Analysis of Volatility Spillover Across Industry Indices: Evidence from PSX

By

FIZZAH BATOOL

325-MSBA/Ibd/S18

SUPERVISOR

Dr. HASSAN RAZA.

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Submitted By: Fizzah Batool **Registration No: 325-MSBA/Ibd/S18**

Master of Science in Business Administration

Management Sciences

Dr.Hassan Raza ______________________________
Name of supervisor Signature of supervisor

Prof. Dr. Naveed Akhtar ______________________________
Name of Dean (FMS) Signature of Dean (FMS)

Brig.(R) Muhammad Badr Malik ______________________________
Name of Director General: Signature of Director General

____
Date

CANDIDATE DECLARATION FORM

I Fizzah Batool

Daughter of …Amir Mehmood

Registration No 325-MSBA/Ibd/S18

Discipline Management Sciences

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ABSTRACT

Title : Analysis of volatility spillover across industry indices: Evidence from PSX

The basic aim of this study is to examine the return and volatility transmission from one industry to other industry in Pakistan. The research uses the daily data of average industrial stock returns of ten major industries for the period of 2000 to 2018. ARMA (1, 1) GARCH (1, 1) model is used to check the spillover from one industry to other industry. Moreover, the time-varying nature of conditional correlation is further explored by using DCC-ADCC models for both aspects as well. The result of this study provides strong evidence of volatility transmission among various industries but limited evidence is found regarding return spillover. However, the study finds the return and volatility spillover across various industries for the given time period which indicates the limited evidences of diversification. In addition, findings also reveal the time varying nature of conditional correlation. The results also show the presence of asymmetric behavior among various industries. Investors can use the consequences of this study in the process of decision making for investments in various industries. Hence, this study will explore the spillover effect from one industry to other industry within Pakistan and will help investors in the selection of sectors for diversification domestically. Hence, this study provides a gateway to future researchers in a new way.

Key Words: GARCH model, DCC and ADCC model, volatility transmission, conditional correlation, asymmetric behavior.

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All the praises are for the Allah Almighty; the most beneficent and the most merciful; who granted man with knowledge. All salutations are upon the Prophet (P.B.U.H.) whose teachings enlighten my thought and thrive my ambitions.

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CHAPTER 1

INTRODUCTION

1.1 Background of the study

In recent years investors and forecasters have been increasingly concerned about the risk that period of excessive homogeneity of movement in prices of assets across separate financial systems and sectors which pose to our capability to diversify portfolio investments, efficiently. In general it is becoming evident that asset markets seem to have a high correlation beyond basic links in times of global financial instability. This is mainly due to the relatively close instant flow of information and the interlinked structure of global economy
making coordinated actions in modern markets a reality (Kalotychou, Staikouras and Zhao, 2009). As for example, there has been comprehensive study of dampened correlation among stock returns during bull markets and strong correlation in bear markets.

Diversification can be defined as the process in which allocation of investments is done in different industries, financial instruments and other categories that can reduce risk. Diversification of portfolios can be accomplished by investing internationally, among various sectors and in different classes of assets, generally with negative or less correlations. By this method return maximizes when investment is done in different areas (Markowitz,1952). According to professionals of investment, risk can be minimized and financial goals can be achieved through diversification, but it is not guaranteed against loss. It is manager's responsibility to understand the role of diversification for investment. Investment diversification can be defined as ''Not to put all eggs in one basket'' which means that by diversifying the investment it doesn't mean you are creating an unwanted risk. Investors diversify the investment by purchasing different funds. Asset allocation is well known form of diversification.

According to Markowitz (1952) portfolio theory, mostly investors are remunerated in accordance with the variance, mean and co-variance structure of stock returns. Diversification in number of securities can be analyzed and most appropriate portfolio can be selected by this theory. For the allocation of assets in the portfolio, statistical analysis and mathematical programming was applied by Markowitz.

Further two theories which explain diversification are Theory of Concentric Diversification and Theory of Conglomerate Diversification. In Concentric Diversification, the diversification is done by market or product diversification by the companies. For example, one retailer is with bath and kitchen products in its product line and want to expand business by broaden its scope by adding more products in it. Therefore, that retailer is diversifying by adding product line. On the other hand, Conglomerate Diversification focuses on expanding business by opening subsidiaries. Many theories like Dow Jones, Random Walk and Formula theory also explain the diversification.

A hypothesis was formulated by the researcher Charles H. Dow, in 1902 he died that is why he was unable to publish his theory. But many associates have published it. According to Dow Jones theory, the stock market for the guidance of its direction gets influenced by three trends which are cyclic in nature and does not move on a random basis. The three cyclic trends are primary movements, minor movement and secondary reactions. Firstly primary movements are the movements of the prices of the securities on stock exchange which are long term. Therefore these movements can swing the market up or down. Secondly the Secondary reactions are those which act as a limiting force over primary movements. They lasts only for a short time and are opposite in direction of primary movements. Secondary reactions are also called as corrections.

And the last one is Minor movements i.e. these are the daily fluctuations in the market. The minor movements are not significant and have no analytical value as they are of very short duration. The future behaviour of stock exchange prices can be predicted, observed by the Dow Theory.

While, the random walk theory is explained by the help of analysis of different trends of pricing, this theory is stated as the future and present stock prices are not related with each other; therefore the behaviour of prices of stock exchange cannot be predicted. Due to certain changes in the industry, economy and the company the prices of stock changes. The up and down movement of stock prices reflect the changes and the information regarding these changes are captivated in the stock market. Hence, due to new information more changes occur.

Formula plans are mainly tilting to achieve loss minimization rather than return maximization. Investors can gain benefit from price fluctuation, for this purpose different tools and methods are developed and this can only be done by selling stocks when prices are high and when prices are low buy the stocks, hence, these methods comes under Formula Plan theory.

Therefore, Inter sector correlation guides the portfolio managers for decisions regarding portfolio diversification because mostly portfolio managers depend on inert estimates of previous correlations. The portfolio managers are beneficial for investors in few aspects. Firstly, in investing through diversification in stock market the risk can be minimized. Secondly, Portfolio manager facilitate stock market with professional management by experts. The hold on diversified portfolio by small investors is done by pooling of investment funds. Hence, it is concluded that portfolio risk can be minimized by diversification. The variability of returns in investment reduces when we raise the securities. The reduction in return is due to covariance of one security with other security. The ups and downs in one security can cover the ups and downs of other one while when there is less than +1 correlation of securities then the ups and downs don't match among securities. In this study the dynamic nature of co movements among different sectors in home country market is investigated. This study provides a framework to the investors that among the sectors the correlation is not only constant but it is dynamic on the occurrence of certain events. In the period of global financial crises, it is seen that the stock markets generally show a system wide movements.

Hereafter, the behavior of stock market is evaluated by the help of information that whether the market is firm specific or it is macroeconomic. The information of stock market is used by different participants of market which helps in investing in various securities. According to Efficient Market Hypothesis, it is stated that changes occurring in the price of one security affects the other securities. The main problem for the investors and other participants of market is the market asymmetric information. It is observed in the past years that markets, stocks and industries are becoming more coordinated. In recent era of global economic ambiguity, it is proved that stock markets are not isolated now and gone away from basic linkages. This occurs due to the transmission of information from market to market and the association of global financial system. Investing abroad as well as investment in different sectors gives the benefits of portfolio diversification.

Thus, it 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. For the analysis of dynamic correlation among sectors this study uses two methods Asymmetric-DCC Multivariate Generalized Autoregressive Conditional Hetero-skedasticity (MV-GARCH) and Dynamic Conditional Correlation (DCC) to isolate conditional correlations from the conditional variance element. In 2002, Engle proposed a model naming DCC-GARCH while in 2006, Cappiello, Engle and Sheppard introduced ADCC model. These models are used to gain maximum hedging effectiveness. There are several advantages of using DCC-GARCH, i.e. to examine the stability in financial time series, to study time fluctuating correlations among financial commodities and variables.

ADCC model is further more addition to the DCC model, in which imbalance in financial time series is taken into consideration. In the last after finding out the hedge ratios gained from GARCH process, these are compared for hedging effectiveness. Therefore, there are also significant leverage impacts in the dynamics of co movement among the industry pairs, with greater levels of co movement being followed in all times by undesirable shocks.

So, the findings indicates that periods of increased national and worldwide market uncertainty expand sector to sector co movement and weaken investors ' capacity to diversify across local industries. As In previous studies the co movement among different markets exists but in those studies only the volatility and return association among different countries were observed. Therefore, this study will explore the spillover effect from one industry to other industry within Pakistan and will help investors in the selection of sectors for diversification domestically

Hence, this research investigates the dynamics of co movement among Pakistan's biggest financial sectors, specifically in order to shed light on national investor's intersectoral diversification opportunities over time. Investors have been noted to have a home-bias when it comes to investment and as such may be subject to periods of improved co-movement between assets held locally across different sectors in their portfolios. Such periods of increased homogeneity in the movement of asset prices negate the benefits of diversification of the domestic financial market.

This study examines the dynamics of return co-variations among different sectors in Pakistan, especially the inter-sector diversification prospective of domestic investors. It is believed that investors prefer diversification in their own country (Katzke, Garch, Correlation, & Indices, 2019)

1.2 Problem Statement:

The concept of diversification gain high importance immediately after the publication of Markowitz (1952) work. Portfolio theory is known as major pillar in finance which states investing in multiple assets decrease their risk while return will remain intact. According to him, investors are risk averse and they prefer to invest in less risky securities. Diversification is the key ingredient that decrease risk in a portfolio, so the importance of diversification cannot be ignored. . Investors require a minimum risk or avoid down markets by hedging or diversifying portfolios by using alternative investment classes that maintain negative or low correlations with portfolio stocks (Chkili, 2016).

Therefore, the variability of returns in investment reduces when we raise the securities. The ups and downs in one security can cover the ups and downs of other one while when there is less than +1 correlation of securities although the ups and downs don't match among securities. Understanding what typically corresponds to magnified inter-sector correlation could provide investors and investment institutions with valuable insights into optimized portfolio diversification strategies. This is particularly important for portfolio managers who often rely on static estimates of past correlations to guide portfolio diversification decisions. Volatility transmission is important for hedging strategy and portfolio allocation. The spillover effect is more across the global economy, when an economy is large.

The researchers Tse & Tsui (2002) indicated the spillover transmission from one industry to other but their study assumes that the co-movements of different sectors of South Africa is constant. While recent studies i.e Joyo & Lefen (2019) claims that this inter-sector co movement is not constant, and to capture the said phenomena these studies recommend to use DCC GARCH model and ADCC GARCH methodology.

Hence, the understanding of connection among sectors of Pakistan is critical. With the passage of time the industries are no more in isolation now and coming closer to each other. This research investigates the dynamics of co movement among Pakistan's biggest financial sectors, specifically in order to shed light on national investor's intersectoral diversification opportunities over time. Investors have been noted to have a home-bias when it comes to investment and as such may be subject to periods of improved co-movement between assets held locally across different sectors in their portfolios.

Gap Analysis:

In previous studies the co movement among different markets exists but in those studies only the volatility and return association among different countries were observed. Therefore, this study will explore the spillover effect from one industry to other industry within Pakistan and will help investors in the selection of sectors for diversification domestically. Hence, this study provides a gateway to future researchers in a new way. So, this study bridges the gap by employing advances methodology to test the inter-sector phenomena by using recent data on the Pakistan stock markets.

1.3 Research Objectives:

The main objective of this study is to examine the co-movements of stock return among different sectors of Pakistan and about the benefits which investors get from portfolio diversification. So the study designs the following objectives;

- To study the association among sectors of Pakistan in term of investment in various securities.
- To examine the volatility spillover across the different industries in Pakistan stock exchange.
- To examine, the intensity and volatility time decay across different industries

1.4 Research Objective:

- Is the portfolio diversification among different sectors of same country benefits or not?
- Is the diversification among sectors enhances the stock return or not?
- Are the intensity and volatility time decay over different industries matters?
- How does volatility spill over across different industries effects inter sector investment?

1.5 Significance of the study:

This study is about how Pakistan stock returns co-movements among sectors vary and how the co- movements of the return affect the portfolio diversification of investors. Understanding what typically corresponds to magnified inter-sector correlation could provide investors and investment institutions with valuable insights into optimized portfolio diversification strategies. This is particularly important for portfolio managers who often rely on static estimates of past correlations to guide portfolio diversification decisions. This study focuses specifically on the dynamic nature of such co-movement in the domestic market between the main economic sectors.

The major contribution of the study is to use the most recent and appropriate methodology for inter-sector diversification. In the first the time-varying conditional correlations between the different sectors will be extracted by means of Dynamic Conditional Correlation (DCC).

Additionally, this study also helps policy maker, decision makers and consumer in relevance to take decision. Readers can know and understand how well the investment diversification can be done in different sectors or inter sectors. Besides, it will also give information to investors to take better decisions about their investments or portfolio diversification in inter sector and how to get benefits from investment.

1.6 Organization of the study

- **Chapter 1:** Chapter 1 includes introduction, background of the study, problem statement, research questions, research objectives and significance of the study.
- **Chapter 2:** Chapter 2 includes all the literature related to volatility spillover .It consists all the previous work done related to the subject. The gap pertaining to the study and facts from the literature will be added in this chapter.
- **Chapter 3:** Chapter 3 includes data description and methodology. It includes research design, sample technique, sample size, unit of analysis, data collection methods and research methodology. It also includes all the equations related to the topic.
- **Chapter 4:** Chapter 4 is related to results and discussions. All the results obtained after analysis are put in tabular forms and their interpretation is done in this chapter.
- **Chapter 5:** Chapter 5 includes conclusion and recommendations. All the implications, results and limitations are discussed in this chapter. Recommendation for future research is also added in this study for future.
- **References:** It contains the list of all the references in APA style.

CHAPTER 2

Literature Review

In this research, a review of literature will be followed to assess the industrial stock return correlations and co-movements of industrial stock returns among different sectors. The variables will be determined and further discuss through various resources by past studies.

Since, past two decades the illustration and modeling of the volatility dynamics with in the financial time series has developed significantly.

As the Global financial exchanges are the consequence of expanded improved globalization, and securities exchange players are progressively mindful of how mean and instability overflow or the change of stuns starting with one market then onto the next happens after some time. The presentation of stocks is gathered by some specific markets that are abridged by sectorial records. Speculators utilize this outline as a benchmark to evaluate the presentation of specific stock or market. Development and improvement of a nation is estimated by utilizing these sectorial records.

There are numerous variables that assume an imperative job in the advancement of Pakistani financial exchange, for example, Pakistani stock trade and volume of exchanging, size, different intermediaries, absolute number of recorded stock at Pakistani stock trade, stock files and stock turnovers. In the past, the cooperation among various markets and ventures is reported by numerous specialists in their examinations. Ewing (2002) thought about the associated connection among the five mechanical industries (industrials & transportation, capital products, financial and utilities) by utilizing the VAR and utilized the methodology of hedged errors decomposition of variance. In his investigation he reported that, any unexpected shock in one industry significantly affects the volatility and the mean and of different parts. Furthermore, in the year 1987, many researchers like Ewing et al. (2003) researched on the association among five major sectors enlisted in stock exchange and other macroeconomic factors. In addition, they likewise found an influence of the macroeconomic factors that cannot be expected on securities costs that are individual in nature in contrast to the events that can be expected.

In 1982, Engle worked on ARCH (Autoregressive Conditional Heteroskedasticity models). In contrast, to the empirical advantages of monitoring the conditional heteroskedasticity in the series of asset return, it is of great practical importance to model the conditional correlation among assets across sectors. This facilitates better asset and derivative product pricing, risk management and portfolio selection decision-making. Diversification can be defined as the process in which allocation of investments is done in different industries, financial instruments and other categories that can reduce risk. Diversification of portfolios can be accomplished by investing internationally, among various sectors and in different classes of assets, generally with negative or less correlations. By this method return maximizes when investment is done in different areas. According to professionals of investment, risk can be minimized and financial goals can be achieved through diversification, but it is not guaranteed against loss. It is manager's responsibility to understand the role of diversification for investment. As it is highlighted in the

Markowitz theory that the examination of estimates of asset returns correlations is based on past knowledge, which indicates that investors are remunerated in terms of the covariance, variance and mean structure of asset returns.
In Markowitz, (1952) portfolio theory, it is explained that mostly investors are remunerated in accordance with the variance, mean and co-variance structure of stock returns. Many portfolios of a number of securities are analyzed by this theory and by the help of this theory most appropriate portfolio can be selected. For the arrangement of allocation of assets in the portfolio, the statistical analysis and mathematical programming was used by Markowitz.

Similarly, by the use of variance or standard deviation among the returns from same security, the Volatility can be measured. Mainly when the volatility is higher, it is considered that the security is more risky. The impact in relevance to the events in one country can have on the other country's economies is known as Spillover effect. Positive spillover effect includes negative impact of a domestic event on the other country. The spillover effect is more across the global economy, when an economy is large. Volatility transmission is important for hedging strategy and portfolio allocation. Basically inter sector correlation facilitates the investors as well as different investment institutes with awareness about strategies of portfolio diversification. Inter sector correlation guides the portfolio managers for decisions regarding portfolio diversification because mostly portfolio managers depend on inert estimates of previous correlations. In this study the dynamic nature of co movements among different sectors in home country market is investigated.

Few researchers observed stock market integration among various countries and industries. **Ferreira (2017)** studied Portuguese and Brazilian stock market integration: a non-linear and detrended approach. In this article he uses non linear methodologies i.e. detrended moving average cross-correlation analysis, detrended fluctuation analysis and detrended cross-correlation analysis. He splits the sample in six different periods by using main stock indexes. As a result the author concluded that the integration increased over time among the above mentioned two countries but during economic crises, since 2013 Portuguese and Brazilian stock markets suffered and the integration among both has been decreased. He explained that stock market integration depends upon economical crises.

Financial Market Integration in Pakistan which is evidence by Using Post-1999 Data **(Economics, 2019)**. Here he used data which is taken from data steam data base. He used daily basis observations on the interest rate, stock prices and exchange rate for the period 12th October 1999 (it is a period of military takeover). He said that stock price depends on changes in value of currency.

