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The dynamics of Industrial Level Volatility Spillovers in Emerging Equity Market: Evidence from PSX

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ABSTRACT

The research study examines the return and volatility transmission from one industry to other industries listed on PSX. The research uses the daily data of average industrial stock returns of ten major industries from 2002 to 2021. Furthermore, ARMA (1,1) GARCH (1,1) model is used to check the spillover from one industry to other industries. Moreover, the time-varying nature of conditional correlation is further explored by using DCC-ADCC models for both aspects as well. The result of our study provides strong evidence of volatility transmission among various industries, but limited evidence is found regarding return spillover. The study finds the return and volatility spillover across various listed industries for the given time period which indicates the limited evidence of diversification. In addition, findings also reveal the time-varying nature of conditional correlation. The outcome of the various econometrics model reveals the presence of asymmetric behaviour among various industries. Market players may consider these market spillovers to effectively predict each other's future movement. The stock market may be an essential quality for multinational corporations interested in projecting exchange rates. Because of the spillover stock and foreign exchange markets, there are some fascinating implications for portfolio managers. This understanding would aid in the creation of a successful fund. Furthermore, the findings can assist regulators and policymakers in better understanding the market structure and designing policies.

***Keywords*:** Spillover, industrial indices, volatility transmission, conditional correlation, asymmetric behaviour, hedging, multivariate GARCH model.

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INTRODUCTION:

Financial market integration is rapidly developing over the world because of globalisation and the development of new information technologies. As a result, the link between financial markets and sectors has become increasingly entangled. Volatility spillovers have been used to characterise most of these relationships. Portfolio managers and politicians must understand these interrelationships, especially as a hedging technique. Investors and forecasters have become more worried in recent years about the risk that a period of excessive homogeneity in asset price movement across different financial systems, markets, and industries. These movements and spillovers across markets pose decision-makers and experts' capacity to effectively diversify portfolio investments. In times of global financial instability, it is becoming clear that asset markets have a significant connection beyond fundamental linkages. This is mostly due to the relatively close instantaneous flow of information and the global economy's interconnected structure, which allows for coordinated actions in modern markets Kalotychou, Staikouras and Zhao, (2009).

In financial market practices, diversification is the practice of allocating assets among several businesses, financial instruments, and other categories to decrease risk. Portfolio diversification may be achieved by investing abroad, across numerous industries, and in diverse asset classes, with negative or low correlations. When multiple regions are invested in, the return is maximized using this strategy (Markowitz,1952). Risk can be reduced, and financial goals can be met, according to investment pros, but diversification does not guarantee against loss. The management must recognize the importance of diversity in investing. Investment diversification may be described as "not putting all your eggs in one basket," which implies that diversifying your investments does not imply that you are diversifying your risk but investing in a variety of funds to diversify your portfolio. Diversification is also referred to as asset allocation.

In these asset allocation and portfolio construction decisions, most investors are compensated based on the variance, mean, and co-variance structure of stock returns, according to Markowitz's (1952) portfolio theory. This approach may be used to examine diversification in terms of the number of securities and pick the best-suited portfolio. Markowitz used statistical analysis and mathematical programming to allocate the assets in the portfolio. Because most portfolio managers rely on inactive estimates of prior correlations, inter-sector correlation aids portfolio managers in making judgments about portfolio diversification. In a few ways, portfolio managers are advantageous to investors. For starters, the risk may be reduced by investing in the stock market through diversification. Second, portfolio managers enable stock market management by professionals. Small investors might keep a diverse portfolio by combining their investing capital. As a result, it is argued that diversity can reduce portfolio risk.

Following that, the stock market's behaviour is assessed using data to determine if the market is firm-specific or macroeconomic. Different market players utilize stock market information to aid in the investment of various assets. The Efficient Market Hypothesis states that changes in the price of one asset impact the prices of other securities. The major issue for investors and other market players is unequal information in the market. Markets, equities, and sectors have become increasingly coordinated in recent years. It has been demonstrated in the current period of global economic uncertainty that stock markets are no longer separate and have broken away from essential links. This is due to information transfer from market to market and the global financial system's linkage. Portfolio diversification may be achieved by investing internationally and in various areas.

As a result, this study looks into the dynamics of co-movement among Pakistan's largest financial sectors, to throw light on the intersectoral diversification options available to national investors over time. When it comes to investing, investors have been known to have a home bias, and as a result, their portfolios may experience times of enhanced co-movement between assets owned locally across different industries. The benefits of diversification of the local financial market are negated during periods of greater asset price homogeneity. In this research study dynamics of return co-variations among different sectors in Pakistan are investigated, with a focus on domestic investors' inter-sector diversification prospects. Investors are said to desire diversity inside their nation (Katzke, Garch, Correlation, & Indices, 2019). Understanding the links between Pakistan's various industries is crucial. Over time, the industries are no longer isolated and are becoming more integrated. This study looks into the dynamics of co-movement across Pakistan's most important financial sectors, intending to shed light on national investors' intersectoral diversification prospects throughout time. When it comes to investing, investors have been known to have a home bias, and as a result, their portfolios may experience times of enhanced co-movement between assets owned locally across different industries. Co-movement between different markets has been identified in previous studies, but only the volatility and return relationship between different nations was observed. As a result, this research will look at the spillover impact from one industry to another in Pakistan, and it will aid investors in selecting industries for local diversification. As a result, this finding opens a new door for future researchers. As a result, this study fills in the gaps by utilizing cutting-edge techniques to examine inter-sector phenomena using current data from Pakistan's stock markets.

