monetary and macroeconomic developments.

To examine the spillover effects of macroeconomic variables, energy and agriculture commodities, Manera et al. (2013) employ DCC-GARCH model in their study by taking the time frame of 1986 to 2010. They found a significant relationship between commodity futures and macroeconomic variables. Moreover, they also observe the a significant positive impact of oil market on the other energy commodities and report a possible spillover effect across other commodities. In addition, they also conclude that the effect of dynamic conditional correlation DCC is more after 2004 (particularly in energy markets they even doubled) than before and a significant weak financial speculation in modeling commodity returns.

During the period of 2001 to 2011, Creti et al. (2013) use DCC GARCH model on 25 commodities & stocks and explore the mechanism of conditional correlation.

Prime importance in this paper is given to examine the linkage between S&P 500 and each commodity. The authors find that there exists a high conditional correlation throughout the whole period, critically more in sub-prime crises of 2008. In addition, they also examine that for crude oil, cocoa and coffee, speculative movements are found. In conclusion, they report that only gold is mostly negative associated or correlated with stocks and that the financialization of commodity market lowers their strong use in diversification, with main expectation for gold, cocoa and coffee.

Chong and Miffre (2010) chose the weekly data of prices from the period of 1981 to 2006 and investigate the hedging of stocks and treasury bills by using DCC-GARCH models with 25 different future contracts of commodities. The authors find a decreasing trend of correlation between commodity futures and S&P 500, over the time. This suggests that, for short term interest rate securities and strategic asset allocation, commodities are instruments very important. The study of Chong and Miffre (2010) embeds the sample period until 2006, so results are less influenced by the phenomenon of financialization (2004 onwards). Choi and Hammoudeh (2010) use the most important macroeconomic variable; Crude Oil as an industrial commodity, and study the behavior of volatility. In their study, they measure the volatility regimes and conditional correlations by using GARCH switching approach and DCC GARCH models, respectively. The results obtained from data sample of 1990 to 2006, they report that, correlation shows an increasing trend since 2003, Iraq war but decreasing with S&P 500. Again, a short period of financialization is also covered as the sample is until 2006.

Demiralay and Ulusoy (2014) investigate the relationship between S&P 500 and commodity markets. Using the asymmetric dynamic conditional correlation ADCC GARCH model, they study conditional correlation between Dow Jones-UBS-commodity index and its sub indices with S&P 500. In their study, they employ the weekly returns data and use Exponential GARCH EGARCH model during the time period from 1992 to 2013. They report that the correlation between equities and commodity indices are found to be highly volatile. Moreover, they also find an increasing trend during the financial crises.

Using the weekly data sample from 1997 to 2009, Syllignakis and Kouretas (2011) investigate the correlation between CEEC countries (the Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia and Slovenia) vis--vis the U.S. Germany & Russia by using DCC GARCH model. The authors find that the correlation in the these countries stock market is time varying and exhibit an increasing trend over the time but this increase also reduced the benefits of diversification for these CEEC countries. The authors explore that, a huge degree of financial openness can broadly explain the shits occur in the coefficient of correlation, provided on the availability of the outside investors in this region, leading to the final entry of the EU.

Chang et al. (2011) exhibit the hedging strategies to hedge crude oil prices and crude oil futures markets by using BEKK, CCC, DCC, and VARMA-GARCH. They take the sample of both WTI and BRENT crude oil prices. Their findings provide an evidence on the time varying nature of hedging ratios that, they all show a changing behavior over the time. Comparison is made on the basis of hedging effectiveness by using both DCC and BEKK hedging models in which, hedges calculated from DCC prove the best rather than BEKK as they prove to be worst. Pan et al. (2014) conducts a study to determine the hedging effectiveness between crude oil prices and other petroleum products like oil and gasoline by using regime switching asymmetric dynamic conditional correlation RS-ADCC GARCH model. In this study, the hedging effectiveness of BEKK model is proved to be the best for hedging crude future with gasoline futures. The highest hedging effectiveness for hedging crude oil and heating oil is provided by the regime switching RS-ADCC model.

To study the dynamic linkage of volatility between equity prices of Ghana and oil prices of Nigeria, Lin et al. (2014) use VAR-GARCH and DCC-GARCH models in their study for the time frame of 2002 to 2010. They explore that, the variation for optimal hedge ratio different for these both countries as; the optimal hedge ratio varies from 0.51 to 0.40 for Ghana and 0.56 to 0.50 for Nigeria. Sadorsky (2014) examines the link of volatility and conditional correlations between Dow Jones Specially Responsible Investments equity portfolio, gold and oil by using

CCC and DCC GARCH models for weekly returns data. The results are same as of S&P 500 that, the investors of SRI can hedge their investment in gold and oil market by paying a similar amount as that of investors in S&P 500 expect to pay. For example, the difference between the average hedge ratio of SRI with oil and S&P 500 with oil is 0.02 (as the hedge ratio of SRI with oil is 0.05 and hedge ratio between the S&P 500 and oil is 0.07) that is very small.

Although, there is an extensive amount of literature on time-varying conditional correlations and contagion on the stock and bond markets of developed countries (Engle, 2002; Cappiello et al., 2006; Bartram et al., 2007; Dungey and Fry, 2009; Kenourgios et al., 2011; Missio and Watzka, 2011) However, there is limited related literature on emerging markets conditional correlations among industries, stock and bond markets. Most of the developing countries like Pakistan are the importer of their refined products i.e. oil & gas. So, if the variations come in any major industry of a developing country, then ultimately it will reflect in the other industries and their sectoral indices. The evidences on the correlations between different industries and markets are limited in previous literature that must capture the positive or negative asymmetric effects over the time.

2.4 Hypotheses of the Study

Hypothesis 1: There exists a return spillover from Exchange rate-to-Industries in Pakistan.

Hypothesis 2: There exists a volatility spillover from Exchange rate-to-Industries in Pakistan.

Hypothesis 3: There exists a return spillover across different industries in Pakistan.

Hypothesis 4: There exists a volatility spillover across different industries in Pakistan.

Hypothesis 5: There exists a time-varying conditional correlation between exchange rate and different industries.

Hypothesis 6: There exists a time-varying conditional correlation & industrial interdependence across different industries.

Hypothesis 7: There exists an asymmetric behaviour of time-varying conditional correlation.

Chapter 3

Research Methodology

The methodology for this research is split in two main parts. The first part of this study examines the return and volatility transmission from exchange rates-to-industries and industries-to-industries in Pakistan by using ARMA (1,1) GARCH-In-Mean model presented by Liu and Pan (1997) In second part, time-varying conditional correlations between different industries are measured by using Dynamic Conditional Correlation (DCC) and Asymmetric-DCC (ADCC) Multivariate Generalized Auto-regressive Conditional Heteroscedasticity (MV-GARCH) models proposed by Engle (2002) and Cappiello et al. (2006), respectively.

3.1 Data Description

3.1.1 Population & Sample

The sample period is taken of 18 years starting from 6/2000 to 6/2018. This study employs the daily closing prices of Exchange rates and 14 industrial indices (Automobiles, Cement, Chemicals, Commercial Banks, Engineering, Fertilizers, Oil & Gas, Pharmaceuticals, Power Generation & Distribution, Refineries, Sugar, Technology & Telecommunication, Textiles and Tobacco) of Pakistan to examine the impact of return and volatility spillovers from currency market-to-industries and industries-to-industries in Pakistan and time varying conditional correlations, respectively. The data of the firms was obtained from Pakistan stock exchange and exchange rates were obtained from state bank of Pakistan.

3.2 Description of Variables

3.2.1 Exchange Rate - PKR to USD

Exchange rate is the price of a nation's currency in terms of another currency (Oxford dictionaries online, 2017).

The current study uses the daily closing prices of PKR to USD for the period of 6/2000 to 6/2018 from state bank of Pakistan.

$$r_t = \ln\left(\frac{ER_t}{ER_{t-1}}\right)$$

Where,
ln = Natural Log
ER_t = Exchange rate of t day in terms of rupees
ER_{t-1} = Exchange rate of t-1 day in terms of rupees

3.2.2 Industrial Indices - 14 Industries

The current study uses the daily closing prices of the firms selected on the basis of market capitalization from 6/2000 to 6/218. Equally weighted index is used to determine the average industrial returns of each industry. The detail about industries, firms and sample size is mentioned in the following Table 3.1. While, the detail of companies by each industry (i.e. name & market capitalization/size) is mentioned in attached Appendix-A.

TABLE 3.1: Industrial Indices

Sr. No.	Industries	Listed Firms	Sample Size
1.	Automobiles Assemblers	12	7
2.	Cement	22	15
3.	Chemicals	29	15
4.	Commercial Banks	24	10
5.	Engineering	18	9
6.	Fertilizers	7	5
7.	Oil & Gas	12	7
8.	Pharmaceuticals	9	5
9.	Power Generation & Distribution	19	10
10.	Refineries	4	4
11.	Sugar & Allied Industries	34	20
12.	Technology & Telecommunication	10	4
13.	Textiles	155	50
14.	Tobacco	3	2

3.3 Econometric Models

3.3.1 Return & Volatility Spillover - ARMA GARCH

3.3.1.1 Exchange Rate-to-Industries

Two-stage GARCH-in-mean approach (GARCH-M), presented by Liu and Pan (1997) was used to examine the return and volatility transmission of exchange rate on different industries of Pakistan. In the first stage, the relevant exchange rate return series are modeled through an ARMA (1, 1)-GARCH (1, 1)-M econometric model.

$$r_{p,t} = \rho_o + \rho_1.r_{p,t-1} + \rho_2.v_{p,t} + \rho_3.\epsilon_{p,t-1} + \epsilon_{p,t}, \epsilon_{p,t} \sim N(0, v_{p,t}) \tag{3.1}$$

$$v_{p,t} = \omega_o + \omega_1.\mu^2_{p,t-1} + \omega_2.v_{p,t-1} \tag{3.2}$$

Where $r_{p,t}$ is the daily returns of currency markets at time t and $\epsilon_{p,t}$ is the residual or unexpected return in other words, the error term. Basically, the major objective to include the ARMA (p,q) GARCH structure in the model is the adjustment of serial correlation in the data.

In the second stage, the influence of return and volatility transmission across markets are determined by obtaining the standardized error term and its square in the first stage and putting them in to the equations of return and volatility of other markets also with the inclusion of a structural break as ...

$$r_{q,t} = \rho_{q,o} + \rho_{q,1}.r_{q,t-1} + \rho_{q,2}.v_{q,t} + \rho_{q,3}.\epsilon_{q,t-1} + \phi_q.\epsilon_{p,t} + \phi_q.smf + \epsilon_{q,t}, \epsilon_{q,t} \sim N(0, v_{q,t}) \tag{3.3}$$

$$v_{q,t} = \omega_{q,o} + \omega_{q,1}.\mu^2_{q,t-1} + \omega_{q,2}.v_{q,t-1} + \lambda_q.e^2_{p,t} + \lambda_q.smf \tag{3.4}$$

Where $\epsilon_{p,t}$ is the standardized error term for currency market and is capturing the mean return spillover effect from these sources. In order to examine the volatility spillover, the exogenous variable $e^2_{p,t}$ - the square of the standardized error term is included in the conditional volatility equation and is defined as $e^2_{p,t} = \frac{\epsilon^2_{p,t}}{v_{p,t}}$. Smf is a stock market freeze dummy variable that is capturing the effect of structural break of 2008 in KSE stock Exchange. The subscript q refers to one of the industry of Pakistan as detailed in above Table 3.1.

3.3.1.2 Industries-to-Industries Spillover

The same two-stage GARCH-in-mean approach (GARCH-M) is used to examine the return and volatility transmission across different industries of Pakistan. In the first stage, the relevant industry return series are modeled through an ARMA (m,n)-GARCH (m,n)-M econometric model.

$$r_{m,t} = \eta_o + \eta_1.r_{m,t-1} + \eta_2.v_{m,t} + \eta_3.\epsilon_{m,t-1} + \epsilon_{m,t}, \epsilon_{m,t} \sim N(0, v_{m,t}) \tag{3.5}$$

$$v_{m,t} = \theta_o + \theta_1.\mu^2_{m,t-1} + \theta_2.v_{m,t-1} \tag{3.6}$$

Where $r_{m,t}$ is the daily returns of one industry at time t and $\epsilon_{m,t}$ is the residual or unexpected return in other words, the error term. Basically, the major objective to include the ARMA (m,n) GARCH structure in the model is the adjustment of serial correlation in the data. The subscript m refers one of the industry ranges from 1,2,3 ... 14 as detailed in above Table 3.1.

In the second stage, the influence of mean return and volatility spillover across markets are determined by obtaining the standardized error term and its square in the first stage and substituting them into the mean and volatility equations of other markets as follows

$$r_{n,t} = \eta_{n,o} + \eta_{n,1}.r_{n,t-1} + \eta_{n,2}.v_{n,t} + \eta_{n,3}.\epsilon_{n,t-1} + \psi_n.\epsilon_{m,t} + \epsilon_{n,t}, \epsilon_{n,t} \sim N(0, v_{n,t}) \quad (3.7)$$

$$v_{n,t} = \theta_{n,o} + \theta_{n,1}.\mu^2_{n,t-1} + \theta_{n,2}\,.v_{n,t-1} + \tau.e^2_{m,t} \quad (3.8)$$

Where $\epsilon_{m,t}$ is the standardized error term for one industry and is getting the return transmission effect from these sources. In order to examine the volatility transmission, the exogenous variable $e^2_{m,t}$ - the square of the standardized error term is included in the conditional volatility equation and is defined as $e^2_{m,t} = \frac{\epsilon^2_{m,t}}{v_{m,t}}$. The subscript n refers to the other industry ranges from 1,2,3 ... 14 as detailed in above Table 3.1.

3.3.2 Time-Varying Conditional Correlation - DCC and ADCC

The above model assumes that the correlation is constant over the period of the time but that correlation may be time varying. So in that case, dynamic conditional correlation DCC GARCH model is used and possibility of any asymmetry in the model will be captured by ADCC GARCH model. Dynamic Conditional Correlation model or DCC, models the volatilities and correlations in two steps. The detail about the dynamics of correlation is reached out to permit asymmetries vital for financial practice. The DCC furnishes a joint thickness work with tail dependence more prominent than the ordinary. This is investigated both by simulation and experimentally. The time aggregated DCC is exhibited as a valuable copula for financial decision making.

At the point when two stocks move same way, the correlation is expanded marginally. On the opposite side, when similar two stocks move inverse way, this correlation is diminished. In down markets, this effect of movement of stocks can be stronger. The correlations often are assumed to only temporarily deviate from a long run mean. A symmetric DCC model gives higher tail dependence for both upper and lower tails of the multi-period joint density while, an asymmetric DCC or ADCC gives higher tail dependence in the lower tail of the multi-period density.

- Dynamic Conditional Correlation DCC

  DCC is defined as ...

$$Q_t = \overline{R} + \sum_{i=1}^{m} \pi_i(\epsilon_{t-i}\epsilon_{t-i}^{\prime} - \overline{R}) + \sum_{i=1}^{m} \xi_i(Q_{t-1} - \overline{R}) \tag{3.9}$$

  For most of the data sets used in the research, DCC (1,1) is proved to be an adequate model.

- Diagonal Generalized GDCC

  For the estimation of Diagonal Generalized DCC, the following steps are followed ...

  1. Choose a parameterization for P and Q as,

$$P = \alpha\acute{\alpha} = \beta\acute{\beta} \tag{3.10}$$

  2. So that for any Z,

$$A.Z = diag\{\alpha\}.Zdiag\{\alpha\} \tag{3.11}$$

  3. Hence for any i and j,

$$Q_{i,j,t+1} = \overline{\vartheta}_i, j + \alpha_i\alpha_j(\epsilon_{i,t} - \overline{\vartheta}_{i,j}) + \beta_i\beta_j(Q_{i,j,t} - \overline{\vartheta}_{i,j}) \tag{3.12}$$

- Asymmetric Dynamic Conditional Correlation ADCC

  ADCC is defined as ...

$$\sigma_t = min(\epsilon_t, 0), \overline{N} = \frac{1}{T}\sum_{t=1}^{T} \sigma_t\acute{\sigma}_t \tag{3.13}$$

1. Asymmetry can be introduced with terms that are zero except when both returns are negative such as,

$$\mu\sigma_{i,t}\sigma_{i,t} \tag{3.14}$$

2. Or more generally (and averaging to zero),

$$G(\sigma_t\acute{\sigma}_t - N) \tag{3.15}$$

- Asymmetric Generalized DCC AGDCC

  The Asymmetric Generalized DCC can be expressed as,

$$Q_t = \overline{R} + A.(\epsilon_{t-1}\acute{\epsilon}_{t-1} - \overline{R}) + B.(Q_{t-1} - \overline{R}) + G.(\sigma_t\acute{\sigma}_t - \overline{N}) \tag{3.16}$$

  And assuming a diagonal structure for A,B and G, the typical equation becomes,

$$Q_{i,j,t+1} = \overline{\vartheta}_{i,j} + \alpha_i\alpha_j(\epsilon_{i,t}\epsilon_{j,t} - \overline{\vartheta}_{i,j}) + \beta_i\beta_j(Q_{i,j,t} - \overline{\vartheta}_{i,j}) + \gamma_i\gamma_j(\sigma_{i,t}\sigma_{j,t} - \overline{N}_{i,j}) \tag{3.17}$$

Chapter 4

Data Analysis & Discussion

This chapter covers the various tests applied to explore the phenomena under discussion and interprets the results obtained.

4.1 Graphical Representation

4.1.1 Stationarity of Series

In research, the first basic step of every analysis is to see the behaviour of data by visualization. Visualization of data means to check the Stationarity of series that, data must be stationary for further spillover analyses. In short, the mean of the series must be constant. All Stationarity graphs are attached in Appendix-B.

4.1.2 Descriptive Statistics

The second step is to examine the behavior of data though descriptive statistics of each series including Independent and dependent variables. this study, Exchange rate-ER is independent and all other industries are taken as dependent variables as show in the Table 4.1.

Table 4.1 includes the first 4 important moments i.e. Mean, Variance, Skewness and Kurtosis. Moreover the spread of data is also assessed by Maximum &

Table 4.1: Descriptive Statistics

	Mean	Maximum	Minimum	SD	Skewness	Kurtosis
ER	0.0002	0.0375	-0.0332	0.0031	1.1416	33.1184
AA	0.0007	0.2555	-0.2580	0.0137	-0.2176	60.1955
CEM	0.0003	0.1832	-0.1901	0.0153	0.2941	15.3711
CHEM	0.0004	0.2973	-0.3117	0.0133	-0.8543	126.0207
CB	0.0002	0.0812	-0.0801	0.0124	-0.3689	7.4617
ENG	0.0002	0.5752	-0.9485	0.0217	-14.9267	925.1223
FERT	0.0002	0.0487	-0.2636	0.0112	-2.7986	66.1996
O&G	0.0003	0.0983	-0.1073	0.0119	-0.3757	8.4777
PHAR	0.0005	1.3603	-1.7374	0.0387	-10.4738	1165.9385
P&D	0.0001	0.0768	-0.0754	0.0078	-0.0576	14.0069
REF	0.0002	0.3546	-0.6885	0.0221	-5.8253	231.9454
SUG	0.0004	0.9114	-0.8002	0.0216	1.6896	1072.2379
T&T	0.0000	0.1039	-0.1398	0.0157	-0.3413	11.1132
TEX	0.0003	0.7648	-0.8317	0.0208	-7.5785	973.6591
TOB	0.0009	1.8006	-1.8416	0.0565	-0.5688	827.9920

This table covers the descriptive statistics for the series of exchange rate and all other industries. Useable observations for this study are 5093

Minimum average responses. The sample period is taken of 18 years starting from 6/2000 to 6/2018. The study employs the daily closing prices of Exchange rate and 14 industrial indices.

Average mean returns measure the performance of the industrial indices of different industries. The study reports that mean returns of all industries are positive. The highest mean return value is of Tobacco-TOB that is (0.09%) and lowest is of Power Generation & Distribution-P&D that is (0.01%). In addition, all industries have a positive standard deviation however, Tobacco-TOB exhibits the higher volatility (5.65%) that confirm the logical relationship of risk and return as well that; higher the risk the higher will be the return. It also tell that, this sector is more volatile than others. While, Fertilizers-FERT exhibits the lowest volatility (1.12%) that gives the evidence of less volatile. Maximum and Minimum statistics show the max. and min. return earned/day for each industry. For example, the average return/ day for Automobile Assemblers is (0.07%), maximum return earned/day is (25.5%) and min return earned or max loss earned/day is (25.8%) and so on.

Skewness tells about the asymmetric behavior of data. Skewness values of Automobile Assemblers-AA, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Textiles-TEX and Tobacco-TOB show that distribution of returns are negatively skewed. On the other hand, Cement-CEM shows only positive skewness. The negative trend of skewness shows the continuous depreciation in the stock returns i.e. the crises of 2005, 2008 and almost 20 to 25% depreciation in previous years. Kurtosis tells about the tailedness of the probability distribution. All the values of Kurtosis are positive and ¿3 that indicates, all series are leptokurtic i.e. fat tails with high peak and get highly effected with the bubbles of stock market.

Exchange rate-ER also show a positive mean return (0.02%) and standard deviation (0.03%). Values of maximum and minimum show the max return earned/day and max loss earned/day that is (3.75%) and (3.32%), respectively.

4.2 Return and Volatility Spillover from Exchange Rate-to-Industries

After preliminary analyses, the first part of methodology is to examine the return and volatility spillover from exchange rate-to-industries and industries-to-industries by using a suitable econometric model.

Table 4.2 shows the estimates of return and volatility spillovers from Exchange rate-to-Industries by using an ARMA GARCH (p,q) model. Moreover, a dummy variable is also used in the study as a ”Structural Break” with both return and volatility spillover. All ARCH and GARCH coefficients are also reported with their p-value (in parenthesis). For Automobile Assemblers-AA, Chemicals-CHEM & Commercial Banks-CB, ρ_1 is found to be significant and positive that means, the mean returns of these industries can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries that indicate, there exists no opportunities of diversification in these industries.