Siami-namini (2017) wrote an article naming China's Economy and the Global Financial Crisis. In this article he discussed about china's economy that how it get affected by the global financial crises. For this purpose he applied vector auto regression models (VAR) in which he examined the relationship among two foreign outputs including Germany and US and China's output over a period of 1979 till 2013. It was analyzed that after the application of VAR Granger casualty the US and China's output affects each other.

Yang, Min, & Li (2003)European Stock Market Integration: Does EMU Matter? The author investigated that there is short run, contemporaneous and long run integration structures between US and 11 European stock markets and furthermore he examined the issue of effectiveness of stock market integration between major non-EMU and EMU markets by establishment of the economic and monetary union (EMU). For this purpose he used data based on daily closing prices of 10 EMU countries stock indexes to analyse the short, long and contemporaneous patterns of European stock market integration.
Ali & Butt (2011) wrote an article naming Co movement Between Emerging and Developed Stock Markets: An Investigation Through Co integration Analysis. In this article the author has taken the data from July 1998 till June 2008 by co integration test on monthly stock prices.

Finally it was examined that equity markets of Pakistan with USA, Taiwan, UK, Singapore and Malaysia have no co movement. Hence, by investment in these countries investors can reduce risk.

Huyghebaert & Wang (2009) worked on The co-movement of stock markets in East Asia Did the 1997–1998 Asian financial crises really strengthen stock market integration? He analysed by using data from July 1992 till June 2003 from daily stock market in local and US dollar terms that East Asian stock market relations are time varying. On the other hand interactions among stock market are limited before the crises in Asia.

Countries having less segmented financial markets are with trade structure which is undiversified (Chambet & Gibson, 2005). Hence the finding is that those countries which have more segmentation are less open to the trade. In this article multivariate GARCH (1, 1) M return generating model is used. This model is used just to check partial market integration side by side the pricing of systematic emerging market risk.

Su & Yip (2014) applied recursive co integration procedure and analysed that foreign and US stock markets are not co integrated in the whole sample period. Therefore, it is concluded that this integration among US and foreign market increased during the period of financial crises (2007).

Working & Series (2019) examined the effect on stock market integration by global crises by using data from late 1800's. Mixed frequency base regression approach is used which is derived from (FDA) Functional Data Analysis. To explain the time varying correlations between stock markets the author analyzes the main role of currency, inflation crises and global banking.

In 2010, Mishra and Mukherjee investigated the probability of volatility spillover as well as stock market integration between asian countries and India the GARCH model is applied according to Engle and Bollerslev (1982 & 1986).
Apart from different degrees of correlations, both in terms of return and squared return series, among Indian stock market with that of other Asian countries, the contemporaneous intraday return spillover among India and almost all the sample countries are found to be positively significant and bi-directional
In 1988, Bollerslev, Engle and Wooldridge introduced VECH model (first MV GARCH model), which clearly determine the conditional covariance matrix among series (Katzke et al., 2019). Direct simplification of the univariate approach is the VECH approach. In 2002, Engle later permissive the dependability of the structure of correlation of the CCC model with the (DCC), on the other hand in 2006, Cappiello et al., expanded the DCC model to the Asymmetric-DCC (ADCC) model.

Mainly the MV-GARCH in the literature is used when infectivity effects and market spillover has to be examined. In 1995, Koutmos and Booth explained that negative and positive shock spillovers are different from each other originating from important news events and how it influences the volatility association among equity markets (Katzke et al., 2019). Main advantage of utilizing MV-GARCH technique is for diversification purposes (De Santis and Gérard, 1998, Katzke et al., n.d.). Subsequent to the latest financial crisis, there is also a raising literature, which explained that an association among volatility conduction between different markets and stock return co variations exists by using MV-GARCH technique. Katzke et al., (2019) enlisted South African index of emerging economies, only to examine European regional and global instability spillover.

By applying BEKK MV-GARCH technique, the conditional relationship among the major sectors of numerous large economies as well as South Africa (Horvath and Poldauf, 2012)The major use of VECH-GARCH and BEKK techniques is to investigate volatility overflow effects. The main spotlight of this study is to extort provisional correlations among domestic sectors. Hence, DCC as well as ADCC-GARCH technique is applied for the observation of its dynamic structure. Basically, these techniques are random combination of GARCH models. DCC MV-

GARCH models are applied during economic ambiguity just to demonstrate the code of conduct among investors (Corsetti, Pericoli and Sbracia, 2005).

ADCC-MVGARCH methodology is applied among the complex catalogs of the developed countries and Balkan just to explore the dynamic relationship (Syriopoulos and Roumpis, 2009). Dynamic Relationship between Stock Prices and Exchange Rates: evidence from three south asian countries (Rahman and Uddin, 2014). They checked if co integrating relation is possible or not by using Johansen procedure as well as for checking causal relationship among exchange rate and stock prices they used Granger causality test. Hence it is concluded that stock prices and exchange rates are not related with each other.

Billio & Caporin (2010) examined market linkages; correlation stability and variance spill over. In this article a concurrent equation system with Garchx errors was recommended to model a relationship between American and Asian stock market. As a result a correlation matrix was introduced (this allows graphical analysis of contagion and evaluate this matrix over rising and falling windows).

Sarfraz, Shehzadi, Hussain, & Altaf (2012) wrote an article on co integration of KSE with major Asian Markets and analyzed that there is no or weak co integration among four markets including India, Indonesia, Malaysia and Pakistan. Mostly changes in these countries are due to their own factors according to variance decomposition. Here he applied different tests on data including correlation, descriptive statistics and co integration test just to find out the co movements and behaviour of markets. On the other hand due to change in one market the decomposition of variance in another market is held by variance decomposition technique. For inspecting the relationship of lead lag Granger causality test is used usually. The standard deviation changes in markets are studied by impulse response. Therefore it is briefly studied that how emerging markets co integration is effected by the global financial crises.

The VEC-DCC-GARCH model was used to find dynamic correlation between industries(He, Liu, & Chen, 2019). Therefore, it is investigated that correlations are high among CSI 300 industries, but most probably there was chance of the fluctuation of index. Moreover variance decomposition method is used to calculate spill over indicators with intraday return and volatility. In 2010, Mishra and Mukherjee investigated the probability of volatility spillover as well as stock market integration between Asian countries and India the GARCH model was applied. Apart from different degrees of correlations, both in terms of return and squared return series, among Indian stock market with that of other Asian countries, the contemporaneous intraday return spillover among India and almost all the sample countries are found to be positively significant and bi-directional. In 2005, Collins & Biekpe illustrated that there exists infectivity effects on African stock markets, including South Africa due to 1997 Asian crises and applied Pearson's correlation coefficients. Nigeria, South Africa and Kenya's variance structures were justified by using MA-TGARCH technique (ogum, 2001).

The literature on financial linkages has evolved along a strand in recent years. This strand has been focusing on the domestic transmission of asset price shocks and its determinants.

Now days, association between domestic financial markets are increasing. In 1992, two authors naming Beltratti and Shiller worked on spillover among various asset prices on domestic level and found that bond yields and stock return are positively correlated with each other (Michael Ehrmann, 2005) & (Ammer, 1993). Al though the analysis of these studies is frequently base on data with low frequency. Kuttner (2004) found that in U.S the equity prices respond sturdily to the monetary policy. According to Rigobon (2003) monetary policy has been exposed to react to equity markets. In 2003, Rigobon and Sack analyzed that the causality of the process of transmission might run in numerous directions, therefore, the equity prices and short term interest rates of United States changes towards negative from positive and this transmission depends upon the dominant nature of asset prices that which asset price is dominant in that particular period. To analyze spillovers there are many endeavor. In 1990, few researchers

Hamao, Masulis and Ng worked on analysis of spillovers, based on GARCH models and noticed some spillovers both for conditional volatility and returns from United States towards United Kingdom and Japanese equity markets (Graham, Kiviaho and Nikkinen, 2012). Many researchers in 1995, naming Becker, Finnerty and Friedman came across the fact that spillovers among the U.K and U.S exists. They study mainly the transmission of volatility among short interest rate markets and stock markets across countries.

An associated literature focuses on the impacts on different asset prices of macroeconomic statements. Andersen and Diebold (2005) and Michael Ehrmann (2005) indicate that macroeconomic reports in specific on the US dollar, euro exchange rate has a considerable impact. In case of, bond markets, Goldberg and Leonard (2003)discovered that not only macroeconomic reports are an important driver of modification in bond returns, but there are also significant global bond market linkages among the United States as well as the euro area. Paper and Bank (2004) illustrated that spillovers towards Euro from United States region market are greater, but the spillovers have been present in the reverse direction since the euro was introduced in 1999. Negro (2002)contended that international investment returns can be explained mainly by country specific shocks, by worldwide and industry specific shocks. Moreover, numerous articles highlight the consequence of linkages to illustrate spillovers on the financial market by capital flows and trade.

Vries (2001) indicated that the links among the exchange rates reinforce a wide range of emerging markets during financial crises. Billio and Caporin (2010) found that the degree of bilateral trade instead of country specific fundamentals only plays a significant role in understanding economic co-movements during period of crisis. Focusing on mature economies, Kali and Reyes (2010) determined that the country specific variables have become somewhat less essential, while bilateral trade and economic linkages are now considerably more significant variables to clarify global spillovers across bond markets and equity. A main feature of the economic transmission literature is that it has developed along separate routes, one, the global transmission within individual asset markets and the other on concentrating solely on national cross-market connections. In order to obtain a better awareness of the fundamental nature of the transmission channels of economic shocks, few systematic efforts were formed to connect these strands.

The bitcoin is a potential tool for diversification and its strength as well as its Shari'ah compliance is justified. In 2015, Evans illustrated about the compliance of Bitcoin with Shari'ah requirements as well as how it can be better exchange medium as compared to other currencies. For the identification of diversifying properties of Bitcoin for main stock indices like oil, gold, United States dollars and bonds, DCC technique is used (Jin Lim and Masih 2017). By the help of using modern methodology, the Islamic stock markets have done various studies. Personal, Archive and Faiq (2014) found that MENA, European and developed markets are best for diversification. Therefore, this study supported the usage of index of Dow Jones Islamic Developed Market and index of Dow Jones Islamic European markets.

For capturing diversification on region wise Dow Jones Islamic European Markets index is used while on the other hand, for capturing Emerging Markets index market wise diversification is used. For studying Malaysian Islamic investor's diversification opportunities, the MGARCH and Wavelet techniques were applied (Hanif and Khan, 2017). The purpose of this study was to provide a structure for assessing the interaction of financial market shocks in national and global transmission. The essential information was daily nominal indexes of local currency stocks from global financial data and data stream.

It is drastically different, responsive to financial occurrences and wide ranging. Some of these occurrences are significant, which includes; The East Asian monetary crisis at the end of the year 1997 i.e. (the devaluation of Thai Baht in the month of July, 1997, spreading to Hong Kong in the month of October, 1997 & to other significant markets in the region such as South Korea, Malaysia and Indonesia in the month of January, 1998).

The crisis in Russia June-August in the year 1998 i.e. (the first wave was presided over by the declaration by the IMF of a support package in the month of June 1998 and in the month of August, 1998 the final outbreak was held. The powerful United States signals were followed by the reversal of emerging market capital flows. The financial market unrest linked to the subprime mortgage market which started in the month of July and August in the year, 2007. The major spillover volatility occurrences comprises i.e. Brazilian crisis in the month of January, 1999. The United States terrorist attack in the month of September, 2001 and Euro crisis were linked with statements by policymakers in several developing and industrialized nations in the month of the March and the year was 2005 i.e.(China, South Korea, India, Japan & Russia) demonstrating that they were considering diversification in the Central bank reserve from the U.S. dollar. In any case, the key insight is that large volatility spillover was produced by many well-known events, whereas, with the possible exception of the recent subprime episode (which generates the Spillover Index's highest volatility value since the year 1997 and 1998 during East Asian crisis), there was no return spillovers. The information covers the 3 main daily industry indicators for 4 of the 6 (GCC) countries, Qatar, Saudi Arabia, the United Arab Emirates and Kuwait. The industries includes banking industries, service and industrial of the first 3 nations and the insurance, service and banking industries of the United Arab Emirates, having no Industrial sector index (ISI).

Bahrain modified its index series in 2003 and it is excluded, so there are no appropriate series for its industries at the moment. In addition, Oman does not have adequate sector information. The average weekly index yield differs within the same nation between industries and across the 4 nations for the same industry. The industrial sector in Saudi Arabia provided the largest average return compared to the other 2 industries. It is not surprising that Saudi Arabia's industry produces the maximum average yield as the nation has the biggest economy in the MENA and Middle East and defined in terms of GDP. As a result, the economy of this country can support a large industrial base.

Banking sector and Service sector in Qatar and Kuwait respectively produce the maximum yields. Qatar has the highest economic center in the region competing with Bahrain and Dubai, but it has a weak industrial base. The yield of insurance sector is less than the yield of the service and banking industries in the UAE. Other industries stock is liquid as compared to insurance sector. Overall, the service industry in Kuwait yields the largest average return among the three industries in the 4 nations and the insurance industry in the UAE yields the lowest. In case of Industry danger, most of the danger is in Saudi Arabia, the United Arab Emirates and Kuwait service sector, but in Qatar's industrial sector, whose extremely focused sectors are based on volatile oil and gas, as described by the standard deviation. Therefore, in U.A.E and Kuwait the industry return and risk is directly proportional.

Mostly the returns are tilted to the left, suggesting that in a specified period of time there is a maximum possibility that the industries will go down. This outcome indicates investors are investing for the long pull in these industries to override intermittent reduction. Kurtosis is mixed, with some indices i.e. greater than normal distribution and smaller for the others. Here, for modeling volatility, GARCH was used. The basic aim was the application of latest volatility modeling techniques to improve the usage of the GARCH from a uni-variate strategy to a multivariate scheme.

This strategy would allow examining the conditional volatility and interdependence of GCC markets ' equity industries. With this strategy, it could be concentrated more on estimating significant, interpretable parameters with minimal computational difficulty than with several other models. It was concentrated on literature using GARCH multivariate models with significant worldwide coverage. The linkages among macroeconomic circumstances and inventory market volatility are also investigated (Engle and Rangel, 2006). In 1990, King and Wadhwani concentrated on elaborating the uniformity, with which the world markets fell after the crash of United States stock market in the month of October, 1987. They found a proof of infection in the United States, Japan and United Kingdom from July 1987 till February 1988 using the coefficients of cross market correlation. They also concluded that greater volatility is usually linked with greater market correlation.

K. F. R. Rigobon (1999) demonstrated that owing to heteroskedasticity in market yields; the correlation coefficients were "based." If the correlation coefficients for heteroskedasticity are fixed, they will not find any proof of contagion during the 1997 Asian crisis, 1994 Mexican crisis, and the 1987 U.S. crash From January 1986 to December 1987, the adjusted unconditional correlation coefficients were 0.53 between the U.S. and Canada, while, 0.21 among the U.S. and the U.K., 0.17 among the U.S. and Germany, 0.14 among the U.S. and Hong Kong. Masulis (1990) investigated the markets of the United States, the United Kingdom, and Japan from April 1985 to March 1988. They found statistically significant volatility spillovers from the U.S. to Japan and the U.K. using the generalized autoregressive conditional heteroskedastic (GARCH) model towards Japan. The spillovers from Japan to the other two markets are much weaker. Lee, (1993) reviewed the weekly results of the year 1980 to 1991of German, U.S., U.K., Canadian and Japanese stock markets. They evaluated the degree of interdependence between these economies using the multivariate GARCH model. First, they presented market yields cross border correlations. They also found United Kingdom spillovers with some weak proof to Canada and to Japan from Germany. They concluded the U.K. return volatility. And, unlike Japanese and German, Canadian markets originate largely from the U.S. stock market. It was discovered that the German industry was least integrated. In 1995, Karolyi studied the effect on yields and volatility of the U.S. shocks on the Canadian stock market from year 1981 to 1989. He utilized the U.S. and Canadian S and P 500 and TSE 300 indices.

Arolyi (1998) found shocks originating in the U.S. have a declining effect on the Canadian market's yields and volatility over the period under this study. For Canadian shares that are not dually listed on the exchanges, the size and persistence of U.S. shocks is higher. Dumas, Kaplanis, Harvey and Kroner (1995) studied the long-term development of conditional correlations between seven major stock markets (Germany, France, the United Kingdom, the United States, Switzerland, Japan, and Canada) over the period 1960 till 1990, by using the monthly excess returns. From the year 1989 to 1999, Johnson and Soenen (2003) used daily information to explore the integration of equity markets and their driving forces with the U.S. market in Argentina, Brazil, Chile, Mexico, Canada, Colombia, Peru and Venezuela. They found statistically significant returns between the U.S. stock market and the 8 remaining markets. With the peak in the middle of 1990s, the degree of co movement is discovered to differ over time. Their findings showed that the intensity of bilateral trade with the U.S. has a beneficial effect on co movement. While the volatility of the exchange rate and greater market capitalization has an adverse impact on comovement.

Worthington and Higgs (2004) examined spillovers in between nine Asian stock markets (Hong Kong, Japan, Singapore, Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand) developed as well as emerging from the year 1988 to 2000. They found that it was extremely embedded in all markets. Muhleisen, Roache and Zettelmeyer (2007) explored the connections between the financial markets (stock, currency and bond markets) in the United States and seven Latin American nations (Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela) in 1996 to 2006. They found that over the period, Latin American inventory markets ' sensitivity to the U.S. shock has risen. Sun and Zhang (2009) used daily information from the month of January 2005 to October 2008 to examine the effect of the recent U.S. financial crisis on stock markets in China and Hong Kong. Innovatively, Personal et al. (2014) used the Malaysian Index to depict venture capital (PLS investments) that are the cornerstones of Islamic investment and discovered possibilities for investors to optimize portfolios in other Shari'ah inventory indices in Malaysia.