The remaining of the paper proceeds as follows. Section 2 presents the empirical review of the scholarly studies. Section 3 delimitates the research design and econometric methodology applied for testing study hypotheses. Section 4 presents the discussion of the empirical results to corroborate the spillover effects from one industry to others and the final section provides the conclusion and limitations of our research study.

Review of the Empirical Studies

According to the efficient market hypothesis, stock markets are typically efficient, and there is no dependency on the return series, hence future markets cannot be anticipated from previous data (Fama, 1965). Initially, certain finance scholars, such as Charest (1978), Thompson (1978), and Watts (1978), believed this concept was correct (1978). It was later claimed that markets are inefficient following the advent of modern technologies. Diebold and Yilmaz (2009), Hoerger et al. (1990), Hu et al. (1997), Jebran et al. (2017), ztürk and Volkan (2015), and Theodossiou and Lee (2015), among others, corroborate this idea (1993). Such inefficiency emphasizes the need of having an actively managed portfolio to achieve exceptional results.

The degree and direction of correlation between returns of various securities and markets must be determined to construct an optimum portfolio. Engle et al. (1990) used the term "volatility spillover" to describe this link. The phrase "spillover" refers to the repercussions of any action that spreads wider than expected (Botshekan and Mohseni, 2017). It refers to something that expands out instead of being steady. As a result, volatility spillover may be defined as the phenomenon of volatility being communicated from one market to another.

Numerous research studies were undertaken to investigate the notion of spillover since it was first introduced in finance literature. The majorities of these early investigations was carried out at the country level and were limited to industrialized nations. For example, The odossiou and Lee (1993) looked at the UK, US, Japan, Canada, and Germany stock markets and found volatility spillover from the US market to all chosen markets, from the UK stock market to the Canadian market, and from the German market to the Japanese stock market. The small volatility spillover between London and New York financial markets was investigated by Susmel and Engle (1994). Koutmos and Booth (1995) investigated the relationship between the stock markets of New York, Tokyo, and London, and discovered that all three markets had volatility spillover. Due to deregulation, the introduction of the euro, and financial crises, Billio and Pelizzon (2003) investigated the volatility spillover from the German market to other European markets. They found that following the EMU, volatility transmission from the world market index and the German market to European markets increased.

The financial or actual relationship between several markets might be one of the reasons for market instability and spillover impact (Bollerslev et al., 1992; Nguyen et al., 2017; Hassan et al., 2006). Volatility spillover is also caused by investor reactions to various market scenarios (Ito and Lin, 1994; Munier, 1991; Sola et al., 2002). Another key driver of spillover is advanced technology and communication since investors can absorb information fast and make judgments accordingly (Boonvorachote and Lakmas, 2016). These variables also produce spillover effects between various sectors of a country. Investors who wish to diversify their portfolios inside their native nation must understand how volatility is transmitted between sectors. They may be able to estimate future volatility based on this knowledge by studying the present market environment.

Given the significance of this factor, finance literature provides research that examines the spillover effects among various sectors of a country. Al-Hashel (2003), for example, examined seven sectors listed on the Kuwait stock exchange and concluded that the Food industry is the most important in terms of both return and volatility spillover. Hassan and Malik (2007) found considerable volatility spillover across all US sector indexes (Consumer, Energy, Financial, Health, Industrial, and Technology). ztürk and Volkan (2015) measured volatility spillover across four major industries in 11 North African and Middle Eastern nations. The oil and gas industry had the lowest volatility spillover, while the financial sector had the greatest. Barunk et al. (2016) investigated volatility spillover in seven US market sectors. They discovered asymmetric volatility transmission between sectors, implying that positive and negative historical volatility had distinct effects on current volatility. Chiang et al. (2016) looked at the interconnections across ten industries in the United States, Hong Kong, Europe, China, South Korea, and Japan. The findings revealed a strong link across all industries, except for healthcare, telecommunications, and utilities.

Botshekan and Mohseni (2017) investigated 14 of Iran's major businesses and discovered a correlation between banking and five other sectors: basic materials, transportation and warehousing, computer, interdisciplinary, and investment. Nguyen et al. (2017) looked at the impact of company relationships on the degree of volatility spillover in a few US sectors. They discovered significant volatility transmission across industries. Furthermore, the degree to which enterprises are linked influences the size of volatility spillover. Alomari et al. (2018) studied the time-varying association between 10 key sectors of the Amman Stock Exchange. They stated that all industries were interconnected, and that news from other areas had an influence on each sector. Concerning volatility transmission, Majumder and Nag (2018) analyzed three sectors (IT, FMGC, and finance) on the National Stock Exchange (NSE). Their findings show that historical volatility in each industry has an impact on present volatility. They discovered a bidirectional volatility spillover between the IT and finance sectors, as well as a unidirectional volatility transmission from FMGC to the IT and finance sectors when it came to cross volatility spillover. Hussain Shahzad et al. (2019) looked at the spillover between 14 sectors of the Eurozone credit markets and discovered that the oil and gas, construction goods, and chemical industries are more significant than others. Simiyu et al. (2020) investigated the relationship between the

Nairobi Securities Exchange's three sectors (banking, manufacturing and allied, and investment). The findings revealed a relationship between the investing and banking industries along with allied and manufacturing sectors.