Table 4.2: Return & Volatility Spillovers from Exchange Rate-to-Other Industries - ARMA GARCH Model

	ER	**AA**	**CEM**	**CHE**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
ρ_o	**4.94E-05**	0.0002	0.0003	-2.05E-05	0.0003	0.0002	-0.0003	-0.0206	-8.41E-05
	(0.1779)	(0.2717)	(0.3362)	(0.9397)	(0.1264)	(0.2291)	(0.1838)	(0.0000)	(0.6348)
ρ_1	**0.0617**	0.6647	0.2188	1.2049	0.3843	0.2586	-1.0957	0.0086	-0.0659
	(0.5028)	(0.0000)	(0.0716)	(0.0001)	(0.0005)	(0.1217)	(0.3468)	(0.9426)	(0.6882)
ρ_2	**4.9011**	-0.1828	0.6636	-0.3093	-0.1676	2.4322	13.1909	-0.0026	0.6667
	(0.2752)	(0.9144)	(0.7383)	(0.8569)	(0.9243)	(0.1805)	(0.0682)	(0.0000)	(0.5692)
ρ_3	**-0.2798**	-0.4642	-0.101	-1.1566	-0.2605	-0.1679	1.0992	0.107	0.1566
	(0.0017)	(0.0000)	(0.4049)	(0.0002)	(0.0194)	(0.3183)	(0.3459)	(0.3857)	(0.3449)
ϕ	-	0.0008	-0.0004	-0.0044	-0.0001	-8.09E-05	-6.03E-05	-0.0041	-0.0001
		(0.0000)	(0.0005)	(0.0001)	(0.0011)	(0.3477)	(0.3684)	(0.0000)	(0.1216)
ϕ***smf**	-	-0.0005	0.0009	-0.0088	0.0009	0.0006	-0.0007	0.0054	0.0159
		(0.0000)	(0.8485)	(0.0000)	(0.5962)	(0.8147)	(0.5694)	(0.4317)	(0.0000)
ω_o	**7.10E-07**	0.0001	0.0001	0.0001	0.0001	0.0001	6.13E-05	8.21E-05	0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-(0.0002)	(0.0000)	(0.0000)	(0.0000)
ω_1	**0.6944**	0.6000	0.6000	0.6000	0.6000	0.6000	0.6000	0.6000	0.6000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ω_2	**0.2483**	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500	0.1499	0.1500
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
λ	-	-1.93E-13	-1.51E-12	-1.90E-12	-9.00E-13	-1.22E-12	-3.49E-13	9.68E-11	-2.26E-12
		(0.0000)	(0.0000)	(0.0000)	(0.0524)	(0.0549)	(0.2437)	(0.0000)	(0.3518)
λ***smf**	-	-7.79E-10	-7.15E-10	-7.07E-10	-6.22E-10	-5.76E-10	-2.58E-10	-2.15E-10	-2.80E-10
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7614)	(0.5919)

*Where ER=Exchange rate, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. Smf=Stock Market Freeze Dummy Variable. ϕ denotes the parameters of mean spillover and λ denotes the parameters of volatility spillover. The interaction terms (ϕ*smf and λ*smf) show the effect of stock market freeze with mean and volatility spillovers.*

The GARCH coefficient ρ_2 is only significant for Refineries-REF which shows that, mean returns can be predicted by using forecasted volatility. The coefficient of standardized residual error term, ρ_3 also has a significant negative impact on the same 3 industries that shows, these markets make some necessary adjustments for the next day on the basis of past shocks. Simply, the market will move opposite to make correction. The coefficient of ω_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of ω_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. Aloui (2007) examines the same relationship between stock returns and exchange rate and finds the persistence of volatility in his study as well.

The results of mean spillover ϕ shows a significant negative impact on Cement-CEM, Chemicals-CHEM, Commercial Banks-CB & Refineries-REF that mean, the returns of all these industries are influenced by the fluctuations in the Exchange rate. This negative relationship indicate that, the mean returns of foreign exchange rate decreasing the mean returns of Cement-CEM, Chemicals-CHEM, Commercial Banks-CB & Refineries. In contrast, the insignificant variations are found in Oil & Gas-O&G, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T which shows, there exists no return spillover across these industries. In a previous study, Franck and Young (1972) also report that there exists no significant impact of one variable on another variable. Meanwhile, when the effect of structural break is applied with mean spillover i.e. ϕ*Smf, all results become insignificant which provides a strong theoretical evidence that when stock market freezes, any variation comes from exchange rate is not reflected across these industries.

On the other hand, Automobile Assemblers-AA & Chemicals-CHEM exhibit a significant negative impact that means the firms which are not the part of these industrial indices, still showing some trading pattern in case of stock market freeze. There is only one industry Technology & Telecommunication-T&T which shows a significant positive impact during the period of structural break that implies, the mean returns of exchange rate increasing the mean returns of Technology &

Telecommunication-T&T instead of stock market freeze. The evidence about the spillover effect (excluding dummy variable) can also be given from a study done by (Bodart and Reding, 2001). Their study show a mean and volatility transmission from exchange rate to expected sectoral indices with a significant negative impact. In addition, the intensity of this spillover is found quite less as well.

Similarly, the results of volatility spillover show a significant negative impact on Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G and Refineries-REF. It reveals that, the volatility of the exchange rate decreasing the volatility of these industries. In short, it is bringing the cooling down effect of all these industries. However, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T indicate that, the volatility of these 2 industries are not influenced by exchange rate changes or variations. Refineries-REF shows a significant but positive effect of volatility spillover that categories this industry as a volatile sector. In short the volatility of this sector is high as compared to other sectors. But, the interesting thing is that, when the same structural break variable is used with the volatility spillover i.e. λ*Smf, all results becomes significant and negative except Refineries and Technology & Telecommunication-T&T. Again, it also reveals that when market freezes, although the volatility spillover exists but it is less because of the decrease in trading. However, only Refineries-REF proved to be a sector that didnt show any relationship with exchange rate volatility. It means that, the volatility of this industry is not influenced by exchange rate changes. The increasing and decreasing effect of volatility spillover is also documented by Mishra et al. (2007) in which they find the same trend with respect of the transmission of volatility between exchange rate and stock market indices in India.

Table 4.3 shows the estimates of return spillovers from Exchange rate-to-Industries by using an ARMA (p,q) Model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The application of ARMA model indicates that the return data of these 6 industries is homoscedastic which makes the variance constant so there is no GARCH series in the reported table.

Table 4.3: Return Spillovers from Exchange Rate-to-Other Industries - ARMA Model

	ρ_o	ρ_1	ρ_2	ρ_3	ϕ	ϕ***Smf**
ER	**4.94E-05**	**0.0617**	**4.9011**	**-0.2798**	-	-
	(0.1779)	**(0.5028)**	**(0.2752)**	**(0.0017)**		
ENG	0.0002	-0.1108	-	0.058	-0.0006	0.0009
	(0.4437)	-(0.6752)		(0.8264)	(0.0389)	(0.7791)
FERT	0.0001	0.1265	-	-0.0678	-0.0001	0.0001
	(0.3494)	(0.5957)		(0.7765)	(0.4835)	(0.9192)
PHAR	1.10E-03	-1.236	-	1.2116	-3.75E-05	0.0002
	(0.0661)	(0.0262)		(0.0294)	(0.9451)	(0.9676)
SUG	-0.0003	1.8207	-	-1.7888	-0.0006	0.0004
	(0.3418)	(0.0000)		(0.0000)	(0.0473)	(0.8999)
TEX	0.0009	-2.154	-	2.1427	-5.00E-04	0.0006
	(0.1115)	(0.2159)		(0.2175)	(0.0840)	(0.8486)
TOB	0.0122	-12.6078	-	12.6254	-1.10E-03	0.0020
	(0.0000)	(0.0000)		(0.0000)	(0.1298)	(0.8205)

*Where ER=Exchange Rate, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. Smf=Stock Market Freeze Dummy Variable. Values in parenthesis are the p-values. ϕ denotes the parameters of mean spillover. While the interaction term (ϕ*smf) shows the effect of stock market freeze with mean spillovers.*

Coefficients of ρ_1 is significant for Pharmaceuticals-PHAR, Sugar-SUG & Tobacco-TOB that means, the mean returns of these industries can be predicted by using the past prices behavior. However, the positive sign shows that the effect of this prediction is more in case of Sugar-SUG. ρ_3 is the coefficient of standardized residual error term that is also significant for same 3 industries but here, the effect of the shock is less for Sugar-SUG and more for the rest of 2 industries i.e. Pharmaceuticals-PHAR & Tobacco-TOB. In simple words, the Sugar industry move in opposite direction to make the corrections.

The results of mean spillover has a significant negative impact on just 2 industries; Engineering-ENG and Sugar-SUG. It means, the mean returns of Engineering-ENG and Sugar-SUG industries are influenced by exchange rate returns. However, the negative sign shows that the mean returns of these industries are decreasing with respect to exchange rate. The remaining industries exhibit no transmission from exchange rate. The possible reason can be that, Pakistan is self-sufficient in these industries and some contribute as the major exports in the economy of Pakistan i.e. Textiles. Another possible reason can be that, Pharmaceuticals-PHAR & Tobacco-TOB are small sectors as they have less numbers of listed firms. So thats why, they didnt incorporate any variations with respect to change in exchange rate. Again, the variable of structural break is also applied with mean spillover i.e. ϕ*smf. All results are insignificant which provide a clear evidence of stock market freeze. As the market is not moving so there exists no return spillover across industries from exchange rate.

4.3 Return and Volatility Spillover Across the different Industries

Return and volatility spillovers across industries are also estimated by using same ARMA GARCH (m,n) model. In these analyses, one industry is taken as benchmark industry and then effect is seen on the other 7 industries and so on. In simple words, shocks created from one benchmark industry, transmitted to the other industries to determine that, is there any transmission of return or volatility takes place or not? All ARCH and GARCH coefficients are also reported with their p-value (in parenthesis).

On the other hand, the estimates of return spillovers across 6 industries are measured by using ARMA (m,n) model. The application of ARMA model implies that, the nature of the data is homoscedastic and thus there is no volatility spillover or GARCH equation because the variance becomes constant. So, only return spillover can be captured from this model. As the data of Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB is homoscedastic, so these industries only shows the results of return spillover.

Table 4.4 shows the estimates of return and volatility spillover from Automobile Assembler-to-other industries by using an ARMA GARCH (m,n) model.

Table 4.4: Return & Volatility Spillover from Automobile Assemblers-to-Other Industries - ARMA GARCH Model

	AA	**CEM**	**CHE**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**4.00E-04**	0.0002	-0.0003	2.00E-04	0.0002	-3.5E-05	-0.0035	-0.0001
	(0.1065)	(0.4154)	(0.1253)	(0.1785)	(0.2907)	(0.8689)	(0.7061)	(0.2802)
η_1	**0.3688**	0.2196	1.4413	0.4273	0.2886	0.9071	0.0671	-0.0479
	(0.0000)	(0.0401)	(0.0000)	(0.0000)	(0.0588)	(0.2096)	(0.4291)	(0.7637)
η_2	**-0.2443**	0.4933	0.9234	-0.78	0.7349	-0.2149	-0.0005	1.7275
	(0.8982)	(0.8054)	(0.5110)	(0.6484)	(0.6986)	(0.9666)	(0.6284)	(0.1647)
η_3	**-0.0019**	-0.1113	-1.3999	-0.3054	-0.1945	-0.8922	0.1026	0.1411
	(0.0014)	(0.2977)	(0.0000)	(0.0030)	(0.2053)	(0.2170)	(0.2502)	(0.3783)
ψ	-	0.0052	0.0037	0.0035	0.0037	2.50E-03	9.50E-03	0.0033
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**5.73E-06**	4.03E-06	-2.6E-07	-2.6E-07	3.38E-07	4.06E-06	3.00E-04	-6.05E-07
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2336)	(0.0000)	(0.0000)	(0.0000)
θ_1	**0.8706**	0.8637	0.7857	0.8597	0.8408	0.7728	-0.0338	0.8861
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1780)	(0.0000)
θ_2	**0.1226**	0.0887	0.1604	0.1041	0.1213	0.0962	0.3715	0.0941
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	8.95E-10	1.78E-09	7.31E-10	6.27E-10	4.81E-10	2.15E-09	8.16E-10
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover.

For Cement-CEM, Chemicals-CHEM, Commercial Banks-CB and Oil & Gas-O&G, η_1 is found to have a significant positive impact that means, the mean returns of these industries can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries. While, there found no impact of the past prices behavior on todays returns in Power Generation & Distribution-P&D, Refineries-REF and Technology and Telecommunication-T&T that implies, these markets are efficient and provide investment opportunities. Portfolio manager can get the benefits of diversification. The GARCH coefficient η_2 is only significant for Chemicals-CHEM and Commercial Banks-CB which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, η_3 is proved to be insignificant for all industries except, Chemicals-CHEM and Commercial Banks-CB that shows, these markets didnt account for the process of correction on the basis of past shocks except Chemicals-CHEM and Commercial Banks-CB. Both of these industries move in opposite direction to make correction in future.

The coefficient of θ_1 is significant and positive for all industries except Refineries-REF which indicates that, volatility of the current period can be predicted by using the past prices behavior. While, no lagged effect is found in case Refineries-REF as due to more volatile sector. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D and Technology and Telecommunication-T&T, the sum of θ_1 and θ_2 is closer to 1which indicates the nature of the persistence is in long run.

The results of mean spillover show a significant positive impact on all industries; Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, there exists a mean spillover from Automobile Assemblers-AA to other industries. Similarly, the results of volatility spillover also show a significant positive impact on all same industries which also confirms that, the volatility of Automobile Assemblers-AA quickly transmits to the other industries.

TABLE 4.5: Return Spillover from Automobile Assemblers-to-Other Industries - ARMA Model

	AA	ENG	FERT	PHAR	SUG	TEX	TOB
η_o	**4.00E-04**	0.0002	0.0001	1.10E-03	-0.0003	0.0008	0.0122
	(0.1065)	(0.4482)	(0.3024)	(0.0632)	(0.3090)	(0.1568)	(0.0000)
η_1	**0.3688**	-0.1222	0.1004	-1.2192	1.8503	-1.7991	-12.6983
	(0.0000)	(0.6379)	(0.6551)	(0.0263)	(0.0000)	(0.2970)	(0.0000)
η_2	**-0.2443**	-	-	-	-	-	-
	(0.8982)						
η_3	**-0.0019**	0.072	-0.0436	1.2087	-1.8204	1.8026	12.7195
	(0.0014)	(0.7818)	(0.8465)	(0.0277)	(0.0000)	(0.2960)	(0.0000)
ψ	**-**	0.0040	0.0036	0.0061	0.0019	0.0025	0.0036
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where AA=Automobile Assemblers, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover.*

Table 4.5 shows the estimates of return spillovers from Automobile Assemblers-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering - ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. Coefficients of η_1 is significant for Pharmaceuticals-PHAR, Sugar-SUG & Tobacco-TOB that means, the mean returns of these industries can be predicted by using the past prices behavior. However, the positive sign shows that the effect of this prediction is more in case of Sugar-SUG as compared to others. η_2 is the coefficient of standardized residual error term that is also significant for same 3 industries but here, the effect of the shock is less for Sugar-SUG and more for Pharmaceuticals-PHAR & Tobacco-TOB. In simple words, the Sugar industry move in opposite direction to make the corrections on the basis of past shocks.

The results of mean spillover has a significant positive impact on all industries; Engineering - ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB that means, the mean returns of all these industries are influenced by any change/variation occurred in Automobile Assemblers-AA.

Table 4.6 shows the estimates of return and volatility spillovers from Cement-to-other industries by using an ARMA GARCH (m,n) model. The coefficient of standardized residual error term, η_3 proved to be significantly negative for Automobile Assemblers-AA, Chemical-CHEM, Commercial Banks-CB and Power Generation & Distribution-P&D that implies, these markets make correction for the next day on the basis of previous shocks. The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. As the sum of $\theta_1 + \theta_2$ is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run.

The results of mean spillover show a significant positive impact on all industries; Automobile Assemblers-AA, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all these industries are influenced by Cement-CEM returns. Similarly, the results of volatility spillover also show a significant positive impact on all same industries which also confirms that, the volatility of Cement-CEM quickly transmits to the other industries.

Table 4.7 shows the estimates of return spillovers from Cement-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB that means, the mean returns of all these industries are influenced by any change/variation occurred in Cement-CEM.

Table 4.6: Return & Volatility Spillover from Cement-to-Other Industries - ARMA GARCH Model

	CEM	**AA**	**CHE**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**3.00E-04**	0.0001	0.0004	3.00E-04	0.0004	0.0002	-0.0159	0.0002
	(0.3430)	(0.4320)	(0.0451)	(0.0113)	(0.0035)	(0.1274)	0.0000	(0.0953)
η_1	**0.2453**	0.5492	0.8178	0.3986	0.284	1.7389	0.2374	-0.0941
	(0.0433)	(0.0000)	(0.0041)	(0.0000)	(0.0491)	(0.0086)	(0.0195)	(0.5071)
η_2	**0.4947**	1.8821	-3.1379	-4.3303	-2.6725	-8.8892	-0.0018	-0.4481
	(0.0000)	(0.0848)	(0.0609)	(0.0110)	(0.1255)	(0.0195)	0.0000	(0.7405)
η_3	**-0.1262**	-0.3359	-0.7507	-0.2963	-0.1962	-1.7359	-0.136	0.1748
	(0.0000)	(0.0000)	(0.0078)	(0.0025)	(0.1774)	(0.0087)	(0.1901)	(0.2223)
ψ	**-**	0.0043	0.0051	0.0053	0.005	3.10E-03	6.40E-03	0.0043
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**1.36E-05**	3.79E-05	1.39E-05	-1.2E-07	-1.1E-07	-1.3E-07	3.52E-06	-8.49E-07
	(0.0000)	(0.0000)	(0.0000)	(0.1241)	(0.0467)	(0.0000)	(0.0000)	(0.0000)
θ_1	**0.8443**	0.4141	0.5614	0.7780	0.7910	0.8484	0.7930	0.9234
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.0975**	0.3103	0.2641	0.1418	0.1341	0.0604	0.1514	0.0737
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	**-**	2.55E-09	2.46E-09	1.68E-09	1.38E-09	8.34E-10	3.55E-09	4.00E-10
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where CEM=Cement, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover.

TABLE 4.7: Return Spillover from Cement-to-Other Industries - ARMA Model

	CEM	ENG	FERT	PHAR	SUG	TEX	TOB
η_o	**3.00E-04**	0.0002	0.0002	1.10E-03	-0.0001	0.0007	0.0123
	(0.3430)	(0.3173)	(0.0930)	(0.0613)	(0.5674)	(0.1744)	(0.0000)
η_1	**0.2453**	0.0129	0.1618	-1.1282	1.6572	-1.3992	-12.7348
	-(0.0433)	(0.9599)	(0.4451)	(0.0416)	(0.0000)	(0.4125)	(0.0000)
η_2	**0.4947**	-	-	-	-	-	-
	(0.0000)						
η_3	**-0.1262**	-0.0655	-0.1074	1.1042	-1.6226	1.3923	12.7523
	(0.0000)	(0.7989)	(0.6129)	(0.0462)	-(0.0001)	(0.4148)	(0.0000)
ψ	**-**	0.0052	0.0050	0.0035	0.0040	0.0039	0.0029
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)

Where CEM=Cement, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.8 shows the estimates of return and volatility spillovers from Chemicals-to-other industries by using an ARMA GARCH (m,n) model. The coefficient of standardized residual error term, η_3 proved to be significantly negative for Automobile Assemblers-AA, and Commercial Banks-CB that implies, these markets move opposite to make correction on the next day.

The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using past prices behavior. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. As the sum of $\theta_1 + \theta_2$ is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run.

The results of mean spillover show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Chemicals-CHEM returns. Similarly, the results of volatility spillover also show a significant positive impact on all industries which also confirms that, the volatility of Chemicals-CHEM quickly transmits to the other industries.

Table 4.8: Return & Volatility Spillover from Chemicals-to-Other Industries - ARMA GARCH Model

	CHE	**AA**	**CEM**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**-9.42E-05**	0.0004	0.0008	5.00E-04	0.0004	0.0003	0.0004	0.0003
	(0.7187)	(0.2577)	(0.0048)	(0.0001)	(0.0069)	(0.0001)	(0.8663)	(0.1671)
η_1	**1.2209**	0.4993	0.1662	0.3684	0.1161	-0.0931	0.2438	-0.1485
	(0.0000)	(0.0000)	(0.1296)	(0.0001)	(0.4130)	(0.8980)	(0.0128)	(0.2636)
η_2	**-0.018**	-0.1181	-3.7226	-3.7111	-1.811	-3.7106	1.03E-05	-2.2768
	(0.9915)	(0.9594)	(0.0438)	(0.0248)	(0.3400)	(0.3102)	(0.9717)	(0.1712)
η_3	**-1.1733**	-0.34	-0.0752	-0.2678	-0.0351	0.0891	-0.1393	0.2084
	(0.0001)	(0.0000)	(0.4942)	(0.0045)	(0.8052)	(0.9024)	(0.1612)	(0.1212)
ψ	**-**	0.0057	0.0071	0.0047	0.005	3.30E-03	7.00E-04	0.0058
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**1.41E-05**	6.01E-05	1.54E-07	-9.5E-08	1.2E-07	-4.7E-08	-2.98E-07	-1.01E-07
	(0.0000)	(0.0000)	(0.4952)	(0.0018)	(0.0010)	(0.0000)	(0.0044)	(0.0000)
θ_1	**0.7596**	0.2893	0.8591	0.8714	0.7993	0.8347	0.8415	0.8386
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.178**	0.3482	0.0658	0.0848	0.1236	0.0754	0.1051	0.0813
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ		1.43E-09	1.57E-09	5.88E-10	9.33E-10	5.93E-10	2.42E-09	1.48E-09
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where CHE=Chemicals, AA=Automobile Assemblers, CEM=Cement, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover.*

Table 4.9: Return Spillover from Chemicals-to-Other Industries - ARMA Model

	CHE	ENG	FERT	PHAR	SUG	TEX	TOB
η_o	**-9.42E-05**	0.0002	0.0017	1.10E-03	-0.0003	0.0008	0.0122
	(0.7187)	(0.3897)	(0.2273)	(0.0462)	(0.3540)	(0.1095)	(0.0000)
η_1	**1.2209**	-0.0788	0.1078	-1.2647	1.827	-1.955	-12.6576
	(0.0000)	(0.7559)	(0.6219)	(0.0197)	(0.0000)	(0.2417)	(0.0000)
η_2	**-0.018**	-	-	-	-	-	-
	-(0.9915)						
η_3	**-1.1733**	0.0229	-0.0649	1.2403	-1.7949	1.9472	12.6743
	(0.0001)	(0.9281)	(0.7669)	(0.0223)	(0.0000)	(0.2436)	(0.0000)
ψ	-	0.0061	0.0044	0.0087	0.0052	0.0057	0.0093
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where CHEM=Chemicals, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover., ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.9 shows the estimates of return spillovers from Chemicals-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB that means, the mean returns of all these industries are effected by any change/variation occurred in Chemicals-CHEM.

Table 4.10 shows the estimates of return and volatility spillovers from Commercial Banks-to-Other Industries by using an ARMA GARCH (m,n) Model. The coefficient of standardized residual error term, η_3 proved to be significantly negative for Automobile Assemblers-AA, Chemical-CHEM, that implies, these markets account for the process of correction for the next day on the basis of past shocks. The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility.