Models for observing dynamic conditional correlation (MGARCH-DCC) were used by Kearney and Potì (2005) to study determinants of equity return volatility in significant eurozone indicators. By implementing a vibrant conditional correlation GARCH model, Degiannakis, Filis and Floros (2011) evaluated a relationship between oil price uncertainty and financial markets in oil importing and exporting economies. Their findings indicated that stock markets are responding favorably to higher oil prices resulting from demand side shocks. The panel co integration method was used by Arouri and Rault in the year 2012 and discovered that oil shocks had a beneficial effect on stock markets for most oil exporting nations. Similarly, dynamic conditional correlation model and asset pricing model were used by Broadstock and Filis (2012) concluded that oil prices risk generates a beneficial effect on stock returns. They also argued over the turbulent moment for a greater correlation.

By integrating Vector Autoregressive and Vector Error Correction models, Cunado and de Gracia (2014) explored the effect of oil shocks on European markets. The findings indicate that shifts in oil market prices, driven by shock in oil demand, react favorably to France and Denmark's stock markets. Abhyankar, Xu and Wang (2013) examined a link between Japan's oil price volatility and stock market and discovered an adverse effect on Japanese stock market yields from oil price modifications. Similar outcomes were discovered for oil importers (Chatziantoniou, 2014).

Baur and Lucey, (2006)evaluated the hedging and secure haven potential of gold and discovered that gold did not maintain a secure haven asset for bonds but only retained a comparable asset for stocks during poor stock market moments. In 2011, a researcher Joy researched the gold estate as a secure haven or hedge against U.S. currency to conclude that gold would not retain a secure haven status during market stress periods as gold and dollar move in the same direction during market disturbance. Le, Ceuster, Annaert and Amonhaemanon (2013), for instance, researched Vietnam's gold trait as a hedge against inflation and discovered that gold offers the capacity to hedge against inflation. For Turkey (Omag, 2012) reported the comparable outcomes.

Recently, Bampinas and Panagiotidis (2015) used a big information set to examine the hedging capacity of metal commodities for the United States and the United Kingdom and discovered that gold retains its position in both countries against a rise in the overall price level than silver. Some writers discovered that hedge ratios vary in moment to hedge oil potential. For instance, by integrating several MGARCH models, Mcaleer and Mcaleer (2010) discovered a dynamic trend in hedge ratios. The hedge characteristics are studied by (Jr and Lin, 2016). They found that oil should form part of Ghana and Nigeria's stock portfolio. Abul and Sadorsky (2016) researched petroleum, wheat and copper volatility dynamics in emerging-country stock markets. Study findings revealed that oil provides the cheapest comparative hedge, and investors should frequently update hedge ratios.

For the Pakistan economy, many existing studies can’t capture the time-varying correlations between oil, gold, and inventory. The past studies are also unable to assess the efficacy of hedging in traditional stock portfolio of oil and gold, either that literature included easy econometrics methods without offering a comparison among models or conflicting outcomes are obtained using distinct GARCH models. Dynamic conditional correlations are assessed in specific using the Scalar-BEKK model suggested by Engle and Kroner in the year 1995 to examine the time varying connections. Abhyankar et al. (2013) was the pioneer in studying petroleum prices and macroeconomic indicators. The overall consensus was that the oil & gas industry, as well as the mining industry, tends to be favorably influenced by favorable petroleum price modifications, while the opposite is true for other industries such as transport, manufacturing, food, chemicals, medical, computer, real estate and general services, The Electricity, Engineering and Financial industries report non-conclusive outcomes.

In 2009, Hamilton and Kilian also subscribed to the belief that, unless they separated the origins of oil price shocks. These writers were the first to differentiate between supply side and demand side oil price shocks, arguing that these shocks would cause various reactions from economic and monetary indicators. There has been a favorable connection between aggregate demand shocks and financial and/or inventory market trends, whereas there are particular demand shocks during the oil industry. Chen et al. (2014) focuses on France, Germany, Japan, the United Kingdom and the United States and reports that supply side shocks have a more constant impact on inventory prices. However, the above-mentioned studies have mainly ignored the significance of examining the connection in a time-varying setting between oil prices and stock markets. Models of time-varying correlation have only lately been used to explore interactions between the oil and the stock market. For example, Hammoudeh (2004) applied the Dynamic Conditional Correlation Model (DCC) to explore the relationship between commodity prices, including oil, copper, gold and silver, with the S&P 500 index. And demonstrated the proof of growing correlations between all commodities since 2003 but reduced stock index correlations. Similarly, Mcaleer and Mcaleer (2010) demonstrated that conditional correlations are not continuous in the US among crude oil prices and inventory returns. In their analysis, Degiannakis et al. (2011) has gone further and separate oil imports from exporting countries and by using a DCC generalized conditionally heteroskedastic (DCC-GARCH) specification, show that there is a negative relationship between oil and stock market returns during oil market shocks, while a positive correlation has been observed during aggregate demand shocks.

In 2012, Broadstock and his co workers used a BEKK model to define the time varying relationship between oil prices and energy related stocks in China, found a sharp rise in the correlation during the financial crisis of 2008, while In 2013, Antonakakis and Filis used a DCC-GARCH model to examine the time-varying impacts on stock market correlation of oil price modifications. This research linked two literature strands (oil price shocks and time varying correlation between oil price and inventory market returns) in an attempt to disclose some rather significant result. The oil prices are divided into particular shock sequence using the structure of the researcher Kilian in the year 2009, namely supply, aggregate demand and demand based shocks particular to the oil market. For both aggregate stock market indices and chosen industrial sector indices, the said connection was examined. By using a Scalar BEKK model, it was focused that the linkage was most significant in advanced (US) and developing (China) inventory markets.

As in 2012, researchers i.e. Broadstock et al. argued that despite China being the world's second largest economy and the Chinese stock market being the world's second biggest stock market, there is no comprehensive literature examining China's connection between oil price and stock market behaviour. To demonstrate this, it was discussed earlier that how to use time varying correlations in financial investments, why these correlations vary so much across sectors and economies, and what would be the more direct economic implications. Academics and professionals already agreed that oil and stock markets are often linked to worldwide financial activity. Over the past few centuries, determining the precise nature and sources of the connection between oil and stock markets and worldwide financial activity has proven to be a promising region for scientists. Moreover, Chatziantoniou (2014) concluded that changes in oil prices are important determinants of returns on the stock market. He demonstrated in specific that stock markets react negatively to a favorable shift in the price of oil.

However, there is no connection between oil price shocks and stock market yields among other writers (Jammazi and Aloui, 2010). Bampinas and Panagiotidis (2015) provided a comprehensive literature review in the specific region. Studies specifically concentrated on European stock markets shows that favorable changes in oil prices tend to have a negative impact on stock returns; however, the precise relationship depends on the industry. Oil related stock markets, in specific, tend to grow in the case of a favorable oil price shift, whereas the opposite holds for oil intensive industries (El, Arouri, Jouini and Khuong, 2012). In addition, a strand of that literature separated the impacts on stock market activity of oil price shocks according to their origin. In specific, Hamilton (2009)and Kilian (2006) indicated that distinct oil shocks affect stock markets. Kilian (2006) offered a proof that aggregate returns on stocks vary based on the cause of the oil price shock.

Hamilton (2009) breaks down oil price shocks into two parts, namely demand side oil price shocks (triggered by higher aggregate demand, e.g. owing to China's industrialization) as well as shocks in supply side oil prices (triggered by changes in global oil manufacturing). Furthermore, Kilian (2006) defined a third source, shocks of precautionary demand or shocks of demand particular to oil. These are oil price shocks linked to the uncertainty of future oil accessibility. Baumeister (2012), Basher et al. (2012), Kilian and Lewis (2011), Degiannakis et al., (2011), Lippi and Nobili (2012), Kilian (2007), Apergis, Miller and Miller (2008), Val (2008), Kilian (2006), Barsky and Kilian (2004) also demonstrated the significance of taking into account the roots of the oil price shock in this region of concern. For instance, Hamilton (2009) maintains that shocks in oil prices have been driven primarily by demand in recent decades and therefore supply side incidents do not have important impacts on oil prices.

Lippi (2010) advocated that supply side petroleum price shocks have an adverse economic impact, whereas demand side petroleum price shocks have the reverse impact then demand side shocks. Furthermore, in 2009, Kilian and Park showed that supply side oil price shocks have no impact on stock market yields, while stock markets tend to respond negatively to oil specific demand shocks. On the other side, they discovered that shocks in aggregate demand for oil prices cause a favorable stock market reaction. In the same line of reasoning, Degiannakis et al. (2011) discovered proof that supply side shocks do not appear to affect stock market yields, whereas demand side shocks are the opposite. Likewise, Abul and Alfred (2011) demonstrated that supply side oil price shocks do not affect emerging stock market yields, while aggregate demand petroleum price shocks appear to have a beneficial effect. They discovered proof of downward pressure on stock returns from oil specific demand shocks.

Although proof suggested that the source of the oil price shock triggers distinct stock market reactions, most literature does not consider them while examining their impacts (Hedi and Ben, 2012) ; (El et al., 2012); (Bjørnland, 2008); (Chen et al., 2012) ; (Park and Ratti, 2007). As discussed above, the purpose of the above studies was to direct the research's attention to the impacts on stock market volatility of oil price shocks. Studies in the early 80s and 90s i.e. N. Working and Series (1990) and Bernanke (1980) showed that higher energy prices create uncertainty for the companies, leading in investment choices being delayed. In addition, some writers believe that oil price innovations affect aggregate uncertainty and have important adverse effects on investment (as for example, (Calabrese, Liu, Lorenzo and Ratti, 2011), (S. Rahman, 2010), (Estate, Serletis and Collins, 2010). Furthermore, Bloom and Bloom (2007) recorded that stock market uncertainty improves following significant shocks such as the U.S. terrorist attack of 2001, OPEC oil. Nevertheless, the origins of oil price shocks were not regarded by that research. However, it was claimed that Bloom's selection of significant shocks coincides with incidents that cause certain oil price shocks, as (Hamilton, 2009) and an author Kilian in the years (2007 and 2009) recognized these shocks. For example, the U.S. terrorist attack of 2001 triggered an oil-specific demand shock, while disruptions in the supply of oil caused shocks in the supply side of oil prices. Therefore, it is important to disentangle oil price shocks to understand better stock market uncertainty. Moreover, the literature has well developed that the uncertainty and aggregate uncertainty of the companies can be represented respectively by individual stock price volatility and stock market volatility (Baum et al., 2010) and (Bloom and Bloom, 2007). Although stock market volatility features have been widely studied in the past, the literature continued silent on the impacts on stock market volatility of the various oil price shocks.

Rather, the output of the study has focused on spillover effects between oil price volatility and inventory market yields and the volatility or the connection between oil price volatility and company investment. Three measurements of volatility are used in the above discussed study that are conditional volatility, volatility realized and volatility implied. Conditional volatility is the most commonly used technique of quantifying volatility in economic time series, estimated from a predefined ARCH model. The realized volatility, introduced by Bollerslev (1998) sums the squared log returns of high frequency to produce a reduced volatility metric. Among other things, according to Ebens (1999), the usage of high frequency information to calculate volatility at a reduced frequency offers more precise volatility estimates. Implied volatility stems from the price of the alternative. Conditional volatility was selected in the above mentioned literature because it is the most commonly used variance metric.

The use of realized volatility measure is justified by the latest economic literature results that it offers more precise volatility estimates. On the other side, the use of implied volatility is driven by the reality that portion of the literature shows that this sort of volatility (a forward looking measure) is more informative than other estimates of volatility, which are the current looking volatility metric. Therefore, any variations in their reactions to oil price shocks should be identified. Koopman et al. (2005) suggest that both the volatility implied and the volatility realized were precise in information. In contrast, writers such as Becker et al. (2007) and Corrado and Truong (2007) indicated that implied indicators of volatility do not provide incremental data compared to other indicators of volatility. However, R. Engle (2002) claimed that there is no easy solution to which measure of volatility is the most accurate, as it depends on the statistical strategy taken for forecast assessment. It provided a proof that stock market volatility is not affected by supply side shocks and oil specific demand shocks, while oil price shifts due to aggregate demand shocks lead to a decrease in stock market volatility. The findings were also valid for the volatility of the industrial sectors.

The proof of growing bonding on the stock market depends on the study period and the methodology used; however, most studies show that global bonding on the stock market has risen in latest centuries. Sheikh et al. (2012) used a soft logistic transition model to determine the degree of stock market integration between the US and Latin American stock markets from December 1988 to March 2004. The smooth transition model was adapted to the conventional DCCs between the U.S. equity sector and the markets of Argentina, Brazil, Chile and Mexico. The findings have shown a rise in the degree of co integration between these overtime markets; however, the velocity and extent of inclusion varied with the country being examined. In 2011, Durai and Bhaduri used a comparable strategy, studying the correlations between the some sample economies from July 1997 to August 2006 such as the US, UK, Germany, India, Malaysia, Indonesia, Singapore, South Korea, Japan, and Taiwan. The findings have shown that the correlations between developed market yields are greater and lower between Indian stock market yields with established and Asian stock markets. The Indian market's low correlations continue to suggest the possibility of benefiting from international diversification.

Journal et al. (2013) found that emerging market areas (Latin America, Asia, South East and Middle East) are segmented from other global economies. The correlations between the indicators also reduce when the breaks are associated with a reduction in volatility. Similarly, a sudden rise in volatility is followed by a rise in the DCC model, supporting the existence of an impact of shift contagion. In 2011, an author named Kenourgiosetal also provided a proof of contagion on a sample of BRIC emerging markets (Brazil, Russia, India, China) and two advanced markets (UK and US) using an asymmetric time varying structure (AG-DCC) from the year 1995 till 2006. Similar findings are those of Dimitriou et al. (2013), who applied the FIAPARCH-DCC strategy to a sample of BRICS countries (Brazil, Russia, India, China, and South Africa), as well as the United States, during various stages of the latest crisis. From the beginning of 2009 onwards, increasing co-movements between the US and BRICS are identified, suggesting that correlations tend to be greater in bearish economies. The research of Kenourgios and Christopoulos (2013) has investigated three significant emerging market crises (Asian crisis, Russian default, and Argentine turmoil) along with the latest U.S. subprime crisis. Standard co-integration assessment disclosed long and short term dynamics in evolving stock markets during the Russian and Asian crises, both for inventory and bond markets during the subprime crisis, but Argentina's turmoil had no significant effect.

In relation to the statistical advantages of managing temporary persistence for second order and conditional heteroskedasticity in asset return sequence, it is of excellent practical significance to model the conditional correlation among the assets and across industries over time. It enables better asset and derivative tool pricing, portfolio choice and decision making regarding risk management. Also it is emphasized in the Markowitz finance theory proposed in the year 1952, the significance of studying estimates of asset return correlations is based on previous data (or conditional correlations), which indicates that investors are compensated in terms of average and variance-covariance structure of asset return. A wide range of literature on MV-GARCH models has appeared over the past two centuries, differing in terms of conditional volatility requirements (of which a wide range of literature has developed) as well as conditional variance-covariance matrix requirements.

T. Bollerslev et al. (2014) suggested the first MV-GARCH model just to measure the conditional covariance matrix between series, the VECH model. The VECH method is fundamentally a direct generalization of the univariate strategy, requiring a big number of parameters as such (Katzke, N., Garch, M., C., & Indices, S. 2019). A study on South Africa stock returns correlation has used DCC and ADCC Multivariate GARCH methods to detect the underlying dynamics. Following the latest global financial crisis, an increasing body of literature, using the MV-GARCH methodology, has been studied the magnified inter linkages between asset return co movement and volatility transmission across different economies. Several studies included a composite South African index in their list of emerging economies Christopher, et al (2012) and Maria, Schulze-ghattas and Spagnolo (2009), primarily studying the spill-over impacts of worldwide and regional volatility from Europe. B. R. Horvath, Petrovski and Horvath (2012) for example, used the BEKK MV-GARCH strategy to study the conditional correlation between the major industries of several major countries, including South Africa. Christopher et al. (2012) also derives time-variable conditional correlations between aggregate stock and bond market indexes using the BEKK MV-GARCH framework, using the dynamic correlation structure to explore its long-term relationship with sovereign credit scores using Error Correction Models.

While the time-varying correlations between series can be extracted using methods that are direct generalizations of the univariate volatility models into the multivariate plane, such as the above research using the BEKK and VECHGARCH methods, the primary use of these models is to study the spill-over impacts of volatility. Since the focus of this document will be on extracting the conditional correlations between the national industries and studying their dynamic structure, the more parsimonious DCC and ADCC MV-GARCH models will be used. These methods are non-linear combinations of univariate GARCH models using a two-step operation to divide the covariance matrix into the individual univariate conditional variances and the series of dynamic conditional correlation. Paper and Haven (2001) and Chiang, Nam and Li (2007) used DCC MV-GARCH models to demonstrate that herding behavior among investors in emerging markets during periods of financial uncertainty can have a significant impact on capital market linkages between developing nations and advanced economies.

Kalotychou, Staikouras and Zhao (2009) studied intersectoral correlations of volatility between the economies of Japan, the US and the UK and emphasizes the usefulness of studying the dynamics of asset return correlations for portfolio allocation purposes. They claimed that there are significant advantages to portfolio management not only from timing volatility (as GARCH's multivariate model extensions), but also from the dynamics underlying return correlations. ADCC-MVGARCH methods are used by Syriopoulos and Roumpis (2009) to explore such vibrant correlations between Balkan and developed countries ' overall composite indices and to express comparable feelings from the viewpoint of emerging market investment. Despite several MV-GARCH research including South Africa in a list of other nations (usually as part of a European group of economies), none of the author's understanding focused solely on the structure of dynamic conditional correlations between major national industries. In reality, the dynamics of volatility return on the South African equity market are generally restricted.