Although there is some empirical evidence in Pakistan to evaluate the connectivity between the oil industry and other sectors, such as Malik and Rashid (2017) who explored the return and volatility spillover between oil prices and eight PSX industries. They identified a spillover of volatility from the banking to the energy sectors. However, no additional link was seen between oil prices and any PSX sector. Waheed et al. (2018) investigated the effect of oil prices on PSX sector profits. Their findings revealed that oil prices have a positive substantial impact on the textile, miscellaneous, and chemical sectors and that oil price lags hurt all sectors except jute, Vanaspati, and tobacco. Habiba and Zhang (2020) looked examined the return and volatility spillovers between OPEC oil and six sectors of the Pakistan stock market (automobiles, agriculture, finance, energy, and equipment). The data revealed that there was a volatility spillover impact from the oil market to the chosen industries, but no spillover effect from stock returns in any sector to the oil market.

Mishra and Mukherjee studied the likelihood of volatility spillover and stock market integration between Asian nations and India in 2010. According to Engle and Bollerslev, the GARCH model is used (1982 & 1986). Apart from varying degrees of correlation between the Indian stock market and that of other Asian countries in terms of return and squared return series, the contemporaneous intraday return spillover between India and almost all of the sample countries is found to be positively significant and bi-directional. The VECH model (first MV GARCH model) was presented by Bollerslev, Engle, and Wooldridge in 1988, and it determines the conditional covariance matrix among series (Katzke et al., 2019). The VECH technique is a direct simplification of the univariate approach. Engle later permitted the reliability of the CCC model's structure of correlation with the (DCC) model in 2002, while Cappiello et al. enlarged the DCC model to the Asymmetric-DCC (ADCC) model in 2006.

In the literature, the MV-GARCH is mostly employed to investigate infectivity effects and market spillover. Koutmos and Booth described in 1995 how negative and positive shock spillovers emanating from major news events differ from one another and how this affects the volatility connection across equity markets (Katzke et al., 2019). The main benefit of using the MV-GARCH approach is that it allows for diversification (De Santis and Gérard, 1998; Katzke et al., n.d.). Following the recent financial crisis, there has been an increase in research explaining that using the MV-GARCH approach, there is a link between volatility conduction between multiple markets and stock return co variations. Only to study European regional and global instability, Katzke et al. (2019) enlisted the South African index of developing economies. The ADCC-MVGARCH approach is used to investigate the dynamic interaction between complex catalogues from developed nations and the Balkans (Syriopoulos and Roumpis, 2009). Our research study applied the alike methodology based on various versions of the ARCH and GARCH model to test the return and volatility spillover among sectors listed on the Pakistan stock exchange.

Research Design and Methodology

The main purpose of this study is to examine volatility spillover across industrial stock returns within sectors of Pakistan. Based on this hypothesis, the statistical testing procedure for this study is divided into two sections. First, the return and volatility transmission from industries to industries in Pakistan are investigated using the ARMA (1,1) GARCH model proposed by Liu and Pan (1997). Second, Engle and Cappiello et al. (2006) introduced

DCC and ADCC MV-GARCH models that were applied for measuring time variable conditional correlation among diverse industries.

All the listed firms of PSX are the population of this research. The sample period is taken 20 years starting from 2002 to 2021. This study utilizes 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 spill overs from industries to industries in Pakistan as well as time-varying conditional correlations. The data of the firms was obtained from PSX.

The study is using the daily data of 10 listed sectors. There are 579 listed firms with 35 different sectors. Only 10 sectors sample whose data is available from June 2002 to June 2021 is taken. The industry index is formulated through an equally weighted index method.

Industrial Sectors	No of Firms
Banking	21
Oil & Gas	8
Equity Investment	12
Automobiles	17
Personal Goods	112
Pharmaceuticals & Biotechnology	12
Non-life Insurance	25
Industrial Engineering	7
Equity Investment	13
Financial Services	17

Econometric Methodology

One of the most familiar nonlinear models is 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 is the direct simplification of the GARCH model, and it approximates many parameters while the second one is a linear grouping of univariate GARCH with the specification of OGARCH. The third one is a 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) (Bollerslev, 1990). The covariance changes due to changes in variances. The matrix form of the model is:

$$r_t = \theta x_t + \delta_t$$

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

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

In this econometric equation the (m, 1) vector of returns r_t is formed by using the (m,1) vector of independent variables x_t and the approximation of β (m, k) which is the matrix of parameters is needed. Cholesky factor defined the vector of novelty processes **(ε_t).** (m, m) matrix $\gamma_t^{1/2}$ 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 (γ_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:

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

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

$$r_t = \theta x_t + \delta_t$$

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

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

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

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

It is presumed in this model that the change 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 ($\tilde{\delta}_t$), $\tilde{\delta} = D^{-1}\delta_t$; and (m, m) positive definite unconditional integration matrix is R. The parameters that are not negative explains the conditional integration dynamics i.e. $\sigma_1$andσ_2. Engle, (2002) illustrates the condition $\sigma_1 + \sigma_2$ <1 for the stationarity of the technique.

$$E(\tilde{\delta}_t \tilde{\delta}_t') = I_m$$

In this econometric equation, the identity matrix isI_m.

According to Ding & Engle, (2001):

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

Industrial Indices – Ten Industries

Construction of Industrial Indexes

The method used to compute the index's prices determines the index's categorization. The most common application of indexes for diversity is as fundamental benchmarks. As a result, different types of indexes must be understood because they are used to determine diversification and portfolio decisions. Price and value-weighted indexes, industry equally weighted indexes, and capitalization-weighted indexes are the three basic categories of industrial indexes. In dynamic sectoral portfolio selection, industrial indicators are crucial. The number of outstanding shares, as well as company market prices, are considered in the capitalization-weighted index to determine percentage weighting. Companies are heavily weighted in portfolio investments when their components are significant. While the same amount of money is invested in each stock, the results are not the same. In an evenly weighted index, the same amount of investment is spread throughout the company's equities. In the index, all firms are equally represented.