Table 4.10: Return & Volatility Spillover from Commercial Banks-to-Other Industries - ARMA GARCH Model

	CB	**AA**	**CEM**	**CHE**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**3.00E-04**	0.0005	0.0003	-1.00E-04	0.0003	0.0002	-0.0311	-9.8E-05
	(0.1490)	(0.1619)	(0.2778)	(0.4680)	(0.0383)	(0.8019)	(0.0000)	(0.5643)
η_1	**0.3912**	0.4755	0.1821	1.3533	0.1281	1.178	0.2379	-0.0207
	(0.0004)	(0.0000)	(0.0522)	(0.0000)	(0.3273)	(0.3066)	(0.0276)	(0.8857)
η_2	**-0.0859**	-1.3354	0.5844	-0.3345	0.8242	-7.4016	-0.0037	1.1985
	(0.9611)	(0.6088)	(0.7628)	(0.8512)	(0.7054)	(0.3996)	(0.0000)	(0.3905)
η_3	**-0.2668**	-0.2962	-0.0693	-1.2872	-0.0299	-1.2027	-0.1276	0.1005
	(0.0166)	(0.0000)	(0.4605)	(0.0000)	(0.8193)	(0.2972)	(0.2457)	(0.4894)
ψ	**-**	0.0037	0.0069	0.0042	0.0056	3.40E-03	7.60E-03	0.0048
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**4.91E-06**	2.37E-06	3.7E-06	1.91E-06	2.48E-06	0.000049	2.25E-06	-1.98E-07
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	**0.8516**	0.8898	0.7855	0.7941	0.7698	0.6000	0.8283	0.9184
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.1147**	0.0697	0.1266	0.1938	0.1512	0.1500	0.1041	0.0770
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	**-**	5.20E-10	1.19E-09	4.85E-10	4.10E-10	-1.16E-10	2.93E-09	1.59E-10
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where CB=Commercial Banks, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover

The results of mean spillover show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Commercial Banks-CB returns. Similarly, the results of volatility spillover also show a significant positive impact on all industries which also confirms that, the volatility of Commercial Banks-CB quickly transmits to all other industries.

Table 4.11 shows the estimates of return spillovers from Commercial Banks-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX and Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are effected by any change/variation occurred in Cement-CEM. Again, it provides the evidence of interconnectedness of Automobile Cement-CEM with rest of the other industries.

Table 4.11: Return Spillover from Commercial Banks-to-Other Industries - ARMA Model

	CB	**ENG**	**FERT**	**PHAR**	**SUG**	**TEX**	**TOB**
η_o	**3.00E-04**	0.0003	0.0002	1.20E-03	-0.0002	0.0009	0.0122
	(0.1490)	(0.3021)	(0.0467)	(0.0448)	(0.3943)	(0.0867)	(0.0000)
η_1	**0.3912**	-0.1157	0.0417	-1.2201	1.8535	-2.1675	-12.6577
	(0.0004)	(0.6552)	(0.8390)	(0.0269)	(0.0000)	(0.2073)	(0.0000)
η_2	**-0.0859**	-	-	-	-	-	-
	(0.9611)						
η_3	**-0.2668**	0.063	0.0014	1.1949	-1.8208	2.1573	12.6741
	(0.0166)	(0.8082)	(0.9945)	(0.0302)	(0.0000)	(0.2094)	(0.0000)
ψ		0.0043	0.0056	0.0050	0.0031	3.70E-03	3.10E-03
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)

Where CB=Commercial Banks, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

TABLE 4.12: Return & Volatility Spillover from Engineering-to-Other Industries - ARMA GARCH Model

	ENG	**AA**	**CEM**	**CHE**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**2.00E-04**	0.0003	0.0002	1.00E-03	0.0001	0.0001	-0.0006	0.0456	5.87E-05
	(0.4711)	(0.1689)	(0.4271)	(0.0000)	(0.4483)	(0.3918)	(0.0000)	(0.0623)	(0.7182)
η_1	**-0.1081**	0.5354	0.1175	0.5561	0.3455	0.0814	-1.4745	0.2096	-0.0661
	(0.6827)	(0.0000)	(0.3059)	(0.0584)	(0.0010)	(0.6043)	(0.0114)	(0.0436)	(0.6586)
η_2	-	-0.5474	0.5119	-9.5283	0.5208	2.8373	20.5795	0.0058	0.3651
		(0.7758)	(0.7718)	(0.0000)	(0.7685)	(0.0591)	(0.0000)	(0.0629)	(0.7553)
η_3	**0.0553**	-0.3456	-0.0422	-0.5819	-0.2568	-0.0247	1.4569	-0.0591	0.1395
	(0.8344)	(0.0000)	(0.7119)	(0.0479)	(0.0151)	(0.8760)	(0.0125)	(0.5800)	(0.3555)
ψ		0.1517	0.3965	0.3268	0.2202	2.51E-01	1.55E-01	0.1756	0.1627
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	-	4.58E-06	3.14E-06	2.01E-05	5.96E-06	6.53E-06	5.36E-06	3.00E-04	2.93E-07
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-	0.8767	0.9361	0.6789	0.8404	0.8254	0.8140	0.0423	0.9650
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	-	0.1262	0.0502	0.2020	0.1135	0.1180	0.0953	0.0911	0.0362
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	Constant	Constant	Constant	Constant	Constant	Constant	Constant	Constant

Where ENG=Engineering, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover*

Table 4.12 shows the estimates of return and volatility spillovers from Engineering-to-Other Industries by using an ARMA GARCH (m,n) model. Standardized residual error term, η_3 proved to be significantly negative for Automobile Assemblers-AA, Chemical-CHEM, Commercial Banks-CB that implies, these markets move opposite to make correction on next day. While, Power Generation & Distribution-P&D continue to move in the same direction.

The coefficient of θ_1 is significant and positive for all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all same industries that provides the evidence about persistence of the volatility. The sum of $\theta_1 + \theta_2$ is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run.

The results of mean spillover show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Engineering-ENG returns. As the GARCH model can not be applied on this industry, so the coefficient of volatility spillover is constant.

Table 4.13 shows the estimates of return spillovers from Engineering-to-other industries by using an ARMA (m,n) model across 5 industries; Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries; Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB that means, the mean returns of all these industries are influenced by any change/variation occurred in Engineering-ENG.

Table 4.14 shows the estimates of return and volatility spillovers from Fertilizers-to-Other Industries by using an ARMA GARCH (m,n) model. The coefficient of

Table 4.13: Return Spillover from Engineering-to-Other Industries - ARMA Model

	ENG	FERT	PHAR	SUG	TEX	TOB
η_o	**2.00E-04**	0.0001	0.001	-1.00E-04	0.0004	0.0165
	(0.4711)	(0.3040)	(0.0139)	(0.6441)	(0.2698)	(0.0000)
η_1	**-0.1081**	0.0436	-1.0931	1.2859	-0.5259	-17.511
	(0.6827)	(0.8515)	(0.0049)	(0.0000)	(0.6762)	(0.0000)
η_2	-	-	-	-	-	-
η_3	**0.0553**	0.005	1.0867	-1.2714	0.5179	17.5394
	(0.8344)	(0.9827)	(0.0052)	(0.0000)	(0.6808)	(0.0000)
ψ	-	0.1007	1.2785	0.6891	0.6612	1.68E+00
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Standardized residual error term, η_3 proved to be significantly negative for Automobile Assembler-AA, Chemical-CHEM, Commercial Banks-CB that implies, these markets rely on past shock and move opposite to make the correction on next day.

The coefficient of θ_1 is significant and positive for all industries; except Refineries-REF which indicates that, volatility of the current period can be predicted by using the past prices behavior. But there find no persistence of volatility in Refineries-REF. Coefficient of θ_2 is also significant and positive for all same industries that provides the evidence about persistence of the volatility. As the sum of $\theta_1 + \theta_2$ is closer to 1 for all industries except Refineries-REF, it means the nature of the persistence of the volatility is in long run for these industries.

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Fertilizers-FERT returns.

TABLE 4.14: Return & Volatility Spillover from Fertilizers-to-Other Industries - ARMA GARCH Model

	FERT	AA	CEM	CHE	CB	O&G	P&D	REF	T&T
η_o	**1.00E-04**	-8E-05	0.000031	-1.27E-05	0.0002	0.0002	0.0001	0.1141	-4.9E-05
	(0.3608)	(0.7957)	(0.9318)	(0.9621)	(0.1635)	(0.2199)	(0.6691)	(0.0212)	(0.7493)
η_1	**0.1341**	0.6008	0.2416	1.0799	0.3655	0.1556	1.2493	0.32	0.036
	(0.5732)	(0.0000)	(0.0270)	(0.0000)	(0.0001)	(0.2471)	(0.1135)	(0.0015)	(0.7891)
η_2	-	2.7288	1.5142	-1.2801	-0.8986	1.4545	-5.6647	0.0145	0.795
		(0.1851)	(0.5191)	(0.5400)	(0.6980)	(0.5633)	(0.4931)	(0.0211)	(0.5300)
η_3	**-0.0754**	-0.3805	-0.1422	-1.0167	-0.2552	-0.0676	-1.2468	-0.165	0.0423
	(0.7516)	(0.0000)	(0.1910)	(0.0001)	(0.0063)	(0.6174)	(0.1149)	(0.1101)	(0.7505)
ψ	-	0.3894	0.5839	0.4302	0.474	5.03E-01	2.96E-01	0.6583	0.3855
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	-	5.31E-05	8.93E-06	1.09E-05	3.79E-06	8.05E-06	5.67E-06	3.00E-04	9.61E-08
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-	0.4520	0.8770	0.7951	0.8659	0.7621	0.8049	0.1032	0.9789
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3684)	(0.0000)
θ_2	-	0.3115	0.0758	0.1352	0.0985	0.1507	0.0799	0.0424	0.0221
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	Constant	Constant	Constant	Constant	Constant	Constant	Constant	Constant

Where FERT=Fertilizers, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover.

As the GARCH model can not be applied on this industry that further makes the variance constant, so the coefficient of volatility spillover τ is constant.

Table 4.15 shows the estimates of return spillovers from Fertilizers-to-other industries by using an ARMA (m,n) model across 5 industries; Engineering-ENG, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries; Engineering-ENG, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB that means, the mean returns of all these industries are influenced by any change/variation occurred in Engineering-ENG.

Table 4.15: Return Spillover from Fertilizers-to-Other Industries - ARMA Model

	FERT	**ENG**	**PHAR**	**SUG**	**TEX**	**TOB**
η_o	**1.00E-04**	0.0002	0.0011	-3.00E-04	0.0009	0.0122
	(0.3608)	(0.4481)	(0.0665)	(0.3161)	(0.1212)	(0.0000)
η_1	**0.1341**	-0.1442	-1.2185	1.8307	-2.0838	-12.6589
	(0.5732)	(0.5783)	(0.0273)	(0.0000)	(0.2276)	(0.0000)
η_2	**-**	-	-	-	-	-
η_3	**-0.0754**	0.0903	1.1929	-1.7994	2.0738	12.6757
	(0.7516)	(0.7280)	(0.0308)	(0.0000)	(0.2298)	(0.0000)
ψ	**-**	0.3788	0.4083	0.2233	0.2092	1.58E-01
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0266)

Where FERT=Fertilizers, ENG=Engineering, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.16 shows the estimates of return and volatility spillovers from Oil & Gas-to-Other Industries by using an ARMA GARCH (m,n) model. η_3 proved to be significantly negative for Automobile Assembler-AA, Chemical-CHEM, Commercial Banks-CB, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T that implies, these markets rely on past shock and move opposite to make the correction on next day.

Table 4.16: Return & Volatility Spillover from Oil & Gas-to-Other Industries - ARMA GARCH Model

	O&G	AA	CEM	CHE	CB	P&D	REF	T&T
η_o	**4.00E-04**	0.0005	0.0006	-4.52E-05	0.0004	-2.2E-05	-0.0054	0.0007
	(0.0580)	(0.1203)	(0.0098)	(0.8070)	(0.0032)	(0.8460)	(0.0259)	(0.0000)
η_1	**0.2484**	0.4452	0.1414	1.189	0.3494	1.9357	0.3638	-0.2636
	(0.1367)	(0.0000)	(0.1531)	(0.0000)	(0.0000)	(0.0069)	(0.0002)	(0.0544)
η_2	**0.6346**	-1.4643	-1.7664	-0.7168	-1.9817	-5.0427	-0.0006	-1.8758
	(0.7272)	(0.5507)	(0.3090)	(0.6683)	(0.3190)	(0.2058)	(0.0272)	(0.0639)
η_3	**-0.1581**	-0.2729	-0.0367	-1.1226	-0.2395	-1.9373	-0.2583	0.3601
	(0.3466)	(0.0000)	(0.7096)	(0.0000)	(0.0034)	(0.0069)	(0.0087)	(0.0092)
ψ	-	0.0039	0.0066	0.0046	0.0056	3.10E-03	9.20E-03	0.0067
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**5.27E-06**	1.08E-07	-6.2E-07	3.35E-06	-1.9E-07	-1.5E-07	-2.03E-06	-3.30E-07
	(0.0000)	(0.3661)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	**0.8317**	0.9120	0.8454	0.7436	0.8297	0.8246	0.8821	0.6968
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.1305**	0.0613	0.1106	0.2346	0.1275	0.0985	0.0747	0.2619
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	4.61E-10	8.13E-10	5.35E-10	4.12E-10	3.74E-10	1.80E-09	1.43E-09
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where O&G=Oil & Gas, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover.*

The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all same industries that provides the evidence about persistence of the volatility. As the sum of θ_1 + θ_2 is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run.

The results of mean spillover show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Oil & Gas-O&G returns. Similarly, the results of volatility spillover also show a significant positive impact on all same industries which also confirms that, the volatility of Oil & Gas-O&G quickly transmits to the other industries.

Table 4.17: Return Spillover from Oil & Gas -to-Other Industries - ARMA Model

	O&G	**ENG**	**FERT**	**PHAR**	**SUG**	**TEX**	**TOB**
η_o	**4.00E-04**	0.0003	0.0003	1.20E-03	-0.0002	0.0009	0.0123
	(0.0580)	(0.2221)	(0.0146)	(0.0347)	(0.4426)	(0.0861)	(0.0000)
η_1	**0.2484**	-0.1425	0.0579	-1.2221	-1.8225	-2.0852	-12.6772
	(0.1367)	(0.5811)	(0.7740)	(0.0264)	(0.0000)	(0.2249)	(0.0000)
η_2	**-**	-	-	-	-	-	-
η_3	**-0.1581**	0.0895	-0.0096	1.1968	1.8539	2.0765	12.6934
	(0.3466)	(0.7292)	(0.9618)	(0.0297)	(0.0000)	(0.2269)	(0.0000)
ψ	**-**	0.0047	0.0059	0.0055	0.0031	3.10E-03	3.70E-03
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where O&G=Oil & Gas, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ *denotes the parameters of mean spillover.*

Table 4.17 shows the estimates of return spillovers from Oil & Gas-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by any change/variation occurred in Oil & Gas-O&G.

Table 4.18 shows the estimates of return and volatility spillovers from Pharmaceuticals-to-Other Industries by using an ARMA GARCH (m,n) model. The coefficient of Standardized residual error term, η_3 proved to be significantly negative for Automobile Assembler-AA, Chemical-CHEM, Commercial Banks-CB that implies, these markets make adjustments on the basis of past shocks. In short, markets move opposite to make corrections.

The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all same industries that indicates, there exists persistence of volatility. Sum of $\theta_1 + \theta_2$ is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run for these industries.

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Fertilizers-FERT returns. As the GARCH model can not be applied on this industry that further makes the variance constant, so the coefficient of volatility spillover τ is constant.

Table 4.19 shows the estimates of return spillovers from Pharmaceuticals-to-other industries by using an ARMA (m,n) model across 5 industries; Engineering-ENG, Fertilizers-FERT, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by any change/variation occurred in Pharmaceuticals-PHAR.

Table 4.18: Return & Volatility Spillover frim Pharmaceuticals-to-Other Industries - ARMA GARCH Model

	PHAR	AA	CEM	CHE	CB	O&G	P&D	REF	T&T
η_o	**1.10E-03**	0.0005	0.0021	1.50E-03	0.0003	0.0003	-0.0003	-0.005	-1.2E-05
	(0.0663)	(0.0968)	(0.0000)	(0.0000)	(0.1518)	(0.0739)	(0.1485)	(0.0445)	(0.9496)
η_1	**-1.2357**	0.4312	0.1016	0.6356	0.3106	0.126	-0.8717	0.1336	-0.0707
	(0.0262)	(0.0000)	(0.3972)	(0.0461)	(0.0037)	(0.4304)	(0.4552)	(0.2125)	(0.6451)
η_2	-	-1.0914	-10.0353	-8.852	-0.8274	0.9444	13.2018	-0.0005	0.5182
		(0.5947)	(0.0000)	(0.0000)	(0.6509)	(0.5180)	(0.0774)	(0.0498)	(0.6483)
η_3	**1.2114**	-0.2631	-0.0077	-0.6161	-0.2152	-0.062	0.8722	-0.0464	0.1582
	(0.0294)	(0.0000)	(0.9485)	(0.0517)	(0.0462)	(0.6997)	(0.4553)	(0.6707)	(0.3071)
ψ	-	0.1205	0.2103	0.1805	0.1387	1.64E-01	1.49E-02	0.3048	0.0562
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	-	5.7E-06	2.21E-05	2.05E-05	5.04E-06	0.1134	5.44E-06	1.83E-05	3.00E-07
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-	0.8850	0.7833	0.6800	0.8614	0.8447	0.8173	0.8319	0.9642
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	-	0.0934	0.1071	0.2014	0.1016	-0.0004	0.0940	0.1302	0.0377
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	Constant	Constant	Constant	Constant	Constant	Constant	Constant	Constant

Where PHAR=Pharmaceuticals, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover.

Table 4.19: Return Spillover from Pharmaceuticals-to-Other Industries - ARMA Model

	PHAR	ENG	FERT	SUG	TEX	TOB
η_o	**1.10E-03**	7.24E-05	0.0001	-4.00E-04	0.0011	0.0011
	(0.0663)	(0.7359)	(0.3325)	(0.1353)	(0.0065)	(0.0000)
η_1	**-1.2357**	0.6405	0.0875	1.959	-2.8523	-12.0003
	(0.0262)	(0.0005)	(0.7112)	(0.0000)	(0.0208)	(0.0000)
η_2	-	-	-	-	-	-
η_3	**1.2114**	-0.7162	-0.0335	-1.954	2.8427	12.0197
	(0.0294)	(0.0001)	(0.8874)	(0.0000)	(0.0212)	(0.0000)
ψ	-	0.4018	0.0339	0.3552	0.3777	9.98E-01
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where PHAR=Pharmaceuticals, ENG=Engineering, FERT=Fertilizers, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.20 shows the estimates of return and volatility spillovers from Power Generation & Distribution-to-Other Industries by using an ARMA GARCH (m,n) model except; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The coefficient of Standardized residual error term, η_3 proved to be significantly negative for Automobile Assembler-AA, Chemical-CHEM, Commercial Banks-CB that indicate the reliance of these industries on past shocks for the process of correction in future.

The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all same industries that provides the evidence about persistence of the volatility. As the sum of θ_1 + θ_2 is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run for these industries. For the persistence of volatility, the sum must be equal to 1 otherwise, there will be no persistence in long run.

Table 4.20: Power Generation & Distribution-to-Other Industries - ARMA GARCH Model

	P&D	**AA**	**CEM**	**CHE**	**CB**	**O&G**	**REF**	**T&T**
η_o	**-3.00E-04**	0.0104	0.0005	8.17E-05	0.0001	0.0006	-0.0147	0.0005
	(0.1773)	(0.0028)	(0.0873)	(0.6057)	(0.1665)	(0.0007)	(0.0000)	(0.0010)
η_1	**-1.1144**	0.4877	0.2039	0.9924	0.3139	0.0213	0.1637	-0.1544
	(0.3365)	(0.0000)	(0.0586)	(0.0000)	(0.0014)	(0.8858)	(0.1260)	(0.3138)
η_2	**13.2244**	0.0011	-1.3444	-0.384	0.1155	-1.6019	-0.0017	-1.6535
	(0.0666)	(0.0044)	(0.4833)	(0.7883)	(0.9387)	(0.4108)	(0.0000)	(0.1985)
η_3	**1.1179**	-0.2891	-0.1026	-0.9224	-0.214	0.0537	-0.0605	0.2268
	(0.3356)	(0.0000)	(0.3405)	(0.0000)	(0.0316)	(0.7203)	(0.5799)	(0.1472)
ψ	**-**	0.0039	0.0058	0.0045	0.0043	4.50E-03	5.90E-03	0.005
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**5.45E-06**	4.21E-05	1.75E-06	1.37E-05	2.62E-08	1.53E-06	5.66E-06	-3.84E-07
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	**0.8122**	0.4121	0.8566	0.5531	0.7851	0.8102	0.7982	0.8992
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.1021**	0.3264	0.0828	0.3130	0.1409	0.1225	0.1275	0.0963
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	**-**	5.18E-10	4.77E-10	6.40E-10	4.61E-10	2.73E-10	1.28E-09	1.30E-10
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where P&D=Power Generation & Distribution, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover.

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Power Generation & Distribution-P&D returns. . Similarly, the results of volatility spillover τ also show a significant positive impact on all same industries which also confirms that, the volatility of Power Generation & Distribution-P&D quickly transmits to the other industries.

Table 4.21 shows the estimates of return spillovers from Power Generation & Distribution-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by any change/variation occurred in Power Generation & Distribution-P&D.