Notable instances included In and Financial (2003), who used Pearson's adapted correlation coefficients to study the infectious impacts of the 1997 Asian inventory market crisis in Africa, including South Africa. In 2001, Ogum used a time-varying MA-TGARCH model to study SA, Nigeria and Kenya variance structures between 1985 and 1998. Samouilhan (2006) used univariate volatility models to find proof of aggregate market and sector-level return and volatility linkages between SA and UK equity markets. Chinzara & Aziakpono (2009) used VAR estimates and univariate GARCH methods to explore mean and volatility linkages between the South African inventory market index and numerous other significant worldwide indices. In 2011, Chinzara identifid important volatility spill-over impacts of macroeconomic variables on the aggregate stock market index monthly yields and four other major industries, including the economic, retail, mining and industrial industries, using univariate GARCH methods. He also discovered that these impacts are intensified during periods of economic crisis (specifically using dummy variables for Asian and global financial crises, respectively. Duncan, Kabundi and Duncan (2011) used a generalized self-regressive (GVAR) method to explore national volatility co-movements between currencies, bonds and equities in South Africa. The dynamics of their assessment are based on rolling window regressions to provide a time-varying estimate of transmissions of volatility between the major asset classes. This research aims to add to this literature by demonstrating how global and national macroeconomic uncertainty affects the dynamics of conditional co-movement among the biggest national financial industries. Therefore, the research offers an interesting insight into national investors ' capacity to hedge their portfolios by keeping assets in distinct financial settings across the spectrum of local equity markets. Therefore, the research offers an interesting insight into the capacity of national investors to hedge Alternative multivariate volatility models which can also be used to build comparable time-varying variance-covariance series, including the Orthogonal-GARCH, EWMA10 and Variance Sensitivity Analysis (VSA) models, which will be used for brevity purposes.

Kenourgios & Christopoulos (2013)examine the correlations between Balkan emerging stock markets (Turkey, Romania, Bulgaria, Croatia and Serbia) and developed European markets (UK, Germany and Greece) between January 2000 and February 2009 and provide proof that dependency between the Balkans and advanced equity markets has increased. Samarakoon (2011) performed a comprehensive stock market integration and contagion study from April 2000 to September 2009 between 62 emerging and border economies and the US market. Samarakoon (2011) discovered that shocks more likely to be driven by the US economy during periods of calm, while shocks from emerging markets have an effect on the US during periods of crisis. There are significant interdependencies between emerging and border markets with the US market that stop emerging markets and border markets from acting as efficient hedges for US investors in US shocks. Syllignakis and Kouretas (2011) analysed the conditional correlations with conditional volatility on a sample of US, German, Russian, Czech, Estonian, Hungarian, Polish, Romanian, Slovak and Slovenian inventory exchanges from October 1997 to February 2009.

Their outcome is merely that Central and Eastern European stock markets ' usefulness as a diversification instrument has declined in latest years, mostly not ably in the latest financial crisis and stock market crash of 2008. B. R. Horvath et al. (2012) contrasted the market correlations among the CEE-3 and South-Eastern Europe (Croatia, Macedonia and Serbia). These authors found that the level of co-movement between the CEE-3 markets and the Stock Europe 600 index is much higher during their study period from January 2006 to May 2011 than between the South Eastern European markets and the Stock Europe 600. In the research by Davidson and Number (2012), the asymmetric DCC model was used to predict the correlations among the CEE-3 stock markets and the aggregate Stock 50 euro area index from the month of December 2001 till October 2011. This research found a positive rise in correlations after CEE-3 nations entered the European Union; in addition, correlations stayed at greater concentrations during the latest financial crisis. Even though imbalances in volatility were present in all instances, an asymmetry in correlations was important only for the couple of indices WIG (Poland) and BUX (Hungary) these writers also connected correlations with conditional volatility but not all interactions were substantial.

Subrahmanyam and Mathur's inquired in 1990 celebrated the connection between the Nordic (Sweden, Norway, Denmark, Finland) and US equity markets and discovered that US stock markets had some impact on Denmark, but no impact on Sweden, Finland, and Norway. Sweden's stock market is causing Granger both to Norway and to Finland. Denmark, Norway and Finland's equity markets as shown are not causing Granger to other equity markets. It was also investigated that the amount of interaction among the Nordic stock markets is smaller. In 1992, Kasa investigated a single prevalent trend that could compel the United States, England, Germany, Japan and Canada's equity markets.

He also proposed that there might be a long term connection of co movement among these equity markets. Roca examines the interrelationship between U.S., U.K., Korea, Japan Taiwan, Australia, Singapore and Hong Kong stock markets in 1999 by assessing the co-integration test. It was suggested that Australia and other equity markets that are being studied do not have a long-term connection. In

2002, Ng explored the facts regarding the co-integration of ASEAN equity markets (Malaysia, Singapore, Indonesia, Philippines and Thailand). The research included inventory prices for the period from 1988 to 1997. It was also explored that there is no long-term co-integration connection among the ASEAN equity market where only the short-term connection was discovered. The outcome of the assessment of Correlation indicates that integration is increasing while time-varying assessment indicates that some equity markets are progressing to be closer to co-integrating with Singapore.

Haron, Azmi and shamsuddin also searched for the co-movement between the major trading partners Malaysia (US, Japan and Singapore) and Malaysian stock market in the year 2004. The information that began from January 1995-June 1997 used and applied Vector Error Correction Model, Impulse Response Analysis, Co integration and discovered the connection between nations being studied. It was demonstrated that there was no long-term continuous co-movement before the application of capital measures to be monitored, while a stable co-movement connection was established after the application of capital measures to be controlled between nations being studied.

There was also an effort to investigate the connection between the the Tiger stock markets and Malaysian stock market. A researcher naming Marashdeh researched long-term co-movement among MENA nations as well as developed countries such as United Kingdom, United States and Germany in 2005. The auto-regressive distributed lag method was used to investigate the connection. It was found that, contrary to these MENA countries, MENA nations have not shown any long-term connection with advanced nations. Glezakos et al. compared the main equity markets in the world in year 2007, i.e. In Athens, England, Germany, the Netherlands, Spain, USA, France, Italy, Belgium and Japan. He also studied the interrelationship between these markets. The outcome showed that these markets stayed embedded at the 1st difference stage; in addition, these markets detected multi-directional spillover effects. Hasan (2008) examined the existence of long-term movement of co-integration among the KSE100 index in Pakistan and the United States, United Kingdom, Canada, Germany, France, Italy and Japan. The study included 7-year weekly index time series information starting from January 2000 to Dec 2006. S. A. Journal and Sciences (2015) searched two developing countries (Mexico, Philippines) for long or short-term relationships. Monthly information from the month of Dec, 1998 till Dec, 2008 was used.

Multivariate co integration method applied to the Philippines and Mexico stock market with worldwide stock market exploring long-term ascent. Developing equity markets were explored and demonstrated inclusion with the worldwide equity market. Compared to the Philippines stock market, Mexico's stock market was extremely incorporated with the worldwide equity market. Ampomah found in 2011 that South African stock markets showed independence from significant stock markets around the world, while the South African market showed dependence on international stock market economies. The research showed that no connection has been discovered between these countries ' inventory exchanges. In addition, the favourable data is displayed for the assistance of the interested scientists of foreign investors. Nevertheless, local investors do not have sufficient facilities accessible to ripen portfolio investment fruit. Recently, comprehensive study on the interdependence of regional stock markets has been carried out. Cheung and Ho (1991) & Lai (1993) studied 11 emerging Asian inventory markets and advanced markets and discovered that very little correlation existed between the Asian market group and the advanced market group. Hamid and Hasan (2011) researched the dynamic or causal linkages between KSE-100 and developing equity markets in China, Brazil, Hong Kong, Malaysia, India, Turkey, Thailand and Indonesia as well as advanced equity markets in the United States, France, Japan and the United Kingdom. The research consisted of the period from January 1998 to December 2008. The observation of 132 monthly stock indices has been used.

In 2012, Thao and Daly celebrated the long-term connection between 6 equity markets in the South-east Asian area, namely, Singapore, the Philippines, Thailand, Malaysia, Vietnam and Indonesia using the period long gathered daily market indicators. Three evaluation techniques used in the research which includes; multivariate residual based, co-integration testing based on

VAR model, co-integration testing with structural breaks and bivariate residual-based co-integration testing.

It is recognized that the extensive use of GARCH models to model asset price volatility dynamics. Since hedging has the emphasis in this article, it has restricted the debate to a brief review of appropriate articles that concentrate directly on hedging oil and other associated commodities equities. In 2010, Chang et al. investigated the capacity to hedge oil and gasoline spot prices during bull and bear markets with their corresponding futures prices. Chang, Mcaleer and Tansuchat (2010) studied the capacity during bull and bear markets to hedge oil and petrol spot prices with their consequent futures prices.

Eight common models (GARCH multivariate, OLS, state space and error correction) are used to build hedging effectiveness measures. Their results indicated that the hedging efficiency in bull markets is higher. For the out of sample assessment, CCC and CCC-GARCH error correction models rank highest on efficacy. El, Arouri, Jouini and Khuong (2011) estimated GARCH models using weekly information from the month of January 1998 till December 2009 to explore spill over volatility between European oil, United States and stock markets. They discovered the proof of a spill over effect from Europe's oil to stock markets and a two way spill over effect between the United State stock market industries and oil. Optimal hedge ratios calculated from separate GARCH models are very comparable for a specific equity or oil hedge. The DJ Stoxx Europe 600 has optimum equity or oil hedge ratios ranging from 0.174 to 0.223. The optimum hedge ratios for S and P 500 or oil range from 0.142 to 0.199. Optimum ratios differ across industries of the sector. The economic industry in Europe, for instance, has a maximum hedge ratio of 0.001 compared to the best possible hedge ratio of 0.176 in the European utilities industry. El, Arouri, Jouini and Khuong (2011) estimated bivariate GARCH models in the Gulf Cooperation Council nations for the period 2005-2010 to determine volatility and the transfer of exchange among stock markets and oil prices. Among these markets, they had discovered proof of spill over. Best possible hedge ratios vary from a low of 0.078 (Saudi Arabia) to a high of 0.429 (Oman) between GCC equity markets and oil. By using VAR-GARCH models, in 2012, few authors like El, Arouri, Jouini and Khuong model volatility dynamics among petroleum and European equity markets. Analysis is carried out from the month of January 1998 till December 2009 using weekly information. They discovered the proof of spill over of volatility among oil prices and stock returns from the industry. Maximal hedge ratios among equity and oil differ significantly from 0.001 to 0.200.

In 2011, few authors i.e. Chang et al. has explored DCC, BEKK, CCC and VARMA-GARCH's usefulness in hedging crude oil spot prices with future prices of crude oil. Both the crude petroleum prices of WTI and BRENT are regarded. They present proof of time varying hedge ratios. Calculations of hedging efficacy show that DCC-calculated hedges are the best while BEKK calculated hedges are the worst. In 2012, an author, naming Sadorsky utilized GARCH (1, 1) multivariate models to explore the dynamics of volatility among the inventory prices of clean energy firms, technology businesses and oil prices among 1 January (2001) and 31 December (2010). Clean energy companies ' stock prices correlate more closely with stock prices for technology as compared to the oil prices. The ideal average leverage ratio between oil companies and clean energy was 0.20. The large standard deviation was 0.19 and it ranged from maximum 0.79 to minimum −0.23, which demonstrated the frequent adjustment of the hedge. An asymmetric DCC (RS-ADCC) regime switching model to assess the efficiency of hedging among crude oil and associated petroleum products such as heating gasoline and oil (Pan et al., 2014). The BEKK has the highest efficiency of hedging with gasoline futures for crude futures. The RS-ADCC produces the maximum hedging effectiveness for crude oil with heating oil. Many researchers has worked on exploring the hedge ratios and volatility dynamics among equity prices in Nigeria and Ghana as well as oil prices using DCC-GARCH & VAR-GARCH models. They also discovered that Ghana's optimal hedge ratio varies from 0.51 to 0.40, on the other hand, Nigeria's ideal hedge ratio ranges from 0.56 to 0.50. In 2014, an author Sadorsky utilized GARCH models to analyze the dynamics of volatility among emerging market inventory prices, wheat prices, oil prices and copper prices. The set of daily information includes the period from 3 January 2000 to 29 June 2012. Normally, oil offers the cheapest hedge for emerging market inventory prices (0.12), on the other hand, copper is the most costly (0.25), but as the hedge ratios show significant variability, these hedges should be regularly repetitive and updated.

In 2014, Sadorsky utilized weekly information estimated CCC and DCC GARCH models to model conditional correlations and volatility among the Dow Jones Social Responsible Investment portfolio of gold, equity and petroleum. SRI shares comparable statistical characteristics with the S and P 500 and as a consequence, SRI shareholders can expect to pay a comparable quantity to hedge their investment in the S and P 500 with petroleum or gold. The average hedge percentage among oil and SRI is 0.05, whereas the average hedge ratio of petroleum and S and P 500 is 0.07. Many writers selected a specific GARCH model (e.g. VARMA-GARCH or DCC-GARCH) and then presented their selected model outcomes without comparing how one model compares with another. It is helpful to compare outcomes from distinct technique of GARCH to deepen our knowledge of how hedge ratios differ by method of estimation. While in sample the assessment is helpful in understanding model fit, if one is interested in future oriented decision making, it is not the most helpful method. The sample output for a hedge is more interested in a hedger. There is extensive literature on the connection between oil and agricultural prices, but the nature of this causal connection remains uncertain. There is enhanced interest in spill over volatility as well as transfer of danger between prices of agricultural commodities and oil. The literature, however, appears to be still sparse and calls for greater attention to risk transmission dynamics. In the literature, three main links in between oil and agricultural prices can be distinguished such as bio fuels, oil as a production cost and co movement with agricultural commodities due to investment fund activity.

Baffes and Baffes (2007), Harri, Nalley and Hudson (2015), Chang and Su (2010), Alghalith (2010), Du, Yu and Hayes (2009), Alom, Ward and Hu (2011) examined the connection between oil and agricultural prices as a price of manufacturing in agriculture. Baffes and Baffes (2007) evaluated how spill over in crude oil prices of 35 primary commodities traded globally. In 2010, Baffes re-investigated this connection at a more disaggregated stage and discovered that the largest passage of oil price modifications was to the fertilizer index followed by farming. Serra and Fax (2011), S. Paper, Joint and Meeting (2009), Hassouneh, Serra and Gil (2011), Kristoufek, Janda and Zilberman (2012), Busse, Stefan, Brummer, Bernard, Ihle and Development, (2010) and Zhang, Lohr, Escalante and Wetzstein (2010) have illustrated the connection between oil and agricultural prices in terms of bio fuels.

Serra and Fax (2011) evaluated the spill over volatility among the Brazilian prices of crude oil, sugar and ethanol. She discovered that there are powerful price volatility associations and that shocks in the sugar and crude oil industry are causing a rise in ethanol price volatility. This shows that there is a vibrant connection between the fuel, bio fuel and agricultural markets. Serra and Fax (2011) examined transmission trends and price connections in the U.S. ethanol sector and discovered that there are long term associations among petroleum, ethanol, maize and petrol prices as well as powerful connections between food prices and energy. They revealed a long term equilibrium connection between oil, bio fuel and agricultural markets, similar to Serra in the year 2011.

Hassouneh, Serra and Gil (2011) examined price connections and price propagation trends in Spain among food and energy prices. They discovered that there is a long term, balanced connection between both the prices of bio diesel, crude oil and sunflower; that bio diesel is the only variable that adjusts to long term variations and that the prices of sunflower oil are affected by electricity prices by the help of short term dynamics. The connection between bio diesel, ethanol and associated fuels and commodity prices in the Germany and United States is analyzed by (Kristoufek, Janda and Zilberman, 2012). Their findings indicated that while bio fuel is influenced by food and fuel prices, the prices of bio fuel have restricted ability to determine food prices. They also discovered that depending on the frequency of data used, the links among prices shifts. Busse, Stefan, Brummer, Bernard, Ihle and Development, (2010) explored the vertical cost transmission in Germany's bio diesel supply chain by concentrating on the links among bio diesel, rape oil, soy oil and crude oil prices. They discovered proof of a powerful effect on the cost of crude oil on bio diesel and on the cost of bio diesel on sunflower oil.

Zhang, Lohr, Escalante and Wetzstein (2010) evaluated the connection between both the fuel prices and agricultural commodities, (both long and short term). Their findings indicated that there is no direct long run cost interaction among fuel and agricultural commodity prices, and direct short run connections are restricted. From the month of January 2000 to October 2007, in 2008, a researcher naming, Krichene explored oil price movements. He claimed that the recent fast rise in oil and other commodity prices can be attributed during the early 2000s to the expansionary monetary policies. World demand for commodities increased while supply lagged behind due to the effect of expansionary policies, i.e. placing upward pressure on all commodities prices. After observing for other influencing variables, Du et al. (2009) explored the role of speculation in driving price variation in crude oil. They also attempted to quantify the extent to which volatility on the crude oil market is passing into United States, agricultural products i.e. (maize and wheat) markets. After the fall in 2006, they found confirmation of volatility spill over between wheat, crude oil, corn markets, implying risk transfer between these markets of commodity.

Cevik and Sedik (2011) looked at extreme product price changes (wine and oil) from 1990 to 2010. Macroeconomic variables arise as the primary determinants of commodity prices, according to their outcomes. They also demonstrated that while developed economies account for about half of world expenditure, emerging markets constitute a substantial increase in demand. No matter what the reason for the long term trend or short term fluctuations, a comparable pattern accompanied not only crude oil but some other commodity spot prices. Firstly, they all encountered constantly growing trends and then, following the global crisis, an unexpected decline. Analysing multiple appropriate theories of the 2008 price rise of crude oil, ranging from demand and supply dynamics to commodity speculation, in 2009, an author Hamilton suggests that they may be collectively liable for the price shock rather than being alternative reasons. With respect to the transfer of risk among energy as well as agricultural markets, Harri and Hudson (2009) discovered in one of the initial efforts to search spill over volatility from oil future prices to maize future prices following the food price crisis.

T. Chang, Su and Chiu (2015) supplied proof of uncertainty to corn from crude oil and indicated that the soya bean prices during the greater crude oil price era were important, suggesting a financial substitution impact during the greater crude oil price period. Besides transmitting volatility between both the world agricultural commodities and world oil, some studies focused on transmitting volatility to domestic agricultural commodity prices from world oil prices. In 2010, Alghalith evaluated the effect of uncertain oil prices on food prices in Tobago and Trinidad and discovered that greater oil prices and their volatility yield more food prices. Alom (2011) researched spill over volatility to food prices from world oil prices for preferred nations in the Pacific and Asia and discovered that volatility in world oil prices is strongly associated with volatility in food prices, but the findings differ across nations.