An industry equal-weighted index is a stock market index made up of firms that trade publicly. Industry equally weighted indexes, unlike market capitalization-weighted indexes, have lower risk and are more diverse. Many investors regard industry equally weighted funds to be primarily value investing as part of a bigger investment strategy. An equal-weighted index can be used to calculate the total market value. As a result, investors may use an industry equally weighted index to determine how to get the best return on investment. Industry equally weighted indices are used to build indexes in this study. As a result, these indexes are not adequately available; hence, a need emerges to develop sectoral industrial indexes using a free-float technique. To create the industry weighted index, equal weights are assigned across equities in various industries. Equally Weighted Indexes are commonly used in empirical research.

All industry's daily results are resolved using an equally weighted index. This research includes the following industries: 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 are some of the industries that are represented in this report.

Return & Volatility Spillover – ARMA-GARCH Model

Industries-to-Industries Spillover

With the help of ARMA (1, 1) GARCH, the return & volatility transmission from industries to industries are examined by applying the Mean model. The first step includes the relevant industry return series that is modelled through an ARMA.

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

$sn, t = \sigma o + \sigma 1.sn, t-1 + \sigma 2.wn,t + \sigma 3.\ n, t-1 + n, t,n,t \sim N(0,w\ n, t)$

$wn, t = \epsilon o + \epsilon 1.\rho 2n, t-1 + \epsilon 2.\ wn, t-1$

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 to 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 with the volatility and mean equations of other markets such as:

$so, t = \sigma o, o + \sigma o,1.so, t-1 + \sigma o,2.\ wo,t + \sigma o,3.o,t-1 + \psi o.n,t + o,t,o,t \sim N(0,wo,t)$

$wo, t = \epsilon o, o + \epsilon o,1.\ \rho\ 2\ o, t-1 + \epsilon o,2.\ wo, t-1 + \tau.e2n, t$

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 ranging from 1 to 10

Discussion of Empirical Findings

Various econometric tests are used in this chapter to study the phenomena under discussion and interpret the results. The research uses the closing prices of eleven industrial indexes daily. This step comprises the evaluation of data behaviour using descriptive statistics for each series.

Stationarity of Data Series

Our analysis begins with the test of stationarity based on the ADF test. If the data series selected is non-stationary in its properties, then applied econometric models produce unreliable and spurious results that lead to unreliable and invalid outcomes based on hypothesis testing. The findings of the ADF test are reported in Table 4.1 below.

Table 4.1: Stationarity Test

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 of the ADF unit root test reveal that all industries' mean returns are positive. The results are considered across all sectors, and the data is stationaries for future spillover research.

Descriptive Statistics

Table 4.2.1 includes the 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 -to 2018. The study utilizes the daily closing prices in terms of returns of 10 industrial indices.

	Pharma & Biotech	Nonlife Ins.	Food Prod.	Indus Eng.	Auto & Par.	Per Goods	Equity Invest. Inst	Fin. Ser.	Oil & Gas	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

Table 4.2: Descriptive Analysis

Daily mean returns are used to gauge the performance of several industry indices. The findings show that all industries have positive mean returns. Food Producers have the greatest mean return value (0.056%), while Financial Services have the lowest (0.017 per cent). Furthermore, all businesses have a positive standard deviation, although pharmaceuticals and biotechnology show the most volatility (1.7879 per cent). As a result, this industry is more volatile than others. Personal goods, on the other hand, have the lowest volatility (1.07 per cent), indicating that it is a less volatile industry. As a result, it is clear that the logic relating to risk and return is not covered because the mean return and volatility are higher for two different sectors rather than the same sector, i.e., the mean return for Food Producers is higher and the volatility for Pharmaceuticals and Biotechnology is higher. As a result, the sector of Food Producers has a higher risk, whereas Pharmaceuticals and Biotechnology have a higher return. The maximum and minimum daily returns earned for each industry are shown in the maximum and minimum statistics. For instance, the daily return per day for Food Producers is (0.056%), the highest return per day is (0.07%), and the minimum return per day is (-0.0856%), and so on. The asymmetric behaviour of data is described by skewness. The skewness scores for all sectors reveal that return distributions are negatively skewed.

The constant decline in stock returns is shown in the negative skewness. Kurtosis describes the probability distribution's tailenders. All Kurtosis values are positive, indicating that all series are leptokurtic, i.e., fat tails with high peaks that are heavily influenced by stock market bubbles.

Return and Volatility Spillover across Various Industries

Return and volatility spillover of Banks to other industries based on ARMA GARCH

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	0.000601	0.193333	7.36E-06	0.844632	0.10047	0.010125	0.98917

& parts							8
	(-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)

Financial Services, Equity Investment, Personal Goods, Oil and Gas Product, Automobile and Parts, Pharmaceuticals and Biotechnology, Nonlife Insurance, Food Products, and Industrial Engineering are all proven to have a strong beneficial influence when utilizing previous pricing behaviour. In basic terms, the reported industries have inefficient markets. The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Personal Goods, Oil & Gas Products, Financial Services, Equity Investment, and automobiles & Parts, the coefficient of θ_1 is large and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current period volatility cannot be forecasted using past price behaviour, and no lagged effect is found in the case of these industries because they are more volatile, it is significant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure.