Table 4.21: Power Generation & Distribution-to-Other Industries - ARMA Model

	P&D	**ENG**	**FERT**	**PHAR**	**SUG**	**TEX**	**TOB**
η_o	**-3.00E-04**	0.0002	0.0002	1.10E-03	-0.0002	0.0009	0.0125
	(0.1773)	(0.3328)	(0.0941)	(0.0516)	(0.4204)	(0.1052)	(0.0000)
η_1	**-1.1144**	-0.087	0.0219	-1.2108	1.8037	-2.1115	-12.6315
	(0.3365)	(0.7367)	(0.9192)	(0.0284)	(0.0000)	(0.2220)	(0.0000)
η_2	**13.2244**	-	-	-	-	-	-
η_3	**1.1179**	0.0324	0.0285	1.1854	-1.7731	2.1002	12.6483
	(0.3356)	(0.9006)	(0.8950)	(0.0319)	(0.0000)	(0.2245)	(0.0000)
ψ	-	0.0044	0.0046	0.0043	0.0034	2.00E-03	2.60E-03
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0008)

Where P&D=Power Generation & Distribution, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.22: Return & Volatility Spillover from Refineries-to-Other Industries - ARMA GARCH Model

	REF	**AA**	**CEM**	**CHE**	**CB**	**O&G**	**P&D**	**T&T**
η_o	**4.30E-03**	0.0002	8.75E-05	7.00E-04	0.0012	0.0006	0.0004	-8.4E-05
	(0.7895)	(0.3624)	(0.7404)	(0.0001)	(0.5476)	(0.7560)	(0.0000)	(0.6698)
η_1	**0.2804**	0.4632	0.2191	0.3518	0.5839	0.2832	0.6755	-0.2714
	(0.0299)	(0.0000)	(0.0383)	(0.1868)	(0.0156)	(0.4328)	(0.0406)	(0.0551)
η_2	**0.0005**	1.3065	0.0422	-4.2057	-10.351	-4.3373	-10.8218	0.7985
	(0.7919)	(0.5609)	(0.9774)	(0.0000)	(0.0592)	(0.5029)	(0.0000)	(0.5451)
η_3	**-0.1312**	-0.2558	-0.112	0.3518	-0.4254	-0.1808	-0.6603	0.3480
	(0.3191)	(0.0003)	(0.2870)	(0.1868)	(0.0894)	(0.6221)	(0.0455)	(0.0144)
ψ	**-**	0.0059	0.0083	0.0065	0.0054	5.90E-03	3.70E-03	0.0081
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**8.34E-05**	4.06E-05	1.18E-05	4.65E-05	0.0001	0.0001	1.51E-05	1.36E-05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0000)	(0.0000)
θ_1	**0.7745**	0.4291	0.7514	0.1113	0.6000	0.6000	0.3071	0.5655
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.0596**	0.2388	0.0952	0.1196	0.1500	0.1500	0.1318	0.2191
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
τ	**-**	1.06E-08	9.54E-09	3.39E-08	0.0000	0.0000	8.53E-09	1.98E-08
		(0.0000)	(0.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(0.0000)

Where REF=Refineries, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover.*

Table 4.23: Return Spillover from Refineries-to-Other Industries - ARMA Model

	REF	ENG	FERT	PHAR	SUG	TEX	TOB
η_o	**4.30E-03**	0.0002	0.0001	1.10E-03	-0.0003	0.0008	0.0123
	(0.7895)	(0.4544)	(0.2378)	(0.0498)	(0.3356)	(0.1148)	(0.0000)
η_1	**0.2804**	-0.0835	0.0209	-1.2385	1.8124	-2.0283	-12.8076
	(0.0299)	(0.7488)	(0.9248)	(0.0205)	(0.0000)	(0.2303)	(0.0000)
η_2	**0.0005**	-	-	-	-	-	-
	(0.7919)						
η_3	**-0.1312**	0.0308	0.0276	1.2143	-1.781	2.0199	12.8242
	(0.3191)	(0.9059)	(0.9011)	(0.0232)	(0.0000)	(0.2322)	(0.0000)
ψ	**-**	0.0037	0.0041	0.0108	0.0017	4.90E-03	1.00E-02
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where REF=Refineries, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. denotes the parameters of mean spillover.

Table 4.22 shows the estimates of return and volatility spillovers from Refineries-to-Other Industries by using an ARMA GARCH (m,n) Model. Here, η_3 proved to be significantly negative only for Automobile Assembler-AA, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T which shows that, only these 3 industries account for the process of corrections on the basis of past shocks.

The coefficient of θ_1 is significant and positive for all industries which implies that, volatility of the current period can be predicted by using the past prices behavior. Moreover, coefficient of θ_2 is also significant and positive for all industries which indicates the evidence about persistence of the volatility in all industries. Sum of the coefficients of $\theta_1 + \theta_2$ is closer to 1 for all industries that indicates the long run behaviour of persistence of volatility for these industries.

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T which implies that, mean returns of all industries are influenced by Refineries-REF returns. Similarly, the results of volatility spillover τ also show a significant positive impact on all same industries which also confirms that, the volatility of Refineries-REF quickly transmits to the other industries.

Table 4.23 shows the estimates of return spillovers from Refineries-to-other industries by using an ARMA (m,n) model across 6 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by Refineries-REF returns.

Table 4.24 shows the estimates of return and volatility spillovers from Sugar-to-Other Industries by using an ARMA GARCH (m,n) model across except; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The coefficient of Standardized residual error term, η_3 proved to be significantly negative only for Chemical-CHEM and Commercial Banks-CB that implies, only these 2 industries rely on past shock and move opposite to make the correction on next day.

The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. As the sum of $\theta_1 + \theta_2$ is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run for all industries.

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Sugar-SUG returns. As the GARCH model can not be applied on this industry that further makes the variance constant, so the coefficient of volatility spillover τ is constant.

TABLE 4.24: Return & Volatility Spillover from Sugar-to-Other Industries - ARMA GARCH Model

	SUG	**AA**	**CEM**	**CHE**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**-3.00E-04**	0.0005	0.0002	1.37E-05	0.0002	0.0003	-0.0003	0.0873	5.76E-05
	(0.3298)	(0.7798)	(0.4958)	(0.9628)	(0.2103)	(0.1218)	(0.1705)	(0.1820)	(0.7229)
η_1	**1.8131**	0.3882	0.1629	0.9156	0.3927	0.2555	-0.7922	-0.1227	0.0024
	(0.0000)	(0.0008)	(0.1764)	(0.0048)	(0.0003)	(0.1171)	(0.4642)	(0.5663)	(0.9868)
η_2	-	-0.3801	0.6311	-0.2290	0.0409	1.0058	12.1677	0.0125	0.2681
		(0.9489)	(0.7445)	(0.9050)	(0.9823)	(0.5932)	(0.0967)	(0.1805)	(0.8132)
η_3	**-1.7813**	-0.1867	-0.0658	-0.8783	-0.2732	-0.1705	0.7915	0.2942	0.0831
	(0.0000)	(0.1190)	(0.5872)	(0.0066)	(0.0122)	(0.2987)	(0.4652)	(0.1763)	(0.5783)
ψ	-	0.0059	0.3405	0.1038	0.0566	7.45E-02	4.93E-02	-0.0383	0.1025
		(0.0268)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1845)	(0.0000)
θ_o	-	0.0001	2.67E-06	1.68E-05	4.52E-06	4.32E-06	5.71E-06	4.00E-04	3.10E-07
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0000)
θ_1	-	0.5197	0.9404	0.7377	0.8666	0.8535	0.8066	0.5484	0.9664
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	-	0.0667	0.0488	0.1720	0.1004	0.0000	0.1004	0.0368	0.0343
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0003)	(0.0000)
τ	-	Constant	Constant	Constant	Constant	Constant	Constant	Constant	Constant

Where SUG=Sugar, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ denotes the parameters of mean spillover and τ denotes the parameters of volatility spillover.

Table 4.25 shows the estimates of return spillovers from Sugar-to-Other Industries by using an ARMA (m,n) model across 5 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Textiles-TEX & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by any change/variation occurred in Sugar-SUG.

TABLE 4.25: Return Spillover from Sugar-to-Other Industries - ARMA Model

	SUG	**ENG**	**FERT**	**PHAR**	**TEX**	**TOB**
η_o	**-3.00E-04**	0.0003	0.0001	1.50E-03	0.0019	0.0108
	(0.3298)	(0.1210)	(0.3315)	(0.0012)	(0.0000)	(0.0000)
η_1	**1.8131**	-0.7238	0.0853	-2.038	-5.5892	-11.0979
	(0.0000)	(0.0002)	(0.7182)	(0.0000)	(0.0000)	(0.0000)
η_2	-	-	-	-	-	-
η_3	**-1.7813**	0.6769	-0.0293	1.9893	5.5639	11.1039
	(0.0000)	(0.0004)	(0.9016)	(0.0000)	(0.0000)	(0.0000)
ψ	-	0.6955	0.0597	1.1444	0.704	1.72E+00
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where SUG=Sugar, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.26 shows the estimates of return and volatility spillovers from Technology & Telecommunication-to-Other Industries by using an ARMA GARCH (m,n) model. Here, almost all ARCH coefficients are found to be insignificant except Refineries-REF. It means, the process of correction is not found in any industries when spillover is generated from Technology & Telecommunication T&T. Moreover, there found a consistency in the behaviour of these industries.

On the other side, The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all same industries that provides the evidence about persistence of the volatility.

TABLE 4.26: Return & Volatility Spillover from Technology & Telecommunication-to-Other Industries - ARMA GARCH Model

	T&T	AA	CEM	CHE	CB	O&G	P&D	REF
η_o	**-5.33E-05**	0.0006	-0.0014	9.00E-04	0.0001	-0.0003	0.0002	-0.0112
	(0.7407)	(0.8106)	(0.6936)	(0.5186)	(0.9535)	(0.8692)	(0.8571)	(0.0020)
η_1	**0.0587**	0.3020	0.1455	0.737	0.5679	0.3591	1.1682	0.3967
	(0.6916)	(0.0913)	(0.1766)	(0.3678)	(0.0155)	(0.2925)	(0.3501)	(0.0000)
η_2	**0.5363**	-0.9324	-0.0001	-7.3767	-1.4813	4.2657	-8.9776	-0.0012
	(0.6322)	(0.8655)	(0.6474)	(0.0580)	(0.8048)	(0.4960)	(0.4196)	(0.0025)
η_3	**0.0324**	-0.1907	-0.04	-0.8342	-0.4075	-0.2452	-1.1904	-0.2805
	(0.8286)	(0.3117)	(0.7118)	(0.3081)	(0.0949)	(0.4797)	(0.3419)	(0.0033)
ψ	**-**	0.0045	0.007	0.0058	0.0059	6.30E-03	3.60E-03	0.0081
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	**1.71E-07**	0.0001	6.37E-06	0.0001	0.0001	9.85E-05	4.83E-05	6.03E-06
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0004)	(0.0000)	(0.0000)
θ_1	**0.9743**	0.6000	0.8561	0.6000	0.6000	0.6000	0.6000	0.8443
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	**0.027**	0.1500	0.0892	0.1500	0.1500	0.1500	0.1500	0.0971
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0012)	(0.0001)	(0.0001)	(0.0000)
τ	**-**	0.0000	3.56E-10	0.0000	0.0000	0.0000	0.0000	2.46E-09
		(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)

Where T&T=Technology & Telecommunication, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover.*

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D and Refineries-REF which implies that, the mean returns of all these industries are influenced by Technology & Telecommunication-T&T returns. But here, the volatility spillover is found insignificant in all industries except Cement-CEM and Refineries-REF which indicates that, only these two industries incorporate the effects of volatility while others show no variation. The possible reason is the small size of Technology & Telecommunication-T&T sector. Change in the costs only affect the returns but it doesnt set the direction of the market as there found no volatility transmission across rest of the industries. In short, a scarce evidence is found across the spillover effects from Technology & Telecommunication-T&T to other industries means there exists no spillover effect across this industry.

Table 4.27 shows the estimated results of return spillovers from Technology & Telecommunication-to-other industries by using an ARMA (m,n) model across six industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB.

TABLE 4.27: Return Spillover from Technology & Telecommunication -to-Other Industries - ARMA Model

	T&T	**ENG**	**FERT**	**PHAR**	**SUG**	**TEX**	**TOB**
η_o	**-5.33E-05**	0.0001	0.0001	1.10E-03	-0.0003	0.0008	0.0122
	(0.7407)	(0.5137)	(0.2998)	(0.0666)	(0.3269)	(0.1545)	(0.0000)
η_1	**0.0587**	-0.0556	0.0250	-1.2479	1.7914	-1.8526	-12.6827
	(0.6916)	(0.8299)	(0.9061)	(0.0236)	(0.0000)	(0.2815)	(0.0000)
η_2	-	-	-	-	-	-	-
η_3	**0.0324**	0.0021	0.0284	1.2241	-1.7586	1.8448	12.7002
	(0.8286)	(0.9934)	(0.8938)	(0.0265)	(0.0000)	(0.2853)	(0.0000)
ψ	-	0.0044	0.005	0.0048	0.0026	2.90E-03	2.70E-03
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)

Where T&T=Technology & Telecommunication , ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar, TEX=Textiles & TOB=Tobacco. ψ denotes the parameters of mean spillover.

The results of mean spillover has a significant positive impact on all industries that means, mean returns of all these industries are influenced by Technology & Telecommunication-T&T returns.

Table 4.28 shows the estimates of return and volatility spillovers from Textiles-to-Other Industries by using an ARMA GARCH (m,n) model across all industries except; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG, Textiles-TEX & Tobacco-TOB. The coefficient of Standardized residual error term, η_3 proved to be significantly negative for Automobile Assembler-AA, Chemical-CHEM, Commercial Banks-CB that implies, these markets rely on past shock and move opposite to make the correction on next day.

The coefficient of θ_1 is significant and positive for all industries; except Refineries-REF which indicates that, volatility of the current period can be predicted by using the past prices behavior. But there find no lagged behaviour of volatility in Refineries-REF. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. Sum of $\theta_1 + \theta_2$ is 1 that shows the persistence is in long run for all industries.

The results of mean spillover ψ show a significant positive impact on all industries; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are influenced by Textiles-TEX returns. As the GARCH model can not be applied on this industry that further makes the variance constant, so the coefficient of volatility spillover τ is constant.

Table 4.29 shows the estimates of return spillovers from Textiles-to-Other Industries by using an ARMA (m,n) model across 5 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG & Tobacco-TOB. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by Textiles-TEX returns.

TABLE 4.28: Return & Volatility Spillover from Textiles-to-Other Industries - ARMA GARCH Model

	TEX	**AA**	**CEM**	**CHE**	**CB**	**O&G**	**P&D**	**REF**	**T&T**
η_o	**8.00E-04**	0.0003	-0.0001	1.00E-04	0.0002	0.0002	-0.0003	0.1761	2.19E-05
	(0.0961)	(0.1580)	(0.5584)	(0.4947)	(0.2678)	(0.2143)	(0.2292)	(0.0439)	(0.8883)
η_1	**-1.7098**	0.4363	0.0489	0.5744	0.3656	0.2161	-0.6786	0.2187	-0.0174
	(0.1965)	(0.0000)	(0.6898)	(0.0478)	(0.0007)	(0.1825)	(0.5597)	(0.1830)	(0.9050)
η_2	-	0.2523	3.5839	-0.5153	0.3687	1.6045	11.3901	0.0243	0.4246
		(0.8534)	(0.0226)	(0.7896)	(0.8401)	(0.3947)	(0.1326)	(0.0446)	(0.7006)
η_3	**1.6994**	-0.2795	0.0429	-0.5554	-0.2447	-0.1346	0.6811	-0.0548	0.1007
	(0.1993)	(0.0000)	(0.7275)	(0.0543)	(0.0250)	(0.4091)	(0.5588)	(0.7406)	(0.4938)
ψ	-	0.2116	0.4027	0.2875	0.0551	7.25E-02	6.50E-03	0.2142	0.0845
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_o	-	3.95E-06	5.58E-06	1.9E-06	4.53E-06	4.1E-06	5.23E-06	4.00E-04	2.18E-07
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-	0.8851	0.9038	0.9387	0.8667	0.8642	0.8239	0.3121	0.9689
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0615)	(0.0000)
θ_2	-	0.1110	0.0761	0.0536	0.1002	0.1058	0.0895	0.0334	0.0327
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	Constant	Constant	Constant	Constant	Constant	Constant	Constant	Constant

Where TEX=Textiles, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover.*

Table 4.29: Return Spillover from Textiles-to-Other Industries - ARMA Model

	TEX	ENG	FERT	PHAR	SUG	TOB
η_o	**8.00E-04**	0.0001	0.0001	8.00E-04	-6.4E-05	0.012
	(0.0961)	(0.4242)	(0.3177)	(0.0433)	(0.7911)	(0.0000)
η_1	**-1.7098**	0.1112	0.0582	-0.7415	1.1616	-12.4113
	(0.1965)	(0.5613)	(0.8056)	(0.0599)	(0.0000)	(0.0000)
η_2	-	-	-	-	-	-
η_3	**1.6994**	-0.1739	-0.0023	0.7072	-1.4448	12.4231
	(0.1993)	(0.3644)	(0.9919)	(0.0729)	(0.0001)	(0.0000)
ψ	-	0.7151	0.0601	1.3061	0.7477	1.9632
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Where TEX=Textiles, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar & TOB=Tobacco. ψ denotes the parameters of mean spillover.

Table 4.30 shows the estimates of return and volatility spillovers from Tobacco-to-Other Industries by using an ARMA GARCH (m,n) model. The coefficient of Standardized residual error term, η_3 proved to be significantly negative for Automobile Assembler-AA, Chemical-CHEM, Commercial Banks-CB that implies, these markets rely on past shock and move opposite to make the correction on next day.

The coefficient of θ_1 is significant and positive for all industries which indicates that, volatility of the current period can be predicted by using the past prices behavior. Coefficient of θ_2 is also significant and positive for all same industries that provides the evidence about persistence of the volatility. As the sum of θ_1 + θ_2 is closer to 1 for all industries, it means the nature of the persistence of the volatility is in long run for all industries.

The results of mean spillover ψ show a significant positive impact on all industries except Commercial Banks-CB, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T which implies that, the mean returns of all industries are not influenced by Tobacco-TOB returns.

Table 4.30: Return & Volatility Spillover from Tobacco-to-Other Industries - ARMA GARCH Model

	TOB	AA	CEM	CHE	CB	O&G	P&D	REF	T&T
η_o	**1.22E-02**	0.0008	0.0003	3.21E-05	0.0002	0.0004	-0.0003	0.1434	0.0001
	(0.0000)	(0.0916)	(0.3633)	(0.9128)	(0.2116)	(0.0555)	(0.6048)	(0.0063)	(0.7329)
η_1	**-12.6382**	0.4821	0.2305	0.9305	0.4118	0.2312	1.025	0.2577	-0.087
	(0.0000)	(0.0000)	(0.0543)	(0.0058)	(0.0002)	(0.1632)	(0.2186)	(0.1222)	(0.6213)
η_2	-	-1.6628	-0.169	-0.2427	-0.1574	0.7226	1.9021	0.0203	-0.3915
		(0.3803)	(0.9329)	(0.8959)	(0.9293)	(0.6930)	(0.7653)	(0.0053)	(0.7951)
η_3	**12.656**	-0.3152	-0.1162	-0.8865	-0.2885	-0.1413	-1.0476	-0.0813	0.1729
	(0.0000)	(0.0000)	(0.3351)	(0.0084)	(0.0094)	(0.3969)	(0.2107)	(0.6301)	(0.3310)
ψ	-	0.05	0.025	0.0184	0.0005	1.11E-02	4.90E-03	0.0793	0.0006
		(0.0000)	(0.0000)	(0.0000)	(0.4575)	(0.0000)	(0.1889)	(0.0000)	(0.8082)
θ_o	-	2.22E-06	3.8E-06	1.48E-05	4.44E-06	0.000005	3.04E-05	3.00E-04	8.32E-06
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_1	-	0.9263	0.9438	0.7565	0.8646	0.8368	0.5909	0.5654	0.8738
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ_2	-	0.0709	0.0387	0.1694	0.1045	0.1273	0.1465	0.0297	0.0947
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
τ	-	Constant	Constant	Constant	Constant	Constant	Constant	Constant	Constant

Where TOB=Tobacco, AA=Automobile Assemblers, CEM=Cement, CHE=Chemicals, CB=Commercial Banks, O&G=Oil & Gas, P&D=Power Generation & Distribution, REF=Refineries, T&T=Technology & Telecommunication. Values in parenthesis are the p-values. ψ *denotes the parameters of mean spillover and* τ *denotes the parameters of volatility spillover.*

In simple words, these industries do not exhibit the mean spillover with respect to Tobacco-TOB. While, the remaining ones; Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Oil & Gas-O&G and Refineries-REF show a significant positive impact that implies, mean spillover exists across these industries. As the GARCH model can not be applied on this industry that further makes the variance constant, so the coefficient of volatility spillover τ is constant.

Table 4.31: Return Spillover from Tobacco-to-Other Industries - ARMA Model

	TOB	**ENG**	**FERT**	**PHAR**	**SUG**	**TEX**
η_o	**1.22E-02**	0.0003	0.0001	6.00E-04	-0.0009	0.0039
	(0.0000)	(0.1882)	(0.3503)	(0.1364)	(0.0001)	(0.0000)
η_1	**-12.6382**	-0.5424	0.1150	-0.2978	3.3683	-12.6766
	(0.0000)	(0.0072)	(0.6290)	(0.4558)	(0.0000)	(0.0000)
η_2	-	-	-	-	-	-
η_3	**12.656**	0.5033	-0.0563	0.2843	-3.339	12.6746
	(0.0000)	(0.0127)	(0.8132)	(0.4767)	(0.0000)	(0.0000)
ψ	-	0.2529	0.0062	0.485	0.2599	0.2801
		(0.0000)	(0.0266)	(0.0000)	(0.0000)	(0.0000)

Where TOB=Tobacco, ENG=Engineering, FERT=Fertilizers, PHAR=Pharmaceuticals, SUG=Sugar & TEX=Textiles. ψ denotes the parameters of mean spillover.

Table 4.31 shows the estimates of return spillovers from Tobacco-to-Other Industries by using an ARMA (m,n) model across 5 industries; Engineering-ENG, Fertilizers-FERT, Pharmaceuticals-PHAR, Sugar-SUG & Textiles-TEX. The results of mean spillover has a significant positive impact on all industries that means, the mean returns of all these industries are influenced by Tobacco-TEX returns.

All the above mentioned results of return and volatility spillover across different sectors are also in line with some previous studies. For example, Karmakar and Shukla (2016) study the spillover relationship between Oil & Gas, Banking, Auto & Parts and IT industries of India. They find that all these sectors exhibit mean and volatility transmission in a bi-variate framework. In addition, the study of Singhal and Ghosh (2016) also document the return and volatility transmission from Oil market to Refineries and some other industries like; Automobiles, Energy and Power at 5% significance level and Finance sectors like, Banking at 10% significance level. Volatility in Oil market affect the AUTO sector returns by raising the fuel prices and Finance sector through their effects on monetary policy and interest rate. While on the other side, volatility of Technology & Telecommunication shows no variation with rest of all industries except two industries; Cement-CEM and Refineries-REF. These findings also make a linkage with the study of Majumder and Nag who also reveal that, any unanticipated shocks emanating from the Finance and IT sectors failed to affect others. However, there found a unidirectional transmission from the FMCG sector to the Finance and IT sectors.

4.4 Time-Varying Conditional Correlation - DCC & ADCC

As it is discussed in the methodology that, ARMA GARCH model only incorporate the effect of spillovers by taking the assumption of Constant Conditional Correlation CCC. But if the correlation is time varying, then Dynamic Condition Correlation DCC model is used in this study. Moreover, the effects of any asymmetry is also captured by using the extended version of DCC model that is, Asymmetric Dynamic Conditional Correlation ADCC.

4.4.1 DCC MV - GARCH Models & Estimates Between Exchange Rate & Other Industries

Tables 4.32 and 4.33 show the suitable uni-variate DCC models and estimates from exchange rate-to-other industries, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria - AIC.