The association among the commodity markets changes at the time of crises same as like the financial market dynamics. Kilian & Park (2009) illustrated that how the main industrial sectors and aggregate stock market ' economic returns co vary with dissimilar kinds of oil price shocks, and how this co-variance has been weakened or strengthen with the passage of time. DCC are assessed, by using the Scalar BEKK technique suggested by Engle & Kroner in 1995, to observe the above-mentioned time varying link. In 1983, an author naming Hamilton worked as a pioneer in the research of oil price and macroeconomic indices.

According to few studies, the oil and gas industry, as well as the mining industry, appears to be favourably influenced by favourable petroleum price modifications, on the other hand, the opposite is true for other industries such as manufacturing, food, computer, real estate, chemicals, medical, transport and general services. The Engineering, Financial and Electricity industries accounts non-conclusive outcomes. Hence, it is concluded that oil substitute sectors as well as oil related sectors are positively affected by the oil prices and on the other hand, non oil related sectors have no effect of oil related sectors i.e. financial sectors (Hamilton & Kilian, 2009). Chen et al. (2014) spotlight on Japan, the United Kingdom, France, Germany and the United States and reports that supply side shocks have a more constant impact on inventory prices. However, the above-mentioned studies have mainly ignored the significance of examining the connection in a time-varying setting among stock markets and oil prices. Models of time-varying correlation have only lately been used to explore interactions between stock markets and oil.

Choi & Hammoudeh (2010) implemented the Dynamic Conditional Correlation technique to explore the affiliation among product prices including gold, petroleum, copper and silver with the S&P 500 index and demonstrate proof of growing correlations between all goods since 2003. Chang et al. (2010) demonstrate that conditional correlations are not continuous in the United States among crude oil prices and inventory returns. In their study, Filis et al. separated petroleum imports from exporting countries and applied DCC-GARCH model and demonstrated that there is an adverse connection among stock market and oil yields at the time of oil market shocks, while oil and stock market yield are positively related with each other during aggregate demand shocks. On the other hand, Broadstock et al. (2012) exploit a BEKK model to define the time-varying relation among oil prices and energy related stocks in China, found a rise in co movement during the financial crisis in the year 2008, therefore, Antonakakis & Filis (2013) applied a DCC-GARCH technique to observe the time-varying impacts of changes in oil prices on stock market co movements.

Since the oil price shocks of the 1970s, a number of studies have extensively investigated the effects of oil price changes on real economic variables (Hamilton, 1983 and 2003; Kilian, 2008). Oil price changes are usually shown to have a significant impact on financial operations in different advanced and emerging nations. On the other hand, that study stranded on the prospective connections among oil prices and stock markets has only lately gained ground, with a focus on wide market indices (domestic, regional or international inventory market indicators). Among others, Apergis et al. (2008), Fayyad and Daly (2011), Huang et al. (1996), Park and Ratti (2007)and Sadorsky in the year 1999 also give proof of important stock returns to oil shocks from using multiple methods i.e. VAR models, co integration, global multifactor asset pricing models and VECM. El-Sharif et al. (2005) attained the same consequence on United Kingdom yields from Gas and Oil sector , While, non oil & gas industries are weakly related to the changes in petroleum prices.

Nandha & Faff (2008) query the short term linkage among oil prices and 35 Data stream worldwide sectors and demonstrated that the increase in oil prices has an adverse effect on all sectors apart from Gas and oil. In 2009, Nandha & Brooks were concerned about the transportation sector's response to oil prices in 38 nations worldwide. Their findings show the distinct roles of oil in determining the transport industry yields for developed countries, but do not demonstrated such proof in the nations of Latin America and Asia. El et al. (2010) used various econometric techniques to explore short term links among aggregate oil and inventory prices and sector by sector levels in Europe. Their results show some facts that inventory returns responses to changes in oil prices vary significantly depending on the activity industry. Somehow it is understood about the spill over effects of volatility among the oil and stock markets. In 2006, Agren used an asymmetric version of the BEKK-GARCH model (1, 1) to study the volatility transmission to inventory markets from petroleum prices in five main advanced nations (the United Kingdom, Japan, Norway, Sweden and the United States).

Malik & Hammoudeh (2007) looked at United States equity market volatility transmission, the worldwide crude oil market, and 3 Gulf equity markets, including Saudi Arabia, Bahrain and Kuwait. They pointed out that Gulf equity markets receive volatility from the oil market, but in the case of Saudi Arabia, volatility in the stock market only spills into the oil market. They have shown that Gulf equity markets receive volatility from the oil market, but stock market volatility only spills over into the oil market in the case of Saudi Arabia. In their latest input, by implementing BEKK – GARCH (1, 1) models, in 2009, few authors Malik & Ewing inspected the transmission of volatility among petroleum prices and 5 United States industry indices. The industries considered are Health Care, Financials, Consumer Services, Industrials and Technology.

And empirical findings support important shock transmission as well as volatility among distinct industries of the stock market and oil prices. Chang et al. (2010) applied multiple multivariate GARCH (1, 1) models to study spill over volatility among the both West Texas Intermediate crude oil futures yields and stock returns commonly across the world. Astonishingly, in any return series pair, the empirical results point out no volatility spill over effects. As compared to previous literature, the study builds on the latest VAR–GARCH technique and moves to sector level analysis from market level analysis by taking as a case study the stock market sectors in Europe. It also provides insights into the potential gains from cross-market hedging as well as market operators sharing common information. Almost all prior publications dealing with the problem of volatility representing and commodity price forecasting have given the GARCH approach an exclusive value. When the aim is to investigate transmission processes of volatility as well as interdependence among distinct time series, multivariate settings i.e. Bollerslev's CCC-MGARCH technique in 1990 and Engle and Kroner's BEKK-MGARCH technique in 1995 as well as Engle's DCC-MGARCH technique in 2002 model is more pertinent as compared to univariate models.

Empirical findings recorded by few authors such as Hassan and Malik in the year 2007, Agnolucci in the year 2009 among others, verified the supremacy of these models and demonstrated that the evidence of commodity cost conditional volatility and volatility interaction dynamics are adequately captured. An interesting option is the multivariate VAR (k) GARCH (p, q) model suggested by Mcaleer (2001) as its primary benefit is that it is sufficiently flexible to handle the conditional cross effects and volatility transmission between the series considered with fewer computational complexities than other spill over models.

Hence, the financial markets are moving closer to each other due to more globalization, hence it demands for further research and investigations on the transmission of data based on the development of stocks from one market to another. For making the decision making process efficient for hedging, asset pricing and strategies for trading, these observations are utilized by professionals and policy makers. In 2007, Li & Majerowska illustrated that the globalization contributes to the association of developing markets, thereby increasing global exposure to the capital markets. Strong international connection reduces the security of developing markets of securities from side crises, thereby reducing the level of equal economic policies. In the perspective of foreign investors, low stock market connection is in the form of comparatively fewer as compared to the best affiliation among their earnings provides possible add-ons from the expansion of the portfolio globally, whereas advantages of diversification are excluded by co movement of returns or strong market linkage. An unexpected occurrence in any industry is assumed to have a greater or lesser impact on the stability as well as return of the other industries. Only in one dimension such as volatility or mean, the shocks are generated in one market often transmits to the other markets. Because the volatility spillover is usually used as a measure for risky assets, the volatility analysis is especially valuable in contrast to the return or mean spill over. The equity market interconnections data depends on the date of research and the techniques used; while many observations have demonstrated that in recent times global equity market linkages have risen in.

By the usage of data it is discovered that from both positive inflation as well as higher expected shocks the bond prices gets negatively affected respectively, that the overall size of news impacts generally increases as the instrument matures (Balduzzi, Elton & Green, 2001). The essence of the connection among the stock market and macroeconomic fundamentals is less evident. Share prices rely on the the risk premium, cash flows predicted and the discount rate. Carrying the risk premium constant, a positive macroeconomic shock raises anticipated cash flows, which increases the stock price, ceteris paribus, but it also increases the discount rate, which reduces the stock price, ceteris paribus, so the end result depends on which effect dominates. A number of research works focused on knowledge exchange across the equity markets globally. Early experimental papers incorporate in 1990 by few authors Hamao, Masulis & Ng who analyzed the overflow impacts in the profits and volatilities of day by day value changes for the United Kingdom, Japanese, and United states.

In 1994, researchers like Lin, Engle & Ito utilized a comparative GARCH based technique yet better inspected information. For the most part, just powerless proof of transmission from the United States to different industries, and in no way other path around, has been found, despite the fact that "disease" impacts, or expanded associations, have been reported during times of monetary emergencies, such as the in the year 1987 an accident occurred i.e. (King & Wadhwani, 1990). Less work has been done on cross country security advertise linkages. In 2003, few researchers Ehrmann & Fratzscher, modeled the degree of connections among the United States. Moreover, security markets of Europe proposed that the associations among the economic industries have been expanded, with the overflow impacts to the European territory from the United States. While, it has shown all over the world the security showcase expansion in the light of the arrival of United States macroeconomic reports (Christie David, Chaudhry & Khan, 2002) & (Goldberg & Leonard, 2003).

CHAPTER 3

Data Description and Methodology

This research is composed of two main parts of methodology. Firstly, by the help of ARMA (1, 1) GARCH, the return and volatility transmission from industries to industries are examined in Pakistan with the use of Mean model that is presented by Liu & Pan in 1997. Secondly, DCC and ADCC MV-GARCH models proposed by Engle in 2002 & Cappiello et al. (2006) are used for measurement of time varying conditional correlation among different industries.

3. Research Design and Methodology:

3.1. Data Description:

The main purpose of this study is to examine volatility spillover across industrial stock returns within sectors of Pakistan. This chapter elaborates the sources of data from where the data is collected for this study.

In this chapter the methodological aspects are discussed. This chapter consists of data collection methods and the size of sample used to conduct this research. The structure of this chapter consists of population, sampling technique, unit of analysis, sample size and data collection procedure.

3.2.1Population

All the listed firms of PSX are population of this research. The sample period is taken of 19 years starting from 2000 to 2018. This study utilize the daily closing prices of 10 industrial indices i.e. (Personal goods, Oil and Gas producers, Financial Services, Equity Investment Instruments, Banks, Pharmaceuticals and Biotechnology, Nonlife Insurance, Industrial Engineering, Food producers and Automobiles and Parts) of Pakistan to observe the impact of return and volatility spillovers from industries to industries in Pakistan as well as time varying conditional correlations. The data of the firms was obtained from PSX.

3.3 Sample technique

The study is using the daily data of 10 listed sectors. There are 579 listed firms with the 35 different sectors. Only 10 sectors sample whose data is available from June 2000 to June 2018 is taken. Industry index will be formulated through equally weighted index method.

Sectors	No. of Firms
BANKS	23
Equity investment	24
Financial services	43
Oil and gas product	08
Personal goods	111
Automobile and parts	19
food producers	31
Pharmaceuticals and Biotechnology	11
Nonlife Insurance	28
Industrial Engineering	06

3.4 Unit of analysis

The unit of analysis of our research is the industry i.e. the sectors and their returns from Pakistan Stock Exchange.

3.5 Sample Size

"Sample size is the number of observation in a sample" (Evans et al., 2000). The major purpose of conducting the research is to be able to make some claim about larger population. Therefore, it is essential to choose a sample that enables to generalize findings to that larger population. Research will collect all those sectors data in which mostly investors wish to diversify their investments. So this study uses purposive sampling technique to collect the data. Ten sectors returns are used as sample ranging from 2000-2018

3.6 Data collection method

The data collection methods for this study are the secondary data and all the data of firms registered in Pakistan Stock Exchange, State bank of Pakistan and many other banks of Pakistan. Data is collected from data stream and other related sources.

3.7 Data Analysis Software and Statistical Methods:

One of the most familiar non linear models are MGARCH i.e. Multivariate Generalized Autoregressive Conditional Heteroskedasticity. These models are applied to represent the co-movements of risk, return and assets. In the last two decades, these models are models built up. In accordance with the survey on such models it is examined that financial unpredictability moves collectively among market and time (Bauwens, Laurent, & Rombouts, 2006). Hence, there is a need to use an accurate methodology. In this methodology multiple models are included. There are three groups, first one are the direct simplification of GARCH model and it approximate many parameters while second one is a linear grouping of univariate GARCH i.e. OGARCH. The third one is, non-linear grouping of univariate GARCH which includes DCC and CCC techniques, these are mostly thrifty. It is believed that the third group is triumphant in detaining the varying dynamics. In this study two models are applied: Dynamic Conditional Correlation (DCC, 1, 1) and Constant Conditional Correlation (CCC, 1,1) (T. Bollerslev, 1990). The covariance changes due to change in variances. The matrix form of model is:

$$\boldsymbol{r_t = \theta x_t + \delta_t}$$

$$\boldsymbol{\delta_t = \omega_t^{1/2} u_t}$$

$$\boldsymbol{\omega_t = D_t^{1/2} R D_t^{1/2}}$$

In this econometric equation the (m, 1) vector of returns r_t is formed by using (m,1) vector of independent variables x_t and the approximation of β(m, k) which is matrix of parameters is needed. Cholesky factor defined the vector of novelty processes **($\boldsymbol{\varepsilon_t}$).**

(m, m) matrix $\boldsymbol{\gamma_t^{1/2}}$ **and** (m,1) vector of normal i.i.d. innovations u_t . In 2009, Engle illustrate that usually in the literature the postulation of multivariate normal distribution of novelty is done. $the\ (m,m) conditional\ covariance\ is\ represented\ by$ ($\boldsymbol{\gamma_t}$), which is further classified by R (m, m) positive definite unconditional integration matrix and D_t(m,m) diagonal matrix of conditional variances. In D_t the conditional variances are formed by help GARCH (1, 1) technique:

$$\boldsymbol{\rho_{i,t}^2 = \gamma_{0,i} + \gamma_{1,i}\varepsilon_{i,t-1}^2 + \alpha_{1,i}\rho_{i,t-1}^2}$$

According to the above mentioned equation: $\boldsymbol{\gamma_{0,i}}$**>0,** $\boldsymbol{\gamma_{1,i}}$**≥0 and** $\boldsymbol{\alpha_{1,i}}$**≥0.** Therefore, the conditional variances are positive and every conditional variance is finite so $\boldsymbol{\beta_{1,i}}$+$\boldsymbol{\gamma_{1,i}}$**<1** must hold. It is supposed that the integration is fixed over time. Hence, on financial markets the dynamics vary on daily basis. In 2002, Engle introduced DCC (1, 1) model which presumes the changing relationship:

$$\boldsymbol{r_t = \theta x_t + \delta_t}$$

$$\boldsymbol{\delta_t = \omega_t^{1/2} + u_t}$$

$$\boldsymbol{\omega_t = D_t^{1/2} R_t D_t^{1/2}}$$

$$\boldsymbol{R_t = diag(Q_t)\frac{-1}{2} Q_t diag(Q_t)\frac{-1}{2}}$$

$$\boldsymbol{Q_t = (1 - \sigma_1 - \sigma_2)R + \sigma_1 \tilde{\delta}_{t-1} \tilde{\delta}_{t-1} + \sigma_2 Q_{t-1}}$$

It is presumed in this model that the changing over time is represented correlation matrix (R_t). The dynamic is represented by (Q_t). The (m,1) vector of uniform novelty is defined by **($\boldsymbol{\tilde{\delta}_t}$), $\boldsymbol{\tilde{\delta} = D^{-1}\delta_t}$** ; and (m, m) positive definite unconditional integration matrix is R. The parameters that are not negative in nature explains the conditional integration dynamics i.e. $\boldsymbol{\sigma_1}$**and**$\boldsymbol{\sigma_2}$. Engle, (2002) illustrates the condition $\boldsymbol{\sigma_1 + \sigma_2 < 1}$ for the stationarity of the technique.

$$\mathbf{E}\left(\boldsymbol{\tilde{\delta}_t \tilde{\delta}_t'}\right) = \boldsymbol{I_m}$$

In this econometric equation, the identity matrix isI_m.

According to Ding & Engle, (2001):

$$\mathbf{COV}\left(\boldsymbol{\tilde{\delta}^2_{i,t}, \tilde{\delta}^2_{j,t}}\right) = \mathbf{0}\ \ \forall \boldsymbol{i \neq j}\ \textbf{and}\ \mathbf{COV}\left(\boldsymbol{\tilde{\delta}^2_{i,t}, \tilde{\delta}^2_{j,t-k}}\right) = \mathbf{0}, \quad \boldsymbol{k} > 0$$

3.8 Description of Variables

Industrial Indices - TEN Industries

Construction of Industrial Indexes:

The classification of index is in accordance with the technique which is used to determine its prices. Indexes are usually used as fundamental benchmarks for diversification. Therefore, different types of indexes must be understood, because the diversification or portfolio decision depends on such indexes. Industrial indexes are divided into three main parts i.e. price and value weighted index, industry equally weighted index and capitalization weighted index. Industrial indexes play a vital role in dynamic sectoral portfolio selection. For the determination of percentage weighting, the number of outstanding shares as well as market prices of companies is used in capitalization weighted index. As for the portfolio investment the companies are weighted largely when their components are large. While same amount of investment is distributed among stocks of the company in equally weighted index. All the companies are equally represented in index.

Basically industry equal weighted index is the index of stock market which is composed of companies involve in public trading. In contrast with market capitalization weighted index, the industry equally weighted indexes carry minimized risk and are diversified. As a larger strategy of investment, many investors consider industry equally weighted funds are mainly value investing.

An overall market value can be calculated by equal weighted index. Therefore, investors can choose by the help of industry equally weighted index that how the highest return on investment can be gained. In this study the construction of indexes is done by industry equally weighted index. Hence, these indexes are not available properly; therefore, a need arises here to construct the sectoral industrial indexes a free float methodology is used by this index. Equal weights are distributed among stocks in different sectors just to find out the industry weighted index. Empirical research usually uses Equally Weighted Indexes.

Equally weighted index is used to resolve the daily industrial returns of every industry. Following industries are taken in this study:

Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, Automobiles and parts, Personal Goods, Equity Investment Instruments, Financial Services, Oil and Gas Producers, Food Producers and Banks.