The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity investment, financial services, Oil & Gas products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The mean spillover results show a significant positive impact on all industries, including equity investment, financial services, oil and gas products, personal goods, automobiles and parts, food products, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering, implying that there is a mean spillover from banks to other industries. Similarly, the results of volatility spillover reveal a significant beneficial influence on all of the same businesses, confirming that bank volatility quickly spreads to other sectors. These findings are consistent with Hamma et al.

(2014) but not with Jouini (2013). Except for consumer goods and banking industries, sectoral stock prices are not impacted by their lag prices in the near run.

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

Table 4.4: Return and Volatility Spillover from Equity Investment to Other Industries

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Eq. Invest.	-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. Service	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.	0.00015	0.09657	2.49E-05	0.81124	0.10582	0.00334	0.584844

Eng.	4	3		3	7	6	
	(0.5079			(0.0000)			
	)	(0.0000)	0		(0.0000)	-0.8102	-0.0049

Financial Services, Banks, Personal Goods, Oil and Gas Products, Automobiles and Parts, Pharmaceuticals and Biotechnology, Nonlife Insurance, Food Products, and Industrial Engineering mean returns may be forecast from previous price history. In basic terms, the following industries have inefficient markets. For all industries, the GARCH coefficient β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Personal Goods, Banks, Oil & Gas Products, Financial Services, and automobiles & Parts, the coefficient of θ_1 is large and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current period volatility cannot be forecasted using past price behaviour, and no lagged effect is found in the case of these industries because they are more volatile, it is significant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure.

The sum of θ_2 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The results of mean spillover show a significant positive impact on all industries, including banks, financial services, oil and gas products, personal goods, automobiles and parts, food products, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering, implying that equity investment has a mean spillover effect. Similarly, the results of volatility spillover reveal a significant positive influence on all of the same industries, confirming that equity investment volatility quickly spreads to other businesses. Overall, the empirics are consistent with the conclusions of Vardar et al. (2018), which reported similar evidence for the case of China and India.

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

Table 4.5: Return and Volatility Spillover from Financial Services to Other Industries

Sector	**α_0**	**α_1**	**β_0**	**β_1**	**Ω**	**θ_1**	**θ_2**
Fin.		0.15154		0.88429	0.08131	0.00692	
Ser.	0.000379	8	7.51E-06	2	2	7	0.9886
						(-	
	(-0.0641)	0	0	0	0	0.0008)	0

Eq.				0.90063	0.07437	0.00692	
Invest	-1.82E-05	-0.05539	8.10E-06	3	1	7	0.9886
		(-				(-	
	(-0.9293)	0.0001)	0	0	0	0.0008)	0
BANK		0.12732		0.86267		0.00570	0.99315
S	0.0005	9	5.95E-06	3	0.12642	9	4
	(-0.0044)	0	0	0	0	0	0
Oil &		0.11070		0.83323	0.12906	0.00570	0.99315
gas pro.	0.000767	2	1.15E-05	1	4	9	4
	(-0.0007)	0	0	0	0	0	0
Per.		0.08220		0.85012	0.04895	0.01012	0.98917
Goods	0.00014	1	1.22E-05	9	3	5	8
						(-	
	(-0.4701)	0	0	0	0	0.0001)	0
Auto. &		0.19333		0.84463		0.01012	0.98917
parts	0.000601	3	7.36E-06	2	0.10047	5	8
						(-	
	(-0.001)	0	0	0	0	0.0001)	0
food		0.03762		0.91235	0.05118	0.00334	0.58484
pro.	0.000401	7	4.33E-06	5	7	6	4
						(-	(-
	(-0.0061)	(0.0071)	0	0	0	0.8102)	0.0049)
Pharma.		0.10218		0.89261	0.05000		0.94725
& Bio.	4.16E-05	3	1.79E-05	1	3	-0.00061	3
						(-	
	(-0.8798)	0	0	0	0	0.7488)	0
Nonlife		0.04269		0.94089	0.08417		0.94725
Ins.	-0.00103	3	4.12E-07	7	7	-0.00061	3
		(-				(-	
	0	0.0008)	0	0	0	0.7488)	0
Indus.		0.09657		0.81124	0.10582	0.00334	0.58484
Eng.	0.000154	3	2.49E-05	3	7	6	4
						(-	(-
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	0.8102)	0.0049)

The mean returns of Equity Investment, Banks, Personal Goods, Oil and Gas Products, Automobile and Parts, Pharmaceuticals and Biotechnology, Nonlife Insurance, Food Products, and Industrial Engineering may be forecasted from previous price behaviour. In basic terms, the following industries have inefficient markets. The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Personal Goods, Banks, Equity Investment, Oil & Gas Product, and automobiles & Parts, the coefficient of β_1 is large and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current period volatility cannot be forecasted using past price behaviour, and no lagged effect is found in the case of these industries because they are more volatile, it is significant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors. The coefficient of β_2 is likewise significant and positive for all industries, indicating that volatility will endure.

Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. Mean spillover results demonstrate a largely beneficial influence across all industries, i.e., Banks, equity investment, oil and gas products, personal goods, automobiles and parts, food items, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering all have a mean spillover from financial services. Similarly, the results of volatility spillover demonstrate a significant beneficial influence on all of the same industries, confirming that financial services volatility quickly spreads to other businesses. The finding is similar to those in (Liu et al., 2017; Khalfaoui et al., 2015).