Table 4.33 summarizes the results of DCC GARCH model between exchange rate and other industries. This table reports the impact of the past residual shocks

Table 4.32: DCC MV - GARCH Models B/W Exchange Rate & Other Industries

Sr. No.	Industries	Selected Model
1	Automobiles Assemblers	GJR/TARCH
2	Cement	GJR/TARCH
3	Chemicals	GARCH
4	Commercial Banks	EGARCH
5	Engineering	GARCH
6	Fertilizers	GARCH
7	Oil & Gas	GJR/TARCH
8	Pharmaceuticals	GARCH
9	Power Generation Distribution	GJR/TARCH
10	Refineries	GJR/TARCH
11	Sugar & Allied Industries	GJR/TARCH
12	Technology & Telecom	EGARCH
13	Textiles	GJR/TARCH
14	Tobacco	EGARCH

This table shows the optimal uni-variate DCC GARCH model with respect to each industry and then the appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

(θ_1) and lagged dynamic conditional correlation (θ_2) with their respective p-values. The first condition of DCC model is to check the stability condition as it must be less than 1 (i.e. $\theta_1 + \theta_2 < 1$). All industries successfully met the required stability condition. It means, DCC model must be used for measuring the time varying conditional correlation. The parameters of θ_1 is found significantly negative for Automobile Assemblers-AA, Chemicals-CHEM, Oil & Gas-O&G and Tobacco-TOB while, Technology & Telecommunication-T&T shows a highly significant correlation. All the significant variations implies that, there exists the impact of past residual shocks on correlation. The Parameters of θ_1 is found to be highly significant for Cement-CEM, Chemicals-CHEM, Pharmaceuticals-PHAR, Power Generation & Distribution-P&D, Sugar-SUG and Textiles-TEX which indicates that, there exists the lagged dynamic conditional correlation in these industries while, the same parameters of θ_2 is found significantly negative for Automobile Assemblers-AA and Technology & Telecommunication-T&T which indicates the impact of partial lagged dynamic conditional correlation. As Tobacco-TOB is a small sector so it doesnt show any lagged effect on correlation. In contrast, Commercial Banks-CB, Engineering-ENG, Fertilizers-FERT and Refineries-REF show no significant variations with respect to both θ_1 and θ_2.

TABLE 4.33: DCC MV - GARCH Estimates B/W Exchange rate & Other Industries

Industries	**Exchange Rates**	
	θ_1	θ_2
Automobile Assemblers - AA	-0.0017 (0.0000)	-0.7900 (0.0056)
Cement - CEM	0.0038 (0.4805)	0.9532 (0.0000)
Chemicals - CHEM	-0.0017 (0.0000)	0.7805 (0.0000)
Commercial Banks - CB	0.0052 (0.4667)	-0.2860 (0.4705)
Engineering - ENG	0.0237 (0.1666)	0.5135 (0.0987)
Fertilizers - FERT	4.00E-04 (0.9359)	8.31E-01 (0.2233)
Oil & Gas - O&G	-0.0017 (0.0000)	0.7870 (0.1356)
Pharmaceuticals - PHAR	-0.0003 (0.1789)	0.9703 (0.0000)
Power Generation Distribution - P&D	0.0089 (0.2340)	0.8769 (0.0000)
Refineries - REF	0.0062 (0.4665)	0.5604 (0.4405)
Sugar - SUG	0.0017 (0.7757)	0.9336 (0.0000)
Technology & Telecom - T&T	0.0081 (0.0000)	-0.1939 (0.0000)
Textiles - TEX	0.0077 (0.6990)	0.8674 (0.0000)
Tobacco - TOB	-1.20E-03 (0.0000)	7.96E-01 (0.1089)

This table summarizes the estimated coefficients from the DCC-MV-GARCH model in a bi-variate framework for exchange rate and other industries. Values in parenthesis are the p-values. Theta(1) and Theta(2) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable uni-variate GARCH model.

4.4.2 ADCC MV - GARCH Models & Estimates Between Exchange Rate & Other Industries

Tables 4.34 and 4.35 show the suitable uni-variate DCC models and estimates form exchange rate-to-other industries, respectively.

TABLE 4.34: ADCC MV - GARCH Models B/W Exchange Rate & Other Industries

Sr. No.	Industries	Selected Model
1.	Automobiles Assemblers	GJR/TARCH
2.	Cement	GARCH
3.	Chemicals	GJR/TARCH
4.	Commercial Banks	GJR/TARCH
5.	Engineering	GARCH
6.	Fertilizers	GARCH
7.	Oil & Gas	EGARCH
8.	Pharmaceuticals	GARCH
9.	Power Generation Distribution	GJR/TARCH
10.	Refineries	GJR/TARCH
11.	Sugar & Allied Industries	GJR/TARCH
12.	Technology & Telecom	GJR/TARCH
13.	Textiles	GJR/TARCH
14.	Tobacco	GJR/TARCH

This table shows the optimal univariate ADCC GARCH model with respect to each industry and then the appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

Table 4.35 covers the estimates of ADCC GARCH model between exchange rate and other industries. The first two parameters of this table are same as that of DCC GARCH models i.e. the impact of the past residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2). An additional parameter of (θ_3) is used in this model that provides the information about the shocks of positive and negative news on dynamic conditional correlation. Like previous model of DCC, the first condition that is the stability of model is also met in all industries (i.e. $\theta_1 + \theta_2$ <1). It means, the model is stable.

Table 4.35: ADCC MV - GARCH Estimates B/W Exchange rate & Other Industries

Industries	**Exchange Rates**		
	θ_1	θ_2	θ_3
Automobile Assemblers - AA	-0.0017	0.7891	-0.0040
	(0.0000)	(0.0246)	(0.8493)
Cement - CEM	0.0018	-0.2287	0.0984
	(0.0000)	(0.0000)	(0.0000)
Chemicals - CHEM	-0.0017	0.7773	-0.0039
	(0.0000)	(0.0000)	(0.8683)
Commercial Banks - CB	-0.0016	0.7924	0.0056
	(0.0000)	(0.0000)	(0.2025)
Engineering - ENG	0.0274	0.5103	-0.0132
	(0.1691)	(0.0740)	(0.7023)
Fertilizers - FERT	7.00E-04	6.64E-01	3.37E-02
	(0.0000)	(0.0000)	(0.0000)
Oil & Gas -O&G	-0.0015	0.5584	0.0183
	(0.0000)	(0.0000)	(0.0000)
Pharmaceuticals -PHAR	-0.0047	0.8120	0.0172
	(0.1668)	(0.0015)	(0.3713)
Power Generation Distribution - P&D	0.0040	0.6964	0.0523
	(0.5574)	(0.0000)	(0.0015)
Refineries - REF	0.008	-0.0246	0.1156
	(0.4257)	(0.9247)	(0.0083)
Sugar - SUG	-0.0097	0.7951	0.0203
	(0.0000)	(0.1508)	(0.6225)
Technology & Telecom - T&T	0.0096	-0.1641	0.0459
	(0.5748)	(0.5937)	(0.1654)
Textiles - TEX	0.0087	0.8301	0.0432
	(0.7072)	(0.0000)	(0.2756)
Tobacco - TOB	-1.10E-03	8.10E-01	3.75E-02
	(0.0000)	(0.0000)	(0.4771)

This table summarizes the estimated coefficients from the ADCC-MV-GARCH model in a bi-variate framework for exchange rate and other industries. Values in parenthesis are the p-values. Theta(1), Theta(2) and Theta(3) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable uni-variate GARCH model.

The parameters of θ_1 is found significantly negative for Automobile Assemblers-AA, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Sugar-SUG and Tobacco-TOB that shows a partial impact of past residual shocks on dynamic correlation while, Cement-CEM and Fertilizers-FERT show a highly significant positive impact of past residual shocks on correlation. The Parameters of θ_2 is found to be highly significant for Automobile Assemblers-AA, Chemicals-CHEM, Commercial Banks-CB, Fertilizers-FERT, Oil & Gas-O&G, Pharmaceuticals-PHAR, Power Generation & Distribution-P&D, Textiles-TEX and Tobacco-TOB which indicates that, there exists the lagged dynamic conditional correlation in these industries while, the same parameters of θ_2 is found significantly negative only for Cement-CEM that shows the partial impact of lagged dynamic conditional correlation. Engineering-ENG, Refineries-REF and Technology & Telecommunication-T&T show no significant variations with respect to both θ_1 and θ_2. The parametric values of θ_3 also show a significant positive impact for Fertilizers-FERT, Oil & Gas-O&G, Power Generation & Distribution-P&D and Refineries-REF that indicates, the correlation has been increased with the effect of negative news while, the remaining industries show no variations with respect to asymmetric effect. In short, any good or bad news arises in market, didnt effect the correlation. From the both tables reported above, it is clear that ADCC model provides more reliable and authentic results as compared to DCC because it is also capturing the asymmetric effect between the series. So, we can say that the most of the industrial returns in this study show significant time variation in its conditional correlations and few of them show asymmetric behaviour.

4.4.3 DCC MV - GARCH Models & Estimates Across the Industries

For the purpose of the estimation of DCC and ADCC across industries, all DCC & ADCC models and estimates are categorized into four major groups such as ...

- Engineering

  The following category includes 3 industries:

1. Automobile Assemblers
2. Engineering
3. Technology & Telecommunication

- Manufacturing

  The following category includes 4 industries:

  1. Cement
  2. Chemicals
  3. Fertilizers
  4. Pharmaceuticals

- Oil, Power & Gas

  The following category includes 3 industries:

  1. Oil & Gas
  2. Power Generation & Distribution
  3. Refineries

- Others

  The following category includes 4 industries:

  1. Commercial Banks
  2. Sugar
  3. Textiles
  4. Tobacco

1. **Engineering**

   Tables 4.36 and 4.37 show the suitable uni-variate DCC models and estimates across industries for Engineering group, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria - AIC.

Table 4.37 reports the results of DCC MV-GARCH model across industries for Engineering Group. This category contains three industrial groups; Automobile Assemblers, Engineering & Technology & Telecommunication. The table reports the impact of the past residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2) with their respective p-values. First of all, the condition of the stability of the DCC model is met in all industries that $\theta_1 + \theta_2 < 1$. So, DCC model must be used for measuring the time varying conditional correlation.

For Automobile Assemblers, the parameters of θ_1 are found highly significant for all industries which indicates, these industries exhibit the impact of past residual shocks on dynamic conditional correlation. θ_2 is also found highly significant for all industries except Tobacco-TOB. It means, the impact of lagged dynamic conditional correlation also exists. As Tobacco is a small industry, so it is not showing any significant variation.

The parameters of θ_1 for Engineering-ENG are also found highly significant for all industrial pairs that implies, all these industries show the impact of past residual shocks on correlation. Similarly, θ_2 is also found highly significant for all industrial pairs that indicates the impact of lagged dynamic conditional correlation in all of these industries. But here, Refineries-REF shows no significant variation with respect to Engineering-ENG. It means, the returns of Refineries-REF didnt exhibit the lagged dynamic conditional correlation.

Finally, the parameters of θ_1 are found highly significant for all industries with respect to Technology & Telecommunication-T&T. It means, the impact of past residual shocks on conditional correlation exists in these industries. θ_2 is found highly significant only for Textiles-TEX which indicates the impact of lagged dynamic conditional correlation in this sector. Tobacco-TOB didnt show any significant variation with respect to Technology & Telecommunication-T&T that shows, there exists no impact of lagged dynamic correlation in this sector. The possible reason for this insignificant behaviour of Tobacco-TOB can be the small size of the industry.

Table 4.36: Uni-variate DCC GARCH Models - Engineering Group

Industries	*1. Automobile Assemblers*	*2. Engineering*	*3. Technology & Telecom.*
Cement	GJR/TARCH	-	-
Chemicals	GARCH	-	-
Commercial Banks	EGARCH	-	-
Engineering	GARCH	-	-
Fertilizers	GARCH	GARCH	-
Oil & Gas	GJR/TARCH	GARCH	-
Pharmaceuticals	GARCH	GARCH	-
Power Generation Distribution	GJR/TARCH	GARCH	-
Refineries	GARCH	GARCH	-
Sugar	GJR/TARCH	GARCH	-
Technology & Telecom	GARCH	GARCH	-
Textiles	GARCH	GARCH	GARCH
Tobacco	GARCH	GARCH	GARCH

This table shows the optimal uni-variate DCC-GARCH Models - Engineering Group applied on each industry with the rest of other Industries. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

Table 4.37: DCC MV-GARCH Estimates across Industries - Engineering Group

Industries	**1. Automobile Assemblers**		**2. Engineering**	
	θ_1	θ_2	θ_1	θ_2
Cement	0.0386	0.9259	-	-
	(0.0000)	(0.0000)	-	-
Chemicals	0.0498	0.0014	-	-
	(0.0008)	(0.9718)	-	-
Commercial Banks	0.0483	0.8844	-	-
	(0.0000)	(0.0000)	-	-
Engineering	0.0659	0.6077	-	-
	(0.0000)	(0.0000)	-	-
Fertilizers	0.0533	0.8669	0.0433	0.7525
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Oil & Gas	5.04E-02	8.69E-01	2.69E-02	7.90E-01
	(0.0000)	(0.0000)	(0.0011)	(0.0000)
Pharmaceuticals	0.3751	0.8884	0.3310	0.2373
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Power Generation Distribution	0.0242	0.9497	0.0390	0.8445
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Refineries	0.1854	0.4151	0.2493	0.0167
	(0.0000)	(0.0000)	(0.0000)	(0.5768)
Sugar	0.0625	0.732	0.9869	0.0076
	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Technology & Telecom	0.0332	0.9429	0.0442	0.8658
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Textiles	0.0226	0.9268	0.0031	0.8725
	(0.0005)	(0.0000)	(0.0000)	(0.0000)
Tobacco	7.26E-02	1.77E-01	2.18E-02	8.60E-01
	(0.0053)	(0.3006)	(0.0001)	(0.0000)

This table summarizes the estimated coefficients from the DCC-MV-GARCH estimates - Engineering Group in a bivariate framework for each industry with the rest of other Industries. Values in parenthesis are the p-values. Theta(1) and Theta(2) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable univariate GARCH model.

Cont. (4.37) ...	3. Technology & Telecom.	
	θ_1	θ_2
Cement	- -	- -
Chemicals	- -	- -
Commercial Banks	- -	- -
Engineering	- -	- -
Fertilizers	- -	- -
Oil & Gas	- -	- -
Pharmaceuticals	- -	- -
Power Generation Distribution	- -	- -
Refineries	- -	- -
Sugar	- -	- -
Technology & Telecom	- -	- -
Textiles	0.0552 (0.0000)	0.9032 (0.0000)
Tobacco	5.59E-02 (0.0226)	6.02E-02 (0.6375)

Values in parenthesis are the p-values. Theta(1) and Theta(2) are reported above the p-values.

2. **Manufacturing**

   Tables 38 and 39 show the suitable uni-variate DCC models and estimates across industries for Manufacturing group, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria - AIC.

Table 4.38: DCC MV - GARCH Models across Industries - Manufacturing Group

Industries	***1. Cement***	***2. Chemicals***	***3. Fertilizers***	***4. Pharmaceuticals***
Chemicals	GJR/TARCH	-	-	-
Commercial Banks	GJR/TARCH	GARCH	-	-
Engineering	GARCH	GARCH	-	-
Fertilizers	GJR/TARCH	GARCH	-	-
Oil & Gas	GJR/TARCH	GJR/TARCH	GARCH	-
Pharmaceuticals	GARCH	GARCH	GARCH	-
Power Generation Distribution	GARCH	GJR/TARCH	GJR/TARCH	GARCH
Refineries	GJR/TARCH	GARCH	GARCH	EGARCH
Sugar	GJR/TARCH	GJR/TARCH	GJR/TARCH	GARCH
Technology & Telecom	GJR/TARCH	GARCH	GARCH	GARCH
Textiles	GJR/TARCH	GARCH	GARCH	GJR/TARCH
Tobacco	GARCH	GARCH	GARCH	GARCH

This table shows the optimal uni-variate DCC GARCH model with respect to each industry for Manufacturing Group. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

TABLE 4.39: DCC MV - GARCH Estimates across Industries - Manufacturing Group

Industries	***1. Cement***		***2. Chemicals***		***3. Fertilizers***		***4. Pharmaceuticals***	
	θ_1	θ_2	θ_1	θ_2	θ_1	θ_2	θ_1	θ_2
Chemicals	0.0664	0.4834	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Commercial Banks	0.0755	0.6126	0.0081	0.8433	-	-	-	-
	(0.0000)	(0.0000)	(0.0240)	(0.0000)	-	-	-	-
Engineering	0.0447	0.7739	0.046	0.8473	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-	-	-	-
Fertilizers	0.0154	0.978	0.0553	0.7742	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-	-	-	-
Oil & Gas	0.0346	0.9048	0.0515	0.7222	0.0453	0.9113	-	-
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-	-
Pharmaceuticals	0.0099	0.8992	0.1664	0.4827	0.152	-0.0052	-	-
	(0.0074)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-	-
Power Generation Distribution	0.034	0.8266	0.0784	0.606	0.0289	0.9169	0.009	0.9283
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0289)	(0.0000)
Refineries	0.0968	0.3809	0.0719	0.5633	0.1289	0.3342	-0.003	0.8046
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sugar	0.0031	0.9289	0.0299	0.9011	0.0566	0.6459	0.0028	0.9947
	(0.1487)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Technology & Telecom	0.0392	0.9252	0.0093	0.889	0.0497	0.8817	0.0482	0.9033
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Textiles	-0.0003	0.9964	0.0379	0.9367	0.2016	0.015	-0.0005	0.8078
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8754)	(0.0000)	(0.0000)
Tobacco	0.0052	0.9348	0.0656	0.7656	0.0008	0.6373	-0.0003	-0.5342
	(0.0273)	(0.0000)	(0.0006)	(0.0000)	(0.8783)	(0.6349)	(0.2241)	(0.4774)

This table summarizes the estimated coefficients from DCC MV-GARCH model in a bi-variate framework across industries Manufacturing Group. p-values are reported in parenthesis. Theta(1) and Theta(2) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable univariate GARCH model.

Table 4.39 reports the results of DCC MV-GARCH model across industries for Manufacturing Group. This category contains three industrial groups; Cement, Chemicals, Fertilizers and Pharmaceuticals. The table reports the impact of the past residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2) with their respective p-values. The first condition of the stability of the DCC model is met in all industries that $\theta_1 + \theta_2 < 1$. So, DCC model must be used for measuring the time varying conditional correlation.

For Cement-CEM, θ_1 is found significantly positive for all industrial pairs except Textiles-TEX. It indicates that, the impact of past residual shocks on correlation exists in all industries while, Textiles-TEX shows the partial impact of past residual shocks on conditional correlation as the value of θ_1 is less than 0. The parameters of θ_2 are highly significant for all industrial pairs which indicates the impact of lagged dynamic correlation in all of these industries. For Chemicals-CHEM, both θ_1 and θ_2 are found highly significant for all industrial pairs that indicates, there exists an impact of past residual shocks and lagged dynamic conditional correlation in these industries.

Similarly, for Fertilizers-FERT, the parameters of θ_1 are found significantly positive for all industrial pairs that shows the impact of past residual shocks on correlation between these industries. θ_2 is also found significantly positive for all industrial pairs which indicates the impact of lagged dynamic conditional correlation for all of these industries. While, Pharmaceuticals-PHAR shows a negative correlation with Fertilizers-FERT which indicates the partial impact of lagged dynamic conditional correlation in this sector.

Finally, the parameters of θ_1 are found highly significant for all industrial pairs with respect to Pharmaceuticals-PHAR except Textiles-TEX, Refineries-REF and Tobacco-TOB. It means, the impact of past residual shocks on correlation exists in all of these industries while, Textiles-TEX and Refineries-REF exhibit the partial impact of past residual shocks on correlation as the value of θ_1 is less than 0. On the other side, Tobacco-TOB didnt show any significant variation due to small size of industry. θ_2 is also found highly significant for all industrial pairs except Tobacco-TOB which indicates that, there exists the impact of lagged dynamic conditional correlation in these industries except Tobacco-TOB due to low market capitalization.

3. **Oil, Power & Gas**

Tables 4.40 and 4.41 show the suitable uni-variate DCC models and estimates across industries for Oil, Power & Gas group, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria - AIC.

Table 4.41 reports the results of DCC MV-GARCH model across industries for Oil & Gas Group. This category contains three industrial groups; Oil & Gas, Power Generation & Distribution and Refineries. The table reports the impact of the past residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2) with their respective p-values. The first condition of the stability of the DCC model is met in all industries that θ_1 + θ_2 <1. So, DCC model must be used for measuring the time varying conditional correlation.

For Oil & Gas-O&G, the parameters of θ_1 are found significantly positive for all industrial pairs that shows the impact of past residual shocks on correlation between these industries. θ_2 is also found significantly positive for all industrial pairs which indicates the impact of lagged dynamic conditional correlation for all of these industries. While, Tobacco-TOB didnt show any significant variation with Oil & Gas-O&G due to low market capitalization.

Similarly, for Power Generation & Distribution-P&D, the parameters of θ_1 are found significantly positive for all industrial pairs except Textiles-TEX and Tobacco-TOB. It means, the impact of past residual shocks on correlation exists in all of these industries while, Textiles-TEX and Tobacco-TOB exhibit the partial impact of past residual shocks on correlation as the value of θ_1 is negative. θ_2 is found highly significant for all industrial pairs which indicates that, there exists the impact of lagged dynamic conditional correlation in these industries.

Table 4.40: DCC MV - ARCH Models across Industries - Oil, Power & Gas Group

Industries	***1. Oil & Gas***	***2. Power Generation & Distribution***	***3. Refineries***
Pharmaceuticals	GARCH	-	-
Power Generation Distribution	GJR/TARCH	-	-
Refineries	GARCH	GJR/TARCH	-
Sugar	GJR/TARCH	GJR/TARCH	GJR/TARCH
Technology & Telecom	GARCH	GARCH	GARCH
Textiles	GARCH	GJR/TARCH	GARCH
Tobacco	GARCH	GARCH	GARCH

This table shows the optimal uni-variate DCC GARCH model with respect to each industry for Oil, Power & Gas Group. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

Table 4.41: DCC MV - GARCH Estimates across Industries - Oil, Power & Gas Group

Industries	***1. Oil & Gas***		***2. Power Generation & Distribution***		***3. Refineries***	
	θ_1	θ_2	θ_1	θ_2	θ_1	θ_2
Pharmaceuticals	0.0274	0.9144	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-
Power Generation Distribution	0.0341	0.9051	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-
Refineries	0.0118	0.9859	0.0488	0.3906	-	-
	(0.0000)	(0.0000)	(0.0013)	(0.0011)	-	-
Sugar	0.1414	0.5414	0.0037	0.8668	0.0019	0.9862
	(0.0000)	(0.0000)	(0.3196)	(0.0000)	(0.0013)	(0.0000)
Technology & Telecom	0.033	0.9559	0.0412	0.8931	0.139	0.5528
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Textiles	0.0548	0.8893	-0.0006	0.9868	0.0034	0.9603
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0169)	(0.0000)
Tobacco	0.0806	0.0146	-0.0008	0.8717	-0.0006	0.8063
	(0.0016)	(0.7076)	(0.0099)	(0.0000)	(0.0000)	(0.0000)

This table summarizes the estimated coefficients from DCC-MV-GARCH model in a bi-variate framework across industries for Oil, Power & Gas Group. p-values are reported in parenthesis. Theta(1) and Theta(2) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable uni-variate GARCH model.