3.9 Econometric Models

3.9.1 Return & Volatility Spillover - ARMA GARCH

3.9.1.1 Industries-to-Industries Spillover

By the help of ARMA (1, 1) GARCH, the return & volatility transmission from industries to industries are examined by applying Mean model. First step includes the relevant industry return series that are modeled through an ARMA

(n, o)-GARCH (n, o)-M econometric model.

sn, t = σo + σ1.sn,t−1 +σ2.wn,t + σ3.n,t−1 + n,t,n,t ∼ N(0,w n, t) (3.5)

wn, t = ϵo + ϵ1.ρ2n, t−1 + ϵ2.wn,t−1 (3.6)

In these equations s n, t is the daily returns of one industry at time t.

n,t is the unexpected returns or residual i.e. error term.

Behind the inclusion of ARMA (n, o) GARCH structure in the model, the main objective is the adjustment of serial integration in the data. The subscript n refers one of the industry ranges from 1 to 10 industries.

Secondly, the impudence of volatility spillover and mean return across markets are determined by obtaining the uniform error term and its square in the very first step and replacing them into the volatility and mean equations of other markets such as:

so, t = σo,o +σo,1.so,t−1 +σo,2.wo,t +σo,3.o,t−1 +ψo.n,t +o,t,o,t ∼ N(0,wo,t) (3.7)

wo, t = ϵo,o + ϵo,1. ρ 2 o,t−1 + ϵo,2 .wo,t−1 + τ.e2n,t (3.8)

Where n, t is the uniform error term for one industry as well as from the sources it is getting the effect of return conduction. For assessing the volatility transmission, the exogenous variable **e2n, t** (the square of the uniform error term is incorporated in the conditional volatility equation hence it is defined as **e2n, t = 2n, t w n, t**. The subscript **'o'** refers to the other industry ranges from 1 to 10

CHAPTER 4

Results and Interpretation

In this chapter diverse tests are applied to investigate the phenomena under discussion and construe the results obtained. The study utilizes the daily closing prices of ten industrial indices. Here, this stage includes the assessment of behavior of data by the descriptive statistics of every series.

4.1 Graphical Representation

4.1.1. Stationarity of Series

The regression of data is investigated by performing Augmented Dickey Fuller unit root test on the industrial stock returns of Pakistan equity market. To identify the right order of integration, this test will be applied on separate logged series, only when the data is not stationary. The non stationary null is set by analysis of ADF test. For the examination of Stationarity of the series this test is applied which means that there must be stationartity in data for further spillover analysis. By the help of the ADF unit Root Test, in this study the behavior of data is analyzed.

Table 4.1

ADF Test	t-Statistic	Prob.*
Automobiles and parts	-57.7109	0.0001
Banks	-62.1961	0.0001
Equity Investment	-77.4275	0.0001
Food Producers	-31.2777	0
Financial Services	-35.8853	0
Industrial Engineering	-26.0543	0
Non-Life Insurance	-35.5959	0
Oil & Gas	-61.4583	0.0001
Pharm& Bio.	-45.3176	0.0001
Personal Goods	-66.804	0.0001

The results by applying ADF unit root test indicates that the mean returns of all industries are positive. The results for all the sectors are significant and stationarity exists in the data for further spillover analysis.

4.2 Descriptive Statistics

This table includes following: Mean, Variance, Skewness & Kurtosis. However, the spread of data is also assessed by Maximum & Minimum average responses. The sample period is taken of 18 years from 2000 -2018. The study utilizes the daily closing prices in terms of returns of 10 industrial indices.

Table4.2.Descriptive Analysis

	Pharma & Biotech.	Nonlife Ins.	Food Prod.	Indus Eng.	Auto & Par.	Per Goods	Equity Invest. Inst	Fin. Ser.	Oil & Gas Pro	Banks
Mean	.00028	.00032	.00056	.00039	.00053	.00035	.00002	.00017	.00056	.00043
Max.	.121	.171	.070	.114	.057	.113	.239	.219	.105	.140
Min.	-.195	-.382	-.086	-.216	-.064	-.283	-.257	-.229	-.191	-.140
Std. Dv	.018	.014	.011	.017	.012	.011	.018	.015	.017	.017
Skew	-.785	-5.209	-.135	-1.475	-.147	-4.753	-.503	-.271	-.389	-.324
Kurt.	14.709	152.510	7.496	22.647	5.184	125.575	20.888	24.394	9.564	11.003
Obs.	5105	5105	5105	5105	5105	5105	5105	5105	5105	5105

The performance of indices of various industries is measured by daily mean returns. The results indicate that the mean returns of all industries are positive. The highest mean return value is of Food Producers that is (0.056%) and lowest is of Financial Services that is (0.017%). In addition, all industries have a positive standard deviation however, Pharmaceuticals and Biotechnology reveals the higher volatility (1.7879%). Hence, this sector is more volatile than others. While, Personal goods exhibits the lowest volatility (1.07%) that gives the evidence of being less volatile sector. Therefore, it is cleared that the logic regarding the relationship of risk and return is not covered as the mean return and volatility is higher for two different sectors instead of the same sector i.e. the mean return for Food Producers is higher and on the other hand volatility for Pharmaceuticals and Biotechnology is higher. So the risk is higher for the sector Food Producers while Return is higher for the sector Pharmaceuticals and Biotechnology. Maximum & Minimum statistics exhibits the maximum & minimum return earned per day for each industry. For example, the daily return per day for Food Producers that is (0.056%), the maximum return earned per day for Food Producers is (0.07%) and the minimum return earned per day is (-0.0856%) and so on. Skewness tells about the asymmetric behavior of data. The values of skewness for all the sectors show that distributions of returns are negatively skewed. The negative tendency of skewness shows the continuous depreciation in the stock returns. Kurtosis tells about the tailedness of the probability distribution. All the values of Kurtosis are positive, that indicates, all series are leptokurtic i.e. fat tails with high peak and gets highly affected with the bubbles of stock market**.**

4.3. Return and Volatility Spillover across Various Industries:

Return and volatility spillovers across industries can be estimated by the help of ARMA GARCH model. In these analyses, one industry is taken as benchmark industry and then its effect is seen on the other nine industries. Shocks created from one benchmark industry are transmitted to the other industries just 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).

4.3.1. Return and volatility spillover of Banks to other industries by using ARMA and GARCH model:

Table4.3.1

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Equity invest.	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
Fin. Serv	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Auto & parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(-0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharma & Bio.	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.1: Return and Volatility Spillover from bank to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Personal Goods, Oil and Gas Product, Automobile and Parts, Pharmaceuticals and Biotechnology, Nonlife Insurance, Food Products and Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient β_0 is variance equation constant. β_1 is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, Ω is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of θ_1 is significant and positive for Personal Goods, Oil & Gas Product, Financial Services, Equity Investment and Automobile & Parts which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Pharmaceuticals and Biotechnology, and Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Equity investment, financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Banks 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 Banks quickly transmits to the other industries.

4.3.2. Equity Investment to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.2

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Eq. Inves.	-1.82E05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Fin. Serv	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharma. &	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253

Bio.							
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(0.5079)	(0.0000)	0	(0.0000)	(0.0000)	-0.8102	-0.0049

Table4.3.2: Return and Volatility Spillover from Equity Investment to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Banks, Personal Goods, Oil and Gas Product, Automobile and Parts, Pharmaceuticals and Biotechnology, in Nonlife Insurance, Food Products and Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient **β_1** is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, **Ω** is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of **θ_1** is significant and positive for Personal Goods, Banks, Oil & Gas Product, Financial Services and Automobile & Parts which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Pharmaceuticals and Biotechnology, and Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of **θ_2** is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity Investment, Financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Equity investment 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 Equity Investment quickly transmits to the other industries.

4.3.3 Return and Volatility Spillover from Financial Services to Other Industries ARMA GARCH model:

Table 4.3.3

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178

	(-0.4701)	0	0	0	0	(-0.0001)	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharma. & Bio.	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.3: Return and Volatility Spillover from Financial Services to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Equity Investment, Banks, Personal Goods, Oil and Gas Product, Automobile and Parts, Pharmaceuticals and Biotechnology, Nonlife Insurance, Food Products and Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient β_0 is variance equation constant. β_1 is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, Ω is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of θ_1 is significant and positive for Personal Goods, Banks, Equity Investment, Oil & Gas Product and Automobile & Parts which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Pharmaceuticals and Biotechnology, and Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of θ_1 **and** θ_2 is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Financial Services 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 Financial Services quickly transmits to the other industries.

4.3.4. Oil & Gas Products to other industries by using an ARMA GARCH (m, n) model.

Table 4.3.4

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.4: Return and Volatility Spillover from Oil & Gas Products to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Banks, Personal Goods, Nonlife Insurance, Food Products, Product, Automobile and Parts, Pharmaceuticals and Biotechnology, and Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient β_0 is variance equation constant. β_1 is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, Ω is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of θ_1 is significant and positive for Personal Goods, Banks and Automobile & Parts Equity Investment, Financial Services which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Pharmaceuticals and Biotechnology, and Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of **θ_2** is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Oil & Gas Products 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 Oil & Gas Products quickly transmits to the other industries.

4.3.5. Personal Goods to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.5

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.5: Return and Volatility Spillover from Personal Goods to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Banks, Oil & Gas Products, Automobile and Parts, Nonlife Insurance, Food Products Pharmaceuticals and Biotechnology, and Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient **β_0** is variance equation constant. **β_1** is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, **Ω** is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of **θ_1** is significant and positive for Oil & Gas Products, Banks and Automobile & Parts, Equity Investment, Financial Services which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Pharmaceuticals and Biotechnology, and Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of **θ_2** is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Oil & Gas Product, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Personal Goods 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 Personal Goods quickly transmits to the other industries.

4.3.6. Automobile & Parts to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.6

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844

Eng.							
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.6: Return and Volatility Spillover from Automobile & Parts to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Nonlife Insurance, Food Products, Pharmaceuticals and Biotechnology and Industrial Engineering Banks, Oil & Gas Products, Personal Goods, can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient **β_1** is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, **Ω** is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of **θ_1** is significant and positive for Oil & Gas Products, Banks, Equity Investment, Financial Services and Personal Goods which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Pharmaceuticals and Biotechnology, and Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of **θ_2** is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Oil & Gas Product, Personal Goods, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Automobile & Parts 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 & Parts quickly transmits to the other industries.

4.3.7. Pharmaceuticals and Biotechnology to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.7

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq.	-1.82E-	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886

Inves	05						
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.7: Return and Volatility Spillover from Pharmaceuticals and Biotechnology to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Banks, Oil & Gas Products, Personal Goods, Nonlife Insurance, Food Products, Automobile & Parts and Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient **β_1** is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, **Ω** is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of **θ_1** is significant and positive for Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services and Personal Goods which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Industrial Engineering, Nonlife Insurance and Food Product sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of **θ_2** is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Oil & Gas Product, Personal Goods, Food Products, Automobile & Parts, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from Pharmaceuticals and Biotechnology to other industries. Similarly, the results of volatility spillover also show a insignificant positive impact as compared to other all other industries which also confirms that, the volatility of Pharmaceuticals and Biotechnology quickly don't transmits to the other industries.

4.3.8. Food producers to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.8

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.8: Return and Volatility Spillover from Food producers to Other Industries ARMA GARCH model:

α_0 is a mean equation constant. α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Nonlife Insurance, Banks, Oil & Gas Products, Personal Goods, Automobile & Parts and Pharmaceuticals & Biotechnology Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient β_0 is variance equation constant. β_1 is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, Ω is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of θ_1 is significant and positive for Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services and Personal Goods which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Industrial Engineering, Nonlife Insurance and Pharmaceuticals & Biotechnology sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of **θ_2** is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Oil & Gas Product, Personal Goods, Pharmaceuticals & Biotechnology, Food Products, Automobile & Parts, Non Life Insurance, Industrial Engineering which implies that, there exists a mean spillover from food products 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 food products quickly transmits to the other industries.

4.3.9. Nonlife Insurance to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.9

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0
food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)

Table4.3.9: Return and Volatility Spillover from Nonlife Insurance to Other Industries ARMA GARCH model

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Food Products, Banks, Oil & Gas Products, Personal Goods, Automobile & Parts and Pharmaceuticals & Biotechnology Industrial Engineering can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient β_0 is variance equation constant. β_1 is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, Ω is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks.

The coefficient of θ_1 is significant and positive for Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services and Personal Goods which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Industrial Engineering, Food Producers and Pharmaceuticals & Biotechnology sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Oil & Gas Product, Personal Goods, Pharmaceuticals & Biotechnology, Food Products, Automobile & Parts and Industrial Engineering which implies that, there exists a mean spillover from Nonlife Insurance 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 Nonlife Insurance quickly transmits to the other industries.

4.3.10. Industrial Engineering to other industries by using an ARMA GARCH (m,n) model.

Table 4.3.10

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Indus. Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	0.584844
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	(-0.0049)
Pharm. & Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	0.947253
	(-0.8798)	0	0	0	0	(-0.7488)	0
Per. Goods	0.00014	0.082201	1.22E-05	0.850129	0.048953	0.010125	0.989178
	(-0.4701)	0	0	0	0	(-0.0001)	0
Oil & gas pro.	0.000767	0.110702	1.15E-05	0.833231	0.129064	0.005709	0.993154
	(-0.0007)	0	0	0	0	0	0
Fin. Ser.	0.000379	0.151548	7.51E-06	0.884292	0.081312	0.006927	0.9886
	(-0.0641)	0	0	0	0	(-0.0008)	0
Eq. Inves	-1.82E-05	-0.05539	8.10E-06	0.900633	0.074371	0.006927	0.9886
	(-0.9293)	(-0.0001)	0	0	0	(-0.0008)	0
BANKS	0.0005	0.127329	5.95E-06	0.862673	0.12642	0.005709	0.993154
	(-0.0044)	0	0	0	0	0	0
Auto. &parts	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.989178
	(-0.001)	0	0	0	0	(-0.0001)	0

food pro.	0.000401	0.037627	4.33E-06	0.912355	0.051187	0.003346	0.584844
	(-0.0061)	(0.0071)	0	0	0	(-0.8102)	(-0.0049)
Nonlife Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	0.947253
	0	(-0.0008)	0	0	0	(-0.7488)	0

Table4.3.11: Return and Volatility Spillover from Industrial Engineering to Other Industries ARMA GARCH model:

α_1 is found to have a significant positive impact that means, the mean returns of Financial Services, Equity Investment, Banks, Oil & Gas Products, Food Products and Non Life Insurance, Personal Goods, Automobile & Parts and Pharmaceuticals & Biotechnology can be predicted by using past prices behavior. In simple words, market is inefficient for the following industries.

The GARCH coefficient β_0 is variance equation constant. β_1 is significant for all the industries which shows the contribution of forecasted volatility for the prediction of mean returns. The coefficient of standardized residual error term, Ω is proved to be significant for all industries that shows, these markets account for the process of correction on the basis of past shocks. The coefficient of θ_1 is significant and positive for Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services and Personal Goods which indicates that, volatility of the current period can be forecasted by using the past prices behavior. While it is insignificant for Non Life Insurance, Food Products and Pharmaceuticals & Biotechnology sectors which exhibit that volatility of the current period cannot be forecasted by using the past prices behavior for these industries and no lagged effect is found in the case of these industries because these sectors are more volatile. Coefficient of θ_2 is also significant and positive for all industries that provides the evidence about persistence of the volatility. For Banks, Equity investment, Financial Services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering, the sum of **θ_1 and θ_2** is closer to **1** which indicates the nature of the persistence is in long run. The results of mean spillover show a significant positive impact on all industries i.e. Banks, Equity Investment, Financial Services, Oil & Gas Product, Personal Goods, Pharmaceuticals & Biotechnology, Food Products, Automobile & Parts and Non Life Insurance which implies that, there exists a mean spillover from Industrial Engineering 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 Industrial Engineering quickly transmits to the other industries.

4.4. Time-Varying Conditional Correlation – DCC & ADCC

4.4.1. DCC MV - GARCH Models & Estimates among Industries

Table4.4.1.

Sector	Model selected
BANKS	ARCH/GARCH
Equity investment	ARCH/GARCH
Financial services	ARCH/GARCH
Oil and gas product	ARCH/GARCH
Personal goods	ARCH/GARCH
Automobile and parts	ARCH/GARCH
food products	ARCH/GARCH
Pharmaceuticals and Biotechnology	ARCH/GARCH
Nonlife Insurance	ARCH/GARCH
Industrial Engineering	ARCH/GARCH

Table 4.4.1 shows the suitable uni-variate DCC models.

The impact of the past residual shocks is (θ_1) and lagged dynamic conditional correlation is (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 e.g. ($\theta_1 + \theta_2 < 1$). All industries taken for this study successfully meet the required stability condition. It means DCC model must be used for measuring the time varying conditional correlation.

As in case of the Banking sector, Equity investment, financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering the mean and volatility spillover shows a significant positive impact on all industries which means that there exist return and volatility spillover from each sector to other industries. While on the other hand the impact of the past residual shocks (θ_1) is significant for all industries except the four i.e. Food Products, Pharmaceuticals and Biotechnology, Non Life Insurance and Industrial Engineering, in these sectors (θ_1) is insignificant which means are more volatile. (θ_2) also exhibits significant positive impact on all industries. The return and volatility spillover exists in almost all the ten sectors of PSX. The coefficients of volatility and return spillover for all sectors are positive and significant which defines as the returns of one sector enhances by the return of other sectors. Therefore, it is indicated that the taken ten industries are linked with each other i.e. if any kind of change occurs in one industry, then this change easily transmits to all other industries. All sectors are with significant results and are causing spillover effect. Return and volatility spillover exists among different sectors and they can easily be transmitted from one sector to other due to crises or many other economic factors. All the significant stability and variations of models demonstrate that correlation is not constant, so DCC-GARCH model is strongly recommended. If in industries the time variation doesn’t occur for correlation, then DCC and ADCC model will not be applied. Hence, it is concluded that for diversification investors should go for the sectors which are negatively correlated and correlation must be less than 1. If sectors are more volatile then investors should not invest there. Only sectors with less volatility could benefit investors in diversification and investors can gain more benefits.