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

Table 4.6: Return and Volatility Spillover from Oil & Gas Products to Other Industries

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. 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
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.							0.94725
& Bio	4.16E-05	0.102183	1.79E-05	0.892611	0.050003	-0.00061	3
	(-0.8798)	0	0	0	0	(-0.7488)	0
Nonlife							0.94725
Ins.	-0.00103	0.042693	4.12E-07	0.940897	0.084177	-0.00061	3
	0	(-0.0008)	0	0	0	(-0.7488)	0
Indus.							0.58484
Eng.	0.000154	0.096573	2.49E-05	0.811243	0.105827	0.003346	4
							(-
	(-0.5079)	(0.0000)	0	(0.0000)	(0.0000)	(-0.8102)	0.0049)

Financial Services, Equity Investment, Banks, Personal Goods, Nonlife Insurance, Food Products, Product, Automobile and Parts, Pharmaceuticals and Biotechnology, and Industrial Engineering mean returns may be forecast from previous price behaviour. In basic terms, the following industries have inefficient markets. The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Personal Goods, Banks, Automobile & Parts Equity Investment, and Financial Services, the coefficient of β_1 is large and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current period volatility cannot be forecasted using past price behaviour, and no lagged effect is found in the case of these industries because they are more volatile, it is significant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors. The coefficient of β_2 is likewise significant and positive for all industries, indicating that volatility will endure.

The sum of β_1 and β_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The mean spillover results show a significant positive impact on all industries, including Banks, Equity Investment, Financial Services, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, implying that there is a mean spillover from Oil & Gas Products to other industries. Similarly, the results of volatility spillover demonstrate a significant beneficial influence on all of the same industries, confirming that oil and gas product volatility quickly spreads to other businesses similar to the findings of (Liu et al., 2017; Khalfaoui et al., 2015).

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

Table 4.7: Return and Volatility Spillover from Personal Goods to Other Industries

Sector	**α_0**	**α_1**	**β_0**	**β_1**	**Ω**	**θ_1**	**θ_2**
Per.		0.08220	1.22E-	0.85012	0.04895	0.01012	
Goods	0.00014	1	05	9	3	5	0.989178
	(-0.4701)	0	0	0	0	(-	0

						0.0001)	
Oil & gas.	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. 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
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)

Financial Services, Equity Investment, Banks, Oil & Gas Products, Automobile and Parts, Nonlife Insurance, Food Products Pharmaceuticals and Biotechnology, and Industrial Engineering mean returns may be forecast from previous price behaviour. In basic terms, the following industries have inefficient markets. The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Oil & Gas Products, Banks, Automobiles & Parts, Equity Investment, and Financial Services, the coefficient of θ_1 are large and positive, indicating that the current period's volatility may be predicted using previous price behaviour. While it is insignificant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current period volatility cannot be forecasted using past price behaviour, and no lagged effect is found in the case of these industries because they are more volatile, it is significant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure. The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The results of the mean spillover show a significant positive impact on all industries, including banks, equity investment, financial services, oil and gas products, automobiles and parts, food products, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering, implying that there is a mean spillover from personal goods to other industries. Similarly, the results of volatility spillover demonstrate a significant positive influence on all of the same industries, confirming that Personal Goods volatility quickly spreads to other businesses. The results are in line with (Khalfaoui et al., 2015).

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

Table 4.8: Return and Volatility Spillover from Automobile & Parts to Other Industries

Sector	α_0	α_1	β_0	β_1	Ω	θ_1	θ_2
Auto. &		0.19333				0.01012	0.98917
parts	0.000601	3	7.36E-06	0.844632	0.10047	5	8
						(-	
	(-0.001)	0	0	0	0	0.0001)	0
Per.		0.08220			0.04895	0.01012	0.98917
Goods	0.00014	1	1.22E-05	0.850129	3	5	8
						(-	
	(-0.4701)	0	0	0	0	0.0001)	0
Oil &		0.11070			0.12906	0.00570	0.99315
gas pro.	0.000767	2	1.15E-05	0.833231	4	9	4
	(-0.0007)	0	0	0	0	0	0
Fin.		0.15154			0.08131	0.00692	
Ser.	0.000379	8	7.51E-06	0.884292	2	7	0.9886
						(-	
	(-0.0641)	0	0	0	0	0.0008)	0
Eq.					0.07437	0.00692	
Invest	-1.82E-05	-0.05539	8.10E-06	0.900633	1	7	0.9886
	(-0.9293)	(-	0	0	0	(-	0

		0.0001)				0.0008)	
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. 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)

Financial Services, Equity Investment, Nonlife Insurance, Food Products, Pharmaceuticals and Biotechnology, Industrial Engineering Banks, Oil & Gas Products, and Personal Goods mean returns may be forecast from previous price behaviour. In basic terms, the following industries have inefficient markets. For all industries, the GARCH coefficient β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Oil & Gas Products, Banks, Equity Investment, Financial Services, and Personal Goods, the coefficient of θ_1 is substantial and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current period volatility cannot be forecasted using past price behaviour, and no lagged effect is found in the case of these industries because they are more volatile, it is significant in the Pharmaceuticals and Biotechnology, Industrial Engineering, Nonlife Insurance, and Food Product sectors. The coefficient of θ_1 is likewise significant and positive for all industries, indicating that volatility will endure. The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The results of mean spillover show a significant positive impact on all industries, including banks, equity investment, financial services, oil and gas products, personal goods, food products, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering, implying that there is a mean spillover from the automobile and parts industry to other industries. Similarly, the results of volatility spillover demonstrate a significant beneficial influence on all similar industries, confirming that the volatility of the automobile and parts industry swiftly spreads to other businesses. The results are in line with (Khalfaoui et al., 2015).