4. **Others**

Tables 4.42 and 4.43 show the suitable uni-variate DCC models and estimates across industries for Others, respectively. Model is selected through AIC.

Table 4.43 reports the results of DCC MV-GARCH model across industries for Others. This category contains four industrial groups; Commercial Banks, Sugar, Textiles and Tobacco. The table reports the impact of the past residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2) with their respective p-values. The first condition of the stability of the DCC model is met in all industries that $\theta_1 + \theta_2 <1$. So, DCC model must be used.

For Commercial Banks-CB, the parameters of θ_1 are found significantly positive for all industrial pairs except Textiles-TEX. All significant variations shows that, there exists an impact of past residual shocks conditional correlation while, Textiles-TEX shows a partial impact of past residual shocks on conditional correlation. The parameters of θ_2 are also found significantly positive for Fertilizers-FERT, Oil & Gas-O&G, Power Generation & Distribution-P&D, Refineries-REF, Sugar-SUG, Technology & Telecommunication-T&T, Textiles-TEX and Tobacco-TOB which indicates that there exists the impact of lagged dynamic conditional correlation in these industries while, the remaining two industries Engineering-ENG and Pharmaceuticals-PHAR show a partial impact of lagged dynamic conditional correlation.

Similarly, the parameters of θ_1 and θ_2 are found significantly positive for Technology & Telecommunication-T&T that shows the impact of past residual shocks and lagged dynamic conditional correlation against this sector. While, Tobacco-TOB shows the significant variation only for the impact of lagged dynamic conditional correlation. There is only one industry that doesnt fulfill the stability condition of DCC model i.e. Textiles-TEX. So, we can say that the model is not applicable on this sector and finally, the Textiles-TEX industry didnt show any significant variations with respect to other industrial pairs.

Table 4.42: DCC MV - GARCH Models across Industries - Others

Industries	***1. Commercial Banks***	***2. Sugar***	***3. Textiles***	***4. Tobacco***
Engineering	GARCH	-	-	-
Fertilizers	GARCH	-	-	-
Oil & Gas	GARCH	-	-	-
Pharmaceuticals	GARCH	-	-	-
Power Generation Distribution	GJR/TARCH	-	-	-
Refineries	GJR/TARCH	-	-	-
Sugar	GJR/TARCH	-	-	-
Technology & Telecom	GARCH	GJR/TARCH	-	-
Textiles	GARCH	NA	-	-
Tobacco	GARCH	GARCH	GARCH	-

This table shows the optimal uni-variate DCC GARCH model with respect to each industry for Others. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

TABLE 4.43: DCC MV - GARCH Estimates across Industries - Others

Industries	***1. Commercial Banks***		***2. Sugar***		***3. Textiles***		***4. Tobacco***	
	θ_1	θ_2	θ_1	θ_2	θ_1	θ_2	θ_1	θ_2
Engineering	0.0908	-0.0088	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Fertilizers	0.0542	0.9053	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Oil & Gas	0.0483	0.897	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Pharmaceuticals	0.3308	-0.0034	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Power Generation Distribution	0.0339	0.8689	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Refineries	0.2054	0.4322	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Sugar	0.1439	0.5278	-	-	-	-	-	-
	(0.0000)	(0.0000)	-	-	-	-	-	-
Technology & Telecom	0.0383	0.9349	0.068	0.7262	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	-	-	-	-
Textiles	-0.116	1.0062	NA		-	-	-	-
	(0.6927)	(0.0000)			-	-	-	-
Tobacco	0.0065	0.9725	0.0007	0.9227	-6.75E-05	0.8016	-	-
	(0.0395)	(0.0000)	(0.1578)	(0.0000)	(0.8505)	(0.3501)	-	-

This table summarizes the estimated coefficients from DCC-MV-GARCH model in a bi-variate framework across industries for Others. p-values are reported in parenthesis. Theta(1) and Theta(2) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable univariate GARCH model.

4.4.4 ADCC MV - GARCH Models & Estimates Across Industries

1. **Engineering**

Tables 4.44 and 4.45 show the suitable uni-variate ADCC models and estimates across industries for Engineering Group, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria AIC. NA means that, the stability condition for particular industry is not met, so model can not be applied. In short, the dynamic conditional correlation doesnt exists in these specified industries.

Table 4.45 shows the results of ADCC MV-GARCH model across industries for Engineering Group. This category contains three industrial groups; Automobile Assemblers, Engineering & Technology & Telecommunication. The table reports the impact of the past residual shocks (θ_1), lagged dynamic conditional correlation (θ_2) and asymmetric effect of negative news on correlation (θ_3) with their respective p-values. Like previous models of DCC, the first step is to check the stability of the model which is clearly met in all industries. So, ADCC can also be applied on these data sets.

For Automobile Assemblers-AA, θ_1 is found highly significant for all industries which indicates the impact of past residual shock on conditional correlation while, Chemicals-CHEM shows a significant negative correlation that means, there exists a partial impact of past residual shocks on correlation in this industry. The parameters of lagged dynamic conditional correlation, θ_2 is found highly significant for all industrial pairs that shows the impact of lagged dynamic conditional correlation in all of these industries. In addition, θ_3 is also found highly significant for all industries except, Textiles-TEX which indicates that, correlation has been increased with the effect of negative news for all industrial pairs except Textiles-TEX. Here, the decreasing trend of correlation is captured with the effect of negative news.

TABLE 4.44: ADCC MV - GARCH Models across Industries - Engineering Group

Industries	***1. Automobile Assemblers***	***2. Engineering***	***3. Technology & Telecomm.***
Cement	GJR/TARCH	-	-
Chemicals	GJR/TARCH	-	-
Commercial Banks	EGARCH	-	-
Engineering	GARCH	-	-
Fertilizers	GARCH	NA	-
Oil & Gas	NA	GARCH	-
Pharmaceuticals	GARCH	GJR/TARCH	-
Power Generation Distribution	GJR/TARCH	GARCH	-
Refineries	NA	GARCH	-
Sugar	GARCH	NA	-
Technology & Telecom	GARCH	NA	-
Textiles	GARCH	NA	GARCH
Tobacco	NA	GARCH	GARCH

This table shows the optimal uni-variate ADCC GARCH model with respect to each industry for Engineering Group. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

Table 4.45: ADCC MV - GARCH Estimates across Industries - Engineering Group

Industries	***1. Automobiles Assemblers***			***2. Engineering***		
	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3
Cement	0.0233	0.9368	0.0107	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-
Chemicals	-0.0017	0.7789	0.0172	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-
Commercial Banks	0.0301	0.9162	0.0062	-	-	-
	(0.0000)	(0.0000)	(0.0001)	-	-	-
Engineering	0.0142	0.7802	0.0292	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-
Fertilizers	0.0355	0.8867	0.0097		NA	
	(0.0000)	(0.0000)	(0.0001)			
Oil & Gas		NA		0.0091	0.7994	0.0283
				(0.0000)	(0.0000)	(0.0000)
Pharmaceuticals	0.0816	0.9043	-0.0563	0.0189	0.9795	-0.0101
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Power Generation Distribution	0.0117	0.9566	0.0096	0.0226	0.8346	0.0169
	(0.0027)	(0.0000)	(0.0000)	(0.0073)	(0.0000)	(0.0000)
Refineries		NA		0.2376	0.0168	0.0114
				(0.0000)	(0.5855)	(0.3669)
Sugar	0.0294	0.7877	0.0468		NA	
	(0.0000)	(0.0000)	(0.0000)			
Technology & Telecom	0.0424	0.831	0.0165		NA	
	(0.0000)	(0.0000)	(0.0000)			
Textiles	0.0338	0.9336	-0.0194		NA	
	(0.0000)	(0.0000)	(0.0571)			
Tobacco		NA		0.0629	0.8397	-0.0064
				(0.0000)	(0.0000)	(0.0019)

This table summarizes the estimated coefficients from the Asymmetric DCC-MV-GARCH model in a bi-variate framework for Engineering Group. p-values are reported in parenthesis. Theta(1), Theta(2) and Theta(3) are reported above the p-values. The Akaike Information Criteria (AIC) is used for the selection of a suitable univariate GARCH model.

Cont. (4.45) ...	3. Technology & Telecomm.		
	θ_1	θ_2	θ_3
Cement	-	-	-
	-	-	-
Chemicals	-	-	-
	-	-	-
Commercial Banks	-	-	-
	-	-	-
Engineering	-	-	-
	-	-	-
Fertilizers	-	-	-
	-	-	-
Oil & Gas	-	-	-
	-	-	-
Pharmaceuticals	-	-	-
	-	-	-
Power Generation Distribution	-	-	-
	-	-	-
Refineries	-	-	-
	-	-	-
Sugar	-	-	-
	-	-	-
Technology & Telecom	-	-	-
	-	-	-
Textiles	0.0636	0.9074	-0.0200
	(0.0000)	(0.0000)	(0.0180)
Tobacco	0.0112	0.7155	0.0213
	(0.6936)	(0.0656)	(0.1870)

Values in parenthesis are the p-values. Theta(1), Theta(2) and Theta (3) are reported above the p-values.

Similarly, for Engineering-ENG, the parameters of θ_1 are found significantly positive for all industries that shows, there exists an impact of past residual shock on conditional correlation. θ_2 is also found highly significant for all industrial pairs that shows the impact of lagged dynamic conditional correlation in all of these industries, but Refineries-REF didnt show any significant variation with respect to Engineering-ENG that shows, there exists no impact of lagged dynamic conditional correlation. Additionally, θ_3 is also found highly significant for 3 industries; Oil & Gas-O&G, Power Generation & Distribution-P&D and Refineries-REF which indicates that, the effect of correlation has been increased with the effect of negative news in these three industries. The remaining 2 industries; Pharmaceuticals-PHAR and Tobacco-TOB show a significant negative impact that indicates, the correlation has been reduced after the arrival of negative news.

Finally, all parameters of θ_1, θ_2 and θ_3 for Textiles-TEX are found significantly positive with respect to Technology & Telecommunication-T&T that shows, the impact of past residual shocks and lagged dynamic conditional correlation exists in this sector. Moreover, the significant but negative value of θ_3 also reports that, the correlation has been reduced with the effect of negative news in the market for this industry i.e. Textiles-TEX. On the other hand, Tobacco-TOB didnt show any significant results with respect to Technology & Telecommunication-T&T as there found no logical relationship in these industries .

2. **Manufacturing**

Tables 4.46 and 4.47 show the suitable uni-variate ADCC models and estimates across industries for Manufacturing Group, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria AIC. NA means that, the stability condition for particular industry is not met, so model can not be applied. In short, the dynamic conditional correlation doesnt exists in these specified industries.

Table 4.47 shows the results of ADCC MV-GARCH model across industries for Manufacturing Group. This category contains four industrial groups; Cement, Chemicals, Fertilizers & Pharmaceuticals. The table reports the impact of the past residual shocks (θ_1), lagged dynamic conditional correlation (θ_2) and asymmetric effect of negative news on correlation (θ_3) with their respective p-values. Like previous models of DCC, the first step is to check the stability of the model which is clearly met in all industries. So, ADCC can also be applied on these data sets.

TABLE 4.46: ADCC MV - GARCH Models across Industries - Manufacturing Group

Industries	***1. Cement***	***2. Chemicals***	***3. Fertilizers***	***4. Pharmaceuticals***
Chemicals	GJR/TARCH	-	-	-
Commercial Banks	GJR/TARCH	GJR/TARCH	-	-
Engineering	GARCH	GARCH	-	-
Fertilizers	GJR/TARCH	GARCH	-	-
Oil & Gas	GJR/TARCH	GJR/TARCH	GJR/TARCH	-
Pharmaceuticals	GARCH	GARCH	GARCH	-
Power Generation Distribution	GJR/TARCH	GJR/TARCH	GJR/TARCH	GARCH
Refineries	NA	GARCH	GARCH	EGARCH
Sugar	EGARCH	GJR/TARCH	GJR/TARCH	NA
Technology & Telecom	EGARCH	GARCH	GARCH	EGARCH
Textiles	EGARCH	GARCH	GARCH	NA
Tobacco	GARCH	GARCH	GARCH	NA

This table shows the optimal uni-variate ADCC GARCH model with respect to each industry for Manufacturing Group. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

TABLE 4.47: ADCC MV - GARCH Estimates across Industries - Manufacturing Group

Industries	***1. Cement***			***2. Chemicals***			***3. Fertilizers***		
	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3
Chemicals	0.0798	0.4568	-0.0040	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.2230)	-	-	-	-	-	-
Commercial Banks	0.065	0.6396	0.0045	0.0029	0.8789	0.0045	-	-	-
	(0.0000)	(0.0000)	(0.1090)	(0.3891)	(0.0000)	(0.0000)	-	-	-
Engineering	0.0996	0.6521	-0.0211	0.0548	0.8453	-0.0036	-	-	-
	(0.0000)	(0.0000)	(0.0045)	(0.0000)	(0.0000)	(0.0609)	-	-	-
Fertilizers	0.0147	0.9735	0.0027	0.0612	0.7738	-0.0056	-	-	-
	(0.0000)	(0.0000)	(0.1245)	(0.0000)	(0.0000)	(0.2978)	-	-	-
Oil & Gas	0.0266	0.9125	0.0057	0.0474	0.7324	0.0015	0.0284	0.9253	0.0101
	(0.0013)	(0.0000)	(0.0003)	(0.0008)	(0.0000)	(0.6453)	(0.0000)	(0.0000)	(0.0000)
Pharmaceuticals	0.0154	0.9167	-0.0073	0.1671	0.6455	-0.0475		NA	
	(0.0032)	(0.0000)	(0.1437)	(0.0000)	(0.0000)	(0.0000)			
Power Generation Distribution	0.0037	0.9608	0.008	0.141	0.5163	-0.0157	0.0166	0.932	0.0079
	(0.0490)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0019)	(0.0000)	(0.0001)
Refineries		NA		0.0759	0.5751	-0.0055	0.0696	0.4296	0.0303
				(0.0002)	(0.0000)	(0.5179)	(0.0021)	(0.0000)	(0.0000)
Sugar	3.20E-05	0.8167	-0.0059	0.0308	0.9034	-0.0019		NA	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5590)			
Technology & Telecom	0.0521	0.8287	0.0037	0.0404	0.8488	-0.0069	0.0349	0.9002	0.0077
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0024)	(0.0000)	(0.0000)	(0.0001)
Textiles	0.0016	0.806	-0.0116	0.0455	0.9262	-0.0042	0.1952	0.017	0.0058
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1459)	(0.0000)	(0.8613)	(0.7995)
Tobacco	0.0045	0.9352	0.0033	0.0792	0.7326	-0.0034	0.0012	0.6017	-0.0049
	(0.0284)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.3986)	(0.8739)	(0.4260)	(0.8389)

This table summarizes the estimated coefficients from the Asymmetric DCC-MV-GARCH model in a bi-variate framework for Manufacturing Group. p-values are reported in parenthesis. Theta(1), Theta(2) and Theta(3) are reported above the p-values. Suitable model is selected on the basis of Akaike Information Criteria - AIC.

Cont. (4.47) ...	***4. Pharmaceuticals***		
	θ_1	θ_2	θ_3
Chemicals	-	-	-
	-	-	-
Commercial Banks	-	-	-
	-	-	-
Engineering	-	-	-
	-	-	-
Fertilizers	-	-	-
	-	-	-
Oil & Gas	-	-	-
	-	-	-
Pharmaceuticals	-	-	-
	-	-	-
Power Generation Distribution	0.0124	0.9287	-0.0041
	(0.1203)	(0.0000)	(0.5947)
Refineries	-0.001	0.7511	-0.0006
	(0.0000)	(0.0000)	(0.0000)
Sugar		NA	
Technology & Telecom	-0.0002	0.8209	-0.0019
	(0.0000)	(0.0000)	(0.0000)
Textiles		NA	
Tobacco		NA	

Values in parenthesis are the p-values. Theta(1), Theta(2) and Theta (3) are reported above the p-values.

For Cement-CEM, the parameters of θ_1 and θ_2 are found highly significant for all industries which indicates the impact of past residual shock and lagged dynamic conditional correlation in all these industrial pairs. In addition, θ_3 is also found highly significant for four industries; Oil & Gas-O&G, Power Generation & Distribution-P&D, Technology & Telecommunication-T&T and Tobacco-TOB which indicates that, correlation has been increased with the effect of negative news for all these industrial pairs while, the results are opposite for Engineering-ENG, Sugar-SUG and Textiles-TEX that correlation has been reduced with the arrival of negative news in these industries. The remaining industrial pairs didnt show any significant variation so there exists no effect of negative news on correlation.

Similarly, For Chemicals-CHEM, the parameters of θ_1 and θ_2 are found highly significant for all industries which indicates the impact of past residual shock and lagged dynamic conditional correlation in all these industrial pairs. Moreover, θ_3 is found significantly positive for only 1 industry that is Commercial Banks-CB. It means the correlation in Commercial Banks has been increased with the effect of negative news while, Pharmaceuticals-PHAR, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T show a significantly negative impact which indicates that, the effect of correlation has been reduced with the effect of negative news in these industries. All the remaining industries didnt show a significant impact that indicates no effect of negative news on correlation.

For Fertilizers-FERT, all the parameters of are found highly significant for all industrial pairs that shows, there exist the impact of past residual shocks on conditional correlation while, Tobacco-TOB didnt show any significant variation with respect to Fertilizers-FERT as there seems to be no existence of any logical relationship between these industries. θ_2 is also found significantly positive for all industries except Textiles-TEX and Tobacco-TOB which indicates that, there exists a lagged dynamic conditional correlation in these industries except Textiles-TEX & Tobacco-TOB. In addition, θ_3 is also found significantly positive for all industries except Textiles-TEX & Tobacco-TOB. It means, the correlation in these industries has been increased with the arrival of negative news while, Textiles-TEX and Tobacco-TOB shows no variation with respect to negative news on correlation.

Finally, the parameters of θ_1 are found significantly negative for all industrial pairs that indicates the impact of past residual shocks on correlation while, Power Generation & Distribution-P&D shows no significant variation. θ_2 is also found significantly positive for all industries that provide the evidence about the impact of lagged dynamic conditional correlation in all of these industries. Moreover, θ_3 is found significantly negative for all industrial pairs which shows that, the correlation has been reduced with the effect of negative news in these industries while, Power Generation & Distribution-P&D shows no significant variation.

3. **Oil, Power & Gas**

Tables 4.48 and 4.49 show the suitable uni-variate ADCC models and estimates across industries for Manufacturing Group, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria AIC. NA means that, the stability condition for particular industry is not met, so model can not be applied. In short, the dynamic conditional correlation doesnt exists in these specified industries.

Table 4.49 shows the results of ADCC MV-GARCH model across industries for Oil, Power & Gas Group. This category contains three industrial groups; Oil & Gas, Power Generation & Distribution & Refineries. The table reports the impact of the past residual shocks (θ_2), lagged dynamic conditional correlation (θ_2) and asymmetric effect of negative news on correlation (θ_3) with their respective p-values. Like previous models of DCC, the first step is to check the stability of the model which is clearly met in all industries. So, ADCC can also be applied on these data sets.

For Oil & Gas -O&G, the parameters of θ_1 and θ_2 are found highly significant for all industries which indicates the impact of past residual shock and lagged dynamic conditional correlation in all these industrial pairs. Additionally, θ_3 is also found highly significant for three industries; Power Generation & Distribution-P&D, Refineries-REF and Sugar-SUG which indicates that, correlation has been increased with the effect of negative news for all these industrial pairs while, the results for Pharmaceuticals-PHAR, Technology & Telecommunication-T&T, Textiles-TEX and Tobacco-TOB reveal that correlation has been reduced with the arrival of negative news in these industries.

Table 4.48: ADCC MV - GARCH Models across Industries - Oil, Power & Gas Group

Industries	***1. Oil & Gas***	***2. Power Generation & Distribution***	***3. Refineries***
Pharmaceuticals	GARCH	-	-
Power Generation Distribution	GJR/TARCH	-	-
Refineries	GJR/TARCH	GJR/TARCH	-
Sugar	GJR/TARCH	EGARCH	GARCH
Technology & Telecom	GARCH	GARCH	EGARCH
Textiles	GARCH	GARCH	NA
Tobacco	GARCH	GARCH	NA

This table shows the optimal uni-variate ADCC GARCH model with respect to each industry for Oil, Power & Gas Group. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

TABLE 4.49: ADCC MV - GARCH Estimates across Industries - Oil, Power & Gas Group

Industries	***1. Oil & Gas***			***2. Power Generation & Distribution***			***3. Refineries***		
	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3
Pharmaceuticals	0.0709	0.925	-0.0521	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-	-	-	-
Power Generation Distribution	0.0182	0.9331	0.006	-	-	-	-	-	-
	(0.0048)	(0.0000)	(0.0004)	-	-	-	-	-	-
Refineries	0.102	0.755	0.0162	0.0187	0.4114	0.0264	-	-	-
	(0.0000)	(0.0000)	(0.0000)	(0.1600)	(0.0000)	(0.0000)	-	-	-
Sugar	0.0526	0.7821	0.0362	0.0009	0.874	0.0095	0.0021	0.811	0.0321
	(0.0000)	(0.0000)	(0.0000)	(0.3167)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)
Technology & Telecom	0.0346	0.9559	-0.0009	0.042	0.8923	-0.0002	0.0591	0.7721	0.0275
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8500)	(0.0000)	(0.0000)	(0.0000)
Textiles	0.073	0.8716	-0.0241	0.0045	0.8031	-0.0105		NA	
	(0.0000)	(0.0000)	(0.1565)	(0.4736)	(0.0000)	(0.4439)			
Tobacco	0.008	0.9763	-0.004	-0.0002	0.7796	-0.0268		NA	
	(0.0412)	(0.0000)	(0.2203)	(0.0000)	(0.0000)	(0.0000)			

This table summarizes the estimated coefficients from the Asymmetric DCC-MV-GARCH model in a bi-variate framework for Oil, Power & Gas Group. p-values are reported in parenthesis. Theta(1), Theta(2) and Theta(3) are reported above the p-values. Suitable model is selected on the basis of Akaike Information Criteria - AIC.

The estimates of θ_1 for Power Generation & Distribution-P&D is found significantly positive for only 1 industry which is Technology & Telecommunication-T&T that indicates, there exists an impact of past residual shocks on conditional correlation. While, Tobacco-TOB shows a significant negative impact of past residual shocks on correlation. θ_2 is found highly significant for all industrial pairs which indicates that, the impact of lagged dynamic conditional correlation exists in all these industries. Moreover, θ_3 is found significantly positive for only 2 industries that are Refineries-REF and Sugar-SUG. It means the correlation in in these two industries has been increased with the effect of negative news while, Tobacco-TOB shows a significantly negative impact which indicates that, the effect of correlation has been reduced with the effect of negative news in this sector. While, Technology & Telecommunication-T&T and Textiles-TEX show no significant variation on correlation.