CHAPTER 5

Conclusions and Recommendations

The main objective of this study is to analyze the return and volatility spillover across different industrial sectors in Pakistan Stock Exchange (PSX). In this study ten sectors are taken for this purpose. Movement of various sectors i.e. Banking sector, Equity investment, financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Producers, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering has been observed by using GARCH model for the year 2000 to 2018.

The return and volatility spillover exists in all the ten sectors of PSX. The coefficients of volatility and return spillover for all sectors are positive and shows significance which defines as the returns of one sector enhances by the return of other sectors.

Hence, it is indicated that the selected industries are linked with each other i.e. if any kind of change occurs in one industry, then this change easily transmits to all other industries. All sectors are with significant results and are causing spillover effect. In Banking sector, Equity investment, financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Producers, Pharmaceuticals and Biotechnology, Non Life Insurance, Industrial Engineering the mean and volatility spillover show a significant positive impact on all industries which means that there exists return and volatility spillover from one sector to other sectors. The impact of the past residual shocks (θ_1) is significant (positively correlated) for all industries except the four i.e. Food Producers, Pharmaceuticals and Biotechnology, Non Life Insurance and Industrial Engineering, in these sectors (θ_1) is insignificant which means they are more volatile sectors of Pakistan Equity Market. The diversification opportunities also exist in Food Producers, Pharmaceuticals and Biotechnology, Non Life Insurance and Industrial Engineering, as the correlation is insignificant(negatively correlated) for these mentioned sectors i.e. greater than 1. In contrast, both return and volatility spillovers are observed across industries.

Hence, the research objective is fulfilled i.e. return and volatility spillover exists among different sectors and they can easily be transmitted from one sector to other due to crises or many other economic factors. Secondly, this study covers the application of GARCH model. There exists time variation in correlation among variables. For this purpose, Dynamic Condition Correlation (DCC) model is used as well as asymmetric behavior is evaluated by Asymmetric Dynamic Conditional Correlation (ADCC). The consequences from these models are positive as well as negative for the industries. All the significant stability and variations of models demonstrate that correlation is not constant so DCC-GARCH model is strongly recommended. If in industries the time variation doesn't occur for correlation, then DCC and ADCC model will not be applied. It can be understand by DCC and ADCC model that with the passage of time correlation becomes time varying and that industries are interlinked with each other. Hence, it is concluded that for diversification investors should go for the sectors which are negatively correlated and correlation must be less than 1. If sectors are more volatile then investors should not invest there. Only sectors with less volatility could benefit investors in diversification and investors can gain more benefits. In this study, it is demonstrated that correlation among assets of local sectors depends upon static estimates. This study, put emphasis on to realize the dynamics of market integration within Pakistan.

Hence, this study examined the co-movements between the main economic sectors in Pakistan in a dynamic framework, providing a means of differentiating between factors that influence the strength of co-movement over time.

The consequences propose that while assessing the benefits of diversifying domestic portfolio the investors as well as fund managers must have to consider the expectations of market sentiment and macroeconomic forecasts. The unique methodology is used in this study, in its application to Pakistani Industries.

5.1. Recommendations

This study strongly recommends to all market players i.e. investors, portfolio managers and policy makers to keep an eye on the information coming up in different industries of local market. Some important recommendations of this study are given below.

- Investor can use the consequences of this study in the process of decision making for investments in different industries. As compared to return the volatilities are more influenced. So, investors must seek for those sectors in which volatility is less.
- Only DCC GARCH model is used in this study was taken on distribution, meanwhile all GARCH models can also be applied i.e. GARCH, GJR GARCH/TARCH & EGARCH.
- The consequences propose that while assessing the benefits of diversifying domestic portfolio the investors as well as fund managers must have to consider the expectations of market sentiment and macroeconomic forecasts. The unique methodology is used in this study, in its application to Pakistani Industries.
- If sectors are more volatile then investors should not invest there. Only sectors with less volatility could benefit investors in diversification and investors can gain more benefits.
- Risk averse investors should go for diversification in those sectors where risk is minimum and correlation among sectors is less but on the other hand the investors who wants to take more risk by investing in risky securities for getting more return should go for those sectors where correlation is more.

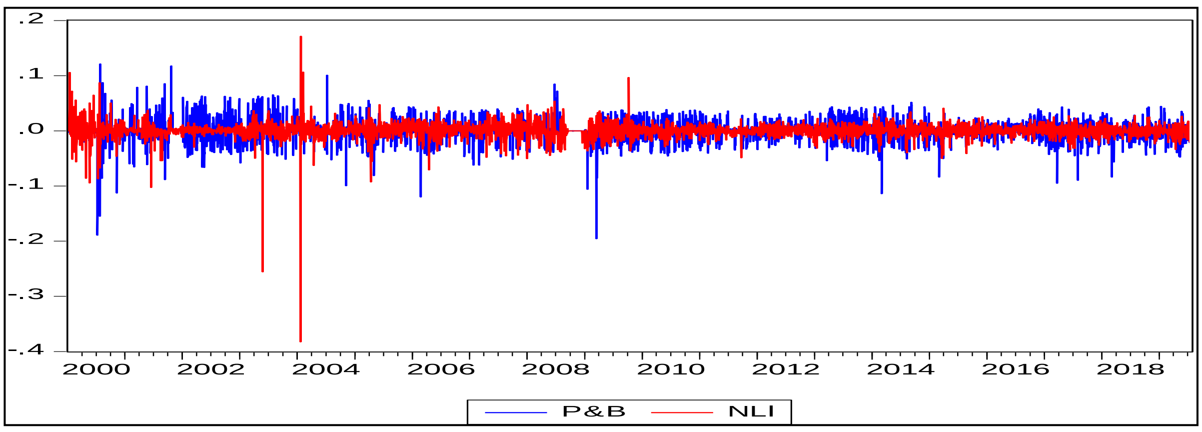
5.2. Limitations & Future Directions

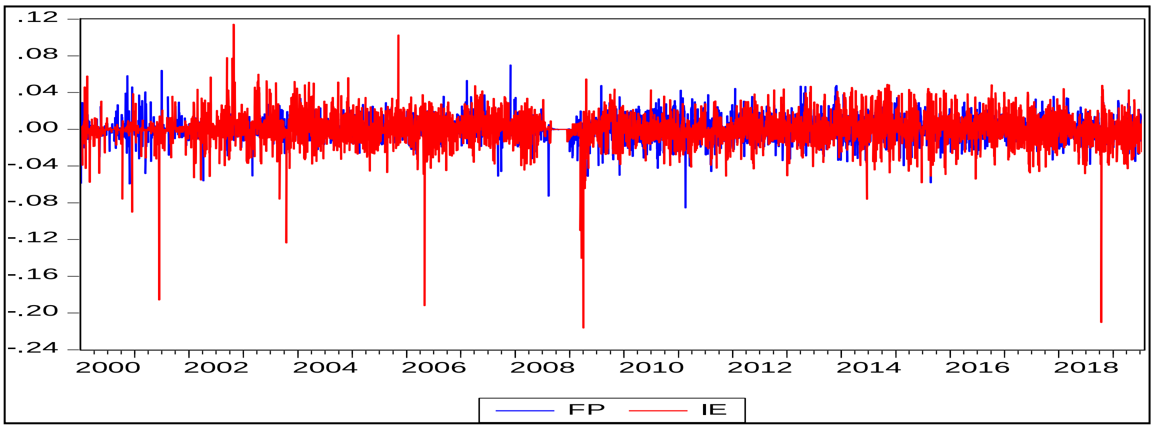
This study provides an inclusive understanding regarding mechanism of transmission across industries and market. This study is restricted only to the Pakistani stock market PSX. Therefore, a relative study by the inclusion of emerging markets can also be conducted in the sample size. In future research the GARCH models can be used to clarify the dynamics of conditional correlation among the Pakistani industries and its foreign counterparts. In this study only few sectors are taken for analysis of return and volatility spillover effect, in future research all the sectors can be taken for research purpose. In future research more risk taking investors can be consider in aspect of diversification.

Appendix-B

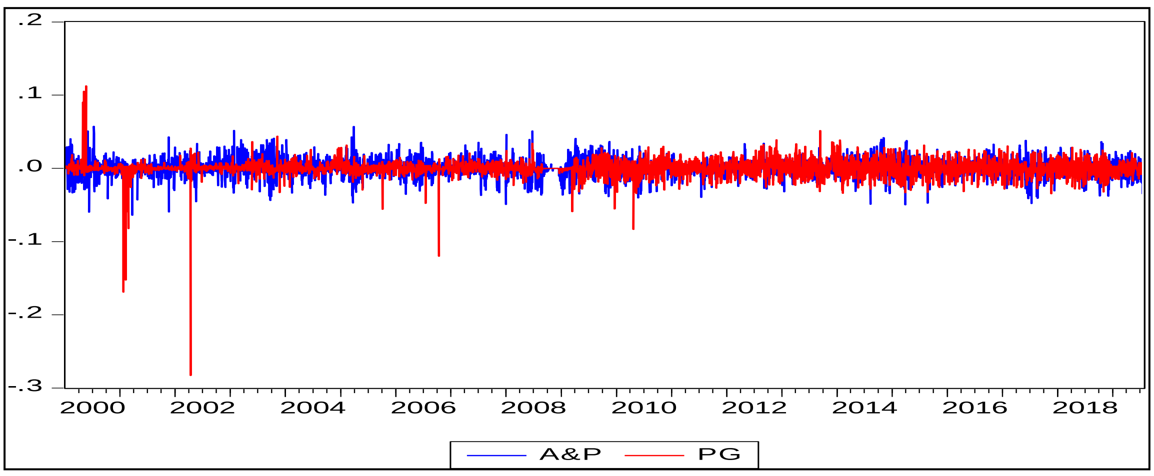
Stationarity Graphs

Graph No. 1



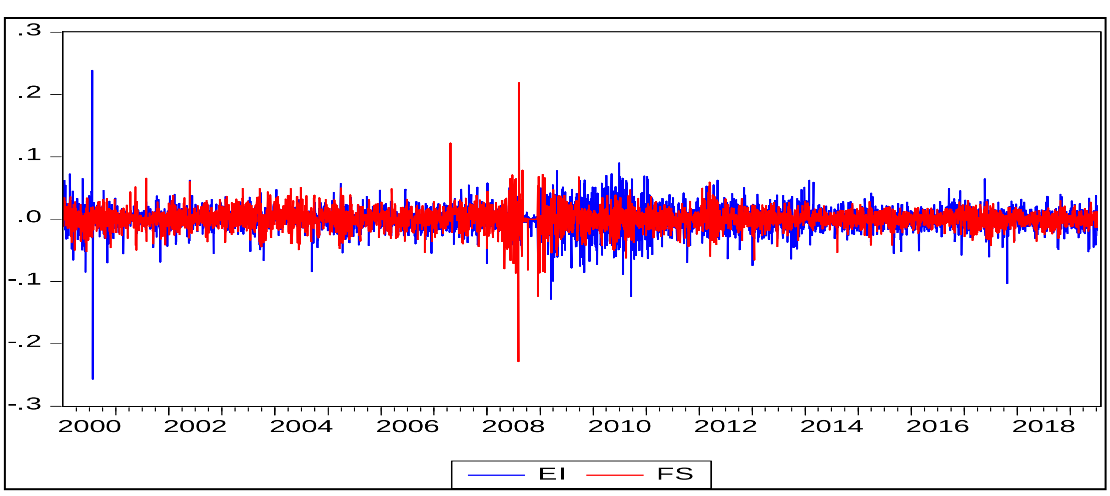


Graph No. 2

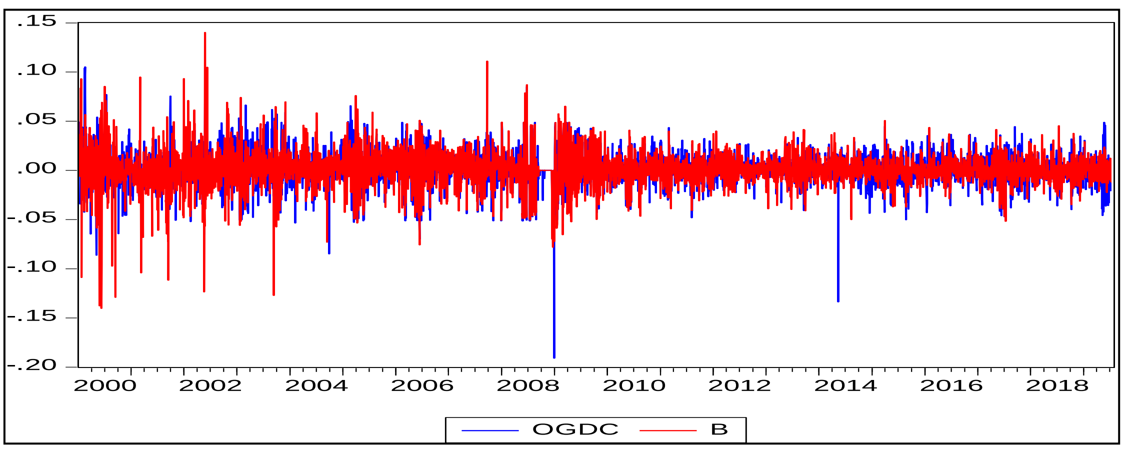


Graph No. 3

Graph No. 4



Graph No. 5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References:

Abhyankar, A., Xu, B., & Wang, J. (2013). Oil Price Shocks and the Stock Market : Evidence from Japan.

Abul, S., & Alfred, A. (2011). Munich Personal RePEc Archive Oil prices , exchange rates and emerging stock markets, (30140).

Abul, S., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil , gold , VIX , and bonds : A comparison between DCC , ADCC and GO-GARCH ☆. *Energy Economics*, *54*, 235–247. https://doi.org/10.1016/j.eneco.2015.11.022

Alghalith, M. (2010). Volume 30 , Issue 3, *30*(3), 2075–2082.

Ali, S., & Butt, B. Z. (2011). 10.1.1.390.5023, *12*(4), 395–403.

Alom, F. (2011). Economic effects of oil and food price shocks in Asia and Pacific countries : an application of SVAR model.

Alom, F., Ward, B., & Hu, B. (2011). Spillover effects of World oil prices on food prices : evidence for Asia and Pacific countries.

Andersen, T. G., & Diebold, F. X. (2005). REAL-TIME PRICE DISCOVERY IN STOCK, BOND AND FOREIGN EXCHANGE MARKETS. *NATIONAL BUREAU OF ECONOMIC RESEARCH 1050 Massachusetts Avenue Cambridge, MA 02138*.

Apergis, N., Miller, S. M., & Miller, S. M. (2008). Do Structural Oil-Market Shocks Affect Stock Prices ? Department of Economics Working Paper Series, (July).

Arolyi, G. A. N. K. (1998). Why Do Companies List Shares Abroad ?: A Survey of the Evidence and Its Managerial Implications, (January).

Baffes, J., & Baffes, J. (2007). Distortions to Cotton Sector Incentives in West and Central Africa Distortions to Cotton Sector Incentives in West and Central Africa, (March), 19–20.

Bampinas, G., & Panagiotidis, T. (2015). International Review of Financial Analysis Are gold and silver a hedge against in fl ation ? A two century perspective. *International Review of Financial Analysis*, *41*, 267–276. https://doi.org/10.1016/j.irfa.2015.02.007

Barsky, R. B., & Kilian, L. (2004). Oil and the Macroeconomy Since the 1970s, *18*(4), 115–134.

Baum, H. Von, Härter, G., Essig, A., Lück, C., Gonser, T., Embacher, A., & Brockmann, S. (2010). Preliminary report : outbreak of Legionnaires ' disease in the cities of Ulm and Neu-Ulm in Germany , December 2009 - January 2010, (January).

Baumeister, C. (2012). The Role of Time-Varying Price Elasticities in Accounting for Volatility Changes in the Crude Oil Market, *32*(0).

Baur, D., & Lucey, B. (2006). Institute for International Integration Studies IIIS Discussion Paper, (198).

Bauwens, L., Laurent, S., & Rombouts, J. V. K. (2006). Multivariate GARCH models: A survey. *Journal of Applied Econometrics*, *21*(1), 79–109. https://doi.org/10.1002/jae.842

Bernanke, B. S. (1980). Nber working paper series irreversibility, uncertainty, and cyclical investment, (502).

Billio, M., & Caporin, M. (2010). Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion. *Computational Statistics and Data Analysis*, *54*(11), 2443–2458. https://doi.org/10.1016/j.csda.2009.03.018

Bjørnland, H. C. (2008). *Oil price shocks and stock market booms in an oil exporting country*.

Bloom, N., & Bloom, N. (2007). THE IMPACT OF UNCERTAINTY SHOCKS Nicholas Bloom Working Paper 13385 http://www.nber.org/papers/w13385 NATIONAL.

Bollerslev, torben G. A. T. (1998). deutsche Mark Dollar Volatility Intraday activity patterns macroeconomic announcements and longer run dependencies.

Bollerslev, T. (1990). Modelling the coherrence in short run nominal exchange rates: A multivariate generalized ARCH model.

Bollerslev, T., Engle, R. F., Wooldridge, J. M., Bollerslev, T., Engle, F., & Wooldridge, M. (2014). All use subject to JSTOR Terms and Conditions A Capital Asset Pricing Model with Covariances, *96*(1), 116–131.

Broadstock, D. C., & Filis, G. (2012). Oil price shocks and stock market returns : New evidence from the United States and China ., (iii).

busse, stefan, brummer, bernard, ihle, R., & Development, R. (2010). Interdependencies between fossil fuel and renewable energy markets: the German biodiesel market.

Calabrese, F., Lorenzo, G. Di, Liu, L., & Ratti, C. (2011). Estimating Origin-Destination flows using opportunistically collected mobile phone location data from one million users in Boston Metropolitan Area.

Cevik, S., & Sedik, T. S. (n.d.). A Barrel of Oil or a Bottle of Wine : How Do Global Growth Dynamics Affect Commodity Prices ?