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

Table 4.9: Return and Volatility Spillover from Pharmaceuticals & Biotechnology to Other Industries

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. 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
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)

Financial Services, Equity Investment, Banks, Oil & Gas Products, Personal Goods, Nonlife Insurance, Food Products, Automobile & Parts, and Industrial Engineering mean returns may be forecast from previous price behaviour. In basic terms, the following industries have inefficient markets. For all industries, the GARCH coefficient β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services, and Personal Goods, the coefficient of θ_1 is substantial and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is minor for the Industrial Engineering, Nonlife Insurance, and Food Product sectors, which show that current-period volatility cannot be predicted using previous pricing behaviour, and no lagged effect is discovered in the case of these businesses since they are more unpredictable. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure. The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The results of mean spillover show that pharmaceuticals and biotechnology have a significant positive impact on all industries, including banks, equity investment, financial services, oil and gas products, personal goods, food products, automobiles and parts, non-life insurance, and industrial engineering, implying that there is a mean spillover from pharmaceuticals and biotechnology to other industries. Similarly, the results of volatility spillover demonstrate a negligible positive influence when compared to all other businesses, confirming that pharmaceutical and biotechnology volatility does not immediately spread to other industries. The findings of the study are in line with (Zhang and Chen, 2014; Khalfaoui et al., 2015; Liu et al., 2017)

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

Table 4.10: Return and Volatility Spillover from Food producers to Other Industries

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.	0.00014	0.08220	1.22E-05	0.85012	0.04895	0.01012	0.98917

Goods		1		9	3	5	8
	(-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. 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
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)

A mean equation constant is α_0. Financial Services, Equity Investment, Nonlife Insurance, Banks, Oil & Gas Products, Personal Goods, Automobile & Parts, and Pharmaceuticals & Biotechnology Industrial Engineering mean returns may be forecast from previous price behaviour. In basic terms, the following industries have inefficient markets. The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services, and Personal Goods, the coefficient of θ_1 is substantial and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant for the Industrial Engineering, Nonlife Insurance, and Pharmaceuticals & Biotechnology sectors, which show that current-period volatility cannot be forecasted using past price behaviour, and there is no lagged effect in the case of these industries because they are more volatile. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure. The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. The results of mean spillover show a significant positive impact on all industries, including banks, equity investment, financial services, oil and gas products, personal goods, pharmaceuticals and biotechnology, food products, automobiles and parts, non-life insurance, industrial engineering, implying that food products have a mean spillover effect. Similarly, the results of volatility spillover demonstrate a significant beneficial influence on all of the same industries, confirming that food product volatility quickly spreads to other businesses. The results are in line with (Zhang and Chen, 2014; Khalfaoui et al., 2015; Liu et al., 2017)

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

Table 4.11: Return and Volatility Spillover from Nonlife Insurance to Other Industries

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. 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
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)

Financial Services, Equity Investment, Food Products, Banks, Oil & Gas Products, Personal Goods, Automobile & Parts, and Pharmaceuticals & Biotechnology are all proven to have a strong beneficial influence when α_1 is used. Past pricing history may be used to forecast Industrial Engineering. In basic terms, the following industries have inefficient markets. The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks.

For Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services, and Personal Goods, the coefficient of θ_1 is substantial and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is insignificant for the Industrial Engineering, Food Producers, and Pharmaceuticals & Biotechnology sectors, which show that current-period volatility cannot be forecasted using past price behaviour, and there is no lagged effect in the case of these industries because they are more volatile. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure. The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. Mean spillover results demonstrate a largely beneficial influence across all industries, i.e., Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Pharmaceuticals & Biotechnology, Food Products, Automobile & Parts, and Industrial Engineering are among businesses where Nonlife Insurance spills over. Similarly, the results of volatility spillover demonstrate a significant beneficial influence on all of the same businesses, confirming that Nonlife Insurance volatility quickly spreads to other industries. These results are in line with (Hammoudeh and Aleisa, 2004; Diaz et al., 2016; Liu et al., 2017)

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

Table 4.12: Return and Volatility Spillover from Industrial Engineering to Other Industries

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. 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
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

Financial Services, Equity Investment, Banks, Oil & Gas Products, Food Products and Non-Life Insurance, Personal Goods, Automobile & Parts, and Pharmaceuticals & Biotechnology have all been found to have a significant positive impact, implying that the mean returns of Financial Services, Equity Investment, Banks, Oil & Gas Products, Food Products and Non-Life Insurance, Personal Goods, Automobile & Part In basic terms, the following industries have inefficient markets.

The variance equation constant is the GARCH coefficient β_0. For all industries, β_1 is significant, indicating the importance of predicted volatility in predicting mean returns. The coefficient of the standardized residual error term is significant for all industries, indicating that these markets account for the process of shock correction based on previous shocks. For Oil & Gas Products, Banks, Equity Investment, Automobile & Parts, Financial Services, and Personal Goods, the coefficient of 1 is substantial and positive, indicating that the current period's volatility may be predicted using prior price behaviour. While it is small for the Non-Life Insurance, Food Products, and Pharmaceuticals & Biotechnology sectors, which show that current-period volatility cannot be projected using previous pricing behaviour, and no delayed impact is seen in the case of these industries since they are more variable. The coefficient of θ_2 is likewise significant and positive for all industries, indicating that volatility will endure. The sum of θ_1 and θ_2 is closer to 1 for Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Automobile and Parts, Food Products, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering, indicating the nature of the persistence is in the long term. Mean spillover results show a significant positive impact on all industries, including Banks, Equity Investment, Financial Services, Oil & Gas Products, Personal Goods, Pharmaceuticals & Biotechnology, Food Products, Automobile & Parts, and Non-Life Insurance, implying that there is a mean spillover from Industrial Engineering to other industries. Similarly, the results of volatility spillover demonstrate a significant beneficial influence on all of the same industries, confirming that Industrial Engineering volatility quickly spreads to other businesses.