Finally, the parameters of θ_1, θ_2 and θ_3 are found significantly positive for all industrial pairs with respect to Refineries-REF that indicates, the impact of past residual shocks and lagged dynamic conditional correlation exists in all these industries. In addition, the correlation in these industries has also been increased with the arrival of negative news in the market.

4. **Others**

Tables 4.50 and 4.51 show the suitable uni-variate ADCC models and estimates across industries for Others, respectively. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria AIC. NA means that, the stability condition for particular industry is not met, so model can not be applied. In short, the dynamic conditional correlation doesnt exists in these specified industries.

Table 4.51 shows the results of ADCC MV-GARCH model across industries for Others. This category contains four industrial groups; Commercial Banks, Sugar, Textiles & Tobacco.

Table 4.50: ADCC MV - GARCH Models across Industries - Others

Industries	***1. Commercial Banks***	***2. Sugar***	***3. Textiles***	***4. Tobacco***
Engineering	GARCH	-	-	-
Fertilizers	GARCH	-	-	-
Oil & Gas	GARCH	-	-	-
Pharmaceuticals	GARCH	-	-	-
Power Generation Distribution	GJR/TARCH	-	-	-
Refineries	NA	-	-	-
Sugar	GARCH	-	-	-
Technology & Telecom	GARCH	NA	-	-
Textiles	GJR/TARCH	GJR/TARCH	-	-
Tobacco	GJR/TARCH	NA	GARCH	-

This table shows the optimal uni-variate ADCC GARCH model with respect to each industry for Others. The appropriate model is chosen on the basis of lowest possible Akaike Information Criteria (AIC).

Table 4.51: ADCC MV - GARCH Estimates across Industries - Others

Industries	***1. Commercial Banks***			***2. Sugar***			***3. Textiles***		
	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3	θ_1	θ_2	θ_3
Engineering	0.0026	0.7774	0.0208	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-	-	-	-
Fertilizers	0.0428	0.9119	0.0069	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-	-	-	-
Oil & Gas	0.0225	0.9355	0.0066	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-	-	-	-
Pharmaceuticals	0.0671	0.2983	0.0918	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-	-	-	-
Power Generation Distribution	0.0187	0.9132	0.0053	-	-	-	-	-	-
	(0.0584)	(0.0000)	(0.0023)	-	-	-	-	-	-
Refineries		NA		-	-	-	-	-	-
				-	-	-	-	-	-
Sugar	0.0331	0.7656	0.0298	-	-	-	-	-	-
	(0.0000)	(0.0000)	(0.0000)	-	-	-	-	-	-
Technology & Telecom	0.0379	0.9349	0.0003		NA		-	-	-
	(0.0000)	(0.0000)	(0.8059)				-	-	-
Textiles	0.0868	0.6696	-0.1540	-0.0008	0.8150	0.0004	-	-	-
	(0.0243)	(0.0000)	(0.0040)	(0.0000)	(0.0000)	(0.0000)	-	-	-
Tobacco	0.0172	0.7888	0.0980		NA		0.0001	0.8019	0.0011
	(0.0000)	(0.0000)	(0.0000)				(0.0000)	(0.0000)	(0.0000)

This table summarizes the estimated coefficients from the Asymmetric DCC-MV-GARCH model in a bi-variate framework for Others. p-values are reported in parenthesis. Theta(1), Theta(2) and Theta(3) are reported above the p-values. Suitable model is selected on the basis of Akaike Information Criteria - AIC.

The table reports the impact of the past residual shocks (θ_1), lagged dynamic conditional correlation (θ_2) and asymmetric effect of negative news on correlation (θ_3) with their respective p-values. Like previous models of DCC, the first step is to check the stability of the model which is clearly met in all industries. So, ADCC can also be applied on these data sets.

For Commercial Banks -CB, the parameters of θ_1 and θ_2 are found highly significant for all industries which indicates the impact of past residual shock and lagged dynamic conditional correlation in all these industrial pairs. Additionally, θ_3 is also found highly significant for all industries except Textiles-TEX. In means, the correlation has been increased with the effect of negative news for all these industrial pairs while, the results for Textiles-TEX and indicates that correlation has been reduced with the arrival of negative news in these industries.

Similarly, for Sugar-SUG, θ_1 for is found significantly negative for only 1 industry which is Textiles-TEX that indicates, a partial impact of past residual shocks on conditional correlation exists. While, θ_2 and θ_3 are found highly significant for Textiles-TEX which also indicates that, the impact of lagged dynamic conditional correlation exists while, the significant positive result of θ_3 reveals that the correlation has been increase with the effect of negative news in Textiles-TEX.

Finally, the parameters of θ_1, θ_2 and θ_3 are found significantly positive for the remaining industry i.e. Tobacco-TOB. It shows that, the impact of past residual shocks and lagged dynamic conditional correlation exists in Tobacco-TOB. Moreover, the estimate of θ_3 reveals that, the correlation has been increased after the arrival of negative news in the market.

All the significant results of DCC and ADCC MV-GARCH models are similar to the findings of some previous researchers. For example, the sectoral correlations using DCC and ADCC models is also studied by Katzke et al. (2013) in which he employs the industrial returns of different sector pair like; Financials, Utilities, Industrials, Consumer Goods, Consumer Services and Telecom and finds the evidence about the dynamic nature of correlation between different sectors of South Africa. Ahmed and Naguib (2017) also report that the DCC model is adequate at measuring time-varying conditional correlations. They also find the dynamic conditional correlation between sector pairs of Financial Services, Banks, Construction and Material and Telecommunication.

Chapter 5

Conclusion & Recommendations

5.1 Conclusion

This study focuses on two major objectives. The first objective of this study addresses the return and volatility spillover from currency market to other industrial indices of Pakistani stock market. Movement of different industries that includes; Automobiles Assemblers, Cement, Chemicals, Commercial Banks, Engineering, Fertilizers, Oil & Gas, Pharmaceuticals, Power Generation & Distribution, Refineries, Sugar, Technology & Telecommunication, Textiles and Tobacco with exchange rates (PKR/USD) has been examined by using ARMA GARCH model for the time frame of June-2000 to June-2018.

For Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB & Refineries-REF, the return spillover is observed in these industries from exchange rate. The results of return spillover is positive only for Automobile Assemblers-AA. The positive sign of Automobile Assemblers-AA shows that, returns of this industry is increasing with respect to variations in exchange rate. It means, good news will increase the returns and bad news will decrease the returns in Automobile Assemblers-AA. In simple words, the depreciation of currency is increasing the returns of this sector. While, the return spillover is negative for Cement-CEM, Chemicals-CHEM, Commercial Banks-CB & Refineries-REF that shows the appreciation of currency. It indicates that, the returns of these industries are decreasing with respect to the variations in exchange rate. As the appreciation and depreciation of currency is concerned with the revenues and expenses and most of the inputs in different industries are imported, that leads the cost to increase. While, there found no evidence of return spillover in Engineering-ENG, Fertilizers-FERT, Oil & Gas-O&G, Pharmaceuticals-PHAR, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T, Textiles-TEX & Tobacco-TOB which shows that, returns of exchange rate have no impact on these industries. In crises period (ϕ*smf), returns are negative for Automobile Assemblers-AA and Chemicals-CHEM that tells about appreciation of currency which further denotes that, returns are decreasing when structural break comes in these industries. While, the remaining industries didnt show any return spillover with exchange rate in crisis period. So, hypothesis 1 is also supported here that, there exists a return spillover from exchange rates to different industries.

Similarly, volatility spillover from exchange rate to different industries is also observed in almost all industrial pairs e.g. Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Sugar-SUG, Technology & Telecommunication-T&T. As the standardized residual error term is positive so size of the shock is observed for decision as compared to good or bad news. All industries show a significant negative volatility spillover with respect to exchange rate. It means, small shocks are creating less volatilities in these industries. Simply, if a shock of depreciation comes, the people will prefer less trading and slow down the process which in result to reduce the volatility in market due to decrease in trading. Only one industry e.g. Refineries-REF shows a positive impact of exchange rate volatility which indicates that, the size of the shock is large and creating more volatility as compared to the rest of the industries. On the other side, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T show no impact of volatility transmission from exchange rate. In crises period (λ*smf), all industries e.g. Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D show negative spillover that also provides the evidence about the less volatility in the market as market is not moving due to a structural break. While, Refineries-REF and Technology & Telecommunication-T&T show no movement of market in crisis period. So here, hypothesis 2 is also supported here that, there exists a volatility spillover from exchange rates to different industries.

On the other side, almost all industries strongly reflect that return and volatility spillover exist between them. All the coefficients of return and volatility spillover are significantly positive that means the returns of one sector increasing the returns of other sectors. In simple words, we can say that all industrial pairs show a strong linkage with each other. So, any change occur in one industry quickly transmit to the remaining ones that indicates, all these industries are connected with each others. While, some industries like Sugar-SUG is not explaining any relationship with other industries i.e. Sugar-SUG is not showing any return spillover with Refineries-REF and Tobacco-TOB is also showing insignificant variations with Commercial Banks-CB, Power Generation & Distribution-P&D and Technology & Telecommunication-T&T. All the significant results across industries are similar to the work done by previous researchers e.g. (Ewing, 2002; Hassan and Malik, 2007; Harris and Pisedtasalasai, 2006; Hammoudeh et al., 2009). In their studies, they also report the transmission mechanism in terms of mean and volatility across sectoral indices of different markets. While, most of the work in this domain is only conducted on the intersection across different countries and at regional level e.g. (Li and Majerowska, 2008; Harrison and Moore, 2009; Scheicher, 2001; Chou et al., 1999; Karolyi, 1995; Worthington and Higgs, 2004; Fujii, 2005; Brailsford and Faff, 1996; Baele, 2005; Allen et al., 2013; Abbas et al., 2013; Beirne et al., 2010; Caporale et al., 2002; Li and Giles, 2015). Moreover, some previous studies explore this transmission and movement of industries from the perspective of short run and long run movement of stocks e.g. (Al-Fayoumi et al., 2009; Sakthivel et al., 2012). This was the domain on which limited studies about return and volatility spillover exist so, hypothesis 3 and 4 also supported that there exists a return and volatility spillover across different industries in Pakistan.

The second aspect of the study covers the extension of previous model. As the correlation between the variables is found time varying, so Dynamic Condition

Correlation DCC model is used and asymmetric behavior is assessed by Asymmetric Dynamic Conditional Correlation ADCC. Results of both these models are found significantly positive as well as negative for most of the targeted industries. All the significant variations and stability of models show that, correlation is not constant so dynamic conditional correlation model is strongly recommended. while, for some industries, the stability of the model is not met that indicates, correlation in these industrial pairs is not time varying so DCC and ADCC models are not applied. The implications of DCC and ADCC models provide a strong conceptual understandings that, industries are interconnected to each others and with the passage of time, correlation also becomes time varying. All these findings about the interconnectedness of industries are similar to the previous studies in which the work of Katzke et al. (2013) provides comprehensive evidences. He also shows that, all sectoral pairs like; Financial, Consumer Services & Goods, Utilities and Telecommunication exhibit a dynamic sectoral co movement over the time. The change in the market conditions are more precisely examined by using these indicators i.e. DCC & ADCC which also provides the support for hypothesis 5 and 6 that, there exists a time-varying conditional correlations between exchange rates and different industries & inter-dependencies across different industries in Pakistan. Moreover, hypothesis 7 is also supported for some industries that exhibit the asymmetric behaviour.

5.2 Recommendations

After concluding all findings, this study strongly recommends to all market players including investors, portfolio managers and policy makers to keep an eye on the information arising in different industries, specially in international market. Some important recommendations of this study are given below ...

- Depreciation of currency increases the returns of Automobile Assemblers-AA while, when currency is appreciated then returns of Cement-CEM, Chemicals-CHEM, Commercial Banks-CB & Refineries-REF decreases that means, the exposure of different industries with respect to exchange rate is different or asymmetric. Additionally, Automobile Assemblers-AA & Chemicals-CHEM show the appreciation of currency during crises period that means the returns in these industries are decreasing in that specific time period.

- Depreciation of currency creates less volatilities in Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G, Power Generation & Distribution-P&D, Sugar-SUG, Technology & Telecommunication-T&T. In case of crisis period, Automobile Assemblers-AA, Cement-CEM, Chemicals-CHEM, Commercial Banks-CB, Oil & Gas-O&G and Power Generation & Distribution-P&D show less volatilities in the market.

- All industrial pairs show return and volatility spillover with each other that means, the returns and volatility of one industry is influencing the return and volatility of other industries. In simple words, industrial interdependence is present between them.

- Most of the industries are showing time-varying conditional correlation which indicates the dynamic nature of correlation present among industries. Moreover, the asymmetric behaviour among industries is also present.

- Investor can use these findings in the process of decision making for investments in different industries. As the volatilities of the industries are found more influenced than returns so, investors must seek for those sectors or financial assets in which volatility is decreasing or low. For example the volatility arising from exchange rates decreasing the volatility for all industries except Refineries so, it implies that this sector is more riskier than others as volatility is not showing any cooling down effect.

- Diversification opportunities also exists in Power Generation & Distribution-P&D and Technology and Telecommunication-T&T. In contrast, both return and volatility spillovers are observed across industries. There are some industries like Refineries-REF and & Telecommunication-T&T that didnt show any effect on volatility for several industries which recommends the portfolio managers of both of these industries to invest in those sectors that are less risky.

- Moreover, the significant variations in financial sector i.e. Commercial Bank-CB also provides the directions to policy makers to devise an effective monetary and fiscal policies with respect to each industry.

5.3 Limitations & Future Directions

Although this study provide a comprehensive understanding on the transmission mechanism across market as well as industries, but obviously it doesnt cover all other aspects. This study is limited only to the Pakistani stock market i.e. a country specific work. So, a comparative study can also be conducted by including more emerging markets in the sample size. Moreover, the data used for this study is time series data that quickly outdates. Thats why, taking another data set these phenomenon can be further explored. In addition, all GARCH models (GARCH, GJR GARCH/TARCH & EGARCH) used in this study was taken on over all distribution. So, a study on extreme movement using tailed distribution can also be conducted in near future.

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Appendix-A

List of Companies By Industries

1. **Automobile Assemblers - AA**

   Total Nos of Companies = 12

   Sample Size = 7

2. **Cement - CEM**

   Total Nos of Companies = 22

   Sample Size = 15

3. **Chemicals - CHEM**

   Total Nos of Companies = 29

   Sample Size = 15

4. **Commercial Banks - CB**

   Total Nos of Companies = 24

   Sample Size = 10

5. **Engineering - ENGG**

   Total Nos of Companies = 18

   Sample Size = 9

6. **Fertilizers - FERT**

   Total Nos of Companies = 7

   Sample Size = 5

7. **Oil & Gas - O&G**

   Total Nos of Companies = 12

   Sample Size = 7

8. **Pharmaceuticals - PHAR**

   Total Nos of Companies = 9

   Sample Size = 5

9. **Power Generation & Distribution - P&D**

   Total Nos of Companies = 19

   Sample Size = 10

10. **Refineries - REF**

    Total Nos of Companies = 4

    Sample Size = 4

11. **Sugar - SUG**

    Total Nos of Companies = 34

    Sample Size = 20

12. **Technology & Telecommunication - T&T**

    Total Nos of Companies = 10

    Sample Size = 5

13. **Textiles - TEX**

    Total Nos of Companies = 155

    Sample Size = 50

14. **Tobacco - TOB**

    Total Nos of Companies = 3

    Sample Size = 3

Sr. No.	Symbol	Company Name	Market Cap.
1.	INDU	Indus Motor Company Limited	91.69 Bn
2.	ATLH	Atlas Honda Limited	42.66 Bn
3.	MTL	Millat Tractors Limited	42.00 Bn
4.	HCAR	Honda Atlas Cars (Pakistan) Limited	30.29 Bn
5.	AGTL	Al-Ghazi Tractors Limited	30.09 Bn
6.	PSMC	Pak Suzuki Motor Company Limited	22.08 Bn
7.	GHNI	Ghandhara Industries Limited	12.93 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	LUCK	Lucky Cement Limited	148.90 Bn
2.	BWCL	Bestway Cement Company Limited	67.97 Bn
3.	DGKC	DG Khan Cement Company Limited	35.90 Bn
4.	FCCL	Fauji Cement Company Limited	27.58 Bn
5.	MLCF	Maple Leaf Cement Factory Limited	22.78 Bn
6.	KOHC	Kohat Cement Limited	17.67 Bn
7.	ACPL	Attock Cement Limited	11.55 Bn
8.	CHCC	Cherat Cement Company Limited	11.25 Bn
9.	JVDC	Javedan Corporation Limited	10.39 Bn
10.	PIOC	Pioneer Cement Limited	8.77 Bn
11.	POWER	Power Cement Limited	7.07 Bn
12.	GWLC	Gharibwal Cement Limited	6.95 Bn
13.	FLYNG	Flying Cement Company Limited	3.03 Bn
14.	FECTC	Fecto Cement Limited	1.69 Bn
15.	THCCL	Thatta Cement Company Limited	1.30 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	COLG	Colgate Palmolive (Pakistan) Limited	110.3
2.	ICI	I.C.I. Pakistan Limited	62.09
3.	LOTCHEM	Lotte Chemical Pakistan Limited	19.37
4.	EPCL	Engro Polymer and Chemicals Limited	19.19
5.	ARPL	Archroma Pakistan Limited	15.91
6.	NICL	Nimir Industrial Chemicals Limited	6.59
7.	SITC	Sitara Chemical Industries Limited	6.28
8.	AKZO	Akzo Nobel Pakistan Limited	5.94
9.	BIFO	Biafo Industries Limited	5.11
10.	DOL	Descon Oxychem Limited	2.87
11.	WAHN	Wah Noble Chemicals Limited	2.48
12.	ICL	Ittehad Chemical Limited	2.39
13.	DYNO	Dynea Pakistan Limited	1.98
14.	AGL	Agritech Limited	1.96
15.	NRSL	Nimir Resins Limited	1.92

Sr. No.	Symbol	Company Name	Market Cap.
1.	MCB	Muslim Commercial Bank	222.74 Bn
2.	UBL	United Bank Limited	168.68 Bn
3.	ABL	Allied Bank Limited	108.78 Bn
4.	MEBL	Meezan Bank Limited	106.72 Bn
5.	NBP	National Bank Limited	100.72 Bn
6.	SCBPL	Standard Chartered Bank Limited	87.88 Bn
7.	BAFL	Bank Al-Falah Limited	84.97 Bn
8.	BAHL	Bank Al-Habib Limited	84.64 Bn
9.	HMB	Habib Metropolitan Bank Limited	47.01 Bn
10.	FABL	Faysal Bank Limited	38.99 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	ASL	Aisha Steel Mills Limited	36.90 Bn
2.	INIL	International Industries Limited	20.75 Bn
3.	ASTL	Amreli Steels Ltd.	17.31 Bn
4.	MUGHAL	Mughal Iron and Steel Limited	11.29 Bn
5.	CSAP	Crescent Allied Products Limited	4.79 Bn
6.	KSBP	K.S.B. Pumps Co. Limited	3.23 Bn
7.	HSPI	Huffaz Seamless Pipe Industries	1.90 Bn
8.	DSL	Dost Steels Limited	1.57 Bn
9.	BCL	Bolan Casting Limited	1.02 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	ENGRO	Engro Corporation Limited	155.64 Bn
2.	FFC	Fauji Fertilizers Company Limited	116.23 Bn
3.	EFERT	Engro Fertilizers Limited	97.58 Bn
4.	FATIMA	Fatima Fertilizer Company Limited	77.09 Bn
5.	DAWH	Dawood Hercules Corporation Limited	47.21 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	OGDCL	Oil & Gas Develop. Company Limited	618.56 Bn
2.	PPL	Pakistan Petroleum Limited	402.25 Bn
3.	MARI	Mari Petroleum Company Limited	163.04 Bn
4.	PSO	Pakistan State Oil Company Limited	76.57 Bn
5.	SNGP	Sui Northern Gas Pipelines Limited	48.82 Bn
6.	APL	Attock Petroleum Limited	42.41 Bn
7.	HASCOL	Hascol Petroleum Limited	37.53 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	ABOT	Abbot Laboratories (Pakistan) Limited	50.41 Bn
2.	GLAXO	GlaxoSmithKline (Pakistan) Limited	40.97 Bn
3.	SEARL	The Searle Company Limited	49.76 Bn
4.	SAPL	Sanofi-Aventis Pakistan Limited	8.68 Bn
5.	HINOON	Highnoon Laboratories Limited	8.49 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	KEL	K-Electric Limited	131.72 Bn
2.	HUBC	Hub Power Company Limited	97.70 Bn
3.	KAPCO	Kot Addu Power Company Limited	48.87 Bn
4.	ALTN	Altern Energy Limited	13.95 Bn
5.	EPQL	Engro Powergen Qadirpur Limited	9.25 Bn
6.	SPWL	Saif Power Limited	8.84 Bn
7.	NPL	Nishat Power Limited	8.33 Bn
8.	NCPL	Nishat Chunnian Power Limited	7.86 Bn
9.	KOHE	Kohinoor Energy Limited	6.23 Bn
10.	LPL	Lalpir Power Limited	5.67n

Sr. No.	Symbol	Company Name	Market Cap.
1.	BYCO	Byco Petroleum Pakistan Limited	44.88 Bn
2.	NRL	National Refinery Limited	22.66 Bn
3.	ATRL	Attock Refinery Limited	13.05 Bn
4.	PRL	Pakistan Refinery Limited	8.79 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	PTC	Pakistan Telecomm. Company Limited	47.79 Bn
2.	SYS	Systems Limited	13.48 Bn
3.	NETSOL	NetSol Technologies Limited	11.40 Bn
4.	HUMNL	Hum Network Limited	5.49 Bn
5.	WTL	World Call Telecom Limited	1.90 Bn

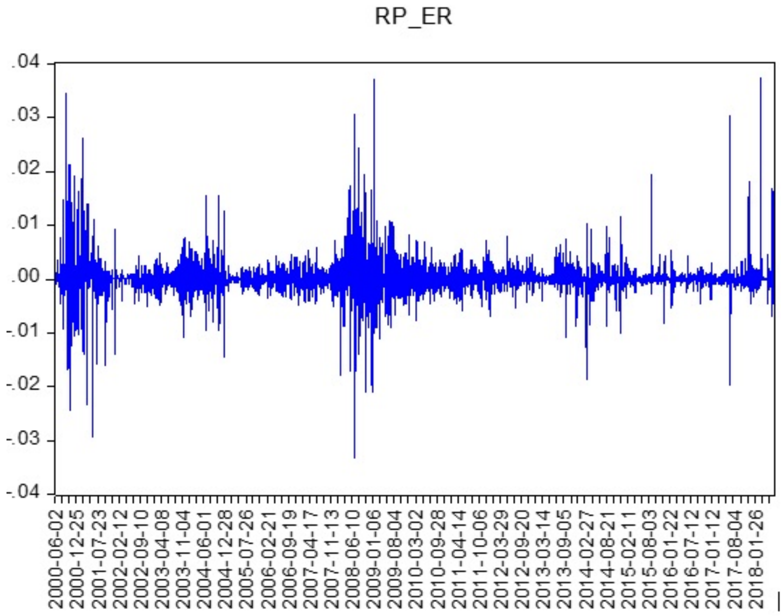
Sr. No.	Symbol	Company Name	Market Cap.
1.	PAKT	Pakistan Tobacco Company Limited	638.73 Bn
2.	PMPK	Philip Morris (Pakistan) Limited	221.57 Bn
3.	KHTC	Khyber Tobacco Company	1.38 Bn

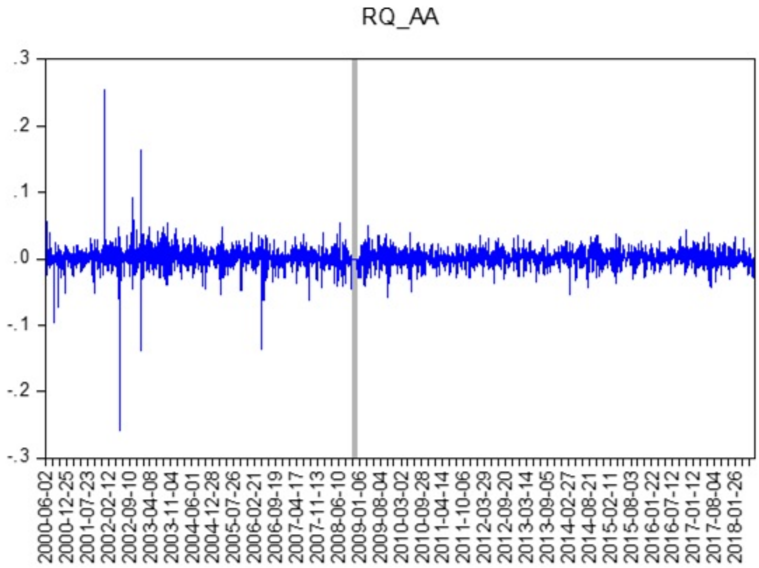
Sr. No.	Symbol	Company Name	Market Cap.
1.	JDWS	J.D.W. Sugar Mills Limited	17.04 Bn
2.	TSML	Tandlianwala Sugar Mills Limited	15.07 Bn
3.	SML	Shakarganj Limited	6.63 Bn
4.	HABSM	Habib Sugar Mills Limited	5.55 Bn
5.	AABS	Al-Abbas Sugar Mills Limited	3.40 Bn
6.	TICL	Thal Industries Corporation Limited	3.30 Bn
7.	MRNS	Mehran Sugar Mills Limited	2.99 Bn
8.	SHSML	Shahmurad Sugar Mills Limited	2.43 Bn
9.	FRSM	Faran Sugar Mills Limited	1.75 Bn
10.	MIRKS	Mirpurkhas Sugar Mills Limited	1.52 Bn
11.	HAL	Habib-ADM Limited	1.44 Bn
12.	CHAS	Chashma Sugar Mills Limited.	1.38 Bn
13.	JSML	Jauharabad Sugar Mills Limited	1.29 Bn
14.	SHJS	Shahtaj Sugar Mills Limited	1.05 Bn
15.	ALNRS	Al-Noor Sugar Mills Limited	0.95 Bn
16.	NONS	Noon Sugar Mills Limited	0.90 Bn
17.	ADAMS	Adam Sugar Mills Limited	0.55 Bn
18.	PMRS	Premier Sugar Mills and Distillery Company Limited	0.32 Bn
19.	SANSM	Sanghar Sugar Mills Limited	0.30 Bn
20.	HWQS	Haseeb Waqas Sugar Mills Limited	0.13 Bn

Sr. No.	Symbol	Company Name	Market Cap.
1.	NML	Nishat Mills Limited	48.51 Bn
2.	FML	Feroze1888 Mills Limited	38.93 Bn
3.	SAPT	Sapphire Textile Mills Limited	23.81 Bn
4.	GATM	Gul Ahmed Textile Mills Limited	19.98 Bn
5.	SFL	Sapphire Fibres Limited	14.82 Bn
6.	NCL	Nishat Chunian Limited	12.53 Bn
7.	KTML	Kohinoor Textile Mills Limited	11.79 Bn
8.	DLL	Dawood Lawrencepur Limited	11.46 Bn
10.	GADT	Gadoon Textile Mills Limited	6.64 Bn
11.	MEHT	Mahmood Textile Mills Limited	6.53 Bn
12.	ANL	Azgard Nine Limited	5.69 Bn
13.	MSOT	Masood Textile Mills Limited	5.64 Bn
14.	ADMM	Artistic Denim Mills Limited	5.46 Bn
15.	FZCM	Fazal Cloth Mills Limited	4.69 Bn
16.	SURC	Suraj Cotton Mills Limited	4.62 Bn
17.	ZAHID	Zahidjee Textile Mills Limited	3.04 Bn
18.	SFLL	SFL Limited	2.86 Bn
19.	FASM	Faisal Spinning Mills Limited	2.54 Bn
20.	BHAT	Bhanero Textile Mills Limited	2.33 Bn
21.	JKSM	J.K. Spinning Mills Limited	2.08 Bn
22.	CRTM	Crescent Textile Mills Limited	1.79 Bn
23.	BTL	Blessed Textiles Limited	1.71 Bn
24.	RCML	Reliance Cotton Spinning Mills Limited	1.54 Bn
25.	KML	Kohinoor Mills Limited	1.37 Bn
26.	SUTM	Sunrays Textile Mills Limited	1.30 Bn
27.	NAGC	Nagina Cotton Mills Limited	1.05 Bn
28.	REWM	Reliance Weaving Mills Limited	0.91 Bn
29.	ELSM	Ellcot Spinning Mills Limited	0.92 Bn
30.	ILTM	Island Textile Mills Ltd	0.84 Bn
31.	MQTM	Maqbool Textile Mills Limited	0.81 Bn
32.	TATM	Tata Textile Mills Limited	0.67 Bn
33.	SALT	Salfi Textile Mills Limited	0.62 Bn
34.	NATM	Nadeem Textile Mills Limited	0.61 Bn
35.	AHTM	Ahmad Hassan Textile Mills Limited	0.58 Bn
36.	SZTM	Shahzad Textile Mills Limited	0.57 Bn
37.	CFL	Crescent Fibres Limited	0.50 Bn
38.	SAIF	Saif Textile Mills Limited	0.40 Bn
39.	SNAI	Sana Industries Limited	0.40 Bn
40.	KOHTM	Kohat Textile Mills Limited	0.38 Bn
41.	HIRAT	Hira Textile Mills Ltd.	0.35 Bn
43.	IDRT	Idrees Textile Mills Ltd	0.30 Bn
45.	SHDT	Shadab Textile Mills Limited	0.23 Bn
46.	BCML	Babri Cotton Mills Limited	0.20 Bn
47.	HAFL	Hafiz Limited	0.14 Bn
48.	QUET	Quetta Textile Mills Limited	0.14 Bn
49.	INKL	International Knitwear Limited	0.12 Bn
50.	ASTM	Asim Textile Mills Ltd.	0.11 Bn

Appendix-B

Stationarity Graphs





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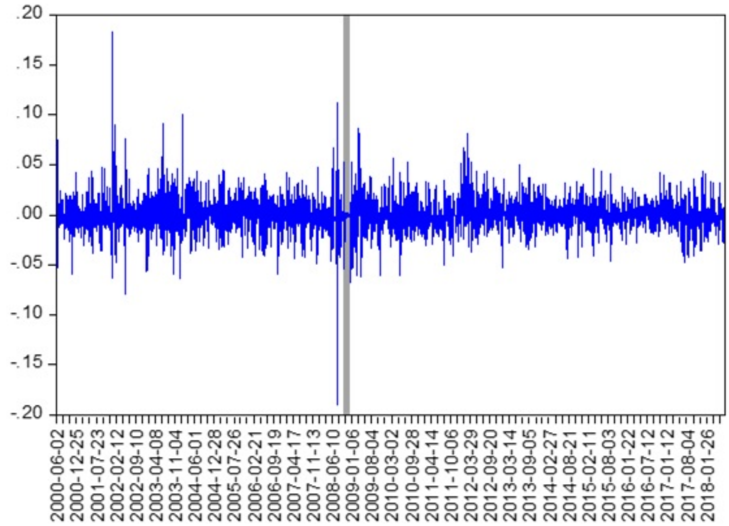

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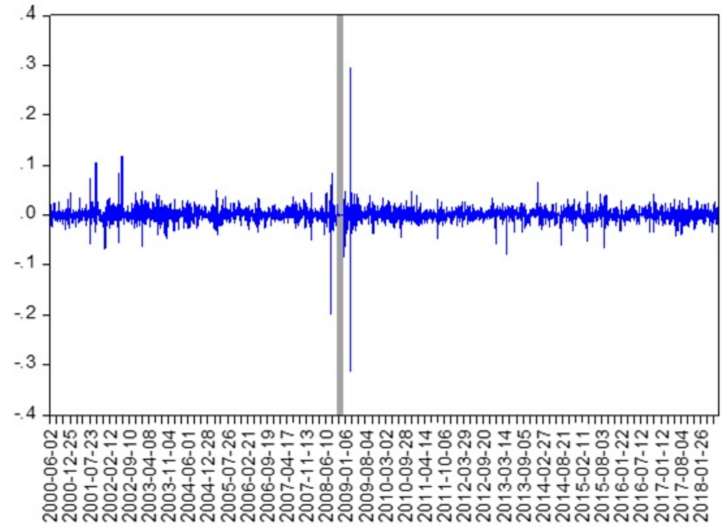

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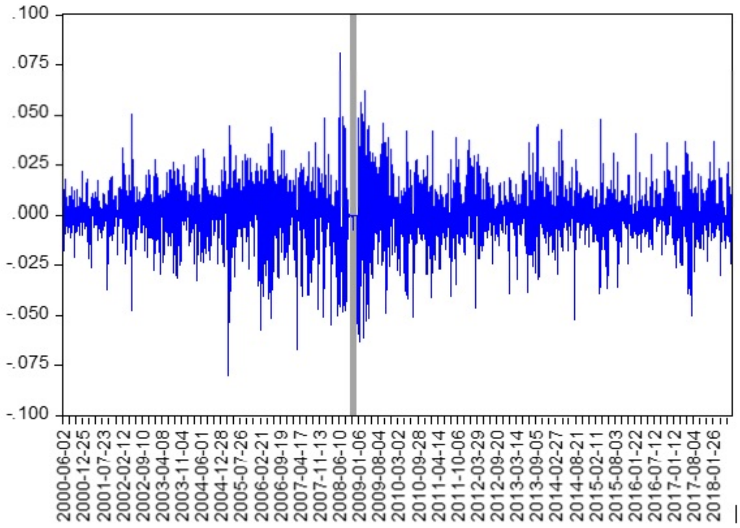

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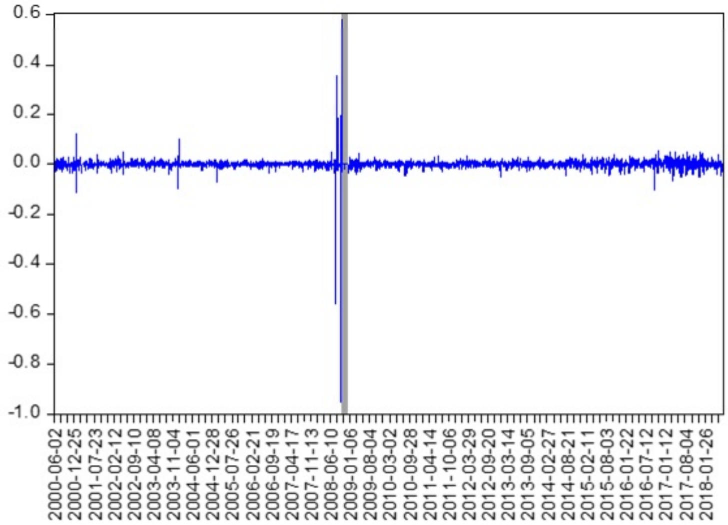

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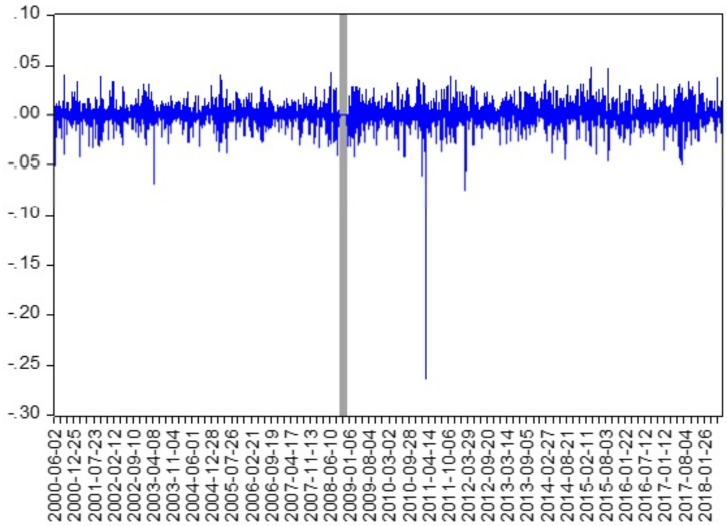

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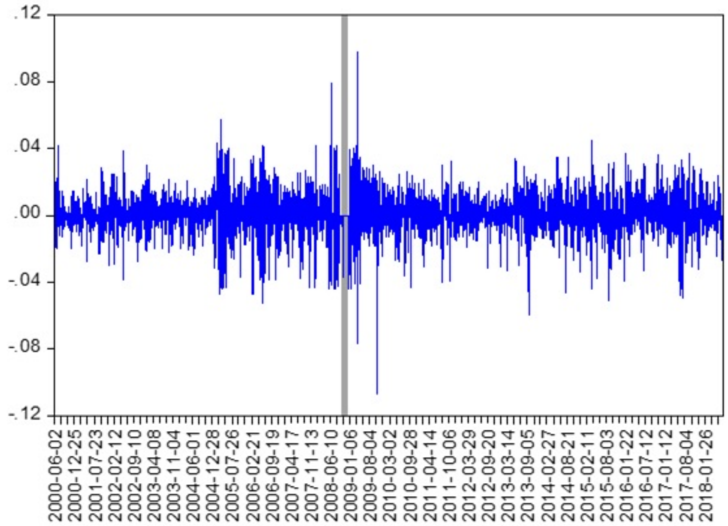

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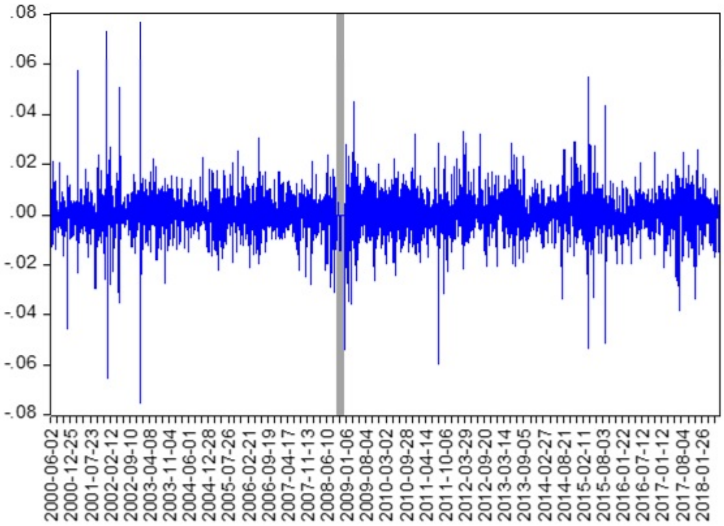

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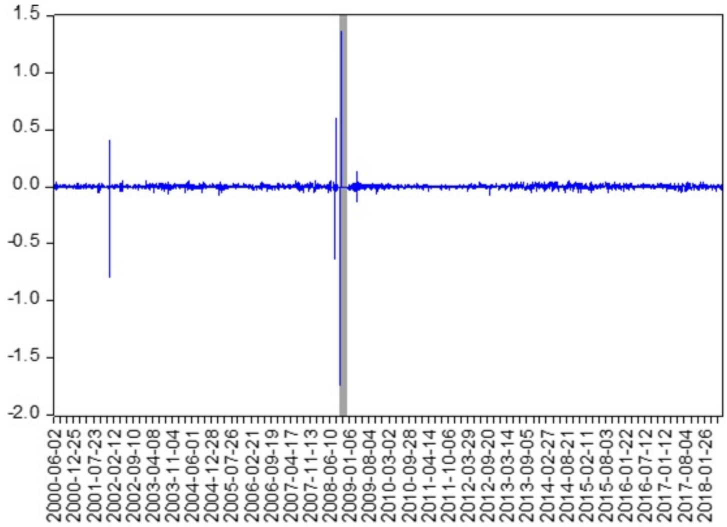

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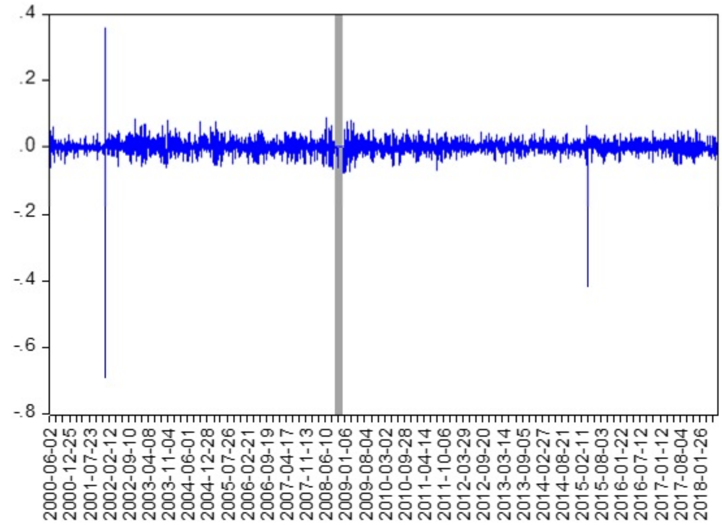

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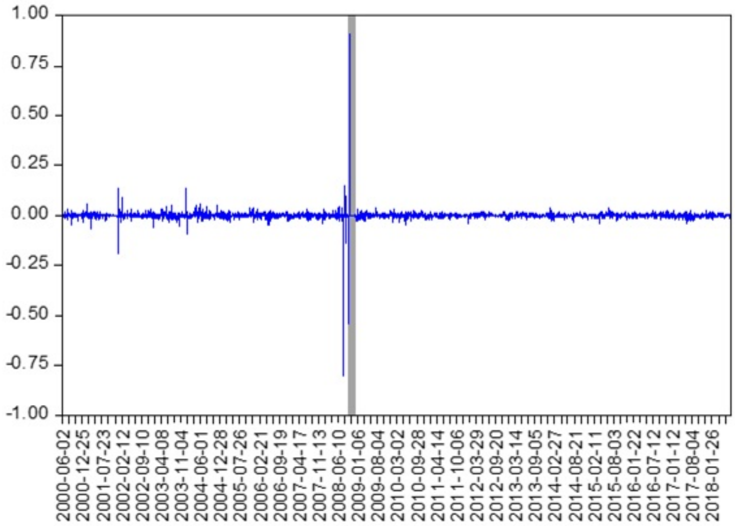

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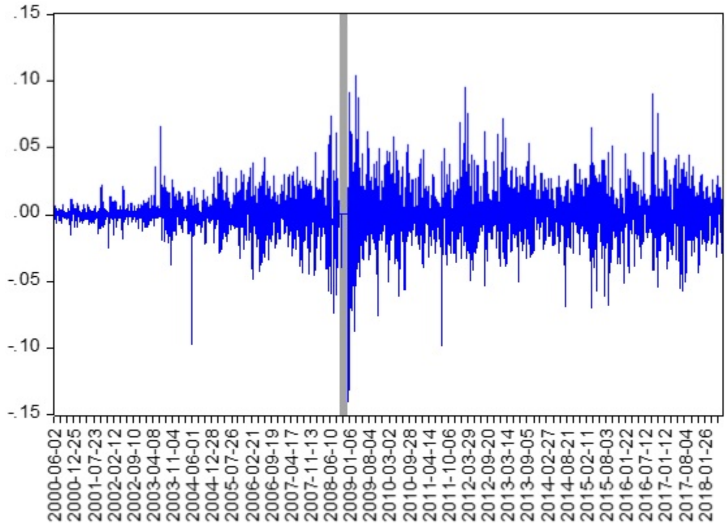

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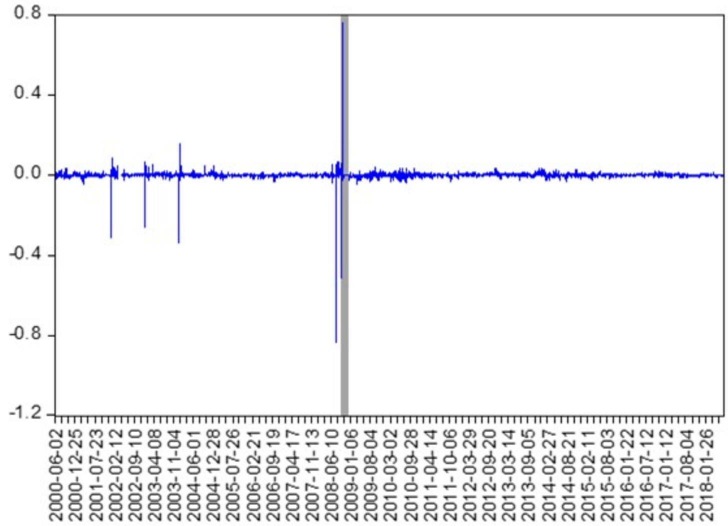

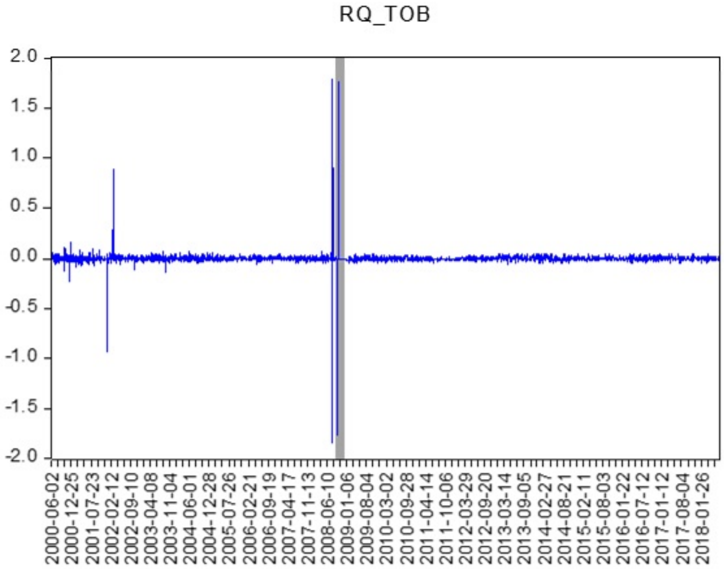
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