Chambet, A., & Gibson, R. (2005). Working Paper Series Financial Integration , Economic Instability and Trade Structure in Emerging Markets Anthony Chambet Financial Integration , Economic Instability And Trade Structure In Emerging Markets ∗, (January).

Chang, C., Mcaleer, M., & Tansuchat, R. (2010). Analyzing and forecasting volatility spillovers , asymmetries and hedging in major oil markets. https://doi.org/10.1016/j.eneco.2010.04.014

Chang, T., Su, H., & Chiu, C. (2015). Value-at-risk estimation with the optimal dynamic biofuel portfolio. *Energy Economics*, *33*(2), 264–272. https://doi.org/10.1016/j.eneco.2010.11.002

Chatziantoniou2, G. F. and I. (2014). Financial and monetary policy responses to oil price shocks: Evidence from oil importing and oil-exporting countries. *1Bournemouth University, Department of Accounting, Finance and Economics, The Executive Business Centre, 89 Holdenhurst Road, Bournemouth BH8 8EB, UK*, *0044*(0), 1–32.

Chen, A. N., Roll, R., Ross, S. A., Chen, N., Roll, R., & Ross, S. A. (2012). Economic Forces and the Stock Market *, *59*(3), 383–403.

Chiang, T. C., Nam, B., & Li, H. (2007). Dynamic correlation analysis of financial contagion : Evidence from Asian markets. https://doi.org/10.1016/j.jimonfin.2007.06.005

Chinzara, Z., & Aziakpono, M. J. (2009). Dynamic Returns Linkages and Volatility Transmission between South African and World Major Stock Markets 1 Dynamic Returns Linkages and Volatility Transmission Between South African and World Major Stock Markets, (146), 14–16.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). "Some contagion, some interdependence": More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), 1177–1199. https://doi.org/10.1016/j.jimonfin.2005.08.012

Davidson, W., & Number, P. (2012). T HE W ILLIAM D AVIDSON I NSTITUTE Stock Market Comovements in Central Europe : Evidence from Asymmetric DCC Model By : Dritan Gjika and Roman Horvath August 2012 Stock Market Comovements in Central Europe : Evidence from Asymmetric DCC Model, (1035).

Degiannakis, S., Filis, G., & Floros, C. (2011). Dynamic correlation between stock market and oil prices : The case of oil-importing and oil-exporting countries.

Du, X., Yu, C. L., & Hayes, D. J. (2009). Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets : A Bayesian Analysis Speculation and Volatility Spillover in the Crude Oil and Agricultural.

Dumas, B., Harvey, C., Kaplanis, E., & Kroner, K. (1995). Is the correlation in international equity returns constant: 1960-1990?, *14*, 3–26.

Duncan, A. S., Kabundi, A., & Duncan, A. S. (2011). Volatility Spillovers across South African Asset Classes during Domestic and Foreign Financial Crises Volatility Spillovers across South African Asset Classes during Domestic and Foreign Financial Crises, (February).

Ebens, H. (1999). Realized Stock Volatility.

Economics, D. (2019). Pakistan Institute of Development Economics , Islamabad Financial Market Integration in Pakistan : Evidence Using Post-1999 Data [with Comments] Author (s): Ahmed M . Khalid , Gulasekaran Rajaguru and Rizwana Siddiqui Source : The Pakistan Development, *45*(4).

El, M., Arouri, H., Jouini, J., & Khuong, D. (2011). Journal of International Money Volatility spillovers between oil prices and stock sector returns : Implications for portfolio management. *Journal of International Money and Finance*, *30*(7), 1387–1405. https://doi.org/10.1016/j.jimonfin.2011.07.008

El, M., Arouri, H., Jouini, J., & Khuong, D. (2012). On the impacts of oil price fl uctuations on European equity markets : Volatility spillover and hedging effectiveness. *Energy Economics*, *34*(2), 611–617. https://doi.org/10.1016/j.eneco.2011.08.009

El, M., Arouri, H., Nguyen, D. K., El, M., Arouri, H., Khuong, D., … Investment, P. (2010). Oil Prices , Stock Markets and Portfolio Investment : Evidence from Sector Analysis in Europe over the Last Decade To cite this version : HAL Id : hal-00507823 Oil Prices , Stock Markets and Portfolio Investment : Evidence from Sector Analysis in Europe over the Last Decade □.

Engle, R. (2002a). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics*, *20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Engle, R. (2002b). DYNAMIC CONDITIONAL CORRELATION – A SIMPLE CLASS OF MULTIVARIATE GARCH MODELS July 1999 Revised Jan 2002 Forthcoming. *Journal of Business and Economic Statistics*, (July 1999), 1–34.

Engle, R. F., & Rangel, J. G. (2006). The Spline-GARCH Model for Low Frequency Volatility and Its Global Macroeconomic Causes, (2004).

Estate, R., Collins, F., & Serletis, A. (2010). Oil Price Uncertainty, (February).

Fayyad, A., & Daly, K. (2011). The impact of oil price shocks on stock market returns : Comparing GCC countries with the UK and USA. *Emerging Markets Review*, *12*(1), 61–78. https://doi.org/10.1016/j.ememar.2010.12.001

Ferreira, P. (2017). Portuguese and Brazilian stock market integration: a non-linear and detrended approach. *Portuguese Economic Journal*, *16*(1), 49–63. https://doi.org/10.1007/s10258-017-0127-z

Goldberg, L., & Leonard, D. (2003). F E D E R A L R E S E RV E B A N K O F N E W Y O R K C urrent I ssues What Moves Sovereign Bond Markets ? The Effects of Economic, *9*(9).

Graham, M., Kiviaho, J., & Nikkinen, J. (2012). Integration of 22 emerging stock markets: A three-dimensional analysis. *Global Finance Journal*, *23*(1), 34–47. https://doi.org/10.1016/j.gfj.2012.01.003

Hamid, K., & Hasan, A. (2011). Casual and dynamic linkage of stock markets : An empirical study of Karachi Stock Exchange (KSE) with emerging and developed equity markets, *5*(19), 7802–7817. https://doi.org/10.5897/AJBM10.1145

Hamilton, J. D. (2009). CAUSES AND CONSEQUENCES OF THE OIL SHOCK OF 2007-08. *NATIONAL BUREAU OF ECONOMIC RESEARCH 1050 Massachusetts Avenue Cambridge, MA 0213*.

Hammoudeh, S. (2004). Relationships_among_U.S._oil_prices_and.pdf.

Hanif, W., & Khan, M. (2017). Hedging Effectiveness of Commodities in the Stock Portfolio : Empirical Evidence from Pakistan Stock Exchange using, *11*(December 2007), 153–175. https://doi.org/10.21621/sajms.2017112.05

Harri, A., & Hudson, D. (2009). Mean and Variance Dynamics between Agricultural Commodity Prices and Crude Oil Prices Ardian, (662).

Harri, A., Nalley, L., & Hudson, D. (2015). Economics : Commodity Prices The Relationship between Oil , Exchange Rates , and Commodity Prices, (2009), 501–510. https://doi.org/10.1017/S1074070800002959

Hasan, A. (2008). Long-Run Relationships between an Emerging Equity Market and Equity Markets of the Developed World an Empirical Analysis of Karachi Stock Exchange, *16*(16).

Hassouneh, I., Serra, T., & Gil, J. M. (2011). Non-parametric and Parametric Modeling of Biodiesel - Sunflower Oil - Crude Oil Price Relationships.

He, F., Liu, Z., & Chen, S. (2019). Industries Return and Volatility Spillover in Chinese Stock Market: An Early Warning Signal of Systemic Risk. *IEEE Access*, *7*, 9046–9056. https://doi.org/10.1109/ACCESS.2018.2888522

Hedi, M. El, & Ben, A. (2012). Energy Consumption, Economic Growth and CO2 Emissions in Middle East and North African Countries.

Horvath, B. R., Petrovski, D., & Horvath, R. (2012). International Stock Market Integration : Central and South Eastern Europe Compared International Stock Market Integration : Central and South Eastern Europe Compared, (1028).

Horvath, R., & Poldauf, P. (2012). International stock market comovements: What happened during the financial crisis? *Global Economy Journal*, *12*(1). https://doi.org/10.1515/1524-5861.1788

Huyghebaert, N., & Wang, L. (2009). The co-movement of stock markets in East Asia. *China Economic Review*, *21*(1), 98–112. https://doi.org/10.1016/j.chieco.2009.11.001

In, V., & Financial, E. (2003). CONTAGION AND INTERDEPENDENCE IN, *71*(2001).

Jin Lim, S., & Masih, M. (2017). Exploring portfolio diversification opportunities in Islamic capital markets through bitcoin: evidence from MGARCH-DCC and Wavelet approaches, *1*(1), 1–25. Retrieved from https://mpra.ub.uni-muenchen.de/79752/

Johnson, R., & Soenen, L. (2003). Economic integration and stock market como v ement in the Americas, *13*.

Journal, S. A., & Sciences, M. (2015). Comparison of Equity Markets of SAARC Nations with the Equity Markets European Union Nations, *9*(1), 23–31.

Journal, T., Guesmi, K., La, P. O., Kaabia, F. O., Ouest, P., La, N., … La, N. (2013). Does Shift Contagion Exist Between OECD Stock Markets During The Financial Crisis?, *29*(2), 469–484.

Joyo, A. S., & Lefen, L. (2019). Stock market integration of Pakistan with its trading partners: A multivariate DCC-GARCH model approach. *Sustainability (Switzerland)*, *11*(2). https://doi.org/10.3390/su11020303

Jr, P. K. W., & Lin, B. (2016). Can African countries ef fi ciently build their economies on renewable energy ? *Renewable and Sustainable Energy Reviews*, *54*, 161–173. https://doi.org/10.1016/j.rser.2015.09.082

Kali, R., & Reyes, J. (2010). Financial contagion on the economic trade network. *Economic Inquiry*, *48*(4), 1072–1101. https://doi.org/10.1111/j.1465-7295.2009.00249.x

Kalotychou, E., Staikouras, S. K., & Zhao, G. (2009). On the Dynamics of Asset Correlations : What Matters to Portfolio Managers, *44*(June 2008), 1–68.

Katzke, N., Garch, M., Correlation, C., & Indices, S. (2019). South African Sector Return Correlations : using DCC and ADCC Multivariate GARCH techniques to uncover the underlying dynamics . Stellenbosch Economic Working Papers : 17 / 13 South African Sector Return Correlations : using DCC and ADCC Multivariate GARC. *Stellenbosch Economic Working Papers*, *17/13 KEYW*.

Kearney, C., & Potì, V. (2005). Correlation Dynamics in European Equity Markets Correlation

Dynamics in European Equity Markets, (June 2003).

Kenourgios, D., & Christopoulos, A. G. (2013). Asset Markets Contagion during the Global Financial Crisis, (December). https://doi.org/10.17578/17-1/2-2

Kilian, L. (2006a). Exogenous Oil Supply Shocks : How Big Are They and How Much Do They Matter for the U . S . Economy ?, (November 2005).

Kilian, L. (2006b). Not All Oil Price Shocks Are Alike : Disentangling Demand and Supply Shocks in the Crude Oil Market.

Kilian, L. (2007). The Economic E ff ects of Energy Price Shocks ∗.

Kristoufek, L., Janda, K., & Zilberman, D. (2012). Correlations between biofuels and related commodities before and during the food crisis : A taxonomy perspective. *Energy Economics*, *34*(5), 1380–1391. https://doi.org/10.1016/j.eneco.2012.06.016

Kuttner, K. N. (2004). WHAT EXPLAINS THE STOCK MARKET'S REACTION TO FEDERAL RESERVE POLICY, *10402*.

Lai, yin wong cheung and kon s. (1993). finite sample sizes of johansens liklehood ratio tests for co integration.

Le, H., Ceuster, M. J. K. De, Annaert, J., & Amonhaemanon, D. (2013). Gold as a Hedge against Inflation : The Vietnamese Case. *Procedia Economics and Finance*, *5*(13), 502–511. https://doi.org/10.1016/S2212-5671(13)00059-2

Lippi, F. (2010). Oil and the Macroeconomy: A Quantitative Structural Analysis, (m).

Malik, F., & Hammoudeh, S. (2007). Shock and volatility transmission in the oil , US and Gulf equity markets, *16*, 357–368. https://doi.org/10.1016/j.iref.2005.05.005

Maria, G., Schulze-ghattas, M., & Spagnolo, N. (2009). CESifo Working Paper no. 2794.

Markowitz, H. M. (1952). American Finance Association Foundations of Portfolio Theory Author (s): Harry M . Markowitz Source. *The Journal of Finance*, *46*(2), 469–477.

Masulis, Y. H. R. W. (1990). correlations in price changes and volatillity across international stock markets.

Mcaleer, M. (2001). Asymptotic theory for a vector ARMA-GARCH model.

Mcaleer, M., & Mcaleer, M. (2010). KIER DISCUSSION PAPER SERIES KYOTO INSTITUTE OF, (743).

Michael Ehrmann. (2005). Stocks, Bonds, Money Markets and Exchange Rates: Measuring International Financial Transmission. *Stocks, Bonds, Money Markets and Exchange Rates: Measuring International Financial Transmission*, *11166*.

Mishra, R., & Mukherjee, K. (2010). Stock market integration and volatility spillover: India and its major Asian counterparts. *Research in International Business and Finance*, (12788). Retrieved from http://www.sciencedirect.com/science/article/pii/S0275531909000488

Mühleisen, M., Roache, S. K., & Zettelmeyer, J. (2007). *WHO ' S DRIVING WHOM ? Analyzing External and Intra-Regional Linkages in the Americas Who ' s Driving Whom ? Analyzing External and Intra-Regional Linkages in the Americas*.

Nandha, M., & Faff, R. (2008). Does oil move equity prices ? A global view, *30*, 986–997. https://doi.org/10.1016/j.eneco.2007.09.003

Negro, D. (2002). international diversification strategies.

Paper, S., Joint, A., & Meeting, A. (2009). PRICE VOLATILITY IN ETHANOL MARKETS Teresa Serra a * and David Zilberman b.

Paper, W., & Bank, E. C. (2004). Taking stock: monetary policy transmission to equity markets.

Paper, W., & Haven, N. (2001). www.econstor.eu.

Park, J. W., & Ratti, R. A. (2007). Oil price shocks and Stock markets in the U . S . and 13 European Countries, (August).

Personal, M., Archive, R., & Faiq, S. (2014). Munich Personal RePEc Archive Does a held-to-maturity strategy impede effective portfolio diversification for Islamic bond (sukuk) portfolios ? A multi-scale continuous wavelet correlation analysis, (56956).

Rahman, M. L., & Uddin, J. (2014). Dynamic Relationship between Stock Prices and Exchange Rates: Evidence from Three South Asian Countries. *International Business Research*, *2*(2), 167–174. https://doi.org/10.5539/ibr.v2n2p167

Rahman, S. (2010). The Asymmetric E ¤ ects of Oil Price Shocks, (403).

Rigobon, K. F. R. (1999). NO CONTAGION, ONLY INTERDEPENDENCE: MEASURING STOCK MARKET CO-MOVEMENTS, (July).

Rigobon, R. (2003). SPILLOVERS ACROSS U.S. FINANCIAL MARKETS, *9640*.

Samarakoon, L. (2011). Stock Market Interdependence , Contagion , and the U . S . Financial Crisis : The Case of Emerging and Frontier Markets.

Samouilhan, N. (2006). The Relationship Between International Equity Market Behaviour and the JSE The Relationship Between International Equity Market Behaviour and the JSE, (42).

Sarfraz, A., Shehzadi, S., Hussain, H., & Altaf, M. (2012). Financial Economics Co-integration of Karachi Stock Exchange (KSE) With Major Asian Markets, *8*(5), 118–129.

Serra, T., & Fax, T. T. (2011). VOLATILITY SPILLOVERS BETWEEN FOOD AND ENERGY MARKETS , A SEMIPARAMETRIC APPROACH.

Sheikh, S. P., Siddiqui, S., Yang, J., Kolari, J. W., Min, I., Ratanapakorn, O., … Abu Hassan, S. M. N. (2012). Comovements and linkages of emerging stock markets: A case study from OIC member countries. *Jurnal Keuangan Dan Perbankan*, *12*(4), 105–120. https://doi.org/10.26905/jkdp.v21i2.1138

Siami-namini, S. (2017). China ’ s Economy and the Global Financial Crisis, (November).

Su, Y., & Yip, Y. (2014). Contagion Effect of 2007 Financial Crisis on Emerging and Frontier Stock Markets. *Journal of Accounting & Finance (2158-3625)*, *14*(5), 97–113. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bsh&AN=100414843&site=ehost-live

Sun, T., & Zhang, X. (2009). Spillovers of the U . S . Subprime Financial Turmoil to Mainland China and Hong Kong SAR : Evidence from Stock Markets.

Syriopoulos, T., & Roumpis, E. (2009). Dynamic correlations and volatility effects in the Balkan equity markets. *Journal of International Financial Markets, Institutions and Money*, *19*(4), 565–587. https://doi.org/10.1016/j.intfin.2008.08.002

Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business and Economic Statistics*, *20*(3), 351–362. https://doi.org/10.1198/073500102288618496

Val, L. (2008). On the Influence of Oil Prices on Economic Activity and Other Macroeconomic and Financial Variables _____________.

Vries, D. (2001). ASSET MARKET LINKAGES IN CRISIS PERIODS.

Working, E., & Series, P. (2019). The Effect of Global Crises on Stock Market Correlations : Evidence from Scalar Regressions via Functional Data Analysis, (January).

Working, N., & Series, P. (1990). Robert Pindyck, (3307).

Worthington, A., & Higgs, H. (2004). Transmission Of Equity Returns And Volatility In Asian Developed And Emerging Markets : A Multivariate Garch Analysis, *9*, 71–80.

Yang, J., Min, I., & Li, Q. (2003). European stock market integration: Does EMU matter? *Journal of Business Finance and Accounting*, *30*(9–10), 1253–1276. https://doi.org/10.1111/j.0306-686X.2003.05535.x

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2010). Food versus fuel : What do prices tell us ? *Energy Policy*, *38*(1), 445–451. https://doi.org/10.1016/j.enpol.2009.09.034