Time-Varying Conditional Correlation – DCC & ADCC

DCC MV - GARCH Models & Estimates among Industries

Table 4.13.1:

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

Suitable Univariate DCC models

The impact of previous residual shocks is (θ_1) and lagged dynamic conditional correlation is (θ_2). (p-values). The initial criterion of the DCC model is to verify the stability condition, which must be less than one, for example ($\theta_1 + \theta_1 < 1$). All of the industries included in this study met the requisite stability criteria. It follows that the DCC model must be employed to assess time-varying conditional correlation.

The mean and volatility spillover shows a significant positive impact on all industries, such as in 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. On the other hand, the impact of previous residual shocks (θ_1) is significant for all industries except four, namely food products, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering. In these industries, the impact of past residual shocks (θ_1) is insignificant, implying that they are more volatile. (θ_2) has a large beneficial effect across all industries. Almost all of PSX's 10 sectors have return and volatility spillover. All of the sectors' coefficients of volatility and return spillover are positive and substantial, indicating that the returns of one sector are boosted by the returns of others. As a result, it may be concluded that the 10 sectors studied are interconnected, i.e., if one business changes, the change rapidly spreads to the others. All industries are producing major outcomes and having a ripple effect. Return and volatility spillover occur across sectors, and they can readily be passed from one to the other as a result of crises or a variety of other economic causes. All of the important model stability and modifications show that correlation is not continuous, hence the DCC-GARCH model is highly recommended. DCC and ADCC models will not be used in businesses where there is no temporal variation for correlation. As a result, investors should seek sectors that are negatively linked and have a correlation of less than one for diversification. Investors should avoid investing in more volatile industries. Only sectors with lower volatility can help investors diversify their portfolios and receive additional rewards.

Conclusion

The prime goal of this research is to examine the return and volatility spillover across several industrial sectors on the Pakistan Stock Exchange (PSX). This research uses ten sectors for this aim. The GARCH model was used to track the movement of various sectors from 2002 to 2020, including banking, equity investment, financial services, oil and gas products, personal goods, automobiles and parts, food producers, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering. All 10 sectors of the PSX have return and volatility spillover. All of the coefficients of volatility and return spillover are positive and significant, indicating that the returns of one sector are boosted by the returns of others.

As a result, it is clear that the selected industries are interconnected, i.e., if one industry changes, the change readily spreads to the other industries. All industries are producing major outcomes and having a ripple effect. The mean and volatility spillover show a significant positive impact on all industries in the banking sector, equity investment, financial services, oil and gas products, personal goods, automobiles and parts, food producers, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering, indicating that there is return and volatility spillover from one sector to another. The impact of past residual shocks (θ_1) is significant (positively correlated) for all industries except four, namely Food Producers, Pharmaceuticals and Biotechnology, Non-Life Insurance, and Industrial Engineering. The impact of past residual shocks (θ_1) is insignificant in these four industries, indicating that they are more volatile sectors of the Pakistan Equity Market. Food producers, pharmaceuticals and biotechnology, non-life insurance, and industrial engineering all provide diversification options since the connection is insignificant (negatively correlated), i.e., larger than 1. Return and volatility spillovers, on the other hand, are evident across industries.

Based on the comparative findings the research objective is testified and confirmed that return and volatility spillover exist among various sectors, and they may readily be passed from one to the other as a result of crises or other economic circumstances. Second, the application of the GARCH model is covered in this research. The correlation between variables varies throughout time. The Dynamic Condition Correlation (DCC) model is used for this, while Asymmetric Dynamic Conditional Correlation is used to assess asymmetric behaviour (ADCC). These models have both beneficial and bad repercussions for the industry. All of the important model stability and modifications show that correlation is not continuous, hence the DCC-GARCH model is highly recommended. DCC and ADCC models will not be used in businesses where there is no temporal variation for correlation. The DCC and ADCC models show that as time passes, the correlation becomes time variable, and businesses grow intertwined. DCC and ADCC models will not be used in businesses where there is no temporal variation for correlation. The DCC and ADCC models show that as time passes, the correlation becomes time variable, and businesses grow intertwined. As a result, investors should seek sectors that are negatively linked and have a correlation of less than one for diversification. Investors should avoid investing in more volatile industries. Only sectors with lower volatility can help investors diversify their portfolios and receive additional rewards. The association among assets of local sectors is shown to be dependent on static estimations in this study. This research focused on understanding the dynamics of market integration in Pakistan.

The study's findings might be used by investors, portfolio managers, and financial institutions that profit from diversity in Pakistan's diverse industries. The findings will aid them in assessing each sector's recent performance and forecasting future changes in the present sector as well as all other related sectors. They can also assess sectors based on their sensitivity to spillover from other sectors and make investment decisions based on proper risk management measures. Healthy investment decisions, in turn, boost the country's economic growth.